Health Assessment and Prognostics of Electronic Products

Jie Gu
Center for Advanced Life Cycle Engineering (CALCE)
University of Maryland,
College Park, MD USA
gujieustc@gmail.com

Daniel Lau
City University of Hong Kong PHM Center
Hong Kong, China
kitlau@cityu.edu.hk

Michael Pecht
Electronics Eng Dept, City University of Hong Kong
and
Center for Advanced Life Cycle Engineering (CALCE)
University of Maryland,
College Park, MD USA
pecht@calce.umd.edu

***Abstract*—Traditional reliability predictions based on handbook methods are inaccurate and misleading. In this paper, we will show a prognostics and health management (PHM) approach, which is more suitable for reliability (remaining life) assessment, since it considers actual operational and environmental loading condition for individual product. The process for PHM implement to electronics has been discussed, as well as numerical implementation examples for both industry and defense purposes.**

Keywords-electronics, health management, prognostics, reliability prediction

I. INTRODUCTION

Traditional handbook-based reliability prediction methods for electronic products include Mil-Hdbk-217 [1], Telcordia SR-332 (formerly Bellcore) [2], PRISM [3], FIDES [4], CNET/RDF (European), and the Chinese GJB-299 [5]. These methods rely on analysis of failure data collected from the field and assume that the components of a system have inherent constant failure rates that are derived from the collected data. It is further assumed that such constant failure rates can be tailored by independent "modifiers" to account for various quality, operating, and environmental conditions. There are numerous well-documented concerns with this handbook prediction approach that have shown the mathematical and physical fallacies of such assumptions and that have also shown that the results predicted by such analysis are grossly incorrect. The overwhelming consensus is that these methods should never be used because they are inaccurate for predicting actual field failures and they provide highly misleading predictions, which can result in poor designs and logistics decisions [6]-[10]. IEEE Standard 1413.1, "IEEE Guide for Selecting and Using Reliability Predictions Based on IEEE 1413" [11]-[12], also found that handbook-based reliability prediction methods do not provide adequate useful information to users. In the face of overwhelming technical and business evidence against their use, there are some misguided practitioners who continue to seek solace in the familiarity of these tools and assume that upgrading them with new data will make them better and more useful. Therefore, many companies do not use these methods anymore and the U.S. military has completely abandoned these approaches. Any patchwork to "correct" handbook-based reliability prediction will not stand up to scientific scrutiny. For example, the Reliability Information Analysis Center recently published 217Plus with a stated goal to address the shortcomings of Mil-Hdbk-217. It includes several additional factors in the prediction models, but its basic assumptions are still based on the constant failure rate of components. The 217Plus handbook assigns constant failure rates for solder joint failure and temperature cycling as two independent values. However, the failure of a solder joint and failure caused by temperature cycling do not occur at a constant rate, and these two types of failures are not independent. As a result of theses and other errors, no useful design feedback or logistics planning can be made from predictions based on this handbook.

A practical alternative way of looking at product reliability and life cycles conditions is called prognostics and health management (PHM). PHM is the process of monitoring the health of a product, and predicting the remaining useful life of the product by assessing the extent of deviation or degradation from its expected state of health and its expected usage conditions [13]. The benefits of PHM 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. In 2003 the U.S. Department of Defense stated that having a prognostics capability has become a requirement for any U.S. military system [14].

II. PROGNOSTICS IMPLEMENTATION APPROACH

The PHM implementation process shown in Figure 1 [15] provides an overview of the concepts of PHM and the techniques being developed to enable prognostics for electronic products and systems. The first step involves failure modes, mechanisms, and effects analysis (FMMEA), which includes

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design data, failure modes, failure mechanisms, failure models, life cycle profile, and possible maintenance records. The next step involves risk assessment to rank the risk priority, which includes the estimation for detection, severity, and occurrence of failure. Then the results for the virtual (reliability) life assessment can be given. This helps in conducting the actual health and prognostics monitoring of a system. The existing sensor data, bus monitor data, and built-in test results are also used to identify abnormal conditions and parameters. Based on this information, the monitoring parameters relevant to key failure mechanisms are selected. Based on the collected operational and environmental data, the health status of the products can be assessed by different methodologies: physics of failure (PoF) models, data trending for precursors, and the hybrid approach, which combines both the data-trending and PoF methodologies. The PHM information can then be used for maintenance forecasting and decisions that minimize life cycle costs and maximize availability or some other utility function.

