Transactions of the Institute of Measurement and Control 31, 3/4 (2009) pp. 309–322

Physics-of-failure-based prognostics for electronic products

Michael Pecht[1] and Jie Gu[2]

[1]Electronics Engineering Department, City University of Hong Kong and CALCE Electronic Products and Systems Center, University of Maryland, College Park, MD 20742, USA
[2]Center for Advanced Life Cycle Engineering (CALCE), University of Maryland, College Park, MD 20742, USA

This paper presents a physics-of-failure (PoF)-based prognostics and health management approach for effective reliability prediction. PoF is an approach that utilizes knowledge of a product's life cycle loading and failure mechanisms to perform reliability design and assessment. PoF-based prognostics permit the assessment of product reliability under its actual application conditions. It integrates sensor data with models that enable *in situ* assessment of the deviation or degradation of a product from an expected normal operating condition (ie, the product's 'health') and the prediction of the future state of reliability. A formal implementation procedure, which includes failure modes, mechanisms, and effects analysis, data reduction and feature extraction from the life cycle loads, damage accumulation, and assessment of uncertainty, is presented. Then, applications of PoF-based prognostics are discussed.

Key words: electronics; physics-of-failure; prognostics; reliability prediction.

1. Introduction to the prediction of reliability

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 of the device. 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 modelling approach that was proven to be flawed (Pecht and Dasgupta, 1995).

Address for correspondence: Michael Pecht, Electronics Engineering Department, City University of Hong Kong and CALCE Electronic Products and Systems Center, University of Maryland, College Park, MD 20742, USA. E-mail: pecht@calce.umd.edu
Figures 1–5 appear in colour online: http://tim.sagepub.com

 10.1177/0142331208092031

Some other handbook reliability prediction methods for electronic products followed the approach of Mil-HDBK-217. These included: 217-PLUS, Telcordia (2001), PRISM (Denson, 1999) and FIDES (2004). All of these methods rely on the collection of field failure data, but rarely is actual root cause analysis conducted. These methods generally assume the components of the product 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 problems with this type of modelling approach (Cushing *et al.*, 1993; Leonard, 1991; Talmor and Arueti, 1997; Wong, 1990). 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 (Cushing *et al.*, 1993; Morris, 1990). Today, good companies do not use these methods.

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 cancelled and the use of this type of modelling approach discouraged.

In 1998, the 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 (IEEE Standard 1413, 1998). 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 (IEEE Standard 1413.1, 2002). It is shown that the Mil-HDBK-217 and the related handbook methods, such as Telcordia, PRISM, FIDES and 217-PLUS, are flawed. There is also discussion of the advantage of reliability prediction methods that use physics-of-failure (PoF).

The PoF approach and design-for-reliability (DfR) methods have been developed by CALCE (Pecht and Dasgupta, 1995) 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 design for and assess reliability. The approach is based on the identification of potential failure modes, failure mechanisms and failure sites for the product as a function of the product's 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.

Assessing the extent of deviation or degradation from an expected normal operating condition (ie, health) for electronics provides data that can be used to meet several critical goals, which include (1) providing advance 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 (Vichare and Pecht, 2006).

The importance of PHM has also been explicitly stated in the U.S. Department of Defense 5000.2 policy document on defence acquisition, which 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' (DoD 5000.2 Policy Document, 2004). Thus, a prognostics capability has become a requirement for any system sold to the U.S. Department of Defense.

2. Prognostic modelling of stress and damage utilizing life cycle loads

A product can be subject to loads that arise during manufacturing, shipment, storage, handling, operating and non-operating conditions. These life cycle loads (thermal, mechanical, chemical, electrical, and so on), can either individually or in various combinations, lead to performance or physical degradation of the product and reduce its service life. The extent and rate of product degradation depends upon the magnitude and duration of exposure to loads (usage rate, frequency and severity). In the PoF-based prognostics approach, the life cycle loads are monitored *in situ*, and used in conjunction with PoF-based damage models to assess the degradation related to cumulative load exposures.

