ABSTRACT

Title of Document: A COMPARISON BETWEEN DATA-DRIVEN AND PHYSICS OF FAILURE PHM APPROACHES FOR SOLDER JOINT FATIGUE.

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Prognostics and systems health management technology 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 to provide benefits such as advance warning of failures, 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. While there are various methods to perform prognostics, including model-based and data-driven methods, these methods have some key disadvantages. This thesis presents a fusion prognostics approach, which combines or "fuses together" the model based and data-driven approaches, to enable increasingly better estimates of remaining useful life. A case study using an electronics system to illustrate a step by step implementation of the fusion approach is also presented. The various benefits of the fusion approach and suggestions for future work are included.

# A COMPARISON BETWEEN DATA-DRIVEN AND PHYSICS OF FAILURE PHM APPROACHES FOR SOLDER JOINT FATIGUE.

By

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# Dedication

This thesis is dedicated to my mother and my friends who have believed in me and supported me in throughout.

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I express my gratitude to Professor Michael Pecht, my advisor, for his perpetual support, encouragement and valuable guidance during my masters. Discussions with him and his constructive criticism helped me overcome minor and major hitches while working on my thesis. I would also like to thank my thesis committee members, Prof. Dasgupta and Prof. Barker for serving on my thesis committee. I extend my thanks to Dr. Azarian, Dr. Das and Sony Mathew for their suggestions during my thesis from time to time.

Finally I would like to thank all the students at CALCE both former and current for the numerous occasions when they have helped me with my work and for all the fun I have had in the process.

# Table of Contents

# List of Figures

# Chapter 1: Prognostics and Health Management

## *1.1. Introduction*

Prognostics and systems health management (PHM) permits the evaluation of a product's reliability in its actual life cycle conditions to assess degradation or change in product health, determine the advent of failure, estimate the remaining useful life (RUL), and therefore make it possible to mitigate system risks [1]. Complex designs and manufacturing techniques in combination with the environmental and operational use conditions have led to increased reliability problems. While reliability measures are used to provide confidence that a product is going to serve its intended purpose for a certain period under specified operating limits, they do not take into account the unforeseen changes in operating environment conditions or operating loads. The field of PHM has emerged as the discipline that can provide the required methods and technology to solve these reliability issues and increase system safety. Implementation of a PHM system involves sensing, analyses and interpretation of environmental, operational and system parameter data that are indicative of system health [1], [4]. The benefits of incorporating PHM in systems include [4]-[6]:

1. Increased safety by way of providing advance warning of failure,
2. Improving system design and qualification,
3. Increased maintainability by minimizing unscheduled maintenance, extending maintenance cycles, and allowing for timely repair actions,
4. Assistance in logistical support systems, and

5. Reduced life cycle costs due to reduced down times, inspection costs, and inventory.

Research has been conducted in PHM of mechanical systems as well as information and electronics-rich systems as a means to provide all of the benefits listed above. An important feature of implementing PHM is that it provides the ability to detect intermittent faults in systems. This feature is particularly important in electronics-rich systems as this ability helps in analyzing data monitored during the occurrence of intermittent faults. This helps reduce the occurrence of no-fault found scenarios that often are exhibited in field failure returns. Although PHM has been implemented in mechanical systems such as bridges, engines, compressors, gears and so on, the technology implementation for electronics systems is still nascent. For electronics, the implementation of PHM is in its infancy due to the complicated architecture, variety of components in current electronic systems, and the variety of environmental and load conditions that the systems experience.

PHM has been traditionally implemented using either model-based or data-driven approaches. The model-based approaches are based on an understanding of the physical processes and failure mechanisms that are occurring in the system while the data-driven approaches are based on using patterns or statistical relationships in system data to carry out prognostics. The model-based approaches include system modeling as well as the physics of failure (PoF) approach. Each of these approaches has certain advantages as well as limitations. The objective of this thesis is to develop and demonstrate a “fusion” methodology that incorporates different aspects of PHM systems to

1. Enable detection of intermittent failures in order to reduce the occurrence of no-fault found type of failures in the field.
2. Enable estimation of RUL using both model-based and data-driven approaches in both operating and non-operating states and provide increasingly reliable estimates of RUL.
3. Isolate the fault and determine the possible root causes of failure using knowledge from the model-based approach and information from the data-driven analysis.

