

## ABSTRACT

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AND HEALTH MANAGEMENT FOR  
ELECTRONIC SYSTEMS

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An assessment has been undertaken to identify the state-of-practice for prognostics and health management of electronics. Based on a review of the prognostic approaches, case studies, publications, and the extent of intellectual property of numerous organizations, I identified the companies, universities, and government branches that are currently researching, developing, and/or implementing prognostics for their products and systems. Next, I developed a sensor selection process such that an optimal sensor system can be chosen prior to in-situ life cycle monitoring of electronic products and systems. I developed a questionnaire that can be used to understand the monitoring requirements of a particular PHM application, and identified criteria that one needs to consider in the sensor selection process in order to make the relevant tradeoffs. Finally, I provided guidelines on sensor selection to help a user validate their final selection. The process was demonstrated for two circuit card assemblies inside an avionics unit.

IMPLEMENTATION OF PROGNOSTICS AND HEALTH MANAGEMENT FOR  
ELECTRONIC SYSTEMS

By

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## Dedication

This thesis is dedicated to my family, who taught me never to give up.

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# Chapter 1: Introduction

## *1.0 Prognostics and Health Management (PHM)*

Prognostics and health management (PHM) is the process of estimating a product's remaining life based on current and historic conditions in terms that are useful to the maintenance decision-making process and the improvement of product design and reliability. PHM permits the reliability of a product to be assessed and predicted in its actual application conditions. If one can measure the life cycle conditions of a product in-situ, this data can be used to 1) provide advanced warning of failures; 2) minimize unscheduled maintenance, extend maintenance cycles, and maintain effectiveness through timely repair actions; 3) reduce life cycle cost of the product by decreasing inspection costs, downtime, and inventory; and 4) assist in the design and logistical support of fielded and future products [1].

## *1.1 Literature Review*

The concept of PHM is not entirely new. In fact, PHM methods have been used to estimate equipment life in applications such as nuclear power plant equipment [2], actuators [3][4], engines [5][6], gearboxes [7], and other mechanical structures [8]-[10], and there is extensive literature available for these types of applications. The possibility of applying PHM to electronic products and systems has become more real in recent years, as evidenced by the increasing amount of literature published in both refereed journals and conference proceedings.

There are three general methods for conducting prognostics and health management of electronic products and systems. The methods have been categorized by Vichare, *et al.*, [1] as: (1) monitoring of precursors to failure, (2) using canary devices (structures that have equivalent circuitry but are calibrated to fail at a faster rate than the actual product), and (3) modeling accumulated damage based on physics-of-failure and in-situ monitoring of the environmental and operational conditions experienced by the product.

#### 1.1.1 Monitoring of Precursors to Failure

Monitoring of precursors to failure is a method in which sensors are attached to the electronic product to monitor and analyze parameters (e.g., performance and defects) that are indicative of impending failure. Since there are numerous different failure mechanisms in electronic devices, it follows that there are a lot of possible precursors to failure and it is even possible for one failure mechanism to have multiple precursors.

Born, *et al.*, [11] conducted a study to investigate the feasibility of detecting incipient failures of several electronic parts by measuring changes in critical parameters that can be correlated with subsequent failures. Methods for monitoring failure precursors were identified for switching power supplies, cables and connectors, CMOS integrated circuits, and voltage-controlled oscillators. In switching power supplies, for example, deterioration of rectifier I-V characteristics were found to be a primary indicator of device degradation leading to eventual failure. High temperature coupled with forward current stressing causes a decrease in the reverse breakdown voltage and an increase in the reverse leakage current.

Vinnakota [12] demonstrated that dynamic power dissipation can be used as a precursor to failure of CMOS circuits. When a fault alters a circuit's functionality, it changes the way internal signals respond to input transitions. As a result, the energy consumption and power dissipation of a circuit are modified by a fault. Both logic-level and transistor-level faults in CMOS circuits, which do not change static dissipation, change the dynamic power dissipation. In many cases, a fault also alters the shape of the Fourier spectrum of the power supply current. This permits detection in the frequency domain.

Zhang, *et al.*, [13] introduced a prognostic approach for predicting the remaining useful life of electronic assemblies using resistance of solder joint interconnects as a precursor to intermittent failure. The test board used to demonstrate their approach consisted of complete electronic components, but with special test silicon die, each independently daisy-chained to facilitate resistance monitoring during testing. Using the in-situ measurements of daisy-chain resistances, their prognostic algorithm predicted the onset of failure for all components on the test board.

Kanniche, *et al.*, [14] developed an algorithm that combines discrete wavelet transform (DWT) and fuzzy logic to detect and identify transistor open-circuit faults and intermittent misfiring faults of pulse width modulation voltage source inverters. Current waveforms were monitored and continuously analyzed using DWT to identify faults that may occur due to constant stress, voltage swings, rapid speed variations, frequent stop/start-ups, and constant overloads. After fault detection, "if-then" fuzzy rules were used for fault diagnosis to pinpoint the fault device. The

algorithm was demonstrated to detect certain intermittent faults under laboratory experimental conditions.

Urmanov, *et al.*, [15][16] have developed a failure precursor approach for early fault detection and prediction of computing servers. Multiple variables such as temperature, voltage, and current are monitored in-situ by sensors distributed throughout the server. After the data is collected from sensors, it is processed by online pattern recognition algorithms, such as Multivariate State Estimation Technique (MSET) and Sequential Probability Ratio Test (SPRT), to look for signal degradation that is usually a primary indicator of failure for most types of mechanisms that cause failures in servers. During its training phase, MSET learns the signal correlations and can then produce a model from which the value of any signal at time  $t$  can be estimated. A signal from a component that is degrading over time will be easy to detect through a disagreement between the MSET estimate and actual value of a signal [17].

Hughes, *et al.*, [18] proposed new algorithms for the SMART (Self Monitoring and Reporting Technology) failure prediction system, which is currently implemented in hard disk drives (HDD). SMART uses failure precursor algorithms to detect anomalies in HDD by monitoring operating parameters, including the flying height of the head, error counts, variations in spin time, temperature, and data transfer rates [19]. Experimental data was collected from drive design reliability testing of two different Quantum Corporation disk drive models. The accuracy of the existing “SMART” failure warning algorithm in drives was compared with the improved

algorithm. The improved algorithm gave 3-4 times higher correct prediction accuracy than error thresholds on will-fail drives, at 0.2% false alarm rate.

Lall, *et al.*, [20]-[22] also demonstrated a methodology for PHM of electronics using damage precursors for assessment of product damage. In this study, several package elements were investigated including, first-level interconnects, dielectrics, chip interconnects, underfills, and semiconductors. Phase growth rate and interfacial shear stress at the chip interface were identified as damage precursors. A mathematical relationship was developed between phase growth rate and time-to-1% failure. The relationship was used to provide an assessment of life consumed based on phase growth rate and a forward-estimate of residual life.

#### 1.1.2 Using Canary Devices

Using canary devices is another method in which structures are installed in the electronic product and are calibrated to fail at a higher rate than the actual product when subjected to the life cycle conditions. Calibration of the failure rate is typically accomplished through scaling. Scaling is a technique whereby the canary circuit is weakened by reducing the area of the current carrying path so that the current density is increased. As the current density increases, the internal heating of the canary circuit is increased, resulting in increased stress. Over time, the increase in stress causes the canary circuit to fail, thereby providing an advanced warning of failure for the actual electronic product.

Mishra, *et al.*, [23] studied the use of a pre-calibrated semiconductor cell (canary) that is co-located with the actual circuit on a semiconductor device. Major semiconductor failure mechanisms that can be monitored using pre-calibrated cells

include time-dependent dielectric breakdown, electromigration, and hot-carrier aging, and radiation damage. These prognostic cells are used along with a software algorithm to calculate the accumulated damage of the actual circuit. By providing early failure prediction, the prognostic cells can help in scheduling maintenance at the proper time.

Anderson, *et al.*, [24] studied the use of canaries for predicting failures of components at the board-level. In this study, the canary circuits were used to assess two different failure mechanisms, including low cycle fatigue of interconnects and corrosion. The test device for corrosion included electrical circuitry that was susceptible to various corrosion-induced mechanisms. Impedance spectroscopy was proposed for identifying changes in the circuits by measuring the magnitude and phase angle of impedance as a function of frequency.

Goodman, *et al.*, [25] designed a prognostic chip to monitor the time dependent dielectric breakdown (TDDB) of MOSFET transistors. The self-stressing integrated MOSFETs that are monitored by the prognostic chip act as the TDDB aging sensors for the host application. The monitored MOS transistors are identical to those used in the host IC, to insure that the extracted data accurately represents the condition of the key components of the host IC. Since TDDB breakdown is caused by oxide charge trapping, acceleration of the breakdown of an oxide can be achieved by applying a voltage higher than the supply voltage, to increase the electric field across the oxide. When the test monitor device fails, a certain fraction of the circuit lifetime has been used up. The fraction of useful circuit life that has been used up is

dependent on the amount of over-voltage applied and can be estimated from the known distribution of failure times.

### 1.1.3 Modeling Accumulated Damage

Modeling accumulated damage based on physics-of-failure and in-situ monitoring of the environmental and operational conditions involves the collection of actual life cycle loads that can be used in conjunction with damage models to assess the degradation due to cumulative load exposures. Life cycle loads are the conditions that a product is exposed to throughout its lifetime. The typical phases of a product's life cycle include manufacturing, storage, handling, operating and non-operating conditions. There are many different types of loads that can cause damage to an electronic product throughout its life cycle. Some examples include temperature, humidity, vibration and shock, solar radiation, electromagnetic radiation, pressure, chemicals, sand, and dust. To model the accumulated damage from a combined loading, one or more sensors are attached to the electronic product to measure the loads which pose the highest risk to the reliability of the product.

Searls, *et al.*, [26] conducted a health and usage monitoring study on desktop and notebook computers. Temperature was monitored in-situ on the heat sink, inside the case, and outside the case, during various usage environments. Each sample's temperature profile was analyzed for number of temperature changes. This study gave an indication of the number of temperature cycling a system typically sees as a function of the temperature cycle's magnitude.

Vichare, *et al.*, [27] also demonstrated health and usage monitoring for a notebook computer. Processing of the raw sensor data during in-situ monitoring was



presented as an effective method to reduce the on-board memory requirements and power consumption of the sensor. Vichare, *et al.*, also presented a method for load parameter extraction prior to input for damage models, which enables data reduction and simplification without losing the relevant load information.

Ramakrishnan, *et al.*, [28] developed a methodology based on virtual reliability assessment for estimating the remaining life of electronic products. This prognostic approach, called Life Consumption Monitoring (LCM), combines in-situ measured loads with physics-based stress and damage models for assessing the life consumed.

Several case studies have been presented to demonstrate the LCM methodology. Shetty, *et al.*, [29] applied the LCM methodology for conducting a remaining life assessment of the end effector electronics unit (EEEU) inside the robotic arm of the space shuttle remote manipulator system (SMRS). In this study, a life cycle loading profile for thermal and vibrational loads was created for the EEEU boards. Using physics-based mechanical and thermo-mechanical damage models, a damage assessment was conducted. Using a combination of damage models, inspection, and accelerated testing, a remaining life estimate showed that there was little degradation in the electronics and they could be expected to last another twenty years.

