Prognostics and Health Management of Electronics

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CALCE Electronic Products and Systems
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Contents

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Preface

Prognostics is the process of predicting the future reliability of a product by assessing the extent of deviation or degradation of the product from its expected normal operating conditions. Health management systems are programs that respond in a preemptive and opportunistic manner to the anticipation of failures.

There is a growing interest among industry, government, and academia to monitor the ongoing reliability, or health, and predict the remaining life of electronic products and systems because most complex systems today contain significant electronics content. Approaches to implement prognostics in electronic products and systems include using expendable devices, such as canaries and fuses that fail earlier than the host product; monitoring and trending of parameters that are precursors to failure; and modeling accumulated damage (e.g., physics of failure) based on system exposure to life-cycle loads and operating conditions.

If one can assess the extent of deviation or degradation of a system in its application environment and predict remaining lifesuccess of a future event or probability of , the information can be used to meet the following powerful objectives:

- Provide advanced warning of system failures
- Enable condition-based (predictive) maintenance
- Obtain knowledge of load history for future design, qualification, and root cause analysis
- Increase system availability through an extension of maintenance cycles and/or timely repair actions
- Lower life-cycle costs of equipment from reductions in inspection costs, downtime, and inventory
- Reduce the occurrence of intermittents and no fault founds (NFF)

At present, there are many organizations conducting research and development into prognostics and even more that wish to implement it in their products and systems. However, research on prognostics and health management (PHM) for electronics has been fragmented, and until now there has been no single reference that describes what is being conducted. To address this, this book discusses the activities of the major players in the prognostics field, including companies, academia, and government organizations. This book also discusses the available sensors that are used for prognostics, the parameters that can be monitored, the functions and principles of these sensors, implementation techniques and guidelines for sensor selection. The prognostics models and algorithms currently in use are also discussed in this book. This book provides an overview of the implementation costs including recurring, nonrecurring, and infrastructure costs and the cost avoidance possible with PHM. A roadmap is then presented to show the challenges and opportunities for research and development of PHM.

Chapter 1 provides a basic understanding of PHM and the techniques being developed to enable prognostics for electronic products and systems. The general approaches for PHM of electronics include (1) the use of fuses and canary devices; (2) monitoring and trending of failure precursors; and (3) monitoring environmental and usage loads for damage modeling. Examples are given to demonstrate each of the general approaches. Steps for implementing an effective PHM strategy for a complete product or system are presented.

Chapter 2 presents the state-of-the-art in sensor systems for in situ health and usage monitoring. Advances in the areas of sensor fabrication, microprocessors, compact nonvolatile memory, battery technology, and wireless telemetry have led to novel sensor systems that can be used for in situ life-cycle monitoring of electronic products and systems. Characteristics of state-of-the-art sensor systems, including on-board power management features, on-board memory, embedded signal processing software, wireless data transmission, low size and weight, high reliability, and low cost are presented. Select state-of-the-art, commercially available sensor systems are included along with their performance characteristics. A final section on emerging trends in sensor system technology is presented.

Chapter 3 discusses the various data-driven models and algorithms that can be utilized for prognostics and health management. The discussion covers statistical, usage-based, state estimation, and general pattern recognition models and algorithms.

Chapter 4 discusses the physics-of-failure-based prognostics approach. This approach permits the assessment of system reliability under its actual application conditions by integrating sensor data with models that enable in situ assessment of the deviation or degradation of a product from an expected normal operating condition. A formal implementation procedure, which includes failure modes, mechanisms, effects analysis, data reduction and feature extraction from the life-cycle loads, and damage accumulation, is presented.

Chapter 5 presents the economics of PHM. This chapter provides an overview of the implementation costs and the cost avoidance possible with PHM. Implementation costs, including recurring, nonrecurring and infrastructure costs are discussed. Maintenance planning is described and an example return-on-investment analysis is performed.

Chapter 6 presents the challenges and opportunities for research and development in PHM of electronics. Included are recommendations on the essential next steps for continued advancement of PHM technologies. A PHM technology roadmap is then provided.

