ABSTRACT

Ideally, systems continue to operate reliably for a long time. But the reality is that systems fail, and the consequences can be serious. In the worst cases, lives may be lost and people may be injured; in all cases, people are adversely affected. The economic repercussions of critical system failure can be staggering. Current reliability methods cannot handle real-time changes in operational and environmental loads on a system, which can cause a system to fail in the field without warning, leading to unplanned downtime.

Prognostics and health management (PHM) is an enabling discipline consisting of technologies and methods to assess the reliability of a product in its actual life cycle conditions to determine the advent of failure and mitigate system risk. The approaches adopted for conducting prognostics for a product include physics-of-failure (PoF) based approaches, including use of canaries to provide advance warning of failure, and modeling of life cycle environment stress to compute accumulated damage; data-driven methods involving monitoring and analysis of product functional parameters; and the fusion approach, which combines the PoF and data-driven techniques to provide an accurate estimate of remaining useful life. This paper describes the various approaches to prognostics and presents case studies of the implementation of different prognostic approaches.

Keywords: Physics of Failure, Data-driven, Fusion, Prognostics

1. INTRODUCTION

Functions such as communications, transportation, energy networks, financial transactions, and healthcare are important for the economic growth and sustainment of nations. Ideally, these systems continue to operate reliably for a long time, but the reality is that these systems fail, and the consequences can be serious: transportation paralysis, airplane accidents, electrical power outages, and telecom system crashes, to name a few. Recent examples include two subway trains colliding in Washington, D.C., killing nine; an Airbus A330 airliner crashing into the Atlantic Ocean with no survivors; the FAA computer system going down, paralyzing air traffic in a large region of the U.S. for half a day and for the third time in two years. The costs of such incidents are enormous. In the worst cases, lives are lost and people are injured; in all cases, people are adversely affected. The economic repercussions of such system failure can be staggering. These failures could be prevented and unplanned downtime could be eliminated if these systems could continuously self-assess their performance, estimate their remaining useful life, and adaptively mitigate failure risks with enhanced life cycle sustainment.

Current reliability design, assessment, and validation methods for products and systems lack the fidelity to prevent failures because of the constant evolution in technological diversity and product changes at all levels in the supply chain where the product integrator does not have the time and resources to know about and evaluate the effects of changes in sub-component parts and raw materials. Current reliability assessment techniques are not able to account for real-time changes in the environmental and operational conditions of products in the field. The two common types of maintenance activities followed by organizations are corrective maintenance and preventive maintenance (Tsang, 1995). Corrective maintenance aims to repair or replace failed parts in a system, while preventive maintenance, conducted at fixed time intervals, seeks to repair or replace parts before a failure occurs. In both cases the product is out of operation until the maintenance activity is completed. A continuous prognostics approach to determine the health of an electronic product is needed so that maintenance, repair, and replacement activities are only conducted when necessary.

Prognostics and health management (PHM) is an enabling discipline consisting of technologies and methods to assess the reliability of a product in its actual life cycle conditions to determine the advent of failure and mitigate system risk. The prognostics of a system can yield an advance warning of impending
failure in a system, thereby enabling appropriate corrective actions, i.e., condition based maintenance (CBM). PHM helps in preventing catastrophic failures and reduces unscheduled maintenance expenses.

Prognostics has become the preferred approach to achieve efficient system-level maintenance and reduce the life cycle cost of systems. The U.S. Department of Defense’s 5000.2 policy document on defense acquisition states that program managers should utilize diagnostics and prognostics to optimize the operational readiness of defense-related systems (U.S. DoD, 2004). This paper describes the various approaches to prognostics and presents case studies that implement different prognostic approaches.

2. PROGNOSTICS APPROACHES

A product’s health is its general state with respect to its expected normal operating conditions. Health monitoring is the process of measuring and recording the extent of deviation or degradation from the normal operating condition. Prognostics is the process of predicting a product’s remaining useful life for its expected future use by assessing the degradation or deviation of current health from the expected state of health (Pecht, 2008). The purpose of prognostics is to identify potential failures in advance and to provide the information necessary for risk mitigation and management.

There are three different approaches for conducting prognostics for a product. They are: (1) physics-of-failure (PoF) based approaches, including the use of canaries to provide advance warning of failure, and modeling of life cycle environment stress to compute accumulated damage; (2) data-driven methods involving monitoring and analysis of product functional parameters; and (3) the fusion approach, which combines the benefits of the PoF and data-driven techniques to provide an estimate of remaining useful life.