Mishra, *et al.*, [30] applied the LCM methodology to an electronic component-board assembly placed under the hood of an automobile and subjected the assembly to normal driving conditions. In this study, the test board included eight surface-mount leadless inductors soldered onto an FR-4 substrate using eutectic tin-

lead solder. The dominant failure mechanism was identified as solder joint fatigue. Temperature and vibrations were measured in-situ on the board in the application environment. Using this monitored environmental data, stress and damage models were developed and used to estimate the consumed life.

Mathew, *et al.*, [31] applied the LCM methodology in conducting a prognostic remaining life assessment of circuit cards inside a space shuttle solid rocket booster (SRB). In this study, vibration time history recorded on the SRB from the pre-launch stage through splashdown was used as input for physics-based models to assess the damage caused due to vibration and shock loads. Using the life cycle profile of the SRBs, the remaining life of the components and structures on the circuit cards were predicted. It was determined that an electrical failure was not expected within another forty missions.

Simons, *et al.*, [32] performed a physics-based prognostic assessment for a gull-wing lead power supply chip on a DC/DC voltage converter PCB assembly. Three-dimensional finite element analyses were performed to determine macro-strains in the solder joint due to thermal or mechanical cycling of the component. The macro-strains were used to set boundary conditions for a probabilistic micro-model to explicitly simulate initiation and growth of cracks in the microstructure of the solder joint. Based on the growth rate of the cracks in the solder joint, estimates of the cycles to failure for the electronic component were made.

Nasser, *et al.*, [33] demonstrated the feasibility for using conventional sensing, combined with thermal modeling, to predict solder degradation due to thermal cycling as a means to predict electronic power supply system reliability. Nasser, *et al.*,

proposed that the material damage accumulated in the power supply was essentially a function of the initial state (manufactured state which has processing variability) and the usage state (flight and operational loadings). This project simulated the flying of two separate aircraft, one that flew a less aggressive mission profile and another one that flew a more aggressive mission profile. The probability of component failure was predicted for each mission up to the 9000<sup>th</sup> flight for both aircraft.

Bounds [34] proposed a method for determining fatigue life consumption based on measured environmental and operational loads for tactical wheeled vehicles. The procedure for fatigue life consumption consisted of three steps: (1) calculate component loading using sensor and vehicle bus data in algorithms based on instrumented testing and dynamic simulation; (2) estimate strain time history using algorithms based on fatigue models; and (3) perform peak-valley editing, rainflow cycle counting and fatigue life estimate using estimated strain data.

Gu, *et al.*, [35] developed a methodology for monitoring, recording, and analyzing the life cycle vibration loads for remaining life prognostics of electronics. Strain gauges were used to monitor the response of printed circuit boards (PCB) to vibration loading in terms of bending curvature. Strain values at the interconnects were then calculated from the measured PCB response and used in a vibration failure fatigue model for damage assessment. Damage was accumulated linearly using Miner's rule and a remaining life estimate was made. The methodology was demonstrated for remaining life prognostics of a test board. The prognostic results were validated against actual time-to-failure data using resistance measurements.

Tuchband, *et al.*, [36] presented the use of prognostics for a military line replaceable unit (LRU) based on measured life cycle loads. This study demonstrated the integration of wireless monitoring devices, remaining life prognostics, and web-enabled databases for enabling cost-effective maintenance and replacement of parts. The web-enabled database was used to provide an effective means for maintaining a history of LRU use, tracking degradation of the LRU, and enabling a user to decide whether to keep the LRU in service and continue monitoring or to remove the system for maintenance.

## 1.2 *Objectives of Thesis*

Based on the literature review, there are numerous studies that have been conducted on the application of PHM to electronic products and systems, including space shuttle electronics, power supplies, inverters, computer servers, semiconductors, transistors, desktop/notebook computers, vehicles, and line replaceable units. To date, there has been few attempted studies to identify the state-of-practice in prognostics and health management of electronics. Furthermore, studies which used modeling of damage accumulation based on measured life cycle loads have not included a procedure on how to select an optimal sensor system for in-situ life cycle monitoring of electronic products.

The broad objective of this thesis is to determine the state-of-practice of PHM for electronics. Three specific research areas have been identified: i) Identify the organizations that are currently researching, developing, and/or implementing PHM for electronics; ii) Determine the core challenges for prognostics research that currently exist; and iii) Develop and demonstrate a sensor selection process for PHM

implementation, which can be integrated into the life consumption monitoring methodology.

### *1.3 Overview of Thesis*

The state-of-practice for PHM of electronics is presented in Chapter 2. A sensor selection process for integration with the life consumption monitoring methodology is presented in Chapter 3. In Chapter 4, the sensor selection process is demonstrated for electronics inside an avionics unit. The contributions of this research are listed in Chapter 5.

## Chapter 2: Assessment of State-of-Practice for PHM of Electronics

### *2.0 Introduction*

This chapter presents an assessment of research and development on prognostics and health management in industry, government, and academia. Research and development on PHM is currently broken up into two general categories: (1) sensor systems and sensor technologies for in-situ life cycle monitoring, and (2) prognostic models and algorithms for remaining life prediction. Due to the shrinking size and increasing portability of electronic devices, it is becoming more of a challenge to use traditional sensors, which are often bulky in size and require wired data transmission, to monitor their environment. Therefore, new wireless, miniature sensor systems are being developed by industry specifically for in-situ monitoring of electronic products and systems. At the same time, research on various types of models and algorithms is being conducted by industry to provide a prognostic capability for their electronic products and systems.

It is intended that the state-of-practice in PHM of electronics be used by industry, government, and academia to identify the critical investment opportunities that currently exist for R&D so that funding and other resources are strategically used to advance the state-of-practice.

## *2.1 PHM State-of-Practice Assessment*

The assessment of the state-of-practice for PHM is based on a review of the prognostic approaches, implementation case studies, technical publications, and the extent of intellectual property of numerous organizations. The assessment includes companies in the commercial and defense industries, organizations within the federal government, and universities.

In order to conduct the state-of-practice assessment, I wrote a summary for each of the organizations based on information that was publicly available. This includes e-mails, presentations, websites, and articles from both journals and conference proceedings. After writing a summary for a particular organization, I sent it to the key contacts at that organization and asked them to review and/or modify the summary. Finally, after receiving the updated summary from the organization, I verified any new information that was added.

However, since the field of PHM is evolving ever-rapidly, the results of this assessment may not cover every single organization involved in PHM. Furthermore, this assessment represents the information that I have collected as of May 2007.

The first objective of the assessment was to identify those organizations that are currently researching, developing, and/or implementing PHM in electronic products and systems, and to identify which methods or approaches are being employed to enable PHM of electronics. In particular, the assessment looked at two main attributes of an organization: (1) the PHM methods; and (2) the applications where PHM is being used.

The PHM methods refer to the specific models and algorithms that the organization is utilizing to detect and predict impending failures of their products and systems. The applications refer to the products and systems that an organization is applying PHM methods towards.

The results of the assessment are shown below in Table 1, Table 2, and Table 3. The first column shows the organizations that are currently involved in PHM research and development. The second column shows the specific divisions of each organization that was assessed. The third column shows the PHM methods that each organization is using. The last column reveals the specific applications (products and systems).

Table 1. PHM state-of-practice assessment results - industry

<b>Companies</b>	<b>Divisions</b>	<b>PHM Methods</b>	<b>Applications</b>
ARINC	All business units	Proprietary	Airplane landing gears [37]
BAE Systems	Advanced Technology Center	Uses the changes in vibration characteristics and engine speed as failure precursors	Aircraft engines [38][39]
The Boeing Company	Commercial Airplanes, Integrated Defense Systems	Uses a database of past trends and outcomes, real-time acquisition of flight data, and built-in decision support tools	Fighter jets, helicopters, commercial airplanes, composites, aircraft wiring [40]-[42]
European Aeronautic Defence and Space Company	Airbus, Eurocopter	Uses life consumption monitoring by measuring engine data in-situ and combining it with physics-based damage models	Aircraft engines [43]-[45]
Emerson	Astec Power	Uses I <sup>2</sup> C bus to continuously monitor voltage, current, and temperature and disables output when internal temperature exceeds safe operating range	AC/DC power supplies [46]



<b>Companies</b>	<b>Divisions</b>	<b>PHM Methods</b>	<b>Applications</b>
Expert Microsystems	All business units	Compares historical sensor readings with current sensor readings to estimate expected values of observed parameters, which are used to determine a pattern of agreement or disagreement with the normal state of equipment	Computer integrated manufacturing, power plants, hazardous gas control systems [47]-[49]
General Dynamics	Advanced Information Systems, Development and Integration Systems	Uses motion of the engine blade tip as failure precursor	Military vehicles, gas-turbine engine blades, aircraft wiring [50]
GMA Industries	All business units	Uses embedded, molecular-sized, self-diagnosing integrated circuits, which measure voltage, current, and other electrical parameters, to provide visual indication of impending failure	Avionics circuit boards [51]-[53]
Honeywell	Aerospace, Automation and Control Systems	Uses regression trending of engine performance data to provide early warning of impending failure	Jet engines, drive trains, gearboxes, helicopters, airplanes, spacecraft [54]-[56]
Impact Technologies	All business units	Uses life consumption monitoring by combining sensed parameters, which correlate with failure progression, with physics-based damage models	Avionics, GPS systems, switch-mode power supplies, flight control actuators, gas turbine engine bearings [57]-[59]
Intelligent Automation Inc.	All business units	Uses the combination of Fast Fourier Transform, Principal Component Analysis, and Fuzzy Cerebellar Model Arithmetic Computer to detect circuit anomalies in real-time	Gearboxes, liquid propellant engines, unmanned aerial vehicles, satellite communications [60]
Lockheed Martin	Aircraft & Logistics Centers, Integrated Systems & Solutions	Proprietary	JSF aircraft, radar systems, flight control actuators [61]-[63]
Northrop Grumman	Newport News (Aircraft Carrier Systems), Integrated Systems, Electronic Systems	Proprietary	JSF aircraft, legacy aircraft, helicopter transmissions, shipyard facility diesel engines, spacecraft [64]-[66]

<b>Companies</b>	<b>Divisions</b>	<b>PHM Methods</b>	<b>Applications</b>
Raytheon	Integrated Defense Systems, Missile Systems, Space and Airborne Systems, Network Centric Systems	Proprietary	Radars, missiles, satellites, processors, fire control systems, infrared systems, communication systems [67]
Ridgetop Group	All business units	Uses canary cells that are pre-calibrated and co-located with the host circuit on an IC to act as early warning sentinels of upcoming device failure	Power converters (MOSFETS), semiconductors [68][69]
Rockwell	Rockwell Automation, Rockwell Collins (Defense Systems and Commercial Systems)	Uses vibration monitoring of rotors, infrared thermography, and oil data collection and analysis; Uses canary cells mounted on host product to provide early warning of failures due to low cycle fatigue of solder joints and corrosion	Rotors, oil, motors [70][71]
Scientific Monitoring	All business units	Uses physics-based damage models combined with neural networks and reasoning algorithms to detect and forecast impending failures	Engines, motion control and fluid power systems, aircraft, industrial equipment [72]-[74]
Sentient	All business units	Uses physics-based damage models for predicting the remaining useful life of bearings and other components that fail due to contact fatigue	Bearings, rotating machinery [75]
SmartSignal	All business units	Compares real-time data collected from equipment with a model of the expected values and uses the residuals to detect early possible signs of equipment malfunction	Industrial equipment [76][77]
Smiths Aerospace	Electronic Systems, Mechanical Systems	Uses combination of Singular Value Decomposition, Principal Components Analysis, and Neural Networks for non-linear multivariate analysis and anomaly detection	Aircraft subsystems including avionics, helicopters subsystems including rotors, engines, transmissions, gearboxes [78]-[80]