It is acknowledged that the field of PHM is evolving rapidly. Furthermore, due to the large amount of published work in PHM, any assessment inevitably leaves out some organizations and topics that we either were not aware of or did not consider relevant in the context of this book

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Companies

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Scientific Monitoring
SmartSignal
Smiths Aerospace
Sun Microsystems
VEXTEC Corporation

Universities

Auburn University
Beihang University– China
Georgia Institute of Technology
University of California at Los Angeles
University of Maryland
University of Tennessee
University of North Carolina
Vanderbilt University

Government

NASA Glenn Research Center
Sandia National Laboratories
U.S. Air Force Research Laboratory
U.S. Army Materiel Systems Analysis Activity
U.S. Army Research Laboratory VTD
U.S. Navy

The following researchers have made special contributions to this book as part of their work and studies at CALCE–University of Maryland or in cooperation with CALCE faculty:

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Andrew Hess is a CALCE consultant, renowned for his work in fixed and rotary wing health monitoring and recognized as the father of naval aviation propulsion diagnostics. He has been the leading advocate for health monitoring in the Navy and has been instrumental in the development of every Navy aircraft application. Mr. Hess managed the development and integration of the prognostic and health management (PHM) system for the Joint Strike Fighter program from his position as Air System PHM IPT Lead. He has been acting on the advisory Red Team for the DARPA Prognosis programs for Propulsion and Structures. He is a NAVAIR senior engineering fellow and has authored over 30 technical papers. He was actively involved in the review of this book.

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Myra Torres, has over 18 years of experience in component reliability engineering and product risk assessment at Sun Microsystems. She managed the electronic component and interconnect technology team as well as a centralized signal integrity group at Sun. Her experience in PHM stems from market demands for reliable and available systems, increasing technology complexity of electronics, and the limitations of conventional reliability methods. At CALCE, Myra served as Assistant Director for PHM research and was involved with PHM methodologies and implementations for electronic systems. She has contributed to Chapter 6.

Brian Tuchband received a B.S. in Mechanical Engineering from the University of Delaware and M.S. in Mechanical Engineering from the University of Maryland, where he conducted research in PHM. He is currently employed by The Boeing Company in Ridley Park, Pennsylvania. His research interests include challenges and opportunities for prognostics, health and usage monitoring systems, and predictive maintenance for military electronic systems. He contributed to Chapter 1 and helped develop the appendices.

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Acronyms

ACARS	Aircraft Communications and Reporting System
ADIP	Army Diagnostic Improvement Program
AEW&C	Airborne Early Warning & Control
AFRL	Air Force Research Laboratory
AHM	Airplane Health Management
AIT	Automatic Identification Technology
AL	Autonomics Logistics
ALIS	Autonomic Logistics Information System
AME	Automated Maintenance Environment
AMSAA	Army Materiel Systems Analysis Activity
AOC	Airline Operational Control
ASIGS	Aircraft Structural Integrity Ground Station
AVPHM	Air Vehicle Prognostics and Health Manager
BAA	Broad Agency Announcements
BIT	Built-in Test
C2MS	Corrosion & Corrosivity Monitoring System
CAA	Civil Aviation Authority
CALCE	Center for Advanced Life Cycle Engineering
CBM	Condition-Based Maintenance
CDF	Common Data Format
CFRS	Computerized Fault Reporting System
CMAC	Cerebellar Model Arithmetic Computer
CMMS	Computerized Maintenance Management System
CNST	Center for Naval Shipbuilding Technology
CSTH	Continuous System Telemetry Harness
DARPA	Defense Advanced Research Projects Agency
DoD	Department of Defense
DoE	Department of Energy
DTPS	Drive Train Prognostics System
EFV	Expeditionary Fighting Vehicle
EHDUR	Engine Health Diagnostics Using Radar
EOTS	Electrical Opto Targeting System
EPRI	Electric Power Research Institute
EPSC	Electronic Products and Systems Center
FCS	Future Combat System
FFT	Fast Fourier Transform
FIRST	F/A-18E/F Integrated Readiness Support Teaming
FOQA	Flight Operations Quality Assurance
FUMS	Flight Usage Management Software
GPS	Global Positioning System
HMS	Health Management System

HUMS	Health and Usage Monitoring System
I2C	Inter Integrated Circuit
ICAS	Integrated Condition Assessment System
IETM	Interactive Electronic Technical Manual
IMIS	Integrated Maintenance Information System
iMP	"intelligent" Medium Power
IPHM	Integrated Prognostics and Health Management
IVHM	Integrated Vehicle Health Management
JAHUMS	Joint Advanced Health and Usage Monitoring System
JITM	Just-in-Time Maintenance
JSF	Joint Strike Fighter
LCM	Life Consumption Monitoring
MEMS	Microelectromechanical System
MoD	Ministry of Defense
MPROS	Machinery Prognostics System
MSET	Multivariate State Estimation Technique
MTE	Molecular Test Equipment
NASA	National Aeronautics and Space Administration
NAVAIR	Naval Air Systems Command
NTF	No-Trouble-Found
ODBC	Open Database Connectivity
ONR	Office of Naval Research
PADHM	Prognostics, Advanced Diagnostics, and Health Management
PBL	Performance-Based Logistics
PCA	Principal Component Analysis
PEDS	Prognostic Enhancements to Diagnostic Systems
PFAD	Predictive Failures and Advanced Diagnostics
PHM	Prognostic Health Management
PHMC	Prognostics and Health Management Consortium
PMA	Portable Maintenance Aid
ProDAPS	Probabilistic Diagnostic and Prognostic System
PSMRS	Platform Soldier Mission Readiness System
PTM	Predictive Trend Monitoring
RASCAL	Rotorcraft Aircrew Systems Concepts Airborne Laboratory
RCFIS	Reconfigurable Control and Fault Identification System
REDI-PRO	Real-Time Engine Diagnostics-Prognostics
RFID	Radio Frequency Identification
RUL	Remaining Useful Life
SAMS	Sensor-Based Aircraft Maintenance Support
SBIR	Small Business Innovation Research
SBM	Similarity-Based Modeling
SCADA	Supervisory Control and Data Acquisition
SDCC	System Dynamics Characterization and Control
SIPS	Structural Integrity Prognosis System
SMPS	Switch-Mode Power Supply
SPOT	Small Programmable Object Technology
SPRT	Sequential Probability Ratio Test
TEDANN	Turbine Engine Diagnostics Using Artificial Neural Networks
TIG	Technology Interest Group
TSMD	Time Stress Measurement Device

