DEFINING PHM, A LEXICAL EVOLUTION OF MAINTENANCE AND LOGISTICS

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Abstract - Prognostics and Health Management (PHM) is an approach to system life-cycle support that seeks to reduce/eliminate inspections and time-based maintenance through accurate monitoring, incipient fault detection, and prediction of impending faults. Coupled with Autonomic Logistics for unprecedented responsiveness, cost effectiveness, and mission availability, PHM is largely automated in its application. Incorporating the principles of Condition-Based Maintenance (CBM) along with the tenets of Reliability-Centered Maintenance (RCM), the PHM paradigm extends these capabilities and provides a robust environment to optimize maintenance and logistics for increased operational availability (A_O), and reduced Life-Cycle Costs (LCC) while potentially increasing the reliability and life expectancy of mechanical, structural, and electronic systems. Driven by a demand for greater reliability at reduced cost and fueled by technological advancements, the PHM contribution to an already robust and confounding vocabulary surrounding maintenance and logistics is significant. As adopters of PHM technology attempt to define requirements and performance parameters, difficulties encountered with various non-standardized terminology indicate that the PHM vocabulary merits a lexical review. This paper will provide a compendium of PHM terminology along with definitions and examples, derived from the authors' experience in the implementation of PHM systems. Coalescing existing vocabularies and introducing, formally, the new lexicon of maintenance and logistics, the authors seek to aid in clarification of the emerging dialogue of life-cycle support.

INTRODUCTION

The world of automated test and diagnosis, along with weapons systems acquisition, logistics, and command & control interests, face an evolving atmosphere of optimism and hope for improved electronic system lifecycle management and increased weapon system reliability enabled by emerging failure prediction capabilities. Fundamental research into incipient fault detection, physics of failure modeling, and fault to failure progression for power electronics and control; radio frequency (RF) systems, and digital logic circuits, has formed an emerging science of electronic prognostics showing success and promise for feasible application in realms once considered impractical for real world deployment. Driven by ever increasing operations and support (O&S) costs, a growing dependence on commercial of the shelf (COTS) electronic hardware, and rising weapon system complexity, along with the predominant role of electronic systems as crucial and integral weapon system components, degradation assessment and remaining useful life prediction are tools demanded by the department of defense to fulfill decision support roles ranging from repair and maintenance to logistics and mission planning.

The total impact of electronic system failure prediction capabilities on the automated test community remains to be determined. The near term effects will require test and measurement (verification and validation) of the performance of prognostic systems. A broader, long term, implication will result in a transformation of electronic systems support from a reactive, on condition, approach to an integrated, condition-based philosophy of maintenance and sustainment of weapon systems. A deployed capability to predict failure of systems, possibly resulting in early removal of components, without an evolution of current automated test systems and the philosophies of maintenance and logistics, may result in a scenario of increased can not duplicate (CND), no trouble found (NTF), and retest OK (RTOK); a situation already plaguing an overburdened support system. In order to prepare for an eventual transition to a sustainment paradigm encompassing prognostics and health management (PHM) to enable condition-based maintenance (CBM) of electronic systems, a common lexicon, enabling more effective communication of ideas, requirements, and performance parameters must emerge. We present here, a compendium of terminology and associated definitions that have found utility in PHM for mechanical, structural, and propulsion technologies and suggest that electronic system PHM can utilize this vocabulary well.

ENCOMPASSING PHILOSOPHY

PHM, CBM, and condition monitoring are broad concepts and terms that encompass a philosophical shift in maintenance, logistics, and mission planning from a preventative/reactive paradigm to a monitor, schedule, and optimize approach to asset management. Seeking to extend useful life, reduce unplanned maintenance events, and optimize availability and sustainment while reducing total lifecycle costs, the condition-based approach utilized within the PHM paradigm provides a powerful tool integrating maintenance, logistics, and operational planning through better decision support.

Prognostics and Health Management (PHM) – A health management approach utilizing measurements, models, and software to perform incipient fault detection, condition assessment, and failure progression prediction. The capability allows end users to improve fault isolation, better plan maintenance, reduce or eliminate inspections, and decrease time-based maintenance intervals with confidence. When coupled with Autonomic or Performance-based Logistics, PHM enables improved mission-critical system reliability and availability, reduced logistics delay time and tail, on-demand repair actions and sparing, as well as an overall decrease in life cycle costs.