<b>Companies</b>	<b>Divisions</b>	<b>PHM Methods</b>	<b>Applications</b>
Sun Microsystems	San Diego Physical Sciences Research Center	Compares real-time sensor data collected from servers with a model (Multivariate State Estimation Technique ) of the expected values and uses a Statistical Probability Ratio Test to monitor the residuals to detect early possible signs of equipment malfunction	Enterprise computing servers, software [81]-[83]
VEXTEC	All business units	Uses physics-based damage models for predicting the remaining useful life of electronic boards by evaluating fatigue failures at the interconnects	JSF aircraft, power supplies [84]-[86]

Table 2. PHM state-of-practice assessment results – government

<b>Government</b>	<b>Divisions</b>	<b>PHM Methods</b>	<b>Applications</b>
National Aeronautics and Space Administration	Ames Research Center (Intelligent Systems Division)	Uses fault detection algorithms such as Gaussian Mixture Models, Hidden Markov Models, Kalman Filtering, and Virtual Sensors to characterize nominal behavior in order to detect off-nominal situations	Spacecraft, actuators, aircraft wiring insulation, power converters, batteries [87]-[89]
Sandia National Laboratories	Optimization and Uncertainty Estimation Department, PHM Center of Excellence	Proprietary	Gearboxes [90]
U.S. Air Force	Air Force Research Laboratory	Proprietary	Aircraft flight control actuators [91]

<b>Government</b>	<b>Divisions</b>	<b>PHM Methods</b>	<b>Applications</b>
U.S. Army	Army Logistics Integration Agency, Army Materiel Command Army Research Office, Army Materiel Systems Analysis Activity, Army Research Laboratory Vehicle Technology Directorate / NASA Glenn Research Center	Uses Artificial Neural Networks, rule-based algorithms, and predictive trend analyses to diagnose and predict failures	Composite structures, bridges, weapon systems, tanks, gas turbine engines, aircraft, helicopters [92]-[95]
U.S. Navy	Naval Surface Warfare Center, Naval Air Systems Command	Compares sensor data collected from equipment to established engineering performance criteria to assess whether actual performance violates specified limit	Propulsion systems, power-drive systems, aircraft, submarines, nuclear aircraft carriers [96][97]

Table 3. PHM state-of-practice assessment results – academia

<b>Universities</b>	<b>Divisions</b>	<b>PHM Methods</b>	<b>Applications</b>
Auburn University	Mechanical Engineering Department	Uses physics-based damage models combined with failure precursor data	Various electronics, MEMS [98]-[100]
Georgia Institute of Technology	Intelligent Control Systems Laboratory	Uses fuzzy logic and wavelet neural network algorithms for fault diagnosis and remaining useful life prediction	Space station thermal control systems, textiles, ships, rotorcraft, gearboxes, oil coolers, engine disks/blades, automotive electrical systems, unmanned aerial vehicles [101][102]
Pennsylvania State University	Applied Research Laboratory	Uses multiple sensors combined with artificial intelligence and neural networks to identify faults in electromechanical systems	Rotating components, weapons systems, machinery networks [103][104]

<b>Universities</b>	<b>Divisions</b>	<b>PHM Methods</b>	<b>Applications</b>
University of California at Los Angeles	Nondestructive Evaluation Research Group	Uses acoustic emission and modal data to calculate the frequency response function from which damage correlation indices are developed and compared to measurements from undamaged structures	Beams, plates, composites [105]
University of Maryland	Center for Advanced Life Cycle Engineering	Uses life consumption monitoring by combining monitored parameters with physics-based damage models to compute damage accumulation and estimate remaining life; Uses IDDQ trending as a failure precursor; Uses Mahalanobis Distance and Principal Component Analysis to identify deviation from expected normal state of equipment	Space shuttle electronics, autonomous robotic ground vehicles, avionics, power converters (MOSFETs, IGBTs), notebook/desktop computers, various electronics [1]
University of Tennessee	Nuclear Engineering Department	Uses Bayesian methods, Neural Networks, non-linear Partial Least Squares, Auto-Associative Kernel Regression, and Multivariate State Estimation Technique	Motor-operated valves, steam generators, heat exchangers, nuclear power plants [106]-[108]
University of North Carolina	Center for Logistics and Digital Strategy	Uses data mining tools to identify the relationship between anomaly occurrences and external historical conditions in order to predict the likelihood of another occurrence of the anomaly	Aircraft [109]
Vanderbilt University	Institute for Software Integrated Systems	Uses forward propagation signatures (Taylor's series expansion) to predict future behavior of measurement variables in response to a fault	Aerospace [110]

In general, I found that all three approaches to prognostics, as identified by Vichare et al. [1], are currently being used in industry. BAE Systems uses the changes in vibration characteristics and engine speed as *failure precursors* of aircraft engines [38][39]. Ridgetop Group uses *canary cells* that are pre-calibrated and co-located with the host circuit on an IC to act as early warning sentinels of upcoming device failure [68][69]. Impact Technologies uses *life consumption monitoring* by combining sensed parameters, which correlate with failure progression, with physics-based damage models for predicting failures in avionics, GPS systems, and power supplies [57]-[59].

However, I found that some organizations are currently exploring other techniques for prognostics that are beyond the approaches identified by Vichare et al. [1]. Smiths Aerospace uses the combination of Singular Value Decomposition, Principal Components Analysis, and Neural Networks for non-linear multivariate analysis and anomaly detection in aircraft and rotorcraft subsystems [78]-[80]. NASA Ames Research Center uses fault detection algorithms such as Gaussian Mixture Models, Hidden Markov Models, Kalman Filtering, and Virtual Sensors to characterize nominal behavior in order to detect off-nominal situations in spacecraft [87]-[89]. Vanderbilt University uses forward propagation signatures (Taylor's series expansion) to predict future behavior of measurement variables in response to a fault in aerospace systems [110].

In regard to the applications, many of them are shared by multiple companies in industry. Common applications include both mechanical/structural systems (i.e., aircraft/rotorcraft engines, gearboxes, actuators) and electronic systems (avionics,

power converters, wiring). Next, if we look at the state-of-practice in government, application of PHM to aircraft subassemblies appears to be a common theme among all the government organizations. Finally, if we look at the state-of-practice in academia, the applications for PHM are really spread out across the board, ranging from composite structures to notebook/desktop computers to space station thermal control systems.

In general, industry is not currently developing hybrid approaches that combine physics-of-failure based prognostics with data-driven prognostics. Another area of prognostics that is currently lacking in industry is a method to assess the return on investment (ROI) for PHM.

## *2.2 Core R&D Challenges for PHM of Electronics*

The second objective of this assessment was to identify the core research and development (R&D) challenges that currently exist in the field of PHM, so that recommendations can be made on where funding and other resources may be directed to help promote the state of research. From this assessment, several challenges have been identified. They include assessing uncertainty in remaining useful life prediction, detection of intermittent failures, in-situ monitoring of life cycle data, assessing the return-on-investment of PHM, defining thresholds for abnormal system performance, building physics-based damage models for electronics, and integration of PHM with legacy electronic systems.

### 2.2.1 Assessing Uncertainty in Remaining Useful Life Prediction

The uncertainty of a measurement is stated by giving a range of values which are likely to enclose the true value. Uncertainty analysis is required when implementing prognostics for electronics because an understanding of the uncertainty enables the prediction to be more realistic. By using uncertainty analysis, a prediction can be given as a distribution rather than a single point estimate, and the prediction can incorporate a failure probability. However, there are several challenges to implement the uncertainty into prognostics.

The first challenge for uncertainty assessment is to identify the source of uncertainty. There are many different sources for uncertainty and it is difficult to collect all the information one needs for proper identification. Some sources of uncertainty that have been identified include measurement uncertainty, parameter uncertainty, failure criteria uncertainty and future usage uncertainty. However, many electronic component datasheets, especially for legacy components, do not include variations on their specifications, which is needed to quantify parameter uncertainty. It is also difficult to determine which uncertainty source(s) contribute the most to the final uncertainty prediction. This information is necessary because computational limitations place restrictions on the ability to monitor only the critical parameters as input to uncertainty computations.

Another challenge for uncertainty assessment is the lack of models to assess the uncertainty quantitatively. Although some methods for uncertainty assessment using physics-based damage models have been developed [120], data-driven methods have not been strongly investigated, and little research has addressed such uncertainty



analysis. Training data is required in order to describe the healthy state of a system, and the quantity and quality of this data effects the uncertainty involved in predictions. Therefore, more consideration needs to be given to the effect of the training data in uncertainty calculations.

Finally, the third challenge for uncertain assessment is that it's difficult to make maintenance and logistics-related decisions based on predictions when the uncertainty range is wide. Unfortunately, this is often the case for the physics-of-failure (PoF) based approach to prognostics because the uncertainty will accumulate along with the damage accumulation [120]. For example, if the final prediction result indicates that the product will fail between 10 and 100 hours, how does one make a decision for when to schedule maintenance? One possible solution is to identify the just-in-time (JIT) point to optimize the prediction and help with the decision-making process. Engel [121] proposed selecting the 5% risk failure probability point as the JIT point. This point is primarily chosen based on the tradeoff between risk and maintenance cost-savings. The challenge is to decide on the usefulness of the uncertainty calculations and more importantly on how to make a decision based on them.

One possible way to reduce the uncertainty is to narrow down the root or source of the uncertainty. For example, increasing the sensor measurements, improving the manufacturing process, and improving the damage models are all helpful ways to reduce uncertainty in remaining life calculations.

### 2.2.2 Detection of Intermittent Failures

Intermittent failures are those failures that cannot be verified, replicated at will, or attributed to a specific failure site, mode and mechanism. Various terms are used to report this kind of failure, including cannot duplicate (CND), no fault indicated (NFI), no fault found (NFF), no trouble found (NTF), and re-test OK (RTOK). Between 40 to 85 percent of all the observed field failures in avionics are CND. This accounts for more than 90 percent of all the maintenance costs [114].

Intermittent failures occur when an electronic system that was observed to fail in the field is later found to function properly during fault detection testing [114]. This is due to the transient behavior of the failure that remains undiscovered until field testing [116]. One possible reason for this behavior may be insufficient test duration. The impact of intermittent failures is that it is not possible to determine the root cause of the failure. This can lead to an increase in warranty costs for a manufacturer.

One of the most frequent causes of intermittent failures and other abnormal electronic system behavior is corrosion in the junctions of the signal-carrying connectors. This is an especially insidious problem because inspection of these connectors can temporarily wipe away corrosion during the process of unmating and remating the connectors [117].