Ramakrishnan and Pecht (2003), and Mishra *et al*. (2002) used PoF-based prognostics to assess an electronic component-board assembly placed under the hood of an automobile and subjected to normal driving conditions. The test board incorporated surface-mount leadless inductors soldered onto an FR-4 substrate using eutectic tin–lead solder. Temperature and vibrations were measured *in situ* on the board in the application environment. Using the monitored environmental data, stress and damage models were successfully used to estimate consumed life.

Shetty *et al*. (2002) applied the PHM methodology to conduct prognostic remaining life assessment of the End Effector Electronics Unit (EEEU) inside the robotic arm of the space shuttle remote manipulator system (SMRS). A life cycle loading profile of thermal and vibration loads was developed for the EEEU circuit boards. Damage assessment was conducted using physics-based mechanical and thermo-mechanical damage models. A prognostic estimate using a combination of damage models, inspection and accelerated testing showed that there was little degradation in the electronics and that their designed for life (of 20 years) could be extended.

Mathew *et al*. (2006, 2007) applied a similar PoF-based prognostics methodology to conduct a remaining life assessment of circuit cards inside the space shuttle solid rocket booster (SRB). Vibration time history recorded on the SRB from the pre-launch stage to splashdown was used in conjunction with physics-based models to assess damage. Using the entire life cycle loading profile of the SRBs, the remaining life of the components and structures on the circuit cards was predicted. It was determined that an electrical failure was not expected within another 40 missions.

Gu *et al*. (2007a) developed a methodology for monitoring, recording and analysing the life cycle vibration loads for remaining life prognostics of electronics in the time domain. The responses of printed circuit boards (PCB) to vibration loading in terms of bending curvature were monitored using strain gauges. The interconnect strain values were then calculated from the measured PCB response and used in a vibration failure fatigue model for damage assessment. Damage estimates were accumulated using Miner's rule after every mission and then used to predict the life consumed and remaining life.

Simons and Shockey (2006) performed a PoF-based prognostics methodology for failure of a gull-wing lead power supply chip on a DC/DC voltage converter PCB assembly. First, three-dimensional finite element analyses (FEA) were performed to determine strains in the solder joint related to thermal or mechanical cycling of the component. The strains could be related to lead bending resulting from the thermal mismatch of the board and chip, and those resulting from local thermal mismatch between the lead and the solder, as well as between the board and the solder. Then the strains were used to set boundary conditions for an explicit model that could simulate initiation and growth of cracks in the microstructure of the solder joint. Finally, based on the growth rate of the cracks in the solder joint, estimates were made of the cycles to failure for the electronic component.

Nasser and Curtin (2006) applied the PHM methodology to predict failure of the power supply. They subdivided the power supply into component elements based on specific material characteristics. Predicted degradation within any single or combination of component elements could be rolled up into an overall reliability prediction for the entire power supply system. Their PHM technique consisted of four steps: (1) acquiring the temperature profile using sensors; (2) conducting FEA to perform stress analysis; (3) conducting fatigue prediction of each solder joint; and (4) predicting the probability of failure of the power supply system.

Searls *et al*. (2001) undertook *in situ* environment loading, such as temperature measurements, in both notebook and desktop computers used in different parts of the world. In terms of the commercial applications of this approach, IBM has installed temperature sensors on hard drives (Drive-TIP; Herbst, 2005) to mitigate risks related to severe temperature conditions, such as thermal tilt of the disk stack and actuator arm, off-track writing, data corruptions on adjacent cylinders, and outgassing of lubricants on the spindle motor.

Vichare *et al*. (2004, 2007) also conducted *in situ* health monitoring of notebook computers. The authors monitored and statistically analysed the temperatures inside a notebook computer, including those experienced during usage, storage and transportation, and discussed the need to collect such data both to improve the thermal design of the product and to monitor prognostic health. After the data was collected, it could be used to estimate the distributions of the load parameters. The usage history was used for damage accumulation and remaining life prediction.