UAV	Unmanned Aerial Vehicle
USAF	United States Air Force
WRA	Weapon Replaceable Assembly

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Chapter 1

Introduction

As a result of intense global competition, companies are considering novel approaches to enhance the operational efficiency of their products. For many products and systems, high in-service reliability can be a means to ensure customer satisfaction. In addition, global competitive demands for increased warranties and the severe liability of product failures are encouraging manufacturers to improve field reliability and operational availability[1], and provide knowledge of in-service use, life-cycle operational and environmental conditions.

Interest has been growing in monitoring the ongoing health of products and systems in order to provide advance warning failure and assist in administration and logistics. Here, health is defined as the extent of degradation or deviation from an expected normal condition. Prognostics is the prediction of the future state of health based on current and historical health conditions [1].

Electronics are integral to the functionality of most systems today, and their reliability is often critical for system reliability [2]. This chapter provides a basic understanding of prognostics and health monitoring of products and systems and the techniques being developed to enable prognostics for electronic systems.

1.1 Reliability and Prognostics

Reliability is the ability of a product or system to perform as intended (i.e., without failure and within specified performance limits) for a specified time, in its life-cycle environment. Traditional reliability prediction methods for electronic products include Mil-HDBK-217 [3], 217-PLUS, Telcordia [4], PRISM [5], and FIDES [6]. These methods rely on the collection of failure data and generally assume the components of the system have failure rates (most often assumed to be constant) that can be modified by independent "modifiers" to account for various quality, operating, and environmental conditions. There are numerous well-documented concerns with this type of modeling approach [7-10]. The general consensus is that these handbooks should never be used, because they are inaccurate for predicting actual field failures and provide highly misleading predictions, which can result in poor designs and logistics decisions [8][11].

Prognostics and Health Management of Electronics. By Michael G. Pecht

[1] Operational availability is defined as the degree (expressed as a decimal between 0 and 1, or the percentage equivalent) to which a piece of equipment or system can be expected to work properly when required. Operational availability is often calculated by dividing uptime by the sum of uptime and downtime.

The traditional handbook method for the reliability prediction of electronics started with Mil-HDBK-217A, published in 1965. In this handbook, there was only a single point failure rate for all monolithic integrated circuits, regardless of the stresses, the materials, or the architecture. Mil-HDBK-217B was published in 1973, with the RCA/Boeing models simplified by the U.S. Air Force to follow a statistical exponential (constant failure rate) distribution. Since then, all the updates were mostly "band-aids" for a modeling approach that was proven to be flawed [12]. In 1987-1990, the Center for Advanced Life Cycle Engineering (CALCE) at the University of Maryland was awarded a contract to update Mil-HDBK-217. It was concluded that this handbook should be canceled and the use of this type of modeling approach discouraged.

In 1998, the Institude of Electrical and Electronics Engineers (IEEE) 1413 standard, "IEEE Standard Methodology for Reliability Prediction and Assessment for Electronic Systems and Equipment," was approved to provide guidance on the appropriate elements of a reliability prediction [13]. A companion guidebook, IEEE 1413.1, "IEEE Guide for Selecting and Using Reliability Predictions Based on IEEE 1413," provides information and an assessment of the common methods of reliability prediction for a given application [14]. It is shown that the Mil-HDBK-217 is flawed. There is also discussion of the advantage of reliability prediction methods that use stress and damage physics-of-failure (PoF) technique.

