Introductory Invited Paper

A prognostics and health management roadmap for information and electronics-rich systems

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ABSTRACT

Prognostics and systems health management (PHM) is an enabling discipline of technologies and methods with the potential of solving reliability problems that have been manifested due to complexities in design, manufacturing, environmental and operational use conditions, and maintenance. Over the past decade, research has been conducted in PHM of information and electronics-rich systems as a means to provide advance warnings of failure, enable forecasted maintenance, improve system qualification, extend system life, and diagnose intermittent failures that can lead to field failure returns exhibiting no-fault-found symptoms.

This paper presents an assessment of the state of practice in prognostics and health management of information and electronics-rich systems. While there are two general methods of performing PHM—model-based and data-driven methods—these methods by themselves have some key disadvantages. This paper presents a fusion prognostics approach, which combines or "fuses together" the model-based and data-driven approaches, to enable markedly better prognosis of remaining useful life. A case study of a printed circuit card assembly is given in order to illustrate the implementation of the fusion approach to prognostics.

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1. Introduction

Two subway trains crash in Washington, DC killing nine. An Airbus A330 airliner crashes into the Atlantic Ocean with no survivors. The suspected causes of both accidents are failures of information and electronics-rich systems. While these failures dominated the front pages of newspapers in early summer 2009, other information system failures have occurred in aerospace [1], telecom networks [2], computers [3], and data servers [4,5], as well as electrical power grids [6], energy generation equipment [7], and healthcare systems [8]. The costs of catastrophic accidents are enormous in terms of human lives. They also have severe economic implications. For example, the failure of a point-of-sale information verification system can result in the loss of $5 million/min [9].

Extremely high operational availability of information systems has been historically difficult to achieve because of the lack of understanding of the interactions of performance parameters and application environments and their effect on system degradation and failure. The fact that most failures in information systems are intermittent makes many predictive methods unacceptable [10].

Combining this complexity with the 40–85% no-fault-found (NFF) failure rate seen in system failure analysis suggests that current reliability practices need improvement. In particular, traditional approaches to failure mitigation have failed because of the reliance on averaged accumulated historical field data (e.g., Mil-Hdbk-217 [11], Telcordia SR-332 (formerly Bellcore) [12], and CNET/RDF (FIDES) (European) [13,14]), rather than relying on in situ data from a particular system. In fact, studies [15,16] have reported that these methods are inaccurate and misleading (i.e., they provide and inconsistent results for any given system subject to given conditions). This is a major reason why the US Army has abandoned these approaches. In addition, the IEEE notes that information system failures are in some sense inevitable, because the current methods of assessing information systems have fundamental flaws [17].

Consequently, there is a pressing need to develop new technologies and methods that utilize in situ system operational and environmental conditions to detect performance degradation and faults and avoid and manage system failures. Furthermore, these new technologies and methods must account for soft faults[1]

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[1] Soft faults are those faults that manifest themselves at the system level without any components in the system being damaged or failing. Typical causes of soft faults include transient failures due to particle radiation and electromagnetic emission; power supply fluctuations; and intermittent faults due to lose connections.

and intermittent[2] failures, which are some of the most common failure modes in today's information systems [18]. The most promising discipline of technologies and methods with the potential of solving reliability, availability, and maintainability problems is called prognostics and systems health management (PHM).

Over the past decade, research has been conducted in PHM of information and electronics-rich systems as a means of providing advance warnings of failure, enabling forecasted maintenance, improving system qualification, extending system life, and diagnosing intermittent failures, which can lead to field failure returns exhibiting no-fault-found symptoms. However, at this time, there is no roadmap for guiding R&D activities and allocating resources.

The purpose of this paper is to present an assessment of the state of practice in PHM of information and electronics-rich systems and some of the R&D opportunities and challenges. We discuss an R&D approach to PHM that fuses two of the current approaches, model-based and data-driven approaches, to overcome their individual limitations while retaining the advantages of both. Then we present an example of implementation of the fusion approach to electronics-rich systems.

2. State of practice in PHM for information and electronics-rich systems

Traditionally, PHM has been implemented using approaches that are either model-based or data-driven. The model-based approaches takes into account the physical processes and interactions between components in the system [20]. The data-driven approaches use statistical pattern recognition and machine-learning to detect changes in parameter data, thereby enabling diagnostic and prognostic measures to be calculated [21]. This section provides the state of practice in PHM for each of the approaches for information and electronics-rich systems.