2.1 Physics of Failure (PoF) Based Approach to PHM

Physics of failure is an approach that utilizes knowledge of a product’s life-cycle loading and failure mechanisms to assess product reliability. PoF methodology is based on the identification of potential failure mechanisms and failure sites for a device, product, or system. A failure mechanism is described by the relationship between the stresses and variabilities at potential failure sites. The methodology proactively assesses reliability by establishing a scientific basis for evaluating new materials, structures, and technologies. PoF-based prognostics permits the assessment and prediction of system reliability under its actual application conditions. It integrates sensor data with models that enable in-situ identification of the deviation or degradation of a product from its expected normal operating condition (i.e., the system’s “health”) and the prediction of the future state of reliability (Pecht 2008). The general PoF-based PHM methodology is shown in FIGURE 1.

![FIGURE 1: Physics-of-failure based approach (Gu, 2008).](image-url)
The first step in PoF-based PHM involves failure modes, mechanisms, and effects analysis (FMMEA), where design data, expected life-cycle conditions, and PoF models are used as inputs for assessment. Using FMMEA it is possible to prioritize the critical failure modes and failure mechanisms to select monitoring parameters and sensor locations for PHM. Based on the collected operational and environmental data, the health status of the products can be assessed. The amount of damage can then be calculated from the PoF models to obtain the remaining life. FMMEA is a systematic methodology to identify potential failure mechanisms and models for all potential failure modes and to prioritize failure mechanisms (Ganesan, 2005). FMMEA is based on understanding the relationships between product requirements and the physical characteristics of the product (and their variation in the production process), the interactions of product materials with loads (stresses at application conditions), and their influence on the product susceptibility to failure with respect to the use conditions (Mathew, 2008).

Based on the FMMEA the critical mechanism can be selected and the life cycle operating and environmental conditions that propagate the mechanism are monitored. The life cycle loading data is used in failure models to derive the extent of degradation under the given conditions and from which the remaining useful life of the product can be estimated. Another method is to use canary devices to estimate the remaining useful life of the product. Again based on the critical failure mechanism the canary device can be designed such that the canary device fails by the same failure mechanism as the product. The canary device fails much earlier than the actual product. By knowing the acceleration factor between the canary device and the product, the time to failure of the actual product can be computed once the canary device fails.

2.2 Data-Driven Approach to PHM

A data-driven approach for prognostics is preferred when models are not available or when monitoring loads and environmental conditions are not possible. FIGURE 2 shows the steps involved in the data-driven approach.

![Diagram of data-driven approach](image)

**FIGURE 2**: Steps in a data-driven approach (Kumar, 2008).

This approach is primarily based on signal processing, pattern recognition, and state estimation. The prognosis is based on state awareness of the product based on the monitored performance parameters...
and forecasting total degradation and time-to failure based on the forecasted degradation. This methodology 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 at to represent system behavior based on 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.

Features can be extracted directly from routinely monitored product operating data or performance data. The measured input/output data are the major source for gaining a deeper understanding of system degradation behavior. Machine learning techniques can be used to process the data features to establish the healthy state of the given product. These approaches are based on statistical and learning techniques from the theory of pattern recognition. This data is also used to identify performance deviation due to the presence of a fault. To be effective, it is necessary that the training data for the machine learning algorithms span the universe of system faults and operational conditions.

The next step is detection of anomalous behavior in a fielded product and isolation of the fault. For this, the system parameters are continuously monitored, features are extracted from the data, and the algorithm compares the expected healthy state to the detected state of the product. A threshold limit on the data features are set to define the start of the performance degradation that will lead to operational failure. Trending of features to a defined failure criteria provides fault or damage progression over time. This information is used to estimate the remaining useful life of the product.

2.3 Fusion Approach

The fusion approach combines the benefits of the PoF and data-driven techniques to provide an estimate of remaining useful life. The fusion approach for the implementation of PHM is illustrated in FIGURE 3.

![FIGURE 3: Fusion Approach (Cheng, 2009).](image)

The fusion approach utilizes data-driven techniques for anomaly detection and classification to detect early degradation of a product. Understanding the physics of failure helps identify the parameters that are causing the anomaly. The faulty parameters are isolated by incorporating the results from the anomaly detection and the PoF information. Further, knowing the physics of failure helps narrow in on the possible root cause of product failure. After the critical parameters are isolated, the PoF models that use the isolated parameters as the primary inputs are selected. The PoF models are used independently to calculate the RUL of the product based on the environmental and parameter data along with information such as the material properties and product specifications.