The PoF approach and design-for-reliability (DfR) methods have been developed by CALCE [15] with the support of industry, government and other universities. PoF is an approach that utilizes knowledge of a product's life-cycle loading and failure mechanisms to perform reliability modeling, design, and assessment. The approach is based on the identification of potential failure modes, failure mechanisms, and failure sites for the product as a function of its life-cycle loading conditions. The stress at each failure site is obtained as a function of both the loading conditions and the product geometry and material properties. Damage models are then used to determine fault generation and propagation.

Prognostics and health management (PHM) is a method that permits the assessment of the reliability of a product (or system) under its actual application conditions. When combined with PoF models, it is thus possible to make continuously updated predictions based on the actual environmental and operational conditions. PHM techniques combine sensing, recording, interpretation of environmental, operational, and performance-related parameters to indicate a system's health. PHM can be implemented through the use of various techniques to sense and interpret the parameters indicative of:

- Performance degradation, such as deviation of operating parameters from their expected values
- Physical or electrical degradation, such as material cracking, corrosion, interfacial delamination, or increases in electrical resistance or threshold voltage
- Changes in a life-cycle profile, such as usage duration and frequency, ambient temperature and humidity, vibration, and shock

The framework for prognostics is shown in Figure 1.1. Performance data from various levels of an electronic product or system can be monitored in situ and analyzed using prognostic algorithms. Different implementation approaches can be adopted individually or in combination. These approaches will be discussed in subsequent sections. Ultimately, the objective is to predict the advent of failure in terms of a distribution of remaining life, level of degradation, or probability of mission survival.

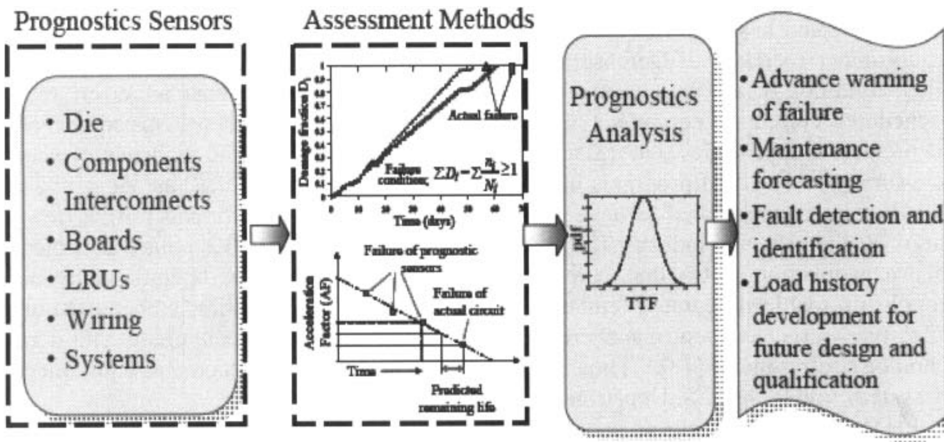


Figure 1.1: Framework for prognostics and health management.

1.2 PHM for Electronics

Most products and systems contain significant electronics content to provide needed functionality and performance. If one can assess the extent of deviation or degradation from an expected normal operating condition for electronics, this information can be used to meet several powerful goals, which include (1) providing advanced warning of failures; (2) minimizing unscheduled maintenance, extending maintenance cycles, and maintaining effectiveness through timely repair actions; (3) reducing the life-cycle cost of equipment by decreasing inspection costs, downtime, and inventory; and (4) improving qualification and assisting in the design and logistical support of fielded and future systems [1]. In other words, since electronics are playing an increasingly large role in providing operational capabilities for today's products and systems, prognostic techniques have become highly desirable.

Some of first efforts in diagnostic health monitoring of electronics involved the use of a built-in test (BIT), defined as an on-board hardware-software diagnostic means to identify and locate faults. A BIT can consist of error detection and correction circuits, totally self-checking circuits, and self-verification circuits [1]. Two types of BIT concepts are employed in electronic systems: interruptive BIT (I-BIT) and continuous BIT (C-BIT). The concept behind I-BIT is that normal equipment operation is suspended during BIT operation. The concept behind C-BIT is that equipment is monitored continuously and automatically without affecting normal operation.

Several studies [16, 17] conducted on the use of BIT for fault identification and diagnostics showed that BIT can be prone to false alarms and can result in unnecessary costly replacement, requalification, delayed shipping, and loss of system availability. BIT concepts are still being developed to reduce the occurrence of spurious failure indications. However, there is also reason to believe that many of the failures actually occurred but were intermittent in nature [18]. The persistence of such issues over the years is perhaps because the use of BIT has been restricted to low-volume systems. Thus, BIT has generally not been designed to provide prognostics or remaining useful life due to accumulated damage or progression of faults. Rather, it has served primarily as a diagnostic tool.