2.1. Model-based approaches

The model-based approaches to PHM use mathematical representations to incorporate a physical understanding of the system, and include both system modeling and physics-of-failure (PoF) modeling. Prognosis of remaining useful life (RUL) is carried out based on knowledge of the processes causing degradation and leading to failure of the system.

In the system modeling approach, mathematical functions or mappings, such as differential equations, are used to represent the system. Statistical estimation techniques based on residuals and parity relations (the difference between the model predictions and system observations) are then used to detect, isolate and predict degradation [20,22]. Estimation techniques such as Kalman filters, particle filters, and parity relations are commonly used to calculate the residuals. For example, this approach to prognostics was demonstrated for lithium ion batteries [23] where a lumped parameter model was used along with extended Kalman filter and particle filter algorithms to estimate remaining useful life (RUL). Model-based prognostics methods are currently being developed for power semiconductors [24,25], digital electronics components and systems such as microprocessors in avionics [26], switched-mode power supplies [27], and diagnostics of software health [28].

The PoF approach utilizes knowledge of a system's life-cycle loading conditions, geometry, and material properties to identify potential failure mechanisms and estimate RUL [21]. This approach is based on the understanding that failures occur due to fundamental mechanical, chemical, electrical, thermal, and radiation processes [29].

The PoF approach involves a number of steps, which generally include some form of failure modes, mechanisms and effects analysis (FMMEA), feature extraction, and RUL estimation [29]. To implement this approach, the potential failure modes, mechanisms, and sites of the system based on the life-cycle loading conditions must be identified. The stress at each failure site is obtained as a function of loading conditions, geometry and material properties of the system. Damage models are then used to determine fault progression and RUL. The failure models require input, such as material properties, geometry, and environmental and operating loads. The loads are typically monitored *in situ,* and features (*e.g.,* cyclic range, mean, and ramp rates) of the data are extracted and used in relevant PoF models to provide estimates of damage and RUL.

PoF-based prognostic methodologies have been applied to estimate RUL in electronic assemblies and components such as power supply chips on a DC/DC voltage converter printed circuit board (PCB) assembly [30]; PCBs subjected to loads under an automobile hood [31,32]; electronics subjected to thermo-mechanical loads [33]; and for monitoring, recording, and analyzing the life cycle vibration loads for estimation of the RUL of PCBs using cumulative damage laws [34]. A PoF-based tool has been developed for real time prediction of RUL of PCBs exposed to thermal cycling environments [35]. The tool integrates information from sensors, PoF models, and data fusion algorithms to enable prognostics.

Using the models developed, it is possible to calculate the damage accumulation and RUL for known failure mechanisms. This is one of the advantages of model-based approaches. As the model-based approaches take into account degradation caused by environmental conditions such as thermal loads, humidity, vibrations, and shock, they can be used to estimate damage in situations where systems are in a non-operating state such as during storage and transportation. Knowledge of failure mechanisms, along with the monitored loads and system parameter data may allow for identification of the nature and extent of the fault. For example, power cycling of insulated gate bipolar transistor (IGBT) modules leads to wire-bond and die attach fatigue that causes a change in the collector–emitter voltage. The magnitude of change in the voltage is an indicator of the extent of the degradation in the component [24,36].

Development of the models requires detailed knowledge of the underlying physical processes that lead to system failure [20], and in complex systems, it is difficult to create dynamic models representing the multiple physical processes occurring in the system [22]. This is one of the limitations of model-based approaches. A requirement of the PoF model-based approach is that system-specific knowledge, such as geometry and material composition, is necessary but may not always be available. Further, failure models or graph-based models are not suitable for detection of intermittent system behavior as they are modeled for specific degradation mechanisms or for the diagnosis of specific faults respectively. Sudden changes in system parameters that characterize intermittent faults are not accounted for in these models.