In 2001, the European Union funded a 4-year project, 'Environmental Life-Cycle Information Management and Acquisition' (ELIMA), which aimed to develop ways to manage the life cycles of products (Bodenhoefer, 2004; ELIMA Report, 2005). The objective of this work was to predict the remaining lifetime of parts removed from products, based on dynamic data, such as operation time, temperature and power consumption. As a case study, the member companies monitored the application conditions of a game console and a household refrigerator. The work concluded that in general, it was essential to consider the environments associated with all life intervals of the equipment. These included not only the operational and maintenance environments, but also the pre-operational environments, when stresses maybe imposed on the parts during manufacturing, assembly, inspection, testing, shipping and installation. Such stresses are often overlooked, but can have a significant impact on the eventual reliability of equipment.

Tuchband and Pecht (2007) presented the use of prognostics for military line replaceable units (LRU) based on their life cycle loads. The study was part of an effort funded by the Office of Secretary of Defense to develop an interactive supply chain system for the U.S. military. The objective was to integrate prognostics, wireless communication and databases through a web portal to enable cost-effective maintenance and replacement of electronics. The study showed that prognostics-based maintenance scheduling could be implemented into military electronic systems. The approach involved an integration of embedded sensors on the LRU, wireless communication for data transmission, a PoF-based algorithm for data simplification and damage estimation, and a method for uploading this information to the Internet. It was shown that the use of prognostics for electronic military systems could enable failure avoidance, high availability and reduction of life cycle costs.

3. PoF-based PHM implementation approach

The general PHM methodology is shown in Figure 1. The first step involves a virtual (reliability) life assessment, where design data, expected life cycle conditions, failure modes, mechanisms and effects analysis (FMMEA), and PoF models are the inputs. Based on the virtual life assessment, the critical failure modes and failure mechanisms are prioritized. The existing sensor data, built-in-test results, maintenance and inspection records, and warranty data are also 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

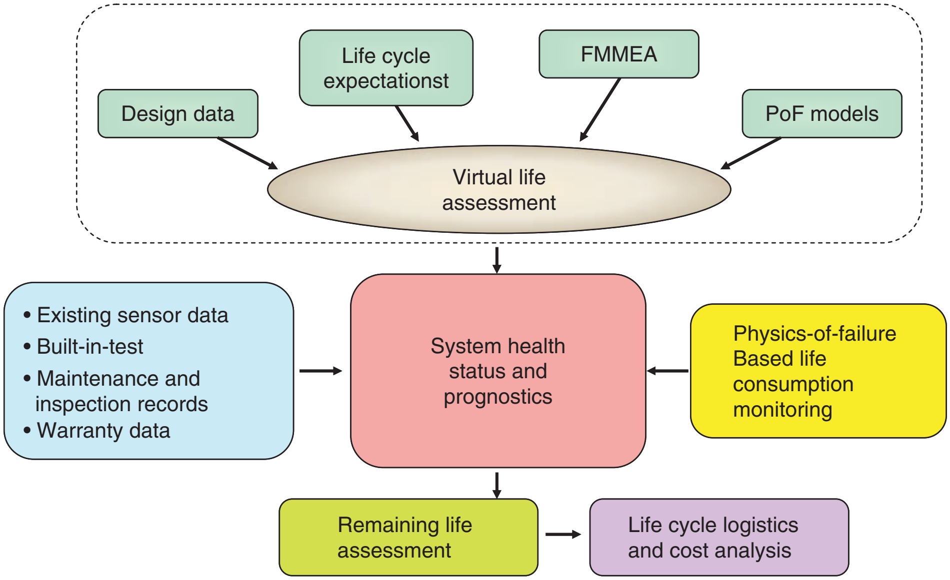

Figure 1 PoF-based PHM methodology

obtain the remaining life. Then PHM information can be used for maintenance forecasting and decisions that minimize life cycle costs, maximize availability or some other utility function.

3.1 Failure mode, mechanism, and effect analysis

Failure modes, mechanisms and effects analysis (FMMEA) used in the PoF-based PHM approach is shown in Figure 2. Design capture is the process of collecting structural (dimensional) and material information to generate a model. This step involves characterizing the product at all levels, ie, parts, systems, as well as physical interfaces. In most cases, this information is developed within the design process.