Currently, precursors to intermittent failures are not well understood. The damage caused by load conditions may sometimes be unpredictable using the existing physics-based damage models [114]. There might be sharp spikes in the response of failure precursors to loads. This intermittent or transient change in behavior might

sometimes be seen as a precursor to failure making the identification of actual precursor to failure difficult. Further research is needed to identify precursors of intermittent failures in electronics and develop a physics-based damage model for these kinds of systems to make the application of PHM for intermittent failures possible.

### 2.2.3 In-situ Monitoring of Life Cycle Data

One of the challenges of in-situ monitoring for electronics is to identify the life cycle parameters that need to be monitored to provide useful data for prognostics. Electronic systems often contain a large number of components and each component may have several measurable performance parameters. Thus, there are a large number of potential failure sources. Furthermore, different components have very complex performance correlations in electronics products. This makes it difficult to monitor an electronic system at the component level. The challenge is to identify the life cycle parameters to monitor that best represent the entire system.

Another challenge of in-situ monitoring of life cycle data results from limitations in sensor system technology. During PHM implementation, continuous monitoring of life cycle loads is needed so that critical data is not missed. To enable continuous monitoring, however, the sensor system either needs to transmit the collected data to a base station in real-time, or contain an onboard memory that is large enough to store all the data for a period of time. If the memory capacity is not large enough, data simplification algorithms can be utilized to compress the size of the data onboard. However, onboard processors with embedded computational ability

consume a substantial amount of power and may significantly reduce battery life of the sensor system.

A third challenge is that there is limited space available on printed circuit boards to mount sensor systems. For new electronic systems, the monitoring and detection strategies can be considered early in the design process so that the circuit board layout takes into consideration space for mounting sensor systems. However, for legacy electronic systems, which are already in production, sensor attachment is a challenge. In many cases, the space on the circuit board is smaller than the size of the sensor system. Furthermore, the effect of sensors on the reliability of the monitored electronic system is still not very clear. The presence of sensor systems can change the performance characteristics of the host system.

Finally, in order to implement PHM, a user usually needs to be able to analyze multiple parameters at the same time. The challenge is collecting data from different variables and fusing the information together into a single timeline of events.

#### 2.2.4 Assessing the Return-on-Investment of PHM

PHM of electronics can provide useful information such as the estimation of remaining useful system life. However, additional information is often necessary to form a decision or to determine a corrective action [111]. One aspect of the decision-making process is the determination of when it makes good business sense to schedule a corrective action. This process, called return-on-investment (ROI), is an analysis of the savings associated with the planned implementation, less the entire cost of the implementation, divided by the investment required [112][113]. ROI can also be expressed as:

$$ROI = (Savings - Implementation Costs) / (Investment Required)$$

One of the challenges of determining the ROI in PHM of electronics is that it is difficult to construct a business case to show the usefulness of PHM approaches for electronic systems. Part of the reason for this is because research and development into PHM of electronics is immature. Although a significant amount of progress has been made recently in the fundamental PHM technologies and methodologies, there have been very few real case studies to help transform the scientific development to practical application. Existing PHM approaches for electronic systems will need to be validated and verified before an evaluation of their usefulness can be made. An example of when it doesn't make good business sense to use PHM in electronic systems is "use and throw" products. Consumer electronics, including cell phones, MP3 players, digital cameras, and camcorders, all fall into this category. Within this category, the replacement cost of a part that has failed is comparable to the cost of a new product. Thus, the application of prognostics to these types of electronics is neither practical nor makes good business sense.

Another challenge of determining ROI in PHM of electronics is that it is difficult to quantify the benefits of PHM results. Standard measures of performance, often called metrics, need to be well-defined in order to assess and justify the ROI. For example, possible metrics for PHM of electronics may include the number of man-hours saved as a result of reduced maintenance actions, the cost savings as a result of reduced maintenance actions, the number of lives saved, and/or the number of system failures avoided. Nonetheless, PHM metrics should be such that they

clearly indicate the positive or negative effects of implementing prognostics in electronic systems on total life cycle costs.

Finally, a balance of the implementation costs associated with PHM versus the cost avoidances associated with PHM needs to be assessed in order to determine the ROI. The investment in a PHM system should not cost more than the return on the investment. This may seem trivial but in order to make this balance, the actual costs associated with each side need to be identified. A list of possible implementation costs and cost avoidances associated with PHM are provided in Table 4 [111].

Table 4. Implementation costs and cost avoidances associated with PHM

<b>Implementation costs associated with PHM</b>	<b>Cost avoidances associated with PHM</b>
<ul style="list-style-type: none"> <li>• Development costs (e.g., hardware, software, and integration)</li> </ul>	<ul style="list-style-type: none"> <li>• Failures avoided (e.g., minimizing unscheduled maintenance, increasing availability, reduced risk of system loss and increased safety)</li> </ul>
<ul style="list-style-type: none"> <li>• Product manufacturing recurring costs (e.g., hardware, testing and installation)</li> </ul>	<ul style="list-style-type: none"> <li>• Minimizing the loss of remaining life</li> </ul>
<ul style="list-style-type: none"> <li>• Infrastructure costs (e.g., documentation, training and changing the logistics/maintenance culture)</li> </ul>	<ul style="list-style-type: none"> <li>• Reduction in logistics footprint of the system (e.g., better spares management, minimization of external test equipment)</li> </ul>
<ul style="list-style-type: none"> <li>• Sustainment costs (e.g., data collection, data archiving, logistics footprint of the PHM structures and the cost of false positives)</li> </ul>	<ul style="list-style-type: none"> <li>• Reduction in repair costs (e.g., better fault isolation, reduced collateral damage during repair)</li> </ul>
<ul style="list-style-type: none"> <li>• Financial costs (e.g., cost of money)</li> </ul>	<ul style="list-style-type: none"> <li>• Reduction in redundancy</li> </ul>
	<ul style="list-style-type: none"> <li>• Reduction in no-fault-founds</li> </ul>
	<ul style="list-style-type: none"> <li>• Reduced waste stream costs</li> </ul>
	<ul style="list-style-type: none"> <li>• Reduced liability</li> </ul>
	<ul style="list-style-type: none"> <li>• Eases design and qualification of future systems</li> </ul>

### 2.2.5 Defining Thresholds for Abnormal System Performance

Electronic systems contain numerous components that are highly interactive and can influence the performance of one other. A small change in performance in one parameter can result in changes in other parameters, making it difficult to establish hard thresholds on each parameter. Defined thresholds for abnormal system performance that do not take into consideration the interaction between multiple parameters may lead to incorrect decisions for PHM, and problematic components may go undetected. This underlines the importance to study and understand the cross component interaction. However, since different types of components can have a range of specifications within different environmental and operating settings, studying their interactions becomes a challenge.

Furthermore, electronic systems may encounter many different environmental and operational conditions during their life cycle. One threshold limit might not be sufficient to capture the variability of system parameters in different usage scenarios. Several different threshold limits might be needed to capture the variability. Therefore, establishing a baseline for normal system performance is difficult for electronic systems.

To be able to define thresholds for use in prognostics, it is essential to understand the performance and life cycle profile for each component in different environmental and usages conditions. However, it is difficult to simulate all scenarios and determine the end of useful life for each component separately. The complexity of the system and its usage under different environmental conditions underlines the difficulty in defining a threshold limits for prognostics.

## 2.2.6 Building Physics-Based Damage Models for Electronics

Failure mechanisms are the processes by which specific combinations of physical, electrical, chemical and mechanical stresses induce failure [116]. Failure mechanisms are determined based on combinations of potential failure modes and causes of failure [118], as well as the selection of appropriate available mechanisms corresponding to the failure mode and cause. Failure mechanisms are typically categorized as being either overstress or wearout mechanisms. Overstress failure mechanisms are those that arise because of a single load (stress) condition. Wearout failure mechanisms, on the other hand, involve a failure that arises as a result of cumulative load (stress) conditions.

One of the challenges in using the physics-of-failure based approach to reliability assessment is that failure mechanisms may be limited by the availability and accuracy of models for quantifying the time to failure of the system. It may also be limited by the ability to combine the results of multiple failure models for a single failure site and the ability to combine results of the same model for multiple stress conditions [119]. If no failure models are available, the appropriate parameters to monitor has to be selected based on an empirical model developed from prior field failure data or models derived from accelerated testing.

## 2.2.7 Integration of PHM with Legacy Electronic Systems

One of the challenges for implementing PHM in electronic systems is the integration into legacy systems. A legacy system is a system that continues to be used because of the prohibitive time and/or cost of replacing or redesigning it, and often despite its poor competitiveness and compatibility with modern equivalents.



Existing infrastructure is not always set up to provide prognostics analysis with the necessary data input. In legacy electronic systems such as old aircraft avionics, the modes and mechanisms of failure are potentially ill-documented, untested or unknown. In addition, the lack of expertise in the specific applications of the legacy systems leads to immature and ineffective prognostic modeling in PHM algorithms for such systems.

Another challenge for PHM integration with legacy systems is the difficulty in combining various technologies in a manner that is compatible. A PHM system can consist of sensors, electronics, computers, and software, which most likely are commercial-off-the-shelf (COTS) products. These COTS products often have specific requirements about the operating environment, input parameters, and usage conditions. A PHM system needs to first overcome integration roadblocks with its own sub-systems before it can be integrated with electronic products.

### 2.3 *Conclusions*

The current driver of PHM R&D appears to be the increasing usage of electronics in military vehicles and weapon systems. Development of health management systems for aircraft/rotorcraft, weapons, electronic power supplies, and computer systems represent the majority of PHM-related research in industry and government at this time. Development of prognostic algorithms for detecting deviation from normal performance of electronic systems represents the majority of PHM-related research in universities and research institutions.

The toughest challenges that currently exist for PHM R&D are assessing the uncertainty in remaining life predictions and detecting intermittent failures in

electronics. Therefore, it is recommended that organizations direct their R&D funding towards these opportunities to get the most value for their money.

In addition to challenges for R&D, there exists yet another barrier to PHM implementation which cannot be overcome through research. This is called the psychological barrier. Prognostics is often referred to by skeptics as the “scientific crystal ball”. There is due to the widespread belief that electronic failures are not predictable because they happen randomly. Case studies that demonstrate accurate prognostics for real system applications are the only way to effectively dispel this myth. Data produced by these experiments will be used to generate a more definitive set of correlations linking environmental and operational stresses to resulting degradation rates and failure prognostics.

Another psychological issue that remains as a barrier to PHM implementation is going against the “status quo”. People tend to want to keep things the way they presently are, until a newer way of doing things becomes more commonplace. Again, a greater number of case studies that bring out the benefits of prognostics are needed in order to change the mindset of people.

## Chapter 3: Sensor Selection for PHM of Electronics

### *3.0 Introduction*

The ability to design a product for prognostics and health management implementation can enable cost-effective maintenance and reduce the life cycle cost by decreasing inspection, downtime, and inventory costs. One type of prediction for remaining life is made by modeling the accumulated damage due to measured environmental and usage exposure. However, for new products, it is not a priori known which loads need to be monitored. As a result, the selection of sensor systems for in-situ life cycle monitoring is not a simple task.