2.2. Data-driven prognostics approach

Data-driven techniques are used to learn from the data and intelligently provide valuable decision-making information. They are based on the assumption that the statistical characteristics of the system data remain relatively unchanged until a fault occurs in the system. Anomalies and trends or patterns are detected in data collected by *in situ* monitoring to determine the state of health

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[2] An intermittent failure is the loss of function for a limited period of time and subsequent recovery of the function. This "failure" may not be easily predicted. However, an intermittent failure can be, and often is, recurrent [19]. It can lead to diagnostic conclusions of "re-test OK" or "no-fault-found."

of a system. The trends are then used to estimate the time to failure of the system.

In this approach, *in situ* monitoring of environmental and operational loads and system parameters is carried out. The data collected is analyzed using a variety of techniques depending on the type of data available. For example, if data representing the healthy and faulty states of the system are available, a supervised learning approach is used. When data for only one class, such as the healthy state of the system, are available, then the semi-supervised approach is used. A third approach is the unsupervised learning approach, which is used when no labeled data are available. Decisions about the system health are typically made using assumptions regarding the system data. It should be noted that employing both the supervised and semi-supervised learning techniques requires reliable training data. This is important, as the classification of incoming data is dependent on the training data, and unreliable training data will lead to errors in detection.

In addition to detection, an important aspect of data-driven approaches for PHM is prognostics. Although not as fully developed as detection, prediction of failure has been accomplished using a variety of techniques. The most important techniques are Markov chains, stochastic processes and time series analysis. These techniques use past history to infer the future, continually update the prediction of RUL, and provide an estimate of the associated prediction uncertainty. For example, a methodology has been developed using Markov state models of features extracted from notebook computers to predict state transition probabilities and times [37]. Symbolic time series analysis and Mahalanobis distance were used for feature extraction by Kumar and Pecht [37]. Pattern recognition algorithms and statistical techniques for early fault detection have also been developed for computer servers [38], [39]. Trending methods to predict the RUL of electronics have been suggested using continuously monitored data [39]. Other applications in electronics where data-driven approaches have been used for RUL estimation include global positioning systems [40]; avionics [41]; power electronics devices (IGBTs) used in avionics [42]; and aircraft electrical power systems [43,44].

One of the advantages of data-driven approaches is that they can be used as black-box models as they learn the behavior of the system based on monitored data and hence do not require system-specific knowledge. Further, data-driven approaches can be applied to complex systems, such as computer servers and notebooks where a large number of parameters are monitored. This is because data-driven approaches can be used to model the correlation between parameters and interactions between subsystems as well as effects of environmental parameters using *in situ* data from the system. It is also possible to reduce the dimensionality of the problem by restricting the analyses to parameters that are contributing to anomalous behavior in the system. These parameters can be detected using methods such as principal components analysis. Pattern recognition and statistical techniques employed in detecting changes in system behavior have shown data-driven approaches to be suitable for diagnostic purposes. This attribute makes it possible to detect sudden changes in system parameters allowing for detection and analysis of intermittent faults.

One of the limitations of data-driven approaches lies in the requirement of training data. Data-driven approaches depend on historical (*e.g.*, training) system data to determine correlations, establish patterns, and evaluate data trends leading to failure. In many cases, there will be insufficient historical or operational data to obtain health estimates and determine trend thresholds for failure prognostics. This is true for example in stored, standby, and non-operating systems, which are nevertheless subject to environmental stress conditions, and in systems where failures are infrequent. A solution to this problem is to incorporate (or fuse) system models, such as (PoF) models, with the data-driven models.

3. R&D opportunities

This section provides a description of opportunities in PHM for research and development that aim to integrate the model-based and data-driven approaches to take advantage of the strengths of each approach while overcoming their limitations. The need for methodologies to quantify and manage uncertainty in the prognosis of RUL for information and electronics-rich systems is also addressed.

3.1. A fusion prognostics approach

Fusion prognostic methodologies combine the strengths of the model-based and data-driven approaches, in order to estimate RUL under both operating and non-operating life cycle conditions, detect anomalous behavior or intermittent faults, identify precursors to failure for effective maintenance planning, and identify the potential processes causing system failure and the nature and extent of the fault for effective maintenance strategies. A fusion approach to PHM is illustrated in Fig. 1.