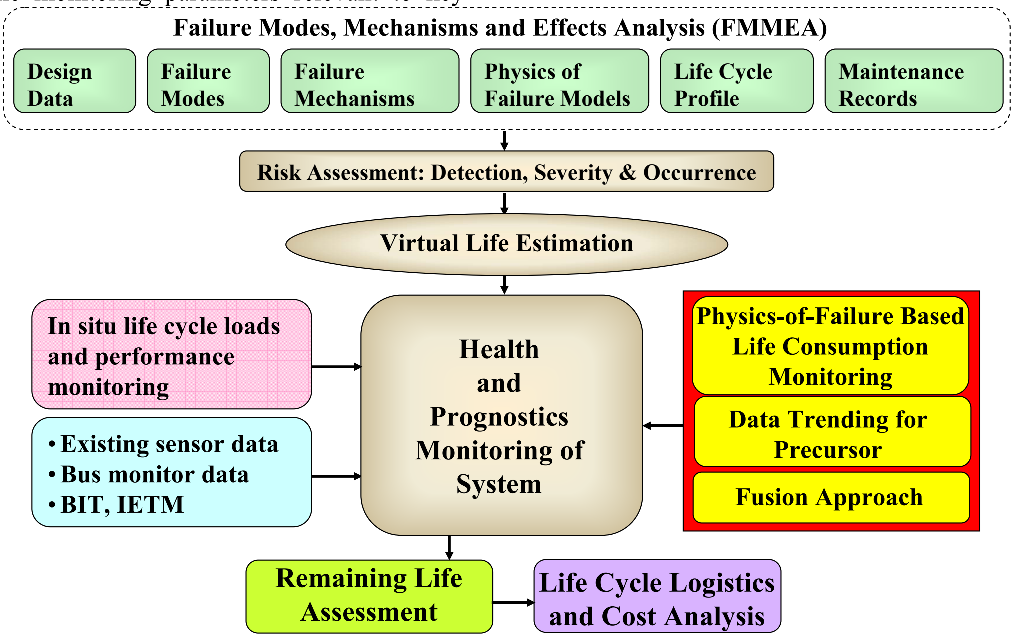

Figure 1. PHM methodology

A. PoF based PHM

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.

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 is shown in Figure 2 [16]. It consists of design capture, identification of potential failure, and reliability assessment. The design capture process includes collecting product material properties and structure geometries. Identification of potential failure includes in the FMMEA process. Reliability assessment includes life cycle environment and operating load recording, damage calculation, and remaining life prediction. This method permits in-situ assessment of system reliability under actual application conditions.