Condition-based Maintenance (CBM) – A philosophy of maintaining equipment based on an estimation of its condition and maintenance logistics. Optimal application of CBM is through the prediction (prognosis) of the equipment remaining useful life. CBM may or may not require human processing.

Condition Monitoring – The application of the appropriate sensors (data), analysis (knowledge), and reasoning (context) to estimate the health and track the degradation of equipment. Usually assumes human-in-the-loop processing.

Condition monitoring capability is largely inherent in modern electronic systems, although its design intent is not PHM. Built-in test (BIT) and automated test systems (ATS) typically report functional failure, by design, rather than incipient fault detection, permitting removal and repair of components on condition (failed). These mechanisms utilize measurement and test data and result in binary outcomes (e.g. pass/fail) or discrete measurements. Early studies have demonstrated that much of the measurement and test data generated during normal operations and maintenance can be utilized, along with other techniques, for incipient fault detection and failure prediction when combined with data logging and advanced reasoning. This fact, relaxing the requirement for additional sensors, makes electronic systems attractive for the application of prognostics. This leaves open the questions, “Who will use the capability?” and “What will be the resultant outcome?” Additional terminology is needed to aid the formulation of the answers.

ESSENTIAL TERMINOLOGY

Incipient Fault – The earliest stage of a condition change, when it is just beginning to come into being or become apparent, that will ultimately progress to functional failure.

Detect – Recognize that a monitored or modeled parameter(s) has departed its normal operating envelope or passed a threshold. Usually automated and tied to an alert or fault code.

Diagnosis – The Oxford American Dictionary defines diagnosis as “a statement of the nature of the disease or other condition made after observing its signs and symptoms”. In our application domain, the disease is an evolving failure in the equipment and the observation of signs and symptoms is accomplished by test, measurement, and reasoning on the results. A working definition, beginning with the verb, "diagnose," is stated as:

Diagnose – Identify, localize, and determine the severity of an evolving fault condition.

-or-

Identify and estimate the changes in gray scale health.

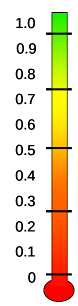
A diagnosis is the resultant conclusion.

Prognosis – Reliably and accurately forecast the remaining useful life (defined later) or risk to complete a planned mission. Track and trend the progression in gray-scale health and produce an RUL based on a predescribed HI threshold. Uncertainty bounds or confidence intervals should be applied and accompany the prediction.

ACTIONABLE INFORMATION

The goal of applied PHM technology is to provide decision support. Therefore, the final form of the output from a PHM system, driven by the context of the user, is actionable information that supports improved decision making. A maintenance organization might utilize a greater fault isolation capability to reduce ambiguity during fault diagnosis. While performing a repair, a capability to opportunistically enact repairs that might otherwise be overlooked, yet represent significant costs if delayed, can significantly improve operational availability (A_O) by reducing mean time to repair (MTTR) or decrease support costs by preventing cascading failures. A logistician may utilize updated reliability estimates, provided a PHM system, to ensure that spares are fielded in the most optimal forward deployment to support faster MTTR through reduced mean logistics delay time (MLDT). PHM technology supports command and control by enabling better asset management and mission planning for optimal asset utilization. These enhanced decision support arenas employ software systems requiring similar data from PHM systems, but operating on that data in an application specific manner. A unifying theme, mapping one variable to multiple possible actions is a gray-scale health index.

Gray-scale Health Index – A gray-scale health index is a continuous variable in the range from 1 to 0. The index indicates component or system health/performance state from new, fully operable, undamaged condition (1.0) to complete functional failure (0.0). Most correctly accompanied by +/- uncertainty bounds or provided as a range under a stated confidence interval, a gray-scale health index permits the mapping of relevant equipment functionality to actionable information or mission capability at the operations, maintenance, and logistics levels (Figure 1). The index is produced by algorithms that assess the equipment performance or health via measured symptoms, modeled data, and/or usage-based predictions. The use of a gray-scale HI lends itself to prognosis as one could predict the time to reach a specific threshold of health to estimate RUL or the next actionable information step.



