Prognostics and Health Management Using Physics-of-Failure

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SUMMARY AND CONCLUSIONS

This paper presents a physics-of-failure based prognostics and health management approach for effective reliability prediction. This method permits in situ assessment of system reliability under actual application conditions. The method uses sensor data with models that enable in situ assessment of the deviation or degradation of a product from an expected normal operating condition (i.e., the system’s “health”) and the prediction of the future state of reliability. The implementation procedure of this approach includes failure modes, mechanisms, and effects analysis, data reduction and feature extraction from the life-cycle loads, damage accumulation, and assessment of uncertainty.

1 INTRODUCTION

Physics-of-failure (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 at a particular life-cycle loading condition. The stress at each failure site is obtained as a function of both the loading conditions and the product geometry and material properties. The use of PoF modeling approaches for electronic components and devices, like those used for mechanical systems, provides a powerful tool in support of prognostic capabilities.

Prognostics and health management (PHM) is a method that permits the assessment of the extent of deviation or degradation from an expected normal operating condition (i.e., health). For electronics, this provides data that can be used to meet several critical goals, which include (1) 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 [1].

2 MODELLING OF STRESS AND DAMAGE UTILIZING LIFE-CYCLE LOADS

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

In the studies of Ramakrishnan, et al., [2] and Mishra, et al., [3], the test vehicle consisted of an electronic component–board assembly placed under the hood of an automobile and subjected to normal driving conditions in the Washington, DC, area. The test board incorporated eight surface–mount leadless inductors soldered onto an FR–4 substrate using eutectic tin–lead solder. Solder joint fatigue was identified as the dominant failure mechanism. Temperature and vibrations were measured in–situ on the board in the application environment. Using the monitored environmental data, stress and damage models were developed and used to estimate consumed life.

Shetty, et al., [4] applied the PHM methodology for conducting a prognostic remaining–life assessment of the end effector electronics unit (EEEU) inside the robotic arm of the space shuttle remote manipulator system (SRMS). A life–cycle loading profile for thermal and vibration loads was developed for the EEEU 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 they could be expected to last another twenty years.

Mathew, et al., [5] applied the PHM methodology in conducting a prognostic remaining–life assessment of circuit cards inside a 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 the damage caused due to vibration and shock loads. 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 forty missions.

Gu, et al., [6] developed a methodology for monitoring, recording, and analyzing the life-cycle vibration loads for remaining-life prognostics of electronics. The responses of
implemented into military electronic systems. The approach of prognostics-based maintenance scheduling could be used to replace of electronics. This study showed that through a web portal to enable cost-effective maintenance and integration of prognostics, wireless communication, and databases into a network system for the U.S. military. The objective was to extend the life of military line replaceable units (LRU) based on their life-cycle consumption and estimate remaining life prediction.

The usage history was used for damage accumulation and remaining life prediction. After the data was collected, it was statistically analyzed to estimate the distributions of the load parameters. The usage history was used for damage accumulation and remaining life prediction.

Nasser, et al., [8] applied 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 one or combination of component elements could be extrapolated into an overall reliability prediction for the entire power supply system. Their PHM technique consisted of five steps: (1) acquiring the temperature profile using sensors; (2) conducting FEA to perform stress analysis; (3) conducting fatigue prediction of each solder joint; (4) predicting the probability of failure of the power supply system.

Vichare, et al., [9] also conducted in-situ health monitoring of notebook computers. The authors monitored and statistically analyzed 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.

Tuchband, et al., [10] 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 the 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. This study showed that prognostics-based maintenance scheduling could be implemented into military electronic systems. The approach involves 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. Finally, the use of prognostics for electronic military systems enabled failure avoidance, high availability, and reduction of life-cycle costs.

3 CANARY DEVICES APPROACH

Canary devices mounted on the actual product have been used to provide advance warning of failure due to specific wearout failure mechanisms. 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 same approach has been employed in PHM. Canary devices have been integrated into a specific component, device, or system design and incorporated failure mechanisms that occur first in the embedded device. These embedded canary devices (also called prognostics cells) were non-critical elements of the overall design providing early incipient failure warnings before actual system or component failure [1].

Mishra, et al., [11] 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 was commercialized by Ridgetop Group to provide an early-warning sentinel for upcoming device failures. The prognostic cells were available for 0.35, 0.25, and 0.18 micron CMOS processes. The time to failure of these prognostic cells could be pre-calibrated with respect to the time to failure of the actual product. The stresses that contributed to degradation of the circuit included voltage, current, temperature, humidity, and radiation. Since the operational stresses were the same, the damage rate was expected to be the same for both the circuits.