Estimation of remaining useful life using data-driven techniques requires information such as the failure thresholds for the parameters. Knowledge of the product’s physics of failure can be used to extract the failure thresholds for the measured product parameters, the failure modes, stages of degradation, and labels of healthy and unhealthy conditions. Failure definitions can also be obtained by referring to other sources, such as standards and a historical failure database for similar products. This input of failure
definitions and labels of healthy and unhealthy states is critical in the selection of appropriate data-driven prediction methodologies for estimating remaining useful life.

The correlation between the precursor data and product failure helps provide an estimation of the RUL and signal product failure. The conservative value of the RUL estimate from the data-driven approach and the PoF model is reported. Alarms can be set off to warn the operator of the product based on the value of the RUL reported to provide adequate time for repair or replacement of the product depending on the criticality of the application.

3. CASE STUDIES

Electronics are used in applications ranging from aerospace, military, commercial, and household applications. Applying prognostics to electronics in different application conditions requires different techniques and methods based on feasibility analysis. Below, a case study demonstrating each of the three PHM approaches is presented.

3.1 PoF Approach: Remaining Life Assessment of an Electronic Circuit Card

Mathew et al. (Mathew, 2007) conducted a remaining useful life assessment of electronic hardware in the solid rocket booster (SRB) of the NASA Space Shuttle. The electronic hardware under study is part of the integrated electronic assembly (IEA) of one of the Space Shuttle’s solid rocket boosters. The electronic circuit cards in the IEA are subjected to random vibration, shock, and thermal loads during their life cycles. For this assessment one circuit card was used as the test unit. FIGURE 4 shows the flight sequence of the SRB.

![FIGURE 4: Flight sequence of SRB.](image)

After an SRB has completed its flight (mission) and upon recovery from the sea, some circuit cards in the IEA had shown electronic component and component lead failures. An FMMEA found that the wearout failure mechanism would dominate among all the failure mechanisms for the circuit card in the IEA. The failure mode was identified to be open/cracking of the solder joint interconnects of the electronic components on the circuit card. A physics of failure analysis was conducted to determine the damage accumulated in the solder joint interconnects of the components on the circuit card. The vibration and shock data was input into the Basquin model for high cycle fatigue, and the temperature cycling information was input into the Manson-Coffin model. The total damage due to vibration, shock, and temperature loads was calculated for each mission for the test unit. Using Miner’s rule, the total damage
to date due to the life cycle operational and environmental conditions was estimated for the components on the circuit card.

Based on the damage to date it was determined that the circuit card would last for 39 more missions without failure of the electronic components. A finite element analysis based on the physics of failure was conducted to simulate the loading conditions and determine the stress states on the circuit card in three dimensions. It was determined that under life cycle application conditions, mechanical mounting and support structures potentially suffered more damage than the damage to the electronic components on the circuit cards (Mathew, 2006). Subsequent physical testing of the test unit under vibration and shock conditions caused the aluminum support brackets to fail when loaded in the out-of-plane direction, thus proving the PoF analysis.

### 3.2 Data-Driven Approach: Detection of Degradation by Continuous Monitoring

Kwon et. al (Kwon, 2009) conducted an experiment to detect the degradation of a solder joint interconnect by continuously monitoring the RF impedance of the circuit. FIGURE 5 shows a test circuit for simultaneous measurement of the RF impedance and the DC resistance.

![Figure 5: Test set-up (Kwon, 2009).](image)

The test circuit consisted of an impedance-controlled circuit board with a surface mount low-pass filter, two bias tees, RF cables, and measurement instruments. The low-pass filter was soldered to this circuit board using eutectic tin-lead solder. Bias tees were incorporated into the test circuit to allow simultaneous monitoring of the RF impedance and the DC resistance of the circuit. A digital multimeter and a vector network analyzer (VNA) were used to monitor the DC resistance and the RF impedance, respectively. An MTS Tytron 250 machine was used to apply a cyclic shear force to the solder joint in order to generate fatigue failure.

The time-domain reflectometer (TDR) reflection coefficient is the ratio of the reflected voltage of the signal sent to a port to that of the transmitted signal from the same port. TDR has been found to be an effective method for evaluating impedance discontinuities in transmission lines. Hence, a solder joint can be characterized by monitoring the reflection coefficient at the solder joint location. The TDR reflection coefficients at particular locations of interest were extracted from the overall time-domain data. When there are no discontinuities, the TDR coefficient remains constant; but as soon as a discontinuity starts due to the skin effect, the impedance of the circuit changes, and hence the TDR coefficient changes as well.