The reliability assessment step involves identification of appropriate PoF models for the identified failure mechanisms. A load-stress analysis is conducted using material properties, product geometry and the life cycle loads. With the computed stresses and the failure models, a damage analysis is conducted and then the accumulated damage is estimated using a damage model.

A failure mode is the effect by which a failure is observed to occur (Pecht, 1995). All possible failure modes for each identified element should be listed. Potential failure modes may be identified using numerical stress analysis, accelerated tests to failure (eg, HALT), past experience and engineering judgment. A failure cause is defined as the specific process, design and/or environmental conditions that initiate a failure, whose removal will eliminate the failure. Knowledge of potential failure causes can help identify the failure mechanisms driving the failure modes for a given element.

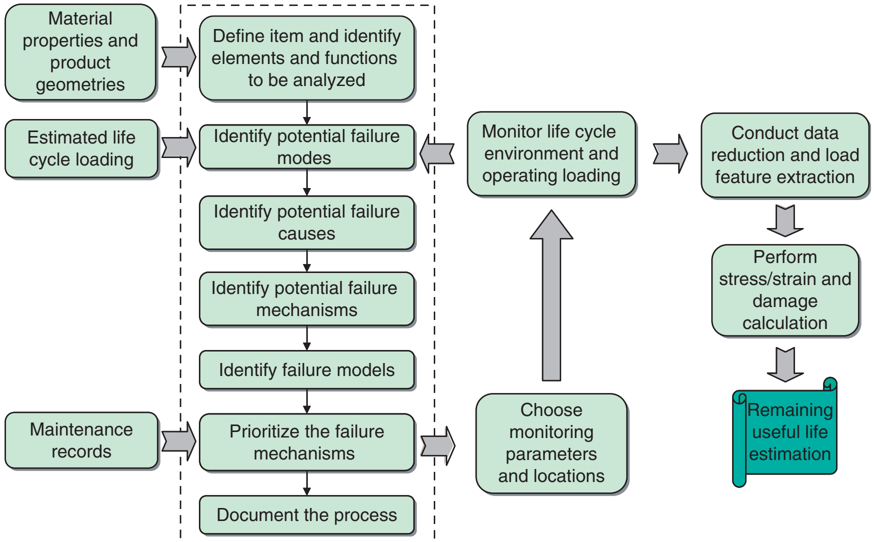

Figure 2 FMMEA analysis used in the PHM approach

Failure mechanisms are the physical, chemical, thermodynamic or other processes that result in failure. Failure mechanisms are categorized as either overstress or wear-out mechanisms. Overstress failure arises as a result of a single load (stress) condition, which exceeds a fundamental strength property. Wear-out failure arises as a result of cumulative damage related to loads (stresses) applied over an extended time. Within current technology, PHM can only be applied in the wear-out failure mechanisms. Some example wear-outs failure mechanisms for electronics are presented in Table 1 (Vichare and Pecht, 2006).

Failure models help quantify the failure through evaluation of time-to-failure or likelihood of a failure for given set of geometries, material construction, environmental and operational conditions. For wear-out mechanisms, failure models use both stress and damage analysis to quantify the damage accumulated.

3.2 Life cycle load monitoring

In the life cycle of a product, several failure mechanisms may be activated by different environmental and operational parameters acting at various stress levels, but in general, only a few operational and environmental parameters, and failure mechanisms, are responsible for the majority of the failures. High-priority mechanisms are those with high combinations of occurrence and severity. Prioritization of the failure mechanisms provides an opportunity for effective utilization of resources. If one can measure these loads *in situ*, the load profiles can be used in conjunction with damage models to assess the degradation related to cumulative load exposures. The typical life cycle loads have been summarized in Table 2 (Vichare and Pecht, 2006).