PHM has also emerged as one of the key enablers for achieving efficient system-level maintenance and lowering life-cycle costs in military systems. In November 2002, the U.S. Deputy under secretary of Defense for Logistics and Materiel Readiness released a policy called condition-based maintenance plus (CBM+). CBM+ represents an effort to shift unscheduled corrective equipment maintenance of new and legacy systems to preventive and predictive approaches that schedule maintenance based upon the evidence of need. A 2005 survey of 11 CBM programs highlighted "electronics prognostics" as one of the most needed maintenance-related features or applications without regard for cost [19], a view also shared by the avionics industry [20]. Department of Defense 5000.2 policy document on defense acquisition states that "program managers shall optimize operational readiness through affordable, integrated, embedded diagnostics and prognostics, embedded training and testing, serialized item management, automatic identification technology, and iterative technology refreshment [18]." Thus, a prognostics capability has become a requirement for any system sold to the U.S. Department of Defense.

PHM is also emerging as a high-priority issue in space applications. NASA's Ames Research Center (ARC) in California is focused on conducting fundamental research in the field of integrated systems health management (ISHM). ARC is involved in design of health management systems, selection and optimization of sensors, in situ monitoring, data analysis, prognostics, and diagnostics. The prognostics center for excellence at ARC develops algorithms to predict the remaining life of NASA's systems and subsystems. ARC's current prognostics projects involve power semiconductor devices (investigation of the effects of aging on power semiconductor components, identification of failure precursors to build a PoF model, and development of algorithms for end-of-life prediction), batteries (algorithms for batteries prognosis), flight actuators (PoF modeling and development of algorithms for estimation of remaining life), solid rocket motor failure prediction, and aircraft wiring health management [21].

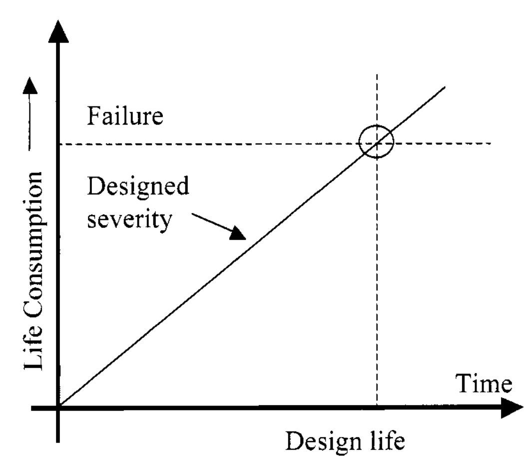
In addition to in-service reliability assessment and maintenance, health monitoring can also be effectively used to support product take-back and end-of-life decisions. Product take-back indicates the responsibility of manufacturers for their products over the entire life cycle, including disposal. The motivation driving product take-back is the concept of extended producer responsibility (EPR) for post-consumer electronic waste [22]. The objective of EPR is to make manufacturers and distributors financially responsible for their products when they are no longer needed.

End-of-life product recovery strategies include repair, refurbishing, remanufacturing, reuse of components, material recycling, and disposal. One of the challenges in end-of-life decision making is to determine whether product lines can be extruded, whether any components could be reused, and what subset should be disposed of in order to minimize system costs [23]. Several interdependent issues must be considered concurrently to properly determine the optimum component re-use ratio, including assembly/disassembly costs and any defects introduced by the process, product degradation incurred in the original life cycle, and the waste stream associated with the life cycle. Among these factors, the estimate of the degradation of the product in its original life cycle could be the most uncertain input to end-of-life decisions. This could be effectively carried out using health monitoring, with knowledge of the entire history of the product's life cycle.

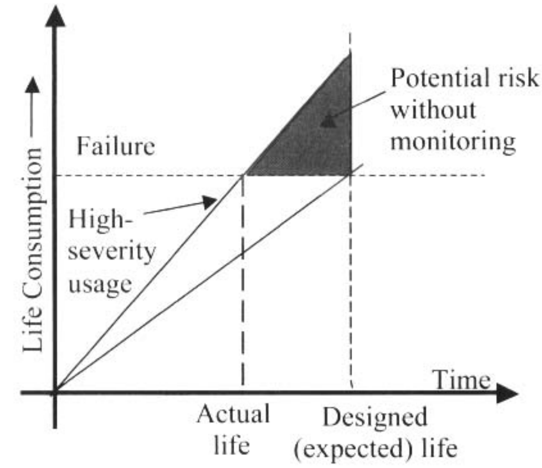
Scheidt et al. [24] proposed the development of special electrical ports, referred to as green ports, to retrieve product usage data that could assist in the recycling and reuse of electronic products. Klausner et al. [25, 26] proposed the use of an integrated electronic data log (EDL) for recording parameters indicative of product degradation. The EDL was implemented on electric motors to increase the reuse of motors. In another study, [27] domestic appliances were monitored for collecting usage data by means of electronic units fitted on the appliances. This work introduced the life cycle data acquisition unit, which can be used for data collection and also for diagnostics and servicing. Middendorf et al. [28] suggested developing life information modules to record the cycle conditions of products for reliability assessment, product refurbishing, and reuse.