In prognostics and health management, sensor systems are the devices which collect information about a product's environment or operational state, and store or communicate that information to a computer or human for health assessment.

In this chapter, a new process for sensor selection is presented as an improvement to life consumption monitoring of electronic products and systems. The new process includes guidelines on the selection of an appropriate sensor system for PHM using several criteria. Using these guidelines, the process enables a user to make the necessary tradeoffs for selecting a sensor system for a particular PHM application.

### 3.1 Background

A method to enable PHM for electronic products was proposed by Ramkrishnan and Pecht, 2003 [28]. This method, referred to as life consumption monitoring (LCM), is a process that combines a study of the different failure modes and mechanisms of the product under consideration, monitoring of relevant environmental and/or operational parameters, and use of physics-of-failure models to assess the damage and ultimately predict remaining life. For application of this approach to electronic assembly, Mishra *et al.*, 2002 [30] and Ramakrishnan and Pecht, 2003 [28] monitored the temperature, humidity, vibration and shock loads experienced by an electronic assembly operated in automotive under-hood environments. This monitored data was applied in conjunction with physics-of-failure models to estimate damage and predict remaining life. The PHM methodology was shown to accurately predict remaining life in the application environment.

The LCM approach consists of three main steps: monitoring, signal processing, and condition assessment. However, one of the major drawbacks of this approach is that there is no procedure or guidelines for the selection of sensor systems for life cycle monitoring. In my work, I have focused in on the monitoring step to enable prognostics and health management of a new product by providing guidelines on sensor selection using several criteria.

### *3.2 Overview of Sensor Selection Process*

The sensor selection process is a new process step that improves the LCM methodology (see Figure 1). Like the original methodology, this approach utilizes failure modes, mechanisms, and effects analysis and virtual reliability assessment to identify the critical failure sites and failure mechanisms of the product, however, before monitoring the appropriate parameters, a questionnaire supplemented with guidelines are used to select the appropriate sensor system for life cycle monitoring. The next few sections will discuss in detail the sensor selection process.

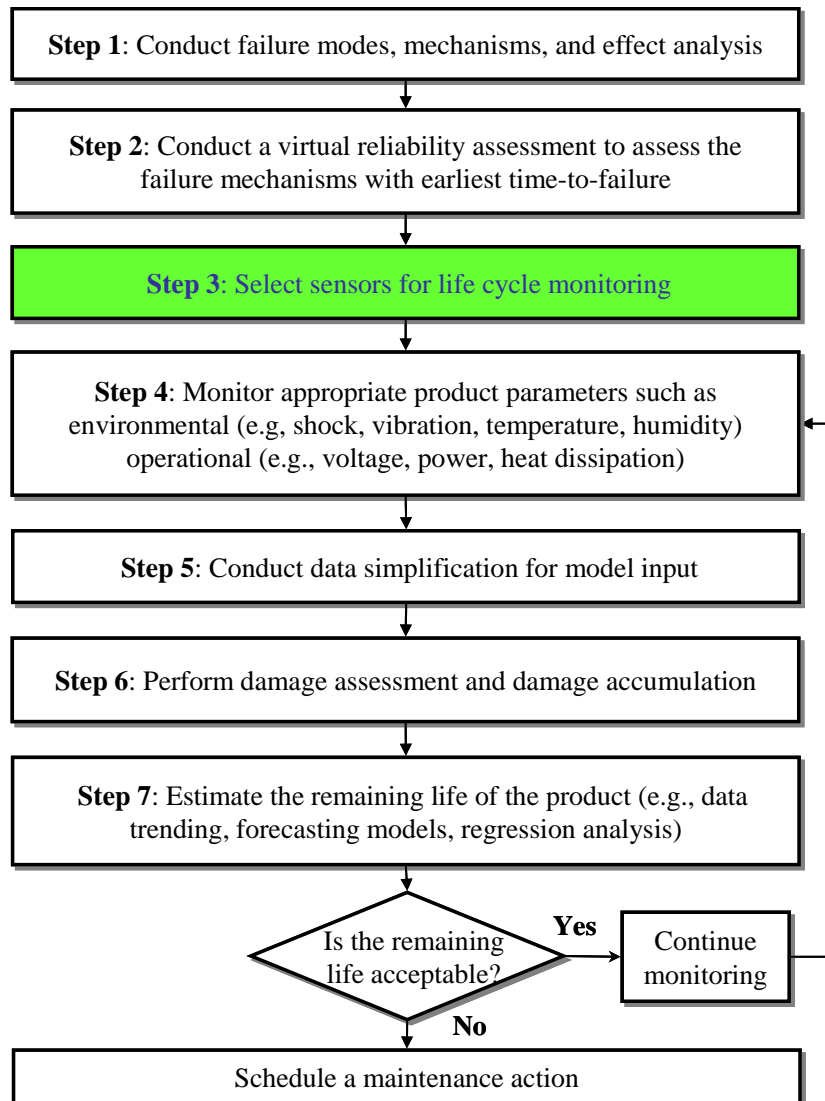


Figure 1. Improved LCM methodology with sensor selection process

### 3.3 Questionnaire for Sensor Selection

In order to provide guidelines on sensor selection for PHM of electronics, the specific application needs to be broken down. A list of questions can be used to determine the needs of the application and from this, the sensor selection criteria and relevant tradeoffs can be assessed to enable a user to select the appropriate sensor.

The following questions can be used to breakdown an application for sensor selection:

Table 5. Questionnaire for Sensor Selection

<p><b>1. What is the expected environmental/operational range for monitoring?</b></p> <ul style="list-style-type: none"> <li>a. Temperature</li> <li>b. Vibration/Shock</li> <li>c. Humidity</li> <li>d. Radiation</li> <li>e. Pressure</li> <li>f. Strain</li> <li>g. Current</li> <li>h. Voltage</li> </ul>
<p><b>2. What is the desired size, weight, and form factor for the sensor system?</b></p> <ul style="list-style-type: none"> <li>a. Size (length, width, height)</li> <li>b. Weight (including batteries, if necessary)</li> <li>c. Form factor (round, rectangular)</li> </ul>
<p><b>3. How does the sensor system need to be attached to the host product?</b></p> <ul style="list-style-type: none"> <li>a. Glue</li> <li>b. Adhesive tape</li> <li>c. Velcro</li> <li>d. Magnet</li> <li>e. Screws</li> <li>f. Embedded in component</li> </ul>
<p><b>4. How will the sensor system be powered?</b></p> <ul style="list-style-type: none"> <li>a. Powered by host product</li> <li>b. Powered by battery</li> <li>c. Powered by environment (vibration, solar)</li> </ul>
<p><b>5. What type of power management is needed for the sensor system?</b></p> <ul style="list-style-type: none"> <li>a. Auto on/off</li> <li>b. Sleep/wake modes</li> <li>c. Programmable threshold monitoring</li> <li>d. None required</li> </ul>
<p><b>6. How long does the product need to be monitored for?</b></p> <ul style="list-style-type: none"> <li>a. Days</li> <li>b. Weeks</li> <li>c. Months</li> <li>d. Years</li> </ul>

<p><b>7. How often will the data be collected?</b></p> <ul style="list-style-type: none"> <li>a. Slower than 1 Hz</li> <li>b. 1 Hz to 500 Hz</li> <li>c. Faster than 500 Hz</li> </ul>
<p><b>8. Is signal processing software needed to simplify/compress the raw data?</b></p> <ul style="list-style-type: none"> <li>a. No</li> <li>b. Yes</li> </ul>
<p><b>9. Does the sensor system need to be purchased from a particular type of supplier?</b></p> <ul style="list-style-type: none"> <li>a. Approved domestic suppliers</li> <li>b. Approved foreign suppliers</li> <li>c. No preference</li> </ul>
<p><b>10. What is the maximum allowable cost for the sensor system?</b></p> <ul style="list-style-type: none"> <li>a. Less than \$100</li> <li>b. \$100-\$500</li> <li>c. \$500-\$1,000</li> <li>d. \$1,000-\$5,000</li> <li>e. More than \$5,000</li> </ul>

### *3.4 Sensor Selection Criteria and Tradeoffs*

Once the application is broken down and understood, there are several criteria that one must consider before selecting an appropriate sensor system for their life cycle monitoring application. The following criteria should be considered when selecting an appropriate sensor system for PHM:

- Ease of integration (size, weight, attachment)
- Power management
- Data storage
- Data transmission
- Signal processing software
- Cost



- Reliability
- Availability

While there are eight criteria listed here, there were a total of ten questions in the questionnaire. The reason for this discrepancy is because a few of the criteria are associated with multiple questions. For example, in order to consider a sensor system's ease of integration, both question 2 and question 3 needs to be answered.

#### 3.4.1 Ease of Integration (Size, Weight, Attachment)

As electronic components and systems continue to decrease in size, sensor systems to monitor their environment and operation will also need to be smaller and weigh less in order to be integrated into the system. The fabrication of micro-electro-mechanical systems (MEMS) and nano-electro-mechanical systems (NEMS) in silicon and other materials will offer significant advantages because of batch fabrication, potential for integration with electronics, fabrication of arrays of sensors, and small size of individual devices [122]. In addition, sensors fabricated using MEMS and NEMS technologies will lead to drastic cost reduction [123].

In electronic product applications, the size of the sensor system may become the significant selection criteria due to limited space available for mounting it or due to the inaccessibility of locations to be sensed. Additionally, the weight of the sensor system may be critical in certain applications such as vibration and shock measurements using accelerometers, since the added mass can change the system response. In the case where a fixture is required to mount the sensor system, the added mass of the sensor and fixture may change the system characteristics. Users

should consider the entire weight of the sensor system, which includes the battery and other accessories such as communication antennas or cables.

The tradeoffs for small size and low weight of a sensor system include higher cost and lower commercial availability. Currently, the smallest sensor systems that are commercially available are about the size of a U.S. dime. While this form factor is good for electronic system applications, there are very small number of sensor systems with this size that are commercially-available.

### 3.4.2 Power Management

Another factor to consider in sensor selection is the ability to control the power consumed by the sensor system. Sensor systems can be divided into two main categories with respect to their powering: non-battery powered sensor systems and battery powered sensor systems. Non-battery powered sensor systems are typically either wired to an external AC power source or use power from an integrated host system. For example, temperature sensors are often integrated within the microprocessors on motherboards inside computers and utilize power from the computer. Battery powered sensor systems, on the other hand, are equipped with an onboard battery. Regarding their power, no interaction is required with the outside world, so they are able to monitor autonomously on a continuous basis.

In addition, replaceable or rechargeable batteries are preferable for battery-powered sensor systems because the sensor's useful life needs to be longer than the estimated lifespan of the components/subsystems it is intended to monitor [122]. Batteries that are replaceable or rechargeable allow the sensor system to operate

continuously, without needing to replace the entire system. Rechargeable lithium-ion batteries are commonly used in battery-powered sensor systems.

Furthermore, the power consumed for sensing varies depending on the parameter being monitored. Periodic sensing can consume less power than continuous monitoring; however there is a risk of missing critical data. Power consumption is also controllable by making measurements at events triggered by defined thresholds. In the case of battery-powered sensors, maximum energy is expended in communication, which involves both the transmission and reception of data.