Operational Capability	Maintenance Action	Logistics Action
Fully Functional	No Maintenance Required	No Logistics Changes
Functional with Degraded Performance	Maintenance at Convenience	Trigger Opportunistic Logistics Sparing
Reduced Functionality	Schedule Maintenance Now	On-Demand Logistics Sparing
Functionality Severely Impinged	Remove from Service ASAP	Logistics Emergency Sparing
No Functionality	Remove from Service Now	Logistics reflect unit out of service

Figure 1 - PHM output must yield actionable information

An example gray-scale health index with bounds and confidence:

Power Supply Health = 0.8 +/- 0.1 with a 95% confidence level

The mean or expected value is 0.8; the uncertainty is symmetric and 0.1. The statistical confidence that the actual health will fall within this range is 95%.

An example gray-scale health index without defined bounds.

Power Supply Health = 0.7 to 0.9 with a 95% confidence level

Similar to above, but one could not necessarily assume the distribution of likely values to be symmetric or the mean to be in the middle.

SUPPORTING DEFINITIONS

The computation of a gray-scale health index utilizes basic output from a PHM enabled system, along with application domain relevant data, such as mission profile, mean logistics delay, mean time to repair, and other variables unique to the end user. The central output from a PHM system is remaining useful life (RUL).

Remaining Useful Life (RUL) – RUL is typically a time, cycle, or mission-based expression, correctly accompanied by uncertainty bounds. Similarly, RUL may be a range of values, correctly accompanied by a confidence interval. The RUL is a prediction of a component or system functional/operational usage expectancy based on measured, detected, modeled, and/or predicted health state. The RUL is dependent on the intended set of operating conditions or mission to be performed.

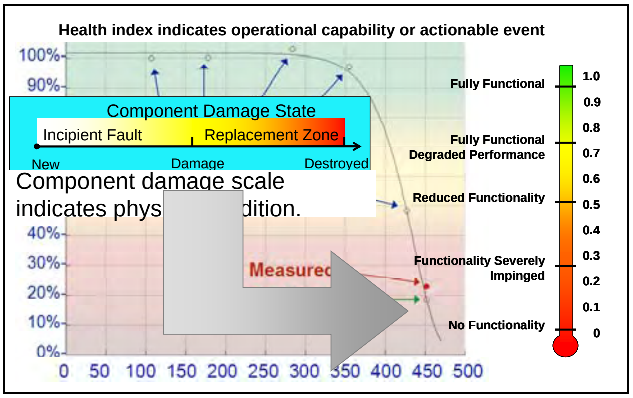


Figure 2 - Mapping damage state feature vector to gray-scale health index

To be truly useful, a remaining useful life estimate must come with an assessment of the quality of the prediction. Quantification of the ability to detect, isolate, and assess anomalous behavior and its implications to the system health is expressed in probabilistic terms.

Uncertainty Bounds – Uncertainty bounds are a numerical expression in base units or in percentage form that encompasses a range of likely values. It represents the precision of the estimate being made. Values for the uncertainty bounds in a prediction is accomplished by empirical engineering judgment or more robustly by using a statistical confidence interval.

Confidence Level and Interval – A percentage or fractional representation that provides a probability that a set of values should appear within the designated range or interval. The confidence level can be chosen by the user and a range of values produced or the interval can be fixed and a confidence level percentage is calculated. The confidence level is typically stated in terms of a multiple of the estimated population variance when symmetrical distributions are used (e.g., 95% confidence equals 2*variance for a normal distribution).

OTHER USEFUL TERMINOLOGY

The following terms are useful for determining and measuring the effectiveness of a PHM system.

Failure Trajectory – Failure trajectory is an evolutionary path in the State Space along which a particular failure mode progresses from "normal" operation to the end of useful life (Figure 3). Most systems have multiple failure modes, and each of these may have a unique trajectory. Initial knowledge of the typical path of a failure trajectory, derived from reliability estimates, provides a baseline estimate of anticipated component life. PHM techniques seek to track and update the actual failure trajectory of the monitored systems failure modes. Detection of anomalous behavior, usage, or updated population baselines permits real-time health state tracking and reliability updating.