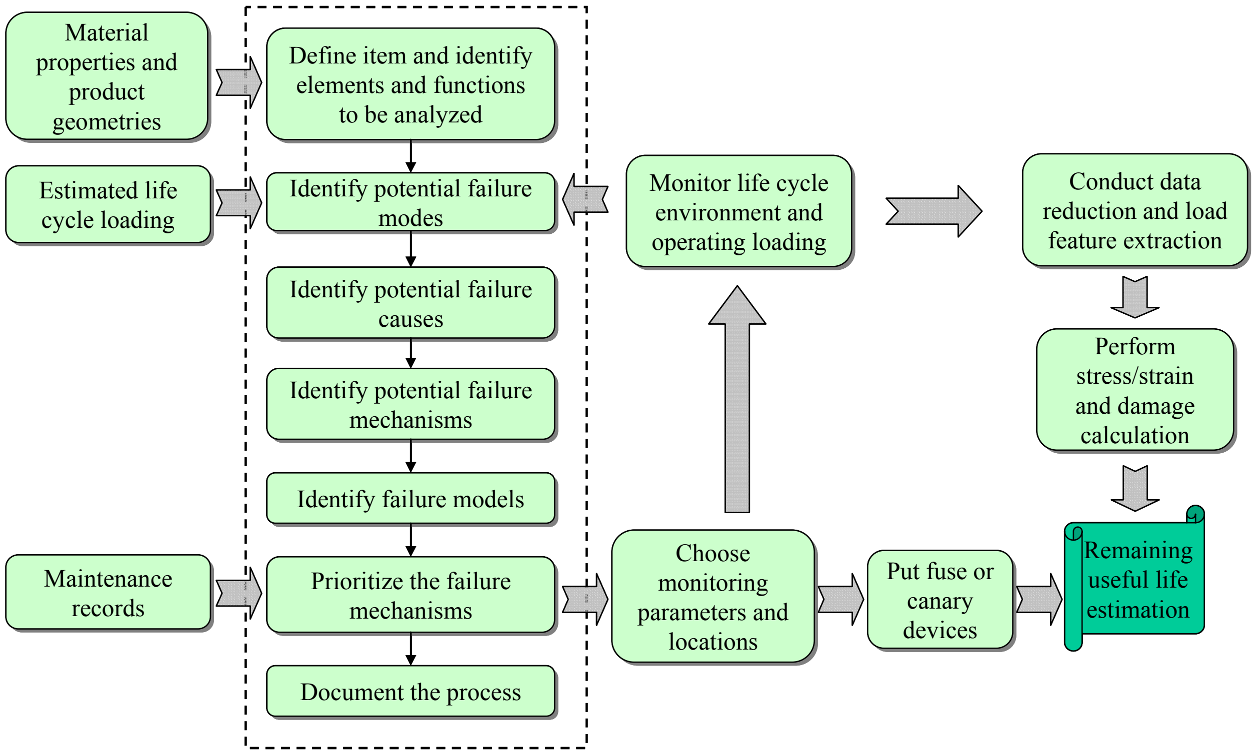

Figure 2. PoF based PHM procedure

B. Data-Trending Based PHM

In some cases, it is either difficult or impractical to use the PoF-based approach for prediction purposes. Data-trending approaches to PHM can be used for reliability prediction by monitoring system operating, environmental data and performance parameters (e.g., power, current, voltage, temperature, humidity, vibration, and acoustic signal). It defines the healthy behavior of the system by learning the previous or historical data to create the baseline distribution that will be used for anomaly detection. The measured input/output data is the major source of data for understanding system degradation behavior. The approach is shown in Figure 3 [17]. It starts with functional evaluation of the system under consideration. After a feasibility study, data acquisition techniques are investigated to gather system performance information in real time. A number of features are looked upon to represent system behavior by sensor information. During this process, data cleaning and data normalization are performed on raw data to reduce the associated noise and remove the scaling effects. Data features are used to establish the healthy state of the system. These features are also used to identify performance deviation resulting from the presence of a fault. The threshold limits on these features are set to define system failure. The trending of features provides fault or damage progression over time. This information is used to perform system prognostics.