The fusion prognostics methodology suggested in this work uses an integration of the model-based and data-driven approaches to provide the above stated objectives. This is accomplished by the fusion or mutual exchange of information between the techniques used by the model-based and data-driven approaches in the different stages of implementation and analysis. The fusion prognostics methodology thereby provides benefits of both the data-driven approaches and the model-based approaches while at the same time overcoming the challenges or limitations of using either approach by itself.

### *1.2. Overview of Thesis*

Chapter 2 provides a description of the model-based approaches including explanations of the system modeling and the PoF approaches to PHM. An overview of the literature that shows the use of various model-based approaches to implement PHM is also presented in this chapter. The advantages and limitations of using the model-based approaches for PHM are then described.

The data-driven approaches to PHM are explained in Chapter 3 along with a review of literature which provides details on studies that used these approaches for diagnostic and prognostic purposes. The last section in this chapter describes the advantages and limitations of the data-driven approaches.

Chapter 4 presents the motivation for a fusion prognostics methodology along with a step-by-step explanation of the methodology. This is followed up with a case study that implements the fusion prognostics methodology for an electronics system.

Contributions and suggestions for future work are presented in Chapter 5.

# Chapter 2: Model-based Approaches to PHM

The model-based approaches to PHM use mathematical representations to incorporate a physical understanding of the system in order to implement diagnostics and prognostics [7]. Prognosis of RUL is carried out based on knowledge of the processes that are taking place in the system as a part of its functioning as well as those processes which lead to system degradation and eventually failure. The model-based approaches can be categorized into system modeling and physics-of-failure (PoF) approaches.

## 2.1. *System Modeling Approach*

An overview of the system modeling approach is shown in Fig. 1. In the system modeling approach, mathematical functions or mappings, such as differential equations (or difference equations), are developed that represent the system or the process of interest in the system [8]. These equations are then used with statistical estimation techniques such as Kalman filters, particle filters, and parity relations for the purpose of estimating the state of the system or process. Residuals which are the difference between the model predictions and observations from the system are then used to detect, isolate and predict degradation [7], [8]. The residuals show the discrepancy or disagreement between the system model and the actual observations. These techniques are based on the assumption that for a healthy system, the residuals will follow a Gaussian distribution with zero mean and variance due to the presence of noise and any deviations from this are caused by degradation in the system. Statistical analysis of the residuals is used for detection of degradation in the system following which prediction is carried out using the estimation techniques into future time steps until the system state exceeds a predefined failure threshold. Therefore, development of appropriate system models requires a thorough understanding of the processes taking place in the system [8].

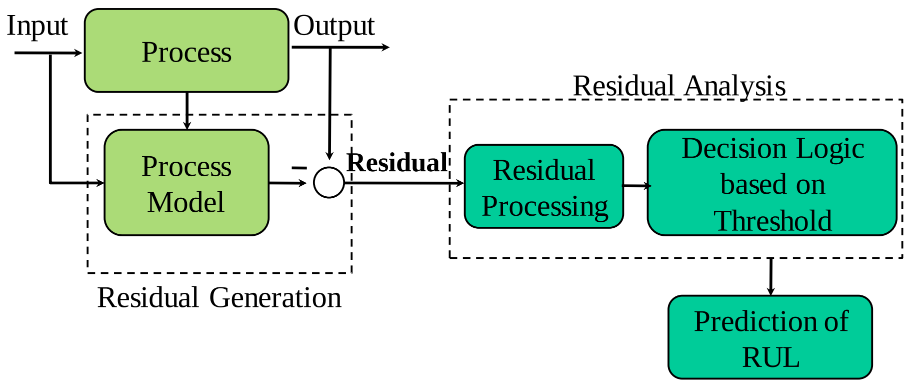



Fig.1: System Modeling Approach

### *2.1.1. <u>Literature Overview</u>*

Various system modeling based diagnostic and prognostic methods have been implemented for mechanical systems such as automotive suspensions [12], engines [13], [14] and robotic systems [15]. The system-model based approach is well suited in situations where there is an understanding of the fast dynamics of the processes occurring in the system as well as of the slower degradation mechanisms that lead to system failure [7], [12].