Table 1 Failure mechanisms, relevant loads, and models in electronics

Failure mechanisms	Failure sites	Relevant loads	Failure models
Fatigue	Die attach, Wirebond/TAB, solder leads, bond pads, traces, vias/PTHs, interfaces	ΔT, Tmean, dT/dt, dwell time, ΔH, ΔV	Nonlinear Power Law (Coffin–Manson)
Corrosion	Metallizations	M, ΔV, T	Eyring (Howard)
Electromigration	Metallization	T, J	Eyring (Black)
Conductive filament formation	Between metallization	M, ∇V	Power Law (Rudra)
Stress driven diffusion voiding	Metal traces	S, T	Eyring (Okabayashi)
Time dependent dielectric breakdown	Dielectric layers	V, T	Arrhenius (Fowler–Nordheim)

T, temperature; H, humidity; Δ, cyclic range; V, voltage; M, moisture; J, current density; ∇, gradient; S, stress.

Table 2 Life cycle loads

Load	Load conditions
Thermal	Steady-state temperature, temperature ranges, temperature cycles, temperature gradients, ramp rates, heat dissipation
Mechanical	Pressure magnitude, pressure gradient, vibration, shock load, acoustic level, strain, stress
Chemical	Aggressive versus inert environment, humidity level, contamination, ozone, pollution, fuel spills
Physical	Radiation, electromagnetic interference, altitude
Electrical	Current, voltage, power

3.3 Data reduction and load feature extraction

Experience has shown that even the simplest data collection systems can accumulate vast amounts of data quickly, requiring either a frequent download procedure or a large capacity storage device (Harris and McNee, 2003). Therefore, data reduction is necessary. Vichare *et al*. (2006, 2007) described the accuracy associated with a number of data reduction methods such as: ordered overall range (OOR), rainflow cycle counting, range-pair counting, peak counting, level crossing counting, fatigue meter

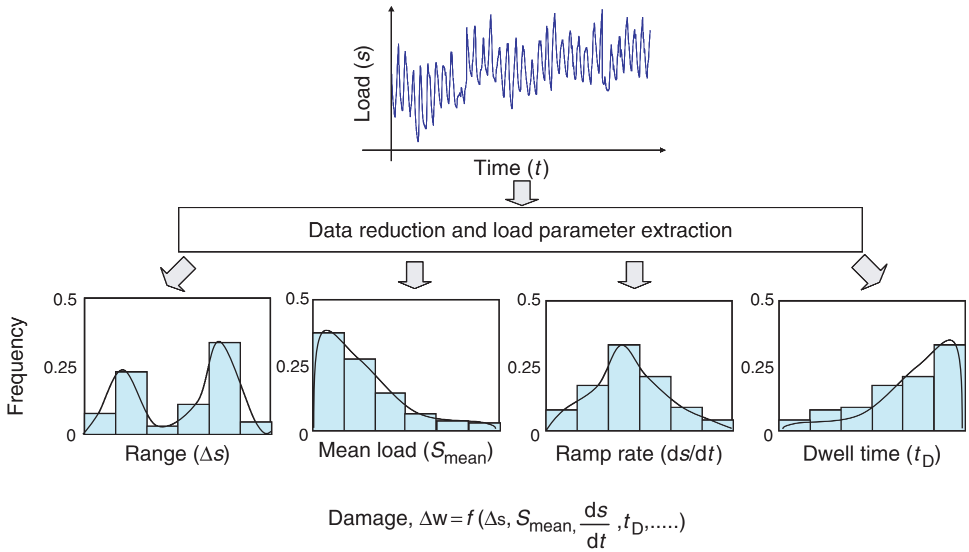

Figure 3 Load feature extraction

counting, range counting, etc. The efficiency measures of data reduction methods include: gains in computing speed and testing time; the ability to condense load histories without sacrificing important damage characteristics; and estimation of the error introduced by omitting data points.

As shown in Figure 3, a time-load signal can be monitored *in situ* using sensors, and further processed to extract (in this case) cyclic range (Δs), cyclic mean load (S_{mean}), rate of change of load ($\mathrm{d}s/\mathrm{d}t$) and dwell time (t_{D}) using embedded load extraction algorithms. The extracted load parameters can be stored in appropriately binned histograms to achieve further data reduction. After the binned data is downloaded, it can be used to estimate the distributions of the load parameters. This type of output can be input to fatigue damage accumulation models. Embedding the data reduction and load parameter extraction algorithms into the sensor modules as suggested by Vichare *et al*. (2006) can lead to a reduction in on-board storage space, lower power consumption and uninterrupted data collection over longer durations.