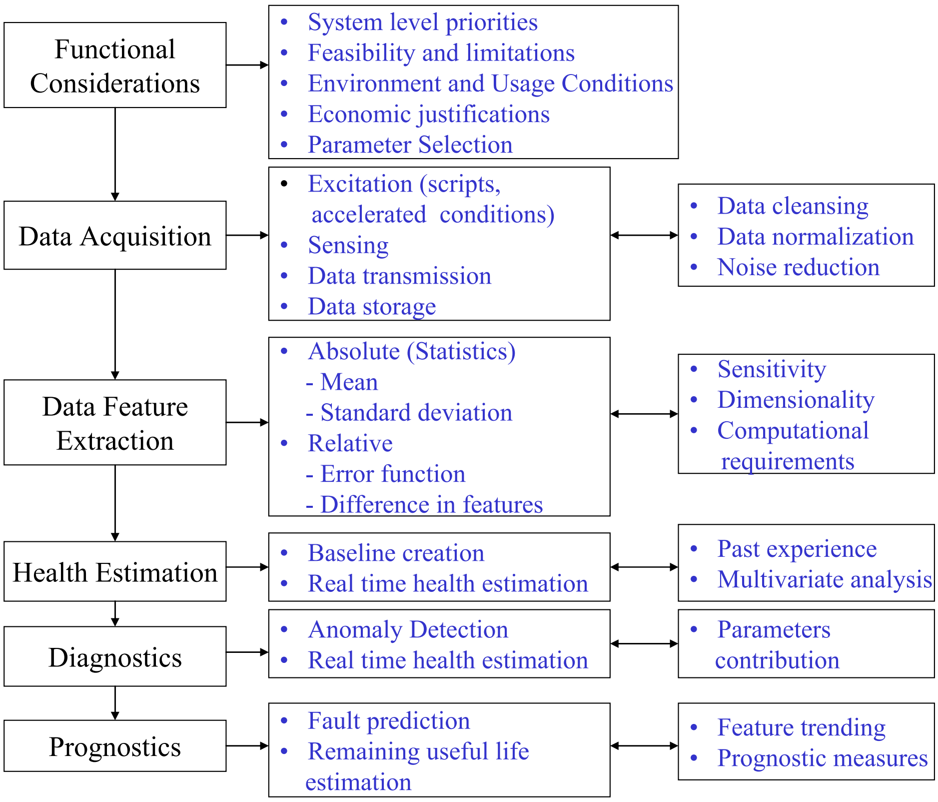

Figure 3. Data-trending based PHM procedure

C. *Fusion Approach for Prognostics*

A fusion approach (PoF + data-trending) can enhance the pure PoF and data-trending approaches. The fusion approach benefits from the merits of both the PoF and data-trending approaches. The advantage of the PoF method is its ability to isolate the root cause and the failure mechanisms that contribute to system failure. The advantage of a data-driven approach is that it addresses the complexity and the density of systems by utilizing system operating data. The fusion prognostics approach is summarized in Figure 4. The first step in the process is to determine the set of parameters that can be continuously monitored. The identification of the parameters for monitoring can be aided by a process such as failure modes, mechanisms, and effects analysis (FMMEA), but in general it can consist of any available data, including operational and environmental loads, as well as performance parameters.

In the fusion approach, the continuously monitored data is compared with a healthy baseline to check for anomalies. A healthy baseline is a collection of parameter data that best represents the possible variations of the normal operation of a system. The healthy baseline is developed using data collected from various combinations of operating states and loading conditions when the system is known to be functioning normally, but is sometimes based additionally on specifications and standards. The parameters that contribute significantly to the observed anomaly are isolated. These parameters help to determine the PoF models most relevant to system degradation and that provide information such as the failure thresholds for system parameters, the failure modes, and the stages of degradation and labels of healthy and unhealthy conditions.

Appropriate PoF models are selected based on real-time anomaly detection and critical parameter isolation. Accepted standards and specifications can be used to aid in the determination of the failure definitions. Reliability assessment is estimated using the selected PoF model. For performance parameters, statistical features and empirical relationships can also be established. The data-driven approach focuses on obtaining primary patterns or relationships, such as the correlation, covariance, residual, and inference patterns between system and component variables and operating and environmental loads. Failure precursor techniques are used to extract the features and track their deviation from the normal operating condition. This is especially useful for early detection of failures, where very distinct distribution patterns have been attributed to a specific failure. The prognostics results from PoF based approach and data-driven approach can also be fused together if they are both available for better decision making.