The first step in the process is to identify parameters that can be monitored *in situ* to aid in determining the real time state of health of the system. Environmental and system parameter data are required to be monitored for the diagnosis and prognosis of a system's health in real time. The process of identifying the parameters for monitoring can be aided by an understanding of the physical processes that lead to system failure. FMMEA, virtual simulations, information from maintenance records and qualification tests, or expert knowledge can be used for identifying parameters and for determining the relevant models for estimation of RUL. Understanding the physical processes occurring in the system helps in identifying critical components, possible failure sites, failure mechanisms, and their effects on the system. Appropriate sensing technology is then selected for the monitoring of the chosen parameters. The sensor data are analyzed in real time in order to assess the current state of the system and determine its RUL using information from data-driven techniques and physics-based models.

Assessment of a system's health is carried out in real time using the *in situ* data and anomaly detection techniques. Knowledge of the physical processes in the system can help in choosing the appropriate data-driven techniques for diagnosis and prognosis. One of the ways to implement anomaly detection is the application of a machine-learning approach, in which the monitored data are compared in real time against a healthy baseline to check for anomalies. This is the semi-supervised learning approach wherein data representing all the possible healthy states of the system are assumed to be available *a priori*.

The healthy baseline consists of a collection of parameter data that represent all the possible variations of the healthy operating states of a system. The baseline data is collected during various combinations of operating states and loading conditions when the system is known to be functioning normally. The baseline can also consist of threshold values based on specifications and standards. It is important that the baseline data should not contain any operational anomalies. The presence of anomalies in the baseline affects the definition of healthy system behavior and hence causes the misclassification of data. Misclassification leads to problems such as false indications of anomalies (false alarms) or failure to detect anomalous behavior of the system (missed alarms).

Although healthy baseline data sets are important for machine-learning approaches to detection, other statistical and probabilistic approaches that rely on parametric and distributional assumptions can also be used. In the machine-learning context, for example, distance-based similarity measures and other features can be ex-
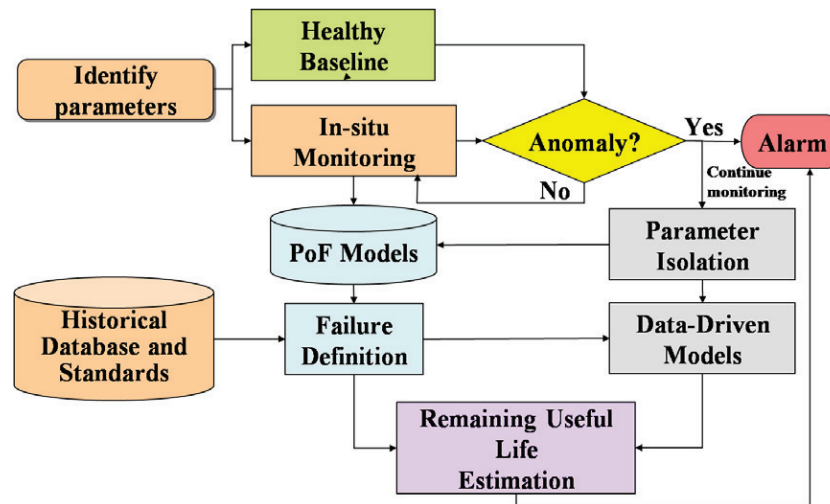
Fig. 1. Fusion prognostics approach.

tracted from multidimensional data. In addition projections and filtering of the data can also be used to extract features from the data. Detection in the machine-learning approach is largely based on these features. These techniques are particularly useful when no *a priori* data is available to create a baseline of healthy states.

After the anomaly detection step, the parameters that contribute significantly to the anomaly are isolated. It is important to pinpoint which parameters reflect or cause changes in system performance: they are critical in identifying and detecting system failure. Parameter isolation can be carried out using a variety of techniques, such as principal components analysis (PCA), least squares (LS) estimation, expectation maximization (EM), and maximum likelihood estimation (MLE). Based on the information from the parameter isolation step, the critical parameters are used to select appropriate models from the database. The parameter isolation step helps determine the models most relevant to the type of failure or degradation the system is undergoing. Physics-based models, which use the isolated parameters as the primary inputs, are selected in this step.