During the course of the experiment, it was seen that the TDR reflection coefficient began to increase about 36 min prior to the separation of the solder joint, while the DC resistance remained almost constant until it exhibited a sudden increase, indicating a DC open circuit. The first occurrences that exceeded the initial TDR reflection coefficient by 5%, 10%, and 15% were recorded 36.5, 3.5, and 1 min prior to the failure, respectively. In order to relate these increases in the TDR reflection coefficient to the physical degradation of the solder joint, a failure analysis was conducted on a partially degraded solder-joint sample generated during another similar test. Failure analysis revealed that the RF-impedance increase resulted from a physical crack, which initiated at the surface of the solder joint and propagated only partway across the solder joint. Thus, using only the data-driven approach it was able to predict the
failure of the solder joint with 24% of life remaining before the event detector signaled solder joint separation.

### 3.3 Fusion Approach: Printed Circuit Board Assembly

A printed circuit board assembly with 256 I/O ball grid array (BGA) components was evaluated to determine its remaining useful life (RUL) using the fusion approach (Jaai, 2009). The board was to operate under thermal cycling conditions ranging from 185°C to -40°C and a ramp rate of 3.5°C/min, with dwell times of 15 minutes at both extremes. From the FMMEA analysis, it was determined that the temperature and resistance parameters were critical to the product failure for the given loading conditions and hence were chosen to be monitored. The resistance of each BGA and the board temperature were therefore recorded once every minute using a separate daisy chain for each BGA to permit in-situ monitoring of resistance, and thermocouples were used to monitor the temperature of the board.

The data collected was then analyzed for the detection of anomalies using a semi-supervised approach. A regression-based residual analysis of the data was carried out along with anomaly detection using the sequential probability ratio test (SPRT) algorithm. SPRT is a statistical likelihood ratio test that can be used to make a decision between two or more statistical hypotheses. The algorithm requires baseline data for training to determine the healthy states of the product. Five cycles of temperature and resistance data from the BGAs were used to define the healthy baseline. The training data was assumed to represent the healthy operating states of the BGA components. Using the healthy temperature and resistance from the baseline, the relationship between the temperature and resistance was modeled as a linear regression. Using the input of temperature and the regression model, estimates of the continuously monitored resistance were calculated. The differences between the resistance estimates and the observations from the product were used to obtain the residual signal. The residuals were statistically tested for anomalies using SPRT. SPRT signals an alarm when it detects the product to be statistically deviating from its normal state. FIGURE 6 shows the residuals of resistance from the regression model and the onset of alarms from SPRT from the 580th cycle. To calculate an estimate of RUL dynamically using data-driven techniques, a failure threshold of 300Ω for the resistance parameter was obtained based on the IPC-SM-785 standard. The resistance from the time of anomaly detection was trended to continuously calculate the cycles to failure based on the failure criterion for the resistance. The cycles to failure was calculated to be 620 cycles.

![FIGURE 6: SPRT alarm (Jaai, 2009).](image-url)
For PoF analysis, resistance is identified as the parameter that correlates to the anomalous behavior. The PoF model (Englemaier model) that characterizes product failure due to thermal fatigue was selected to estimate the damage and time to failure. A wearout mechanism for first order thermal fatigue specific to BGAs was identified to be critical. The 1% and 50% cycles to failure for the 256 I/O BGAs were calculated to be 760 cycles (2014 hours) and 1038 cycles (2750 hours), respectively. The actual time to failure of the BGA component was 693 cycles. In this case both PoF and data-driven techniques was used to estimate the failure time of the electronic component. A process for calculating the weighted average of the RUL based on the data from the PoF and data-driven techniques is being developed to provide an accurate estimate of the RUL.

4. SUMMARY AND CONCLUSION

Prognostics and health management (PHM) is an enabling discipline consisting of technologies and methods to assess the reliability of a product in its actual life cycle conditions to determine the advent of failure and mitigate system risk. There are three different approaches for conducting prognostics for a product. They are: (1) physics-of-failure (PoF) based approaches; (2) data-driven methods; and (3) the fusion approach. Detailed methodologies for implementing these approaches and case studies have been presented in this paper.

It has been experimentally proven that each of the three prognostic approaches can be used to predict the remaining useful life of a given product. Prognostics of a product thus provides an advance warning of impending failure in the product and thereby helps the user take appropriate corrective actions to mitigate the risks that arise from such failure and improve system availability.

5. REFERENCES