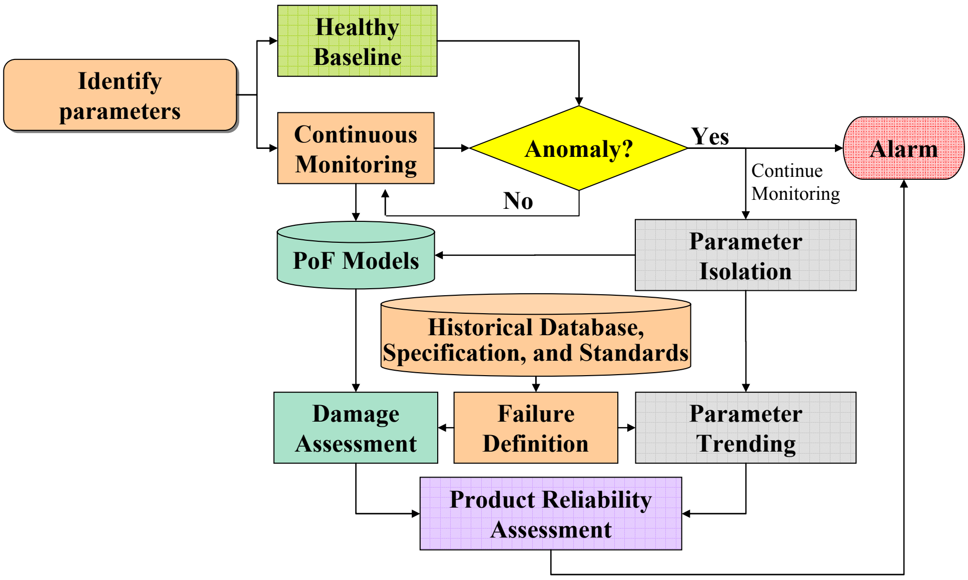

Figure 4. Fusion based PHM procedure

III. EXAMPLES FOR PHM IMPLEMENTATION

At present, there are several organizations conducting research and development in PHM, and there are many more organizations that wish to take advantage of developments in PHM. Examples of PHM implementation in different fields are given below. They include different PHM implementation levels, such as: electronics component, circuit board, device, and system level. They also cover from military and aerospace, to computer and automotive industry, and further to the home application products. It appears everywhere in our daily life.

Military

Tuchband et al. [18] presented the use of PoF based prognostics for military line replaceable units (LRU) based on their life cycle loads. The study was part of an effort funded by the U.S. 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 line replaceable units, wireless communication for data transmission, a data simplification tool, PoF-based damage estimation algorithm, and a method for uploading this information to the Internet. The use of prognostics for electronic military systems enables failure avoidance, high availability, and reduction of life cycle costs.

Aerospace

Shetty et al. [19] applied the PoF based 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. A life-cycle loading profile for thermal and vibration loads was developed for the EEEU boards. Damage assessment was conducted using failure mechanical and thermo-mechanical damage models. A prognostic estimate using a combination of damage models, inspections, 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. [20] applied the PoF based 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 by 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.

Automotive: *Underhood Electronics*

In the studies of Mishra et al. [21] and Ramakrishnan et al. [22], the test vehicle was a circuit board 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. Damage accumulated through solder joint fatigue was updated periodically using in-situ collected data on temperature and vibration. It was found that the predicted life of the solder joint failure based on PHM algorithm was within 8% of the actual experimental life.

Electronic Systems: *Computer Server*

Systems for early fault detection and failure prediction are being developed using variables, such as current, voltage, and temperature, continuously monitored at various locations inside the system. Sun Microsystems [23] refers to this approach as continuous system telemetry harness, and it is a date-trending approach. Along with sensor information, soft performance parameters such as loads, throughputs, queue lengths, and bit error rates are tracked. Characterization is conducted by monitoring the signals (of different variables) to learn a multivariate state estimation technique model. Once the model is established using this data, it is used to predict the signal of a particular variable based on learned correlations among all variables. Based on the expected variability in the value of a particular variable during application, a sequential probability ratio test (SPRT) is constructed. During actual monitoring SPRT is used to detect the deviations of the actual signal from the expected signal based on distributions (and not on single threshold value). The monitored data is analyzed to (1) provide alarms based on leading indicators of failure and (2) enable use of monitored signals for fault diagnosis, root cause analysis of no-fault-founds (NFF), and analysis of faults due to software aging.