Physics-based models are used to calculate the RUL of the system based on the environmental and parameter data along with information such as material properties and system specifications. Knowledge from failure mechanisms and models is also used to extract information such as failure thresholds for the measured system parameters, 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 established failure criteria for the system. This input of failure definitions and labeling of healthy and unhealthy states from the model-based approach is critical in the selection of appropriate data-driven prediction methodologies for estimation of RUL. For example, a Markov model of the failure or degradation process of a system depends on modeling the transition of the system in and out of various "states". These states can, for example, be used to model the various failure mechanisms or violations of failure thresholds as defined by the model-based approach. In other words, the model-based approach can identify precursors to failure that can be used for early annunciation and prediction of system failure.

Using the failure thresholds, methods such as time series analysis or particle filtering techniques can be applied to predict the critical parameter values over time. The time until the parameter crosses the failure threshold is estimated as the time to failure of the system. Therefore, an estimate of the RUL for the system based on the combination of information from anomaly detection,

parameter isolation, physics-based models, and data-driven techniques can be calculated.

Alarms can be set off to warn the system operator of impending failure based on the value of the RUL reported. This can provide adequate time for repair or replacement of the system depending on the criticality of the application.

3.2. Quantifying and managing uncertainty

While a variety of methods are being developed using both model-based and data-driven approaches for the estimation of RUL, one of the major challenges is dealing with prediction uncertainties. Long-term prediction of RUL or time to failure increases the uncertainty bounds due to various sources, such as measurement or sensor errors, future load and usage uncertainty, model assumptions and inaccuracies, loss of information due to data reduction, prediction under conditions that are different from the training data, and so on [21,22]. Decisions regarding the system state (maintenance activities such as repair and replacement) should therefore take into account these uncertainties. Hence, development of methods that can be used to describe the uncertainty bounds (lower and upper limits) and confidence levels for the values falling within the confidence bounds is required. Another research area is uncertainty management, in which methods to reduce the uncertainty bounds by using system data as more data becomes available are being investigated.

There is ongoing research on both model-based approaches and data-driven approaches to quantify and manage uncertainty. The use of a Bayesian framework in the particle filter algorithm has been studied to provide estimates of RUL in the form of probability distribution functions [23]. This method is suitable when state models of the system can be developed. A methodology for uncertainty analysis in the PoF approach was developed and demonstrated for PCBs subjected to vibration loading [45]. This method takes into account sources such as measurement uncertainty, parameter uncertainty, failure criteria uncertainty, and future usage uncertainty. Other methodologies that use neural networks, Dempster–Shafer theory, Bayesian approaches and fuzzy logic have been suggested as a solution to the problem of uncertainty [46,47].

4. Application of a fusion approach to electronics-rich systems

The fusion prognostics approach was implemented on an electronics system consisting of a printed circuit card assembly sub-

jected to temperature cycling conditions. The assembly consisted of representative components such as ball grid array (BGA) packages, quad flat packages and surface mount resistors that can be found in circuit cards of electronics systems such as computers, avionics systems and so on.

In this case study, an FMMEA analysis determined the critical modes and mechanisms affecting the assembly to be interconnect fatigue due to thermal cycling resulting in open circuit. Temperature and resistance parameters therefore were critical to detect system failure for the given loading conditions and hence were chosen to be monitored. The BGAs were identified as the weakest components in the system and hence, *in situ* monitoring of the BGAs' resistances and the board temperature was carried out. The measurements were recorded once every minute.

The anomaly detection was then carried out using a data-driven residual analysis technique. The required training data (baseline) to model the healthy states of the system was created using ten cycles of *in situ* data. The training data was assumed to represent the healthy operating states of the BGA components. Using five out of the ten cycles from the training data, a regression model was created to capture the variation of resistance with temperature. The model was used to estimate component resistance using observed board temperature. The differences between the regression model estimates and the observations of resistance were used to obtain the residual signal. The residuals were statistically tested using the sequential probability ratio test (SPRT) algorithm to detect anomalies. SPRT, a statistical likelihood ratio test for anomaly detection [38,48,49] signals alarms when it detects that the system is statistically deviating from its normal state. The remaining five cycles of training data were used in the regression model to calculate healthy residuals to train SPRT. Following this, every test observation was input into the model for estimation and then analyzed statistically for anomalies using SPRT. The SPRT alarms were set off when the mean of the residuals of the resistance shifts to a value equal to or greater than the threshold value of 0.3. Fig. 2 shows the residuals of resistance from the regression and the onset of alarms from SPRT from the 580th cycle as the mean of the residuals increased. Fig. 3 shows a blow-up of the residuals around the 582nd to 585th cycle along with the SPRT alarms. It can be seen that the SPRT alarms are set off when the value of the residuals increase thereby increasing the mean of the dataset.