One type of strategy to manage the onboard power of sensors is to remotely control the sensors from a base station as required by the specific application. Using the base station, commands can be sent to an idle (inactive) sensor system to essentially wake it up only when it is needed to collect data. Examples of these commands include [124]:

- Wake up, listen for commands, log or send data as commanded (or back to sleep)
- Wake up, log information when an event or threshold crossing is detected
- Wake up, transmit data periodically, go back to sleep

These commands essentially enable the sensor system to carry out the intended functions while reducing its power consumption at the same time.

Since batteries exhibit a shelf life of 5-10 years [124], many PHM applications require elimination of batteries altogether because the application requires that they cannot be replaced. Non-battery powered sensors that are wired to

an external power source can transmit data in real time but they have limitations. Installing and maintaining the wires is costly and labor-intensive. Wires degrade and are prone to interference from electromagnetic signals. Also, wires themselves might get damaged and effect the reliability of the sensor system itself.

### 3.4.3 Data Storage

Effective utilization of memory is also a factor to consider in the selection of sensor systems for PHM. For battery-powered sensor systems, the data is typically stored in an onboard memory. Memory requirements are generally affected by the monitoring interval and frequency. In selecting the monitoring frequency, the user has to ensure that the relevant loads are recorded and, at the same time, the memory is not flooded by irrelevant load data.

In general, there are two types of memory which are used to store data: volatile memory and non-volatile memory. Volatile memory is memory that requires power to maintain the stored information. An example of volatile memory is random-access memory (RAM). Non-volatile memory, on the other hand, is memory that can retain the stored sensor data even when not powered. Examples of non-volatile memory include read-only memory (ROM), flash memory, most types of magnetic computer storage devices (e.g. hard disks, floppy disk drives, and magnetic tape), optical disc drives, and early computer storage methods such as paper tape and punch cards.

Non-volatile memory is usually the preferred memory for both non-battery and battery operated sensor systems because of their ability to retain the collected data in the case of an accident, where power is suddenly lost. This allows a user to go

back to the point in time leading up to the accident and identify the conditions that were present.

In some sensor systems, the user is able control the amount of data that is stored in memory. One way to do this is to define threshold values for measurements. Appropriate setting of thresholds can facilitate efficient data collection. For example, measurements can be recorded or a scan can be triggered only if the stimulus meets the set threshold. Events can be set to trigger above or below an absolute value, for example, recording acceleration levels above 2g or humidity levels above 80% R.H.

Users can also set thresholds based on the value of the slope (positive or negative) of the curve formed by the measurements made by the sensor. This strategy allows usage-based data recording, which can result in a substantial saving in disk space and extend the battery life of the equipment.

Other means of memory utilization involve effectively dividing the memory between periodic measurements and threshold based measurements. A strategic combination of measurement intervals (for periodic measurements) and thresholds can enable recording a higher number of relevant measurements.

#### 3.4.4 Data Transmission

Data transmission is closely linked to power management, but still warrants its own separate consideration for sensor selection. Data transmission is generally categorized by either the use of cables or wires to transmit data or wireless data transmission. Wireless data transmission refers to the transmission of information from sensor to sensor or from sensor to base station without the use of a wired connection. Many new sensor systems now use wireless data transmission.

Wireless monitoring has emerged in recent years as a promising technology that can impact in-situ life cycle monitoring. Wireless sensor systems can be used to remotely monitor inhospitable and toxic environments. Since wireless sensor systems do not depend on extensive lengths of wires for the transfer of sensor measurements, installation and maintenance costs are significantly reduced. The real benefit from wireless sensor systems can be achieved by embedding micro-controllers to improve the data analysis capabilities.

Methods of wireless data transmission include Ethernet [125], radio frequency identification (RFID) [126], vicinity cards (ISO 15693) [127], personal area network (IEEE 802.15) [128], Wi-Fi (IEEE 802.11) [129], and proprietary communications protocols. When selecting which type of wireless data technology to use for a particular application, one should consider the range of communication, power demand, and ease of implementation.

The use of portable devices (such as PDAs and tablet computers) in conjunction with battery powered sensor systems can enable efficient fault diagnosis and prognostics by integrating more complex algorithms in the hand-held device. Customized processing and reporting tools can be programmed on portable devices for efficient maintenance activities. For example, the data collected by a Bluetooth-enabled accelerometer system can be downloaded on a hand-held device by maintenance technicians and can be processed further using Fast Fourier Transforms (FFT) embedded on the hand-held device.

### 3.4.5 Signal Processing Software

Signal processing software is another factor to consider in the selection of sensors for PHM. Signal processing enables the simplification of raw data. The raw environmental data from sensors is usually not in a form that is compatible with physics-of-failure models and reliability prediction models. As a result, for further analysis of the acquired data, it is essential to simplify the raw sensor data to a form that is compatible with the input requirements of the selected models.

By using information that is most relevant to the failure models, an efficient data reduction method should [130]:

- Permit gains in computing speed and testing time
- Condense load histories without sacrificing damage characteristics

This, in turn, enables transmitting fewer amounts of data (processed instead of raw data) to the base station, and hence results in lower power consumption. In the case of a large number of sensor systems working in a network, this would allow decentralization of computational power and facilitate efficient parallel processing of data.

Additionally, sensors with embedded signal processing software can also facilitate efficient data analysis for PHM applications. Embedded computations can be set to provide real time updates for taking immediate action such as powering off the equipment to avoid accidents or catastrophic failures, and also for providing prognostic horizons for conducting next repair and maintenance activities.

Power consumption and non-volatile memory of the microprocessor may limit computationally intensive algorithms to be embedded with onboard processors.

However, even using simple algorithms and routines to process the raw sensor data can achieve significant gains for in-situ analysis [131]. Some examples of simple data simplification algorithms for PHM of electronics include [132]:

- Conversion of irregular temperature history into a regular sequence of peaks and valleys for thermal fatigue analysis
- Conversion of temperature reversals into relevant temperature cycle information
- Conversion of acceleration data in time domain to power spectral density in frequency domain

#### 3.4.6 Cost

The selection of the proper sensor system for a given application also includes an evaluation of the cost of the sensor system. A sensor system should be evaluated in terms of its total cost of ownership, not just the purchase cost. In fact, initial purchase costs can be less than 20% of the product's lifetime costs. Consider the experience of an airline who went with "an affordable" choice only to find out 15 months later that the sensors were surviving for only 12 months on average and needed to be replaced annually. The replacement sensor system selected did cost 20% more but was available off-the-shelf and was previously qualified for aircraft use [133].

In battery-powered sensor systems, the cost is generally determined by the size of the memory for data storage. Sensor systems with onboard memory capacity in the range of kilobytes typically cost on the order of hundreds of dollars. As the



size increases, the cost goes up as well. Sensor systems with onboard memory capacity in the range of megabytes can cost as much as several thousand dollars.

#### 3.4.7 Reliability

Many sensor systems operate only in specific environments, so if a user decides to mix sensor systems and environments without forethought, they may end up with a ruined sensor system and no data. Sensor systems are generally limited to some degree by noise and the surrounding environment, which vary with operating conditions, environmental conditions, and other factors.

To reduce the risk of sensor system failure, the user needs to consider the sensor's operating range and determine if that suits their particular application. The packaging of the sensor system should also be considered as it can shield the unit from unwanted effects such as humidity, sand, mechanical forces, and other environmental conditions [134].

Another way to reduce the risk of sensor system failure is to use sensor validation methods. Sensor validation is used to assess the integrity of the sensor system and adjust or correct it as appropriate. This functionality checks the sensor performance and ensures that the sensor system is working correctly by detecting and eliminating the influence of systematic errors. Self-diagnostics, self-calibration, and sensor fusion are a few methods that can be applied to achieve this functionality.

Another strategy to improve the reliability of sensor systems is to use multiple ones (redundancy) to monitor the same product or system. By using multiple sensor systems, the risk of losing critical data due to sensor system failure is minimized.

While it is essential to consider the reliability of sensor systems, it is equally necessary to consider the effects of the sensor system on the reliability of the product it is intended to monitor. Sensor systems that are heavy may reduce the reliability of circuit boards when attached to the surface over time. In addition, the method of attachment (soldering, glue, screws) can reduce the reliability of the product if the attachment material is incompatible with the materials on the surface of the product.

#### 3.4.8 Availability

Availability of the sensor system is another factor that should be considered in the sensor selection process. The sensor availability can generally be assessed in two ways.

First, a user should determine whether the sensor system is commercially-available. This means that the sensor system has gone from its development phase into production and is being sold on the market. The production volume can then be used as a measure of the sensor system's availability. Since sensor technology is always changing, there are many sensor systems which are advertised and promoted in publications and websites, but are not commercially-available. These sensor systems are generally prototypes and are not available for others to purchase.

Second, a user should look at the supplier of the sensor system. The supplier will be either foreign or domestic. Depending on the particular needs and application, a user may be required to select a sensor system from a domestic supplier due to security reasons. This information is typically not found in product datasheets, but can be verified through simple communication with the supplier.

### 3.5 *Sensor Selection Guidelines*

With the questionnaire and sensor selection criteria, one can decide which sensor system best meets one's requirements. However, there is no general consensus that establishes which sensor system is the best for a given application. As a result, the information that follows contains some guidelines that can also be helpful in making the final selection of a sensor system.

Table 6. Sensor Selection Guidelines

1. The chosen sensor system should have an environmental operating range greater than the life cycle environment it is intended to monitor.
2. The chosen sensor system should be sufficiently small in size and low in weight such that it is easily attachable to the monitored product.
3. For portable applications, the chosen sensor system should operate autonomously using onboard batteries to supply its own power.
4. For portable applications, the battery of the chosen sensor system should be easily replaceable and/or rechargeable; otherwise, the battery should have an expected lifetime of at least the same period of time between normal service intervention.
5. For stationary applications, the chosen sensor system should be able to function continuously and reliably for a period of time.
6. For wireless applications, the sensor system should be chosen such that its memory capacity is large enough to be able to store all of the data prior to data transmission.
7. The cost of the chosen sensor system should be such that the return-on-investment of the sensor system is justifiable.
8. The chosen sensor system should be commercially-available and sold by a reputable supplier who can be approved as per company-specific supplier selection criteria.

### 3.6 *Summary*

The selection of appropriate sensor systems for monitoring the life cycle of electronic products and systems is an essential step in prognostics and health management. There are many criteria that one needs to consider in order to select the right sensor for a particular application, including ease of integration, power management, data storage, data transmission, signal processing software, cost, reliability, and availability.

In addition to the general criteria one needs to look at, guidelines on sensor selection were presented to help a user to select the optimal sensor system for their application. Using these guidelines and the general criteria for sensor selection, one is able to make the tradeoffs necessary to ultimately decide which type of sensor system is best for their application. In the next chapter, the sensor selection process presented here is demonstrated with a case study for an avionics unit.

## Chapter 4: Sensor Selection for an Avionics Unit

### *4.0 Introduction*

An application of the sensor selection process is presented for an avionics unit to be used in aircraft/rotorcraft systems. The objectives of this study were to provide a plan for implementation of PHM for two circuit card assemblies (CCAs) located inside the avionics unit. The steps taken to achieve this objective included:

- Virtual reliability assessment performed to determine the critical failure mechanism/model, and approximate time of failure of the component interconnects at the printed wiring board assembly level.
- Selection of an optimal sensor system to be integrated with the avionics unit for in-situ monitoring of the life cycle loads to enable prognostics and health management.