Electronic Systems: *Notebook Computers*

Vichare et al. [24] 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 was used to estimate the distributions of the load parameters. The usage history was used for damage accumulation and remaining life prediction. This work belongs to the PoF based PHM approach.

Kumar et al. [25] presented a data-trending based prognostics approach for notebook computers. Mahalanobis distance and projection pursuit analysis technology were used for early detection of anomalies in the electronics of the products and systems through the monitoring of various signals collected from the computers (e.g., CPU usage and temperature). This study demonstrated that an “abnormal” system could be distinguished from a “normal” system by monitoring the deviation of a system’s performance.

Electronic Systems: *GPS System*

Brown et al. [26] demonstrated that the remaining useful life of a commercial global positioning system (GPS) system can be predicted by using fusion based PHM approach. First failure analysis was conducted, and the failure modes for the GPS system included precision failure due to an increase in position error and solution failure due to increased outage probability. These failure progressions were monitored in situ by recording system-level features reported using the National Marine Electronics Association Protocol 0183. The GPS system was characterized to collect the principal feature values for a range of operating conditions. The approach was validated by conducting accelerated thermal cycling of the GPS system with the offset of the principal feature value measured in-situ. Based on experimental results, parametric models were developed to correlate the offset in the principal feature value with solution failure. During the experiment the build-in-test (BIT) provided no indication of an impending solution failure.

Electronic Systems: *Power Supply*

Simons et al. [27] performed PoF based prognostics assessment of the failure of a gull-wing lead power supply chip on a DC/DC voltage converter printed circuit board assembly. First, three-dimensional finite element analyses (FEA) were performed to determine strains in the solder joints due to thermal or mechanical cycling of the component. The strains could be due to lead bending resulting from the thermal mismatch of the board and chip or from a 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 et al. [28] also applied PoF based 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 four steps: (1) acquiring the temperature profile using sensors; (2) conducting finite element analysis to perform stress analysis; (3) conducting fatigue prediction of each solder joint; (4) predicting the probability of failure of the power supply system.

Electronic Systems: *Home Appliances*

The European Union funded a project from September 2001 through February 2005 called the Environmental Life Cycle Information Management and Acquisition (ELIMA) for consumer products, which aimed to develop better ways of managing the life cycles of products [29]. The objective of this work was to provide a basic model for predicting the remaining lifetime of parts removed from products based on the dynamic data collected by the ELIMA system, and it is a fusion based PHM approach. The ELIMA technology included sensors and memory built into the product to record dynamic data such as operation time, temperature, and power consumption. This was added to static data about materials and manufacturing. As a case study, the member companies monitored the application conditions of a game console and a household refrigerator. The work concluded that for the remaining life time prediction it was usually essential that the environments associated with all life intervals of the equipment be considered. These included not only the operational and maintenance environments, but also the pre-operational environment, when stresses imposed on the parts during manufacturing, assembly, inspection, testing, shipping, and installation might have a significant impact on the eventual reliability of the equipment. Stresses imposed during the pre-operational phase were often overlooked before the development of ELIMA.

Electronic Components: *Circuit Board Components*

Gu et al. [30] developed a PoF based methodology for monitoring, recording, and analyzing the life cycle vibration loads for remaining-life prognostics of electronics. The printed circuit board (PCB) with electronic components was mounted on the vibration shaker, which could generate random vibration loading. The responses of PCB to vibration loading in terms of bending curvature were monitored using strain gauges in situ. 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 and then used to predict the life consumed and remaining life. The methodology was shown to be effective for the remaining-life prognostics of a printed circuit board.

Jaai et al. [31] applied a data-trending prognostics approach to ball grid array (BGA) components subjected to accelerated temperature cycling tests. This study used the multivariate state estimation technique (MSET) and sequential probability ratio test (SPRT) to detect the onset of failure of BGA components by monitoring the changes in the resistance in the BGAs as a failure precursor. The time to detection of anomalies was found to be earlier than the time to failure of the BGA components, which provided a potential prognostic distance for calculating remaining life.