Designers often establish the usable life of products and warranties based on extrapolating accelerated test results to assumed usage rates and life-cycle conditions. These assumptions may be based on worst-case scenarios of various parameters composing the end-user environment. Thus if the assumed conditions and actual use conditions are the same, the product would last for the designed time, as shown in Figure 1.2 a. However, this is rarely true, and usage and environmental conditions could vary significantly from those assumed. For example, consider products equipped with life consumption monitoring systems for providing in situ assessment of remaining life. In this situation, even if the product is used at a higher usage rate and in harsh conditions, it can still avoid unscheduled maintenance and catastrophic failure, maintain safety, and ultimately save cost. These are typically the motivational factors for use of health monitoring or life consumption monitoring, as shown in Figure 1.2 b.

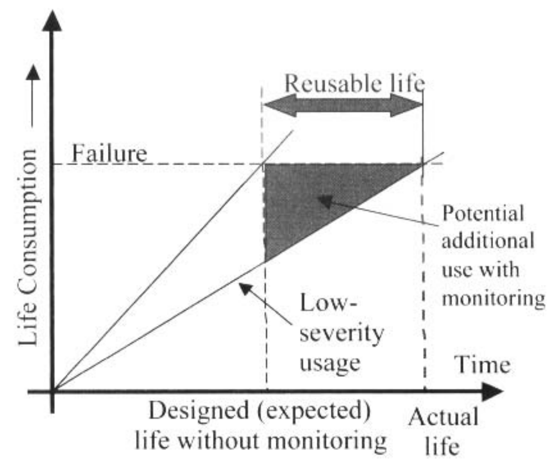
One of the vital inputs in making end-of-life decisions is the estimate of degradation and the remaining life of the product. Figure 1.2 c illustrates a scenario in which a working product is returned at the end of its designed life. Using the health monitors installed within the product, the reusable life can be assessed. Unlike testing conducted after the product is returned, this estimate can be made without having to disassemble the product. Ultimately, depending on other factors such as cost of the product, demand for spares, cost, and yield in assembly and disassembly, the manufacturer can choose to reuse or dispose.



(a) Usage as per design



(b) More severe usage than intended design



(c) Less severe usage than intended design

Figure 1.2: Application of health monitoring for product reuse.

1.3 PHM Concepts and Methods

The general PHM methodology is shown in Figure 1.3 [29]. The first step involves a virtual life assessment, where design data, expected life-cycle conditions, failure modes, mechanisms, and effects analysis (FMMEA), and PoF models are the inputs to obtain a reliability (virtual life) assessment. Based on the virtual life assessment, it is possible to prioritize the critical failure modes and failure mechanisms. The existing sensor data, bus monitor data, and maintenance and inspection record can also be used to identify the abnormal conditions and parameters. Based on this information, the monitoring parameters and sensor locations for PHM can be determined.

Based on the collected operational and environmental data, the health status of the products can be assessed. Damage can also be calculated from the PoF models to obtain the remaining life. Then PHM information can be used for maintenance forecasting and decisions that minimize life-cycle costs, or maximize availability or some other utility function.

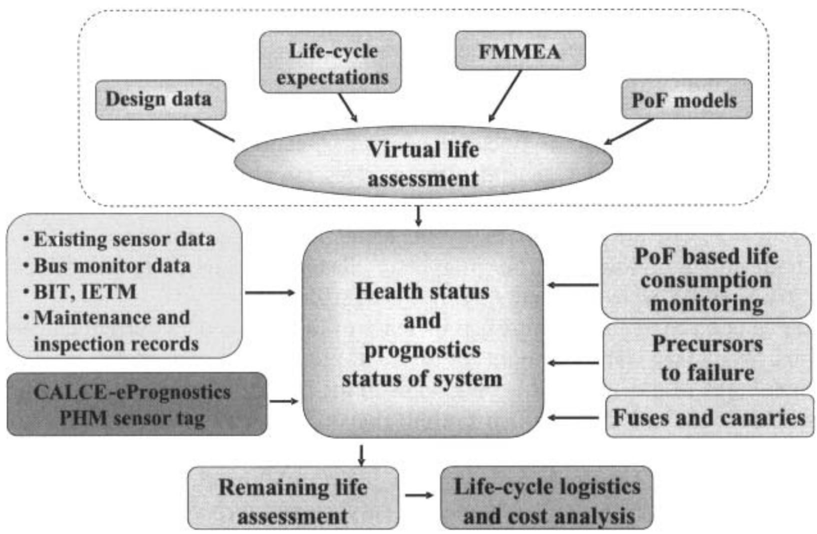


Figure 1.3: CALCE PHM methodology.