### *4.1 Description of Avionics Unit*

The two CCAs located inside the avionics unit are called the Control and Communications processors, and are being developed by L-3 Communications – WESCAM. They are used for high resolution, multi-spectral imaging. These systems are designed to provide image stability and long-range magnification from a wide variety of moving platforms, including rotary and fixed wing aircraft, unmanned vehicles, and ships. This functionality is supported by up to six high-performance payload sensors, including a high magnification infrared thermal imager with 4-step

zoom, a color daylight camera with zoom lens, a night camera with spotter lens, a laser illuminator, and a laser rangefinder. These imaging systems make target identification possible from longer standoff ranges, enabling safer, more covert operations.

## *4.2 Virtual Reliability Assessment for Avionics Unit*

The virtual reliability assessment in this study was conducted on the two circuit card assemblies, Control and Communications. The assessment involved identification of the expected life cycle profile, design model creation, load transformation and validation, and failure risk assessment to identify the potential failure sites and failure mechanisms. The software that was used to conduct the virtual reliability assessment is CalcePWA, which has been developed by the Center for Advanced Life Cycle Engineering at the University of Maryland [135].

### *4.2.1 Expected Life Cycle Profile*

In this study, an expected thermal profile was provided for a fixed wing aircraft, as shown in Figure 2. This profile is based on aggregated values of temperature from years of experience in military avionics. While it is an ideal profile, it is only representative of the actual conditions. In practical application, PHM will tell a user what the actual profile is.

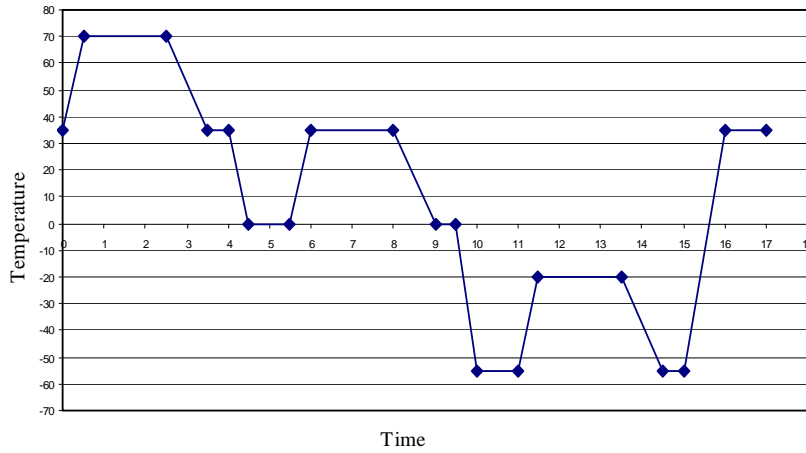


Figure 2. Expected thermal profile for the avionics unit

Vibration testing was also performed on the Control and Communications CCAs to determine the input vibration loading. A vibration shaker table was used to produce random vibrations and accelerometers were placed at the support points on each assembly to measure the input. The measured input was in the form of power spectral density (PSD) versus frequency. An example of PSD input for qualification of the Communications CCA is shown in Figure 3.

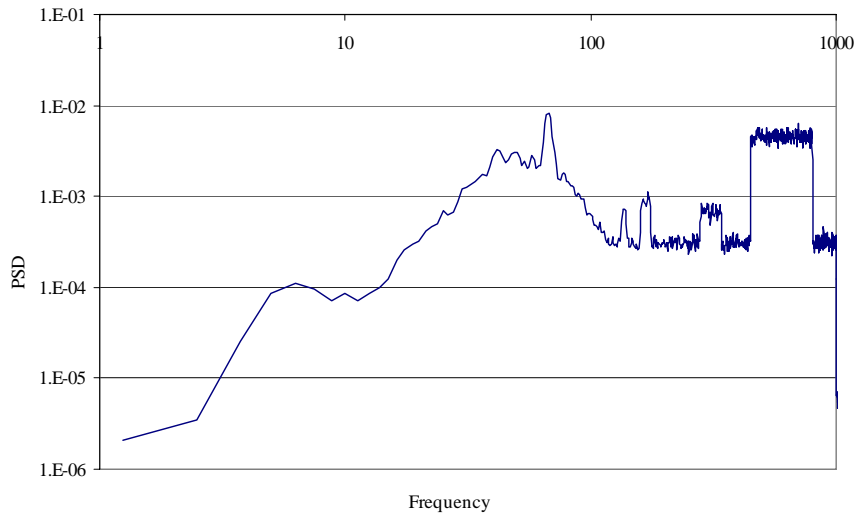


Figure 3. Expected vibration profile for the avionics unit

#### 4.2.2 Design Model Creation

The Control CCA is a 12 layer, double-sided circuit board supporting 559 components belonging to 137 part types. The Communications CCA is a 14 layer, double-sided circuit board supporting 718 components belonging to 154 part types. In the design model, a part represents a specific part number whereas a component represents an instance of a part occurring within the design. The two circuit boards are manufactured with high-temperature FR-4 substrate, and the solder joints are made of eutectic tin-lead solder paste. The design models of the top surfaces of the Control and Communications CCAs are shown in Figure 4.

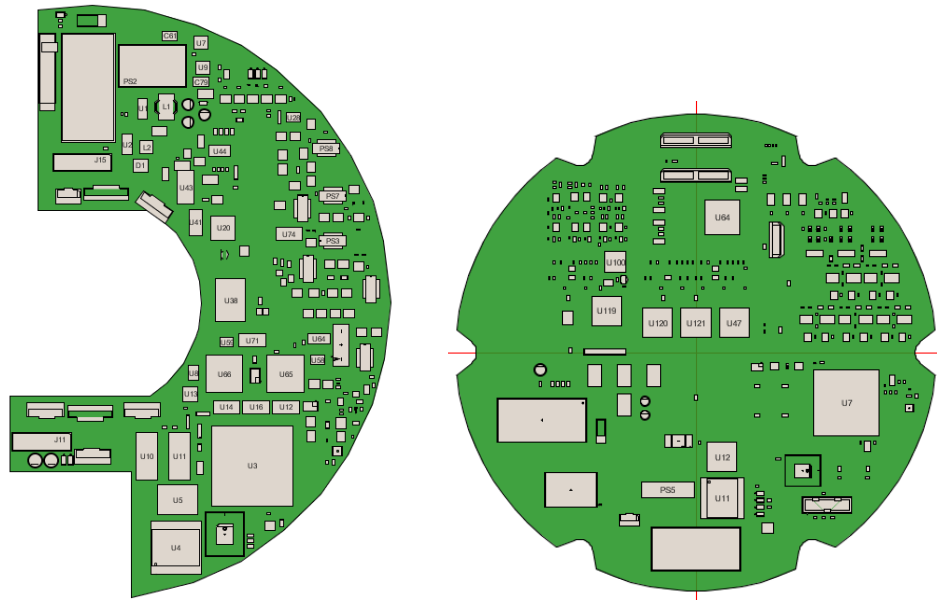


Figure 4. Design model of the top surfaces of the Control processor (left) and the Communications processor (right)

#### 4.2.3 Load Transformation and Validation

For the thermal stress analysis of both CCAs, the analysis conditions used were natural convection with horizontal board orientation and venting of air. For



boundary conditions, the edges of the CCAs were assumed to be insulated. It was also assumed that the fluid pressure is 1atm for all temperatures in the life cycle profile except those which exhibited a lower relative atmospheric pressure due to a higher altitude. For these high altitude temperatures, the fluid pressure was assumed to be 0.5atm.

To validate the results of the thermal stress analysis, photographs were taken of the Control and Communications CCAs while they were powered on using a thermal infrared (IR) camera. The procedure for taking the IR images was as follows: (1) subject the unit to an ambient temperature of 23°C; (2) power on the unit; (3) when thermal equilibrium is reached, lift up the cover and take a picture of each CCA. When the cover was lifted off, the top surface of the Control CCA was photographed, and since the Communications CCA was attached to the underside of the cover, its bottom surface was photographed (see Figure 5). The results of the thermal stress analysis were deemed acceptable as compared to the IR images.

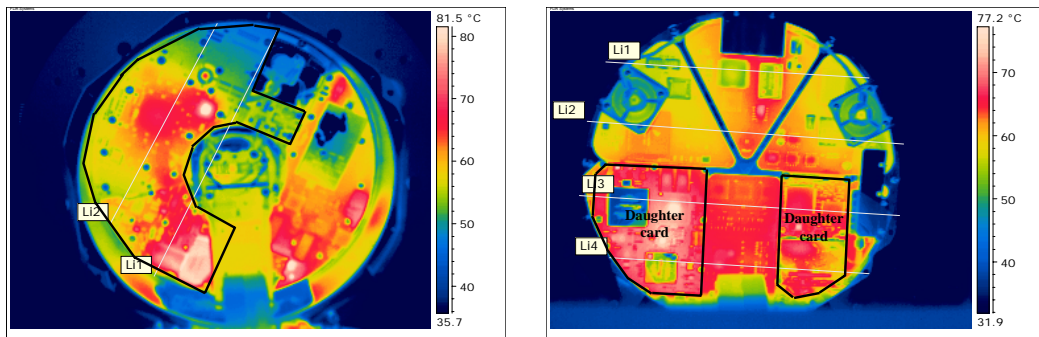


Figure 5. Thermal infrared images of top surface of Control processor (left) and bottom surface of Communications processor (right) at ambient temperature

Next, for the vibration stress analysis, the boundary conditions are based on how the boards are fastened to the whole structure. The Control CCA was fastened at 22 support points, which were assumed to be simply supported. Two additional supports were added to the model to account for the stiffening effect from a daughter card that was attached on top. The Communications CCA was fastened at 38 support points. In addition, the compliance of the board was assumed to increase from the peripheral to the center. This was modeled by adjusting the spring constant values of the springs.

The vibration stress analysis results showed that the first three natural frequencies of the Control board were approximately 618, 771, and 951 Hz, and maximum displacement was at the center of the board. Likewise, the natural frequencies and displacement of the Communications board were found. The results of the vibration stress analysis were validated against measured values of the first three natural frequencies.

#### 4.2.4 Failure Risk Assessment

Simulation of the avionics design model was performed to evaluate the thermal and vibration stress conditions for each component and determine the dominant failure mechanisms and corresponding failure sites. The simulation revealed minimal damage due to random vibration on both processor boards; all components on both boards passed life requirement of 5 years with an estimated life of greater than 30 years. Resistance to vibration-induced failure was expected because the processor boards exhibited a high natural frequency, and accumulated

damage due to random vibration is inversely proportional to the square of natural frequency.

However, the simulation results indicated a failure risk due to thermal fatigue at several locations, two on the Control processor and four on the Communications processor. For these high risk components, an evaluation of their sensitivity to interconnect geometry parameters was performed to determine if modification of solder joint parameters would result in failure avoidance. Three input parameters were varied: standoff height, solder joint height, and solder joint bond area.