Next, the parameters causing or contributing to the anomaly need to be identified for assessment by the appropriate physics-based model from the database. In this case study, the anomalous
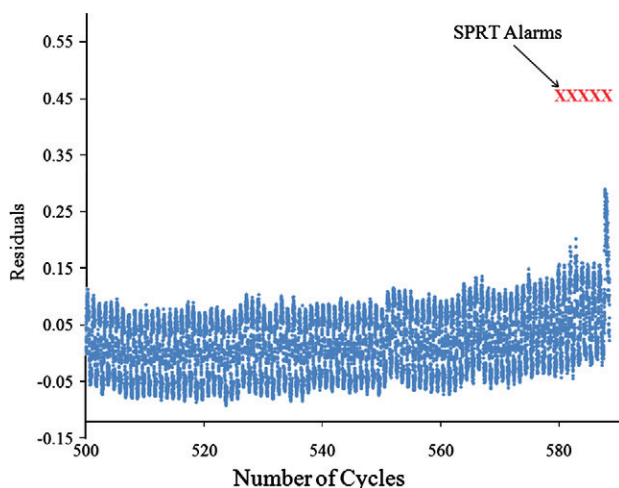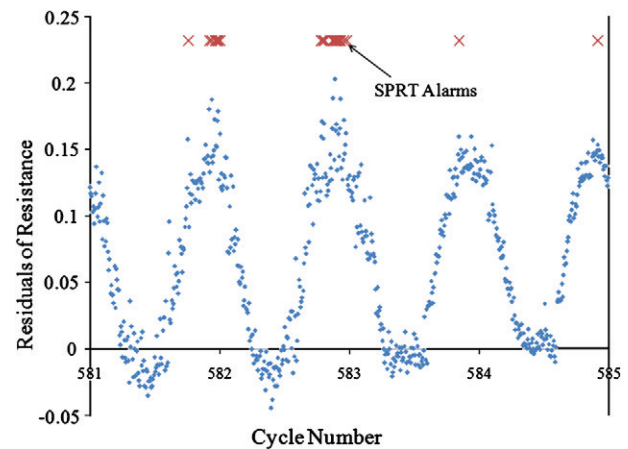

Fig. 3. Zoomed in view of Fig. 2 from cycle 581 to 585 to show residuals of resistance and SPRT alarms.

behavior due to an increase in resistance was identified. But the change in resistance was a result of cyclic temperature loads on the system leading to thermal fatigue. Therefore, the modified Coffin Manson model for leadless components to determine the fatigue life relationship for temperature loading [50] was selected to calculate the RUL. The damage to the components and time to failure due to the thermal cycling on the components were calculated. The mean cycle to failure for the 256 *I/O* BGAs was calculated to be 1038 cycles (2750.7 h). The estimate for 10% cycles to failure was obtained as 817 cycles using Monte-Carlo analysis. The RUL can be calculated dynamically using the PoF model by updating the temperature cycle profile as it is monitored *in situ*. This was not necessary in this case study, as the temperature profile was constant.

To calculate an estimate of RUL dynamically using data-driven techniques, a failure threshold of 300 Ω for the resistance parameter was obtained from the IPC-SM785 standard [51]. The resistance from the time of anomaly detection was trended to calculate the cycles to failure based on the failure criterion for the resistance. The value was updated with every observation of resistance collected from the system. The cycles to failure was calculated at the 601st cycle to be 620 cycles. The RUL was calculated based on the trend from the anomaly to the defined failure threshold. The estimates of RUL from the PoF model and the data-driven technique were then used to obtain a revised conservative RUL estimate for the component. The actual failure of the component was observed after 693 cycles.

This case study showed a step-by-step implementation of the fusion approach to PHM. The cycles to failure estimate of 620 cycles (at the 601st cycle) showed an error of 10% from the actual time to failure of the component. The approach provided a number of advantages such as one) determination of the parameters (resistance and temperature) for *in situ* monitoring using FMMEA analysis, two) determination of threshold value for component failure (resistance value of 300 Ω) from the PoF approach to enable estimation of RUL using the data-trending technique, and three) determination of the failure mechanism and possible failure site information that can be useful in understanding the root cause of failure. Therefore, the fusion approach enabled the determination of RUL using data-driven techniques and provided essential information that can be used in the root cause analysis.