The different approaches to prognostics and the state of research in electronics PHM are presented here. Three current approaches include (1) the use of fuses and canary devices; (2) monitoring and reasoning of failure precursors; and (3) monitoring environmental and usage loading for PoF-based stress and damage modeling.

1.3.1 Fuses and Canaries

Expendable devices, such as fuses and canaries, have been a traditional method of protection for structures and electrical power systems. Fuses and circuit breakers are examples of elements used in electronic products to sense excessive current drain and to disconnect power. Fuses within circuits safeguard parts against voltage transients or excessive power dissipation and protect power supplies from shorted parts. For example, thermostats can be used to sense critical temperature limiting conditions and to shut down the product, or a part of the system, until the temperature returns to normal. In some products, self-checking circuitry can also be incorporated to sense abnormal conditions and to make adjustments to restore normal conditions or to activate switching means to compensate for a malfunction [30].

The word "canary" is derived from one of coal mining's earliest systems for warning of the presence of hazardous gas using the canary bird. Because the canary is more sensitive to hazardous gases than humans, the death or sickening of the canary was an indication to the miners to get out of the shaft. The canary thus provided an effective early warning of catastrophic failure that was easy to interpret. The same approach has been employed in prognostic health monitoring. Canary devices mounted on the actual product can also be used to provide advance warning of failure due to specific wearout failure mechanisms.

Mishra et al. [31] studied the applicability of semiconductor-level health monitors by using pre-calibrated cells (circuits) located on the same chip with the actual circuitry. The prognostics cell approach, known as Sentinel Semiconductor™ technology, has been commercialized to provide an early warning sentinel for upcoming device failures [32]. The prognostic cells are available for 0.35-μm, 0.25-μm, and 0.18-μm complementary metal-oxide-semiconductor (CMOS) processes; the power consumption is approximately 600 μW. The cell size is typically 800 μm^2 at the 0.25-μm process size. Currently, prognostic cells are available for semiconductor failure mechanisms such as electrostatic discharge (ESD), hot carrier, metal migration, dielectric breakdown, and radiation effects.

The time to failure of prognostic canaries can be precalibrated with respect to the time to failure of the actual product. Because of their location, these canaries contain and experience substantially similar dependencies as does the actual product. The stresses that contribute to degradation of the circuit include voltage, current, temperature, humidity, and radiation. Since the operational stresses are the same, the damage rate is expected to be the same for both circuits. However, the prognostic canary is designed to fail faster through increased stress on the canary structure by means of scaling.

Scaling can be achieved by controlled increase of the stress (e.g., current density) inside the canaries. With the same amount of current passing through both circuits, if the cross-sectional area of the current-carrying paths in the canary is decreased, a higher current density is achieved. Further control in current density can be achieved by increasing the voltage level applied to the canaries. A combination of both of these techniques can also be used. Higher current density leads to higher internal (joule) heating, causing greater stress on the canaries. When a current of higher density passes through the canaries, they are expected to fail faster than the actual circuit [31].

Figure 1.4 shows the failure distribution of the actual product and the canary health monitors. Under the same environmental and operational loading conditions, the canary health monitors wear out faster to indicate the impending failure of the actual product. Canaries can be calibrated to provide sufficient advance warning of failure (prognostic distance) to enable appropriate maintenance and replacement activities. This point can be adjusted to some other early indication level. Multiple trigger points can also be provided using multiple canaries spaced over the bathtub curve.

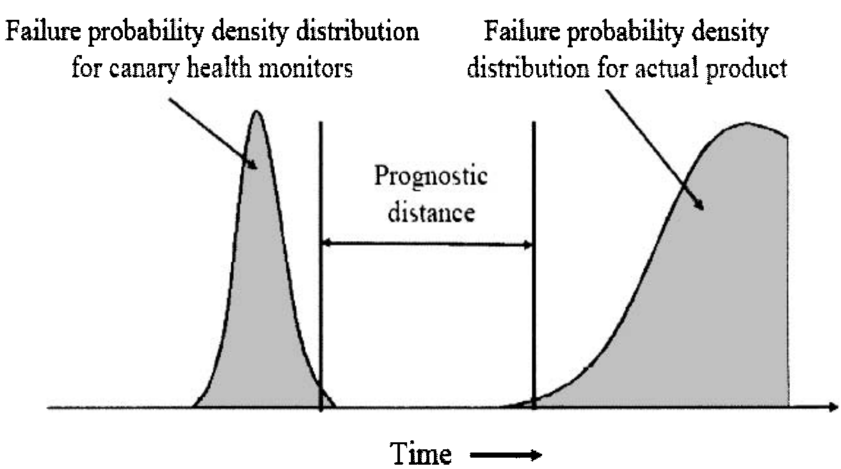


Figure 1.4: Advanced warning of failure using canary structures.