In Vichare's studies (Vichare *et al*., 2004, 2006), temperature data was processed using two algorithms: 1) ordered overall range (OOR) to convert an irregular time–temperature history into peaks and valleys and also to remove noise related to small cycles and sensor variations, and 2) a three-parameter rainflow algorithm to process the OOR results to extract full and half cycles with cyclic range, mean and ramp rates. The approach also involved optimally binning data in a manner that provides the best estimate of the underlying probability density function of the load parameter. The load distributions were developed using non-parametric histogram and kernel density estimation methods. The use of the proposed binning and density estimation techniques with a prognostic methodology were demonstrated on an electronic assembly.

3.4 Damage assessment and remaining life calculation

PoF-based failure models use appropriate stress and damage analysis methods to evaluate the susceptibility to failure based on the time-to-failure or likelihood of a failure for a given geometry, material construction, and environmental and set of operational conditions (Ganesan *et al*., 2005). The loading feature (eg, cyclic range, cyclic mean, ramp rate and dwell time) from raw data (eg, temperature, vibration) after feature extraction can be the input of the failure model to calculate the damage. Then the damage is accumulated over a period until the item is no longer able to withstand the applied load. Remaining life prediction is the process of estimating the remaining life (eg, the time in days, distance in miles) through which the product can function reliably, based on the damage accumulation information (Mishra *et al*., 2002). Some models used to calculate the damage caused by temperature and vibration loadings are summarized in Figure 4. Damage caused by temperature can be calculated in the time domain using Coffin Manson's model. This approach has been demonstrated in Zhang's work (2007) and Cluff *et al*.'s work (1996). Damage caused by vibration can be calculated in both the time and frequency domains. Time domain modelling has been demonstrated by Gu *et al*. (2007a), and frequency domain modelling has been demonstrated by Mathew *et al*. (2007).

3.5 Uncertainty implementation and assessment

The PoF models can be used to calculate the remaining useful life, but it is necessary to identify the uncertainties in the prognostic approach and assess the impact of these uncertainties on the remaining life distribution in order to make risk-informed decisions. With uncertainty analysis, a prediction can be expressed as a failure probability.

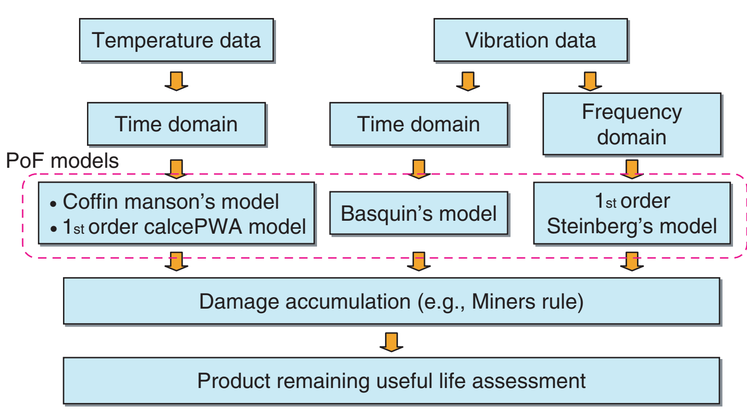

Figure 4 Damage calculation approach for temperature and vibration data

Gu *et al*. (2007b) implemented uncertainty analysis of prognostics for electronics under vibration loading. Gu identified the uncertainty sources and categorized them into four different types: measurement uncertainty, parameter uncertainty, failure criteria uncertainty and future usage uncertainty (Figure 5). Gu *et al*. (2007b) utilized a sensitivity analysis to identify the dominant input variables that influence the model output. With information of input parameter variable distributions, a Monte-Carlo simulation was used to provide a distribution of accumulated damage. From the accumulated damage distributions, the remaining life was then predicted with confidence intervals. A case study was also presented for an electronic board under vibration loading and a step-by-step demonstration of the uncertainty analysis implementation. The results showed that the experimentally measured failure time was within the bounds of the uncertainty analysis prediction.