Electronic Components: *Battery*

Rufus et al. [32] presented prototype battery health monitoring algorithms (support vector machine, dynamic neural network, confidence prediction neural network, and usage pattern analysis). It is a data-trending based approach. The health of batteries is important in back-up environments such as telecommunications, UPS and other storage applications. The various algorithms were used and tested on the battery data (voltage, current, temperature, etc.) collected from several lithium ion battery cells supplied by United Lithium Systems. The battery data was collected under different operating conditions (storage and charge/discharge cycling under room and 50°C temperatures). The results showed that the battery health monitoring algorithms were effective in determining the health status of a lithium ion cell, and allowing for estimation the probability of battery failure with time.

Electronic Components: *Capacitor*

Gu et al. [33] presents a data-trending based prognostics approach that detects the performance degradation of multilayer ceramic capacitors (MLCC) under temperature-humidity-bias conditions and then predicts remaining useful life. In the tests, three performance parameters (capacitance, dissipation factor, and insulation resistance) were monitored in situ. A prognostics approach was developed to detect and predict failures using a multi-parameter regression, residual, detection and prediction analysis on four types of MLCC. It was found that the training process for the prognostics approach depended only on the capacitor type and not on the test conditions (such as different DC bias levels). For 8 failed capacitors out of the 96 capacitors, all failures could be detected with no missed alarms. 5 out of the 8 failed capacitors yielded advanced warning of failure.

Electronic Components: *Transistors*

Insulated Gate Bipolar Transistors (IGBTs) are used in applications such as the switching of automobile and train traction motors, high voltage power supplies, and in aerospace applications such as switch mode power supplies to regulate DC voltage. The failure of these switches can reduce the efficiency of the system or lead to system failure. Patil et al. [34] developed a fusion based prognostics methodology to predict and avert IGBT failures by identifying failure precursor parameters and monitoring them. In this study, failure analysis of IGBTs was conducted, and IGBTs aged by thermal/electrical stresses were evaluated in comparison with new components to determine the electrical parameters that change with stressing. Three potential precursor parameter candidates, threshold voltage, transconductance, and collector-emitter (ON) voltage, were evaluated by comparing aged and new IGBTs under temperature ranging from 25 to 200°C. The trends in the three electrical parameters with temperature were correlated to device degradation. Then these precursors were monitored in-situ and precursor trending data are input into PoF models to allow for anomaly detection and prediction of remaining life of these devices.

Goodman et al. [35] used a PoF based prognostic cell to monitor the time-dependent dielectric breakdown of the metal-oxide semiconductor field-effect transistor (MOSFET) on integrated circuits. The tests were conducted under accelerated conditions. Acceleration of the breakdown of an oxide was 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. Thus the prognostics cell could operate autonomously and give advance warning of impending failure of integrated circuits.

Zhang et al. [36] used a data-trending based prognostics approach for field effect transistors (FETs) that were used in airborne electronic systems. They used direct drain quiescent current (IDDQ) as a failure precursor. A thorough failure mechanism study for FETs was performed in order to select a subset of failure mechanisms that caused progressive degradation and were related to IDDQ signals. With the selected failure mechanisms, they utilized the symbolic dynamics-based method to perform fault degradation status estimation and utilized an uncertainty-adjusted prognostics method to predict the remaining life.

IV. CONCLUSIONS

Traditional reliability predictions based on handbook methods are inaccurate and misleading. PHM is more suitable for reliability (remaining life) assessment, since it considers actual operational and environmental loading condition for individual product. Currently research is being conducted to build-up physics-based damage models for electronics, obtaining the life cycle data of product, and developing data-trending approach in order to make the PHM more realistic. More research is also being conducted on fusion approach, advance sensor technologies, communication technologies, decision making methods, and return of investment methods. In addition, from the applications and examples listed above, it is clear that PHM can be incorporated into various electronics systems and can benefit many facets of daily life. In the future, due to the increasing amount of electronics in the world and the competitive drive toward more reliable products, PHM will be looked upon as a cost-effective solution for predicting the reliability of all electronic products and systems.

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