Goodman et al. [33] used a prognostic canary to monitor time-dependent dielectric breakdown (TDDB) of the metal-oxide-semiconductor field-effect transistor (MOSFET) on the integrated circuits. The prognostic canary was accelerated to failure under certain environmental conditions. Acceleration of the breakdown of an oxide could be achieved by applying a voltage higher than the supply voltage to increase the electric field across the oxide. When the prognostics canary failed, a certain fraction of the circuit lifetime was used up. The fraction of consumed circuit life was dependent on the amount of over voltage applied and could be estimated from the known distribution of failure times.

The extension of this approach to board-level failures was proposed by Anderson et al. [34], who created canary components (located on the same printed circuit board) that include the same mechanisms that lead to failure in actual components. Anderson et al. identified two prospective failure mechanisms: (1) low cycle fatigue of solder joints, assessed by monitoring solder joints on and within the canary package, and (2) corrosion monitoring, using circuits that are susceptible to corrosion. The environmental degradation of these canaries was assessed using accelerated testing, and degradation levels were calibrated and correlated to actual failure levels of the main system. The corrosion test device included an electrical circuitry 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. The change in impedance characteristics can be correlated to indicate specific degradation mechanisms.

There remain unanswered questions with the use of fuses and canaries for PHM. For example, if a canary monitoring a circuit is replaced, what is the impact when the product is re-energized? What protective architectures are appropriate for postrepair operations? What maintenance guidance must be documented and followed when fail-safe protective architectures have or have not been included? The canary approach is also difficult to implement in legacy systems because it may require requalification of the entire system with the canary module. Also, the integration of fuses and canaries with the host electronic system could be an issue with respect to real estate on semiconductors and boards. Finally, the company must ensure that the additional cost of implementing PHM can be recovered through increased operational and maintenance efficiencies.

1.3.2 Monitoring and Reasoning of Failure Precursors

A failure precursor is a data event or trend that signifies impending failure. A precursor indication is usually a change in a measurable variable that can be associated with subsequent failure. For example, a shift in the output voltage of a power supply might suggest impending failure due to a damaged feedback regulator and opto-isolator circuitry. Failures can then be predicted by using causal relationships between measured variables that can be correlated with subsequent failure and for PoF.

A first step in failure precursor PHM is to select the life-cycle parameters to be monitored. Parameters can be identified based on factors that are crucial for safety, that are likely to cause catastrophic failures, that are essential for mission completeness, or that can result in long downtimes. Selection can also be based on knowledge of the critical parameters established by past experience, field failure data on similar products, and qualification testing. More systematic methods, such as FMMEA [35], can also be used to determine parameters that need to be monitored.

Pecht et al. [36] proposed several measurable parameters that can be used as failure precursors for electronic products, including switching power supplies, cables and connectors, CMOS integrated circuits (ICs), and voltage-controlled high-frequency oscillators (see Table 1.1).

Table 1.1: Potential Failure Precursors for Electronics [36]

Electronic Subsystem	Failure Precursor
Switching power supply	• Direct-current (DC) output (voltage and current levels) • Ripple • Pulse width duty cycle • Efficiency • Feedback (voltage and current levels) • Leakage current • Radio frequency (RF) noise
Cables and connectors	• Impedance changes • Physical damage • High-energy dielectric breakdown
CMOS IC	• Supply leakage current • Supply current variation • Operating signature • Current noise • Logic-level variations
Voltage-controlled oscillator	• Output frequency • Power loss • Efficiency • Phase distortion • Noise
Field effect transistor	• Gate leakage current/resistance • Drain-source leakage current/resistance
Ceramic chip capacitor	• Leakage current/resistance • Dissipation factor • RF noise
General purpose diode	• Reverse leakage current • Forward voltage drop • Thermal resistance • Power dissipation • RF noise
Electrolytic capacitor	• Leakage current/resistance • Dissipation factor • RF noise
RF power amplifier	• Voltage standing wave ratio (VSWR) • Power dissipation • Leakage current

In general, to implement a precursor reasoning-based PHM system, it is necessary to identify the precursor variables for monitoring and then develop a reasoning algorithm to correlate the change in the precursor variable with the impending failure. This characterization is typically performed by measuring the precursor variable under an expected or accelerated usage profile. Depending on the characterization, a model is