However, the prognostic cell was designed to fail earlier due to increased stress on the cell structure by means of scaling. For example, scaling could be achieved by controlled increase of the current density inside the cells. With the same amount of current passing through both circuits, if the cross-sectional area of the current-carrying paths in the cells was decreased, a higher current density was achieved. Not only the structure but the loading could be scaled. Further control in current density could be achieved by increasing the voltage level applied to the cells. Higher current density led to higher internal heating, causing greater stress on the cells. When a current of higher density passed through the cells, they were expected to fail faster than the actual circuit [11]. Currently, prognostic cells are available for semiconductor failure mechanisms such as electrostatic discharge (ESD), hot carrier, metal migration, dielectric breakdown, and radiation effects.

The extension of this approach to board-level failures was proposed by Anderson, et al., [12], who created canary components (located on the same printed circuit board) that include the same mechanisms that lead to failure in actual components. They 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 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.

Goodman, et al. [13] used a prognostic cell to monitor time-dependent dielectric breakdown (TDDDB) of the metaloxide semiconductor field-effect transistor (MOSFET) on the integrated circuits. The prognostic cell 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 cell 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.

4 POF-BASED PHM IMPLEMENTATION APPROACH

The PoF methodology is founded on the premise that failures result from fundamental mechanical, chemical, electrical, thermal, and radiation processes. The objective of the PoF methodology in the PHM process is to calculate the cumulative damage due to various failure mechanisms for a product in a given environment. The approach to implementing PoF into PHM can be based on a failure mode, mechanism, and effect analysis (FMMEA), which is shown in Figure 1. This approach consists of design capture, identification of potential failure, and reliability assessment [2].

Design capture is the process of collecting structural (dimensional) and material information about a product to generate a model. This step involves characterizing the product at all levels—that is, parts, systems, and physical interfaces. The potential failure identification step involves using the geometry and material properties of the product, together with the measured life-cycle loads acting on the product, to identify the potential failure modes, mechanisms, and failure sites in the product. This task is best performed through virtual qualification, which is a simulation-based methodology used to identify and rank the potential failure mechanisms. The reliability assessment step involves identification of appropriate PoF models for the specified 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, an analysis is conducted to determine the cycles to failure and then the accumulated damage is estimated using a damage model. Actually, the PoF methodology can provide a systematic approach to reliability assessment early in the design process.

![Figure 1. PoF-based PHM approach](image)

4.1 Failure mode, mechanism, and effect analysis

A failure mode is the effect by which a failure is observed to occur [14]. It can also be defined as the way in which a component, subsystem, or system could fail to meet or deliver the intended function. 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 (e.g., HALT), past experience, and engineering judgment. The failure mode needs to be observable directly by methods such as visual inspection, electrical measurement, or other tests and measurements.

A failure cause is defined as the specific process, design and/or environmental condition that initiated the 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. One method of looking for causes is to review the life-cycle loads item by item to evaluate if any of the loads there can cause the failure.

Failure mechanisms are the physical, chemical, thermodynamic, or other processes that result in failure. Failure mechanisms are categorized as either overstress or wearout mechanisms. Overstress failure arises as a result of a single load (stress) condition that exceeds a fundamental material strength. Wearout failure arises as a result of cumulative damage due to loads (stresses) applied over an extended time or number of cycles. Within current technology, PHM can only be applied to the wearout failure mechanisms. Typical wearouts failure mechanisms for electronics have been summarized in Table 1 [15].