Critical Detection Horizon (CDH) – CDH is the time required by an operator to conveniently and/or safely take the required action for a particular failure trajectory before end of useful life is reached.

In order to be effective, a PHM system must detect changes indicative of an assets evolving condition in time to classify the anomaly root cause and provide decision support. Detection, isolation, and root cause indictment at the time of functional failure is a diagnosis. Detection and isolation in the incipient fault stage, when enough time remains to provide advice to mitigate a failure or its effects is a prognosis, when accompanied by an RUL estimate within a confidence bound that lies within the critical prediction horizon.

Critical Prediction Horizon (CPH) – CPH is defined as the sum of the Critical Detection Horizon and the time required to refine the projection of Remaining Useful Life to a sufficient confidence for the application.

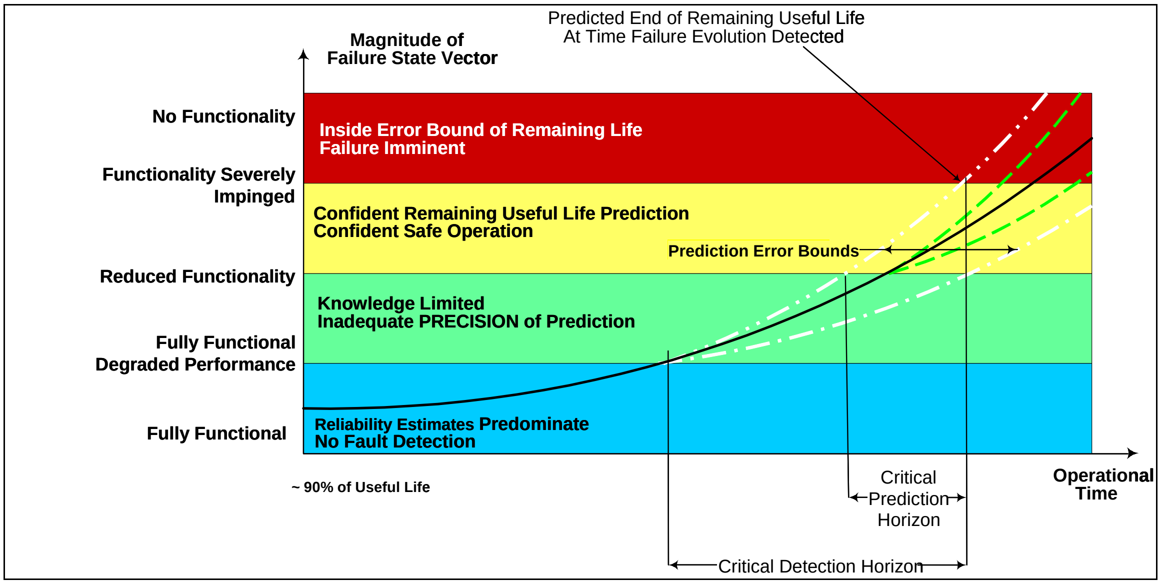


Figure 3 - Failure trajectory concept

Note that the plot illustrated in Figure 3, begins near the end of the monitored system useful life. Prior to detection and classification of anomalous behavior or recognition of extraordinary usage, prediction, beyond initial reliability, is not considered possible or even useful to the operator. Failure of equipment, including electronics, is a non-linear dynamic process. Only during the evolution of a specific failure mode, do the failure mode dynamics dominate the system.

CONCLUSIONS

The sciences and technologies of failure detection and prediction have made significant strides enabling PHM and offering significant potential benefit to the operation and support of weapon systems. Emerging capabilities supporting prognostic and health management for electronic systems support a paradigm shift in maintenance from a reactive, on-condition (failure) approach to one incorporating prediction of functional failure, enabling better planning and subsequently boost operational availability and reduced life-cycle costs. Understanding the lexicon of a technology is key to effectively utilizing and shaping the implementation of that technology. The automated test community should be prepared to utilize the improved fault isolation and advanced support concepts afforded by increased insight into asset health enabled by PHM. Moreover, the test and measurement community will be integral to the development, integration, validation and verification, and ultimately the maintenance of PHM systems. “If they are going to built it, we will need to test it.”, William Birurakis, Comments AutoTestCon, 2005

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