Based on the sensitivity analysis, suggestions for risk mitigation were recommended and implemented. After the suggestions were implemented, the top three high risk failure sites for each CCA were identified (see Table 7 and Table 8). For all components, the failure sites were located at the solder joint interconnect. The actual parts are listed in the first column of each table. The rationale used to select only the top 3 high risk failure sites was because there was a large gap between the third and fourth failure sites on each design.

Table 7. Results of virtual reliability assessment for the Control CCA

<b>Top 3 high risk failure sites, mechanisms, and times</b>		
<b>Failure site: (interconnect)</b>	<b>Failure mechanism:</b>	<b>Life estimation: (life requirement = 588 days)</b>
Leadless thick film chip resistor array	Thermal fatigue	602 days
C-lead transient voltage suppressor	Thermal fatigue	975 days
Leadless power inductor	Thermal fatigue	982 days

Table 8. Results of virtual reliability assessment for the Communications CCA

Top 3 high risk failure sites, mechanisms, and times		
Failure site: (interconnect)	Failure mechanism:	Life estimation: (life requirement = 588 days)
Leadless clock oscillator	Thermal fatigue	606 days
Leadless Ethernet transceiver	Thermal fatigue	613 days
Leadless thick film chip resistor	Thermal fatigue	642 days

Since all of the failure mechanisms are found to be thermal fatigue of the solder joint interconnect due to thermal cycling, the load parameter which is needed for input to this model is temperature. The locations of the high risk failure sites can also be determined using the results of virtual reliability assessment. The locations on the Control CCA and Communications CCA are shown in Figure 6 and Figure 7, respectively.

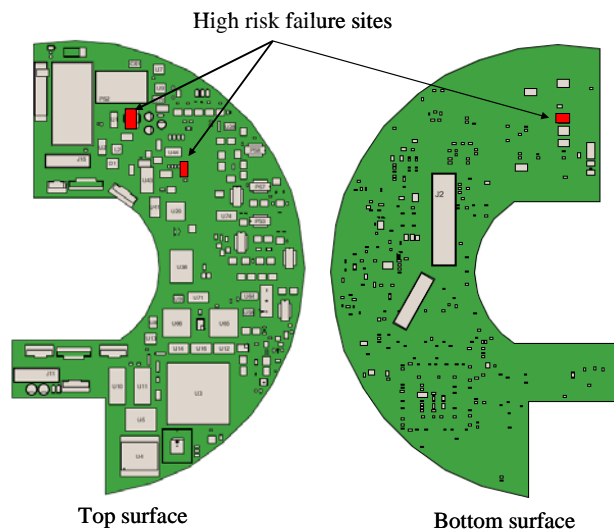


Figure 6. High risk failure sites on the Control CCA

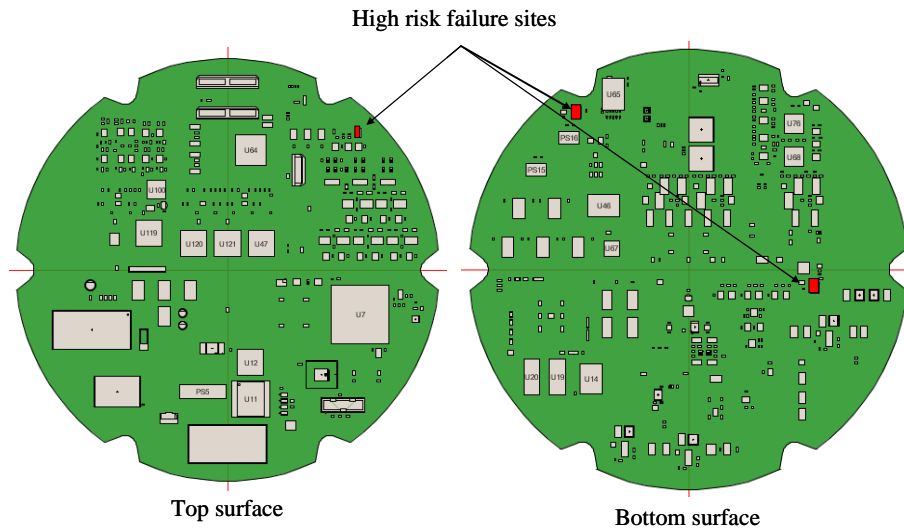


Figure 7. High risk failure sites on the Communications CCA

#### 4.3 Sensor Selection for In-situ Temperature Monitoring

The next task is to search for the optimal sensor system that that can be used for in-situ monitoring of temperature loads on the circuit boards inside the avionics unit. First, to understand the needs of this application, the questionnaire created for sensor selection was filled out. The questionnaire results are shown below.

Table 9. Questionnaire Results for Avionics Unit

<p><b>1. What is the expected environmental/operational range for monitoring?</b></p> <ul style="list-style-type: none"> <li>• Temperature: -55°C to +70°C</li> </ul>
<p><b>2. What is the desired size, weight, and form factor for the sensor system?</b></p> <ul style="list-style-type: none"> <li>• Less than 1 inch in height, less than 10 grams, no preference in shape</li> </ul>
<p><b>3. How does the sensor system need to be attached to the host product?</b></p> <ul style="list-style-type: none"> <li>• Mounted to circuit board using plastic plate</li> </ul>
<p><b>4. How will the sensor system be powered?</b></p> <ul style="list-style-type: none"> <li>• Powered by battery (autonomously)</li> </ul>

<p><b>5. What type of power management is needed for the sensor system?</b></p> <ul style="list-style-type: none"> <li>• None required</li> </ul>
<p><b>6. How long does the product need to be monitored for?</b></p> <ul style="list-style-type: none"> <li>• 1 month trial</li> </ul>
<p><b>7. How often will the data be collected?</b></p> <ul style="list-style-type: none"> <li>• Slower than 1 Hz (~1 sample/minute)</li> </ul>
<p><b>8. Is signal processing software needed to simplify/compress the raw data?</b></p> <ul style="list-style-type: none"> <li>• No</li> </ul>
<p><b>9. Does the sensor system need to be purchased from a particular type of supplier?</b></p> <ul style="list-style-type: none"> <li>• Approved domestic suppliers</li> </ul>
<p><b>10. What is the maximum allowable cost for the sensor system?</b></p> <ul style="list-style-type: none"> <li>• Less than \$100</li> </ul>

Once the needs of the application were understood, the criteria for sensor selection were assessed to see where to make the necessary tradeoffs. Using this process, the optimal sensor system was chosen for monitoring the temperature loads inside the avionics unit. The search focused on low cost, small size, low weight, portability, and wireless data transmission. The data for the chosen sensor system was collected from the manufacturer’s website and product datasheets.

The selected sensor system that best matches the needs of this application is the SmartButton, which is manufactured by ACR Systems [136]. The ACR SmartButton is a single channel temperature logger that costs \$39 per unit. As shown in Figure 8, the sensor system is 17 mm in diameter and 6 mm in height, and weighs approximately 4 grams. Due to its small size and low cost, it is possible to purchase

six units for multiple-site temperature monitoring of the high risk failure sites on the Control and Communications CCAs.

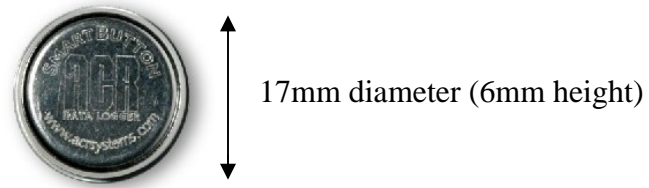


Figure 8. The ACR SmartButton [136]

In addition, using a plastic plate as attachment, the ACR SmartButton can be mounted to the circuit boards, and can operate autonomously using a 3 volt lithium onboard battery. With a desired sample rate of 1 sample/minute and a maximum memory capacity of 2 KB, the collected data can be stored in the local memory for one day before being downloaded from the aircraft/rotorcraft to a computer. After the temperature data is downloaded to the computer, it can be used in conjunction with the damage model for thermal fatigue to calculate the remaining cycles to failure for the avionics unit.

#### 4.4 *Summary of the Case Study*

The PHM implementation methodology was applied to electronics inside an avionics unit in this study to identify the relevant life cycle loads and optimal sensor system for in-situ life cycle monitoring. Thermal fatigue of the solder joint interconnect was identified as the dominant failure mechanism for all high risk failure sites. Thus, the load parameter that was identified as input for the damage model was temperature.

Using the questionnaire created for the sensor selection process, the avionics application was broken down to identify the monitoring requirements. These requirements were assessed in terms of the sensor selection criteria to determine if tradeoffs needed to be made. From this, an optimal sensor system was selected for monitoring the ambient temperature inside the avionics unit at the six high risk failure sites.



## Chapter 5: Contributions

1. **I assessed the state-of-practice for prognostics and health management of electronics.** Based on a review of the prognostic approaches, implementation case studies, technical publications, and the extent of intellectual property of numerous organizations, I identified the companies, universities, and government branches that are currently researching, developing, and/or implementing prognostics for their products and systems. In addition, I identified the specific prognostic methods that each organization is using. I used this information to propose the core challenges for prognostics and health management research, which can be used as a baseline for the development of a technology roadmap.
2. **I developed a sensor selection process for integration with the life consumption monitoring methodology such that an optimal sensor system can be identified prior to in-situ life cycle monitoring of electronic products and systems.** I developed a questionnaire that can be used to understand the monitoring requirements of a particular PHM application. I identified criteria that one needs to consider in the sensor selection process in order to make the relevant tradeoffs. Finally, I provided guidelines on sensor selection to help a user validate their final selection. The process was demonstrated for two circuit card assemblies inside an avionics unit.

# Appendix I

## Publications Originated from Thesis Work

### Books

- N. Vichare, B. Tuchband, and M. Pecht, “Prognostics and Health Monitoring of Electronics,” Handbook of Performability Engineering, ed. K.B. Misra, Springer, 2007.
- M. Pecht, B. Tuchband, N. Vichare, J. Gu, V. Sotiris, S. Kumar, and S. Cheng, “Prognostics and Health Management of Electronics,” CALCE Press, College Park, MD, to be published in July 2007.

### Conference Proceedings

- B. Tuchband and M. Pecht, “The Use of Prognostics in Military Electronic Systems,” *Proceedings of the 32<sup>nd</sup> GOMACTech Conference*, Lake Buena Vista, FL, March 19-22, 2007, pp. 157-160.
- B. Tuchband, S. Cheng, and M. Pecht, “Technology Assessment of Sensor Systems for Prognostics and Health Monitoring,” *Proceedings of the Topical Workshop and Exhibition on Military, Aerospace, Space and Homeland Security (MASH 2007)*, Baltimore, MD, May 7-10, 2007, CD-ROM Paper No. 4-4.
- B. Tuchband, N. Vichare and M. Pecht, “Method for Implementing Prognostics on Legacy Systems,” *Proceedings of the Topical Workshop and Exhibition on Military, Aerospace, Space and Homeland Security (MASH 2006)*, Washington, DC, June 6-8, 2006, CD-ROM Paper No. 4-20.

## **Working Papers**

- B. Tuchband, D. Das, M. Pecht, and D. Heslinga, Prognostics and Health Management Implementation Methodology.
- B. Tuchband and M. Pecht, In-Situ Life Cycle Monitoring of Notebook Computers.

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