Fig. 2. SPRT alarms at 580th cycle due to increase in the mean of the residuals of resistance. The red crosses indicate that SPRT has detected anomalies at the 580th cycle.

5. Roadmap

The failures observed in information and electronics-rich systems such as aerospace, data servers, electrical power grids, energy

generation equipment, and healthcare systems has led to increased research efforts in PHM for electronics systems. Today, model-based approaches are being developed to enable estimation of RUL for electronic systems such as batteries, digital electronics, navigation systems, switched-mode power supplies and printed circuit boards subject to a variety of environmental conditions. Similarly, data-driven approaches are also being developed for diagnostics and prognostics of enterprise servers, navigation systems, and power systems used in avionics and hybrid vehicles.

The model-based and data-driven approaches that are currently used in PHM have certain advantages and limitations. The model-based approaches take into account the physical processes and failure mechanisms that occur in systems, enabling prognosis of RUL. A limitation of this approach is that it cannot detect intermittent failures. The data-driven approach is useful when system-specific information is not available. The strength of this approach is diagnostics. This approach is capable of detecting intermittent failures, thereby reducing no-fault-founds. The limitations of this approach are that it is difficult to determine RUL without historical data, as well as the lack of a standard way of establishing failure thresholds that can be used in RUL determination. The current focus in research, therefore, is to find a means to effectively use available system-specific information, model-based approaches, and data-driven diagnostic and prognostic techniques which are known as fusion approaches to PHM.

A fusion approach enables effective use of information from both the model-based and data-driven approaches to achieve dynamic prognosis of RUL. Analytical techniques such as FMMEA, virtual simulations, and knowledge from maintenance records and experts can help identify the proper parameters for *in situ* monitoring. Understanding the physical processes and system behavior can help in choosing the data-driven techniques for diagnosis and prognosis. The fusion approach is capable of detecting operational anomalies and intermittent behavior allowing analysis of the root causes of no-fault-found errors as it uses appropriate diagnostic (data-driven) techniques. Isolation of the parameters that contribute to the anomalous behavior is carried out using data-driven techniques and system knowledge and leads to the identification of the critical failure mechanisms. Based on the identification of the critical failure mechanisms, identifying the nature and extent of faults and failure modes is possible. RUL estimations can then be calculated using the failure models for the critical failure mechanisms. System understanding can help determine failure thresholds for the parameters that can be used in data-driven techniques for RUL estimation. The fusion approach therefore provides recognition of degraded, but still functional, systems. The approach implemented in our case study on electronic assemblies shows that the fusion of the data-driven and model-based prognostic techniques can be used to effectively detect faulty behavior, determine the critical parameters and nature of a failure and estimate the RUL of the PCB assemblies. This paper uses the conservative RUL estimate from amongst the PoF model and the data-driven technique.

Current R&D challenges in PHM for electronics-rich systems that need to be addressed include uncertainty analysis and investigating techniques to fuse or combine estimates of RUL from various sources to provide single fused RUL values. It is important to understand and quantify uncertainty in predictions from PHM systems for realistic decision-making. Predictions in the form of probability density functions (PDFs) will be more informative in making maintenance and logistics decisions rather than using point estimates. Challenges in uncertainty analysis lie in determining and quantifying all the sources that contribute to prediction uncertainties such as measurement noise, model uncertainties, and missing or unavailable training data. Further, it is also necessary to investigate and develop models and data-driven approaches that take

into account uncertainty in making predictions thereby providing estimates in the form of PDFs.

In order to address the challenge in combining estimates of RUL from model-based and data-driven approaches, it is necessary to investigate techniques that can help in information fusion. These techniques while providing a single output of RUL using predictions from the model-based and data-driven should also take into account uncertainty estimates from each approach. Some techniques that have been suggested for fusing information based on Dempster–Shafer regression, fuzzy set operations, and model-based information fusion techniques. Addressing these challenges in research will help build more robust PHM systems that can be implemented for information and electronics-rich systems.

Acknowledgments

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