<table>
<thead>
<tr>
<th>Failure Mechanisms</th>
<th>Failure Sites</th>
<th>Relevant Loads</th>
<th>Failure Models</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fatigue</td>
<td>Die attach, wirebond/TAB, solder leads, bond pads, traces, vias/PTHs, Interfaces</td>
<td>ΔT, Tmean, dT/dt, dwell time, ΔH, ΔV</td>
<td>Nonlinear Power Law (Coffin-Manson)</td>
</tr>
<tr>
<td>Corrosion</td>
<td>Metallizations</td>
<td>M, ΔV, T</td>
<td>Eyring (Howard)</td>
</tr>
<tr>
<td>Electromigration</td>
<td>Metallization</td>
<td>T, J</td>
<td>Eyring (Black)</td>
</tr>
<tr>
<td>Conductive Filament Formation</td>
<td>Between metallization</td>
<td>M, V T</td>
<td>Power Law (Rudra)</td>
</tr>
<tr>
<td>Stress Driven Diffusion Voiding</td>
<td>Metal traces</td>
<td>S, T</td>
<td>Eyring (Okabayashi)</td>
</tr>
<tr>
<td>Time Dependant Dielectric Breakdown</td>
<td>Dielectric layers</td>
<td>V, T</td>
<td>Arrhenius (Fowler-Nordheim)</td>
</tr>
<tr>
<td>Δ: Cyclic range V: gradient</td>
<td>V: Voltage</td>
<td>T: Temperature</td>
<td>S: Stress</td>
</tr>
<tr>
<td>M: Moisture J: Current density H: Humidity</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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

4.2 Life-cycle loading monitoring

The life-cycle environment of a product consists of manufacturing, shipment, storage, handling, operating and non-operating conditions. The life-cycle loads, either individually or in various combinations, may lead to performance or physical degradation of the product or may reduce its service life [1]. The extent and rate of product degradation depends on the magnitude and duration of exposure (usage rate, frequency, and severity) of such loads. If these loads can be measured in-situ, the load profiles can be used in conjunction with damage models to assess the degradation due to cumulative load exposures. The typical life cycle loads have been summarized in Table 2 [1].

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

Table 2. Life cycle loads

4.3 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 [16]. The main reasons for using data reduction in life consumption monitoring are reduction of storage space, reduction in data-logger CPU load, and alignment with life prediction models. The efficiency measures of data reduction methods should consider 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.

The CALCE group has studied the accuracy associated with a number of data reduction methods, such as ordered overall range (OOR), rainfall cycle counting, range-pair counting, peak counting, level-crossing counting, fatigue meter counting, range counting, and so on.

Embedding the data reduction and load parameter extraction algorithms into the sensor modules as suggested by Vichare, et al., [1] can lead to a reduction in on-board storage space, lower power consumption, and uninterrupted data collection over longer durations. As shown in Figure 2, 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 (Smean), rate of change of load (ds/dt), and dwell time (t0) 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
The frequency domain has been demonstrated by Satchidananda, et al. [5], can use Basquin’s model. The time domain using the Coffin-Manson model. This 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.

4.4 Damage assessment and remaining life calculation

Temperature and vibration are common load conditions that can accelerate the precipitation of electronics failure [17]. Some PoF models used to calculate the damage caused by temperature and vibration loadings are summarized in Figure 3. Damage caused by temperature can be calculated in the time domain using the Coffin-Manson model. This approach has been demonstrated in Satchidananda’s work [18]. Damage caused by vibration can be calculated in both the time and frequency domains. The time domain, which has been demonstrated by Gu, et al. [5], can use Basquin’s model. The frequency domain has been demonstrated by Satchidananda, et al. [18].

4.5 Uncertainty implementation and assessment

The PoF model can be used to calculate the remaining useful life. However, it still may not be possible to make logistics decisions with certainty. Hence, 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. Uncertainty analysis for prognostics implementations gives the prediction more meaning. With uncertainty analysis, a prediction can be expressed as a distribution rather than a single point. The prediction can be expressed as a failure probability.

Gu, et al. [19] implemented the uncertainty analysis of prognostics for electronics under vibration loading. Uncertainty sources were categorized into four different types: measurement uncertainty, parameter uncertainty, failure criteria uncertainty, and future usage uncertainty. Then, the approach for implementing the uncertainty analysis was presented as shown in Figure 4. It utilized a sensitivity analysis to identify the dominant input variables that influence the model output. With information on the 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 that used an experiment with 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.

5 CONCLUSIONS

In this paper, we have provided a methodology for PoF-based prognostics that directly uses life-cycle environmental and operational conditions. The approach incorporates FMEA processes, but includes failure mechanisms in addition to failure modes in the analysis. In the future, due to the increasing volume of electronics in the world and the competitive drive toward more reliable products, PoF-based PHM should be a cost-effective solution to improve the reliability of electronic products and systems. Future research should focus on building a library of physics-based damage models for electronics, obtaining estimates of life-cycle data to
start the prognostics learning process, and continuing the development of uncertainty in remaining useful life predictions.

REFERENCES


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