4. Application of PoF implementation for PHM

A PoF-based prognostics approach can be used in different areas, such as new products and legacy systems. When the new product has not been manufactured, it is impossible to use the data-driven method since there will no data available for training the algorithm. In the PoF method, one only has to change the material properties or geometries to model the new products. Since most new products are not

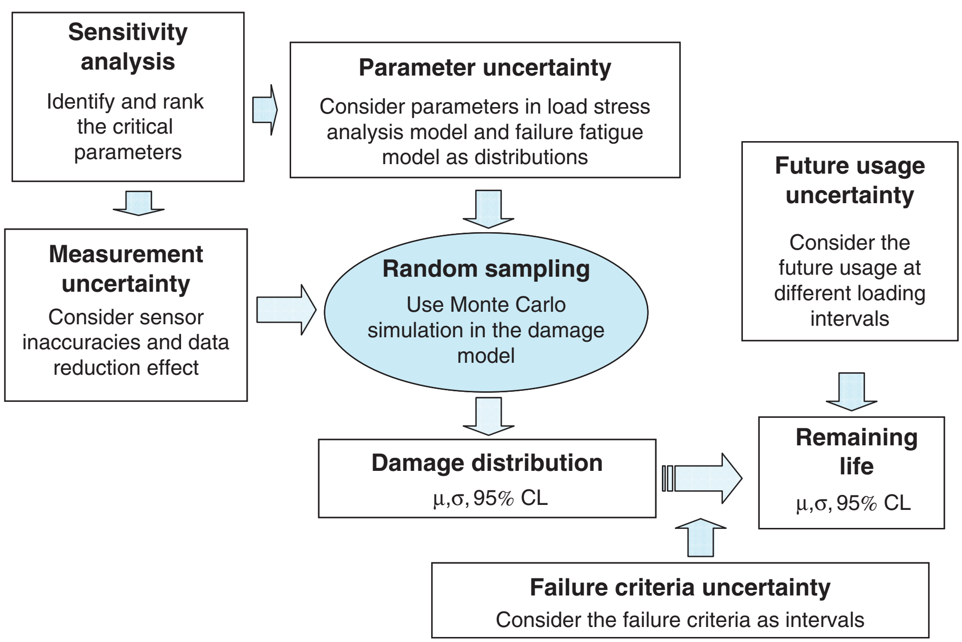

Figure 5 Uncertainty implementation for prognostics

completely different from previous products, similar products can be referenced via a failure modes, mechanisms and effects analysis (FMMEA; Ganesan *et al*., 2005).

For legacy system, training data is difficult to obtain, and it is also very difficult to assess a remaining life if there is no understanding of the failure mechanisms and their influence on collected parameters. The PoF-based PHM approach is based on an understanding of the structure and life cycle conditions of the legacy system and its failure modes and mechanisms. The first step is to utilize available information (such as previous loading conditions, maintenance records and so on) to assess the health status of the legacy system. The second step is to calibrate the health status using individual unit data so that an assessment of individual legacy systems' health can be derived. The third step involves the use of sensors and prognostic algorithms to update the health status on a continual basis to provide the most up-to-date prognosis of the system (Tuchband *et al*., 2006).

5. Summary

Traditional reliability predictions based on handbook methods are inaccurate and misleading. In this paper, we have shown that PoF-based PHM is more suitable for reliability (remaining life) assessment, since it considers actual operational and environmental loading condition for individual product.

Currently research has been done on building physics-based damage models for electronics, obtaining the life cycle data of product, and assessing uncertainty in remaining useful life prediction in order to make the PHM more realistic. More research areas are investigated on advance sensor technologies, communication technologies, decision-making methods and return of investment methods.

In the future, because of the increasing amount of electronics in the world and the competitive drive toward more reliable products, PoF-based PHM is being looked upon as a cost-effective solution to predict the reliability of electronic products and systems, since it can help identify the most critical failure under products' real application condition.

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