Unlike mechanical systems that are modeled using system dynamics from first principles, electronic systems are in general modeled based on failure mechanisms using physics of failure models which are explained in Section 2.2 of this thesis. Currently, research is being conducting to develop system modeling based approaches for PHM purposes for electronics systems such as applications such as for switched mode power supplies [10], and for diagnostics of software health [11].

Luo et al. [12] demonstrated a system-modeling based prognostics approach to estimate RUL for suspension systems and could be used in a variety of applications such as automobiles or aerospace systems. In this paper, a system model was built using singular perturbation techniques of control theory for an automobile suspension system. The failure mode of interest was identified as a crack in the suspension spring caused by fatigue. Monte Carlo simulations were performed using the system-model for different loading conditions. The failure mode was linked to a suspension parameter (i.e., stiffness) which was estimated (tracked) over time to assess the remaining life of the suspension subsystem. The prognostic model for degradation was created using interacting multiple modeling (IMM), a parameter estimation method, based on simulated data. Finally, the RUL of the suspension system was estimated based on assumed future use conditions.

Gertler et al. [13] employed structured parity equations for fault diagnosis in engines. The faults considered include two actuator faults (fuel injectors and exhaust gas recirculation) and four sensor faults (throttle position, manifold pressure, engine speed, and exhaust oxygen).

Luo et al. [14] introduced a look-up table based online diagnostic model for the engine control units of automotive systems. In this approach a diagnostic matrix was created using simulation models and graphical cause and effect models also known as directed graph based models in the failure space. An understanding of the failure modes and their effects, physical and behavioral models, and statistical techniques based on actual failure progression data were used to develop the diagnostic models for the engine control units. A disadvantage of this approach was that with the use of directed graph based models, it would not be possible to detect intermittent faults. Further, if the diagnostic matrix changed with different operating conditions, the look-up table would have to be prepared with residual thresholds defined for every operating condition.

Saha et al. [16] implemented this approach to prognostics for lithium ion batteries. A lumped parameter model was used to represent the batteries and the parameters of the model were calculated using relevance vector machine (RVM) regression on experimental data to find the representative ageing curves. The differential equations were then developed from the model and used along with the extended Kalman filter (EKF) and particle filter algorithms to estimate RUL. Using the particle filter algorithm, prognosis of RUL was provided in the form of probability distribution functions thereby including the related uncertainty values with the estimates of RUL.

### 2.2. *Physics-of-failure (PoF) Approach*

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 [1], [17]. This approach is based on the understanding that failures occur due to fundamental mechanical, chemical, electrical, thermal, and radiation processes [17]. The extent and rate of degradation of a system is considered to be dependent upon the magnitude and duration of exposure to environmental and operational loads which are characterized using features such as usage rate, frequency, and severity of loading [3], [18].

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 [17], [18]. The flowchart illustrating the steps involved in implementing the PoF approach to prognostics is shown in Fig. 2. To implement this approach, the potential failure modes, mechanisms, and sites of the system based on the expected life-cycle loading conditions must be identified. The loading conditions include mechanical, thermal, chemical or electrical loads. Various loads leading to failure mechanisms and their respective models are presented in [4]. Information regarding the materials that make up the system and its dimensions (geometry) are required in order to use or generate a PoF model [19]. In this step the system is characterized at all levels, i.e., components, subsystems, as well as their physical interfaces [18]. The stress at the critical failure site is obtained as a function of loading conditions, geometry and material properties of the system. Relevant PoF models are then used to determine fault progression and RUL. The failure models require input such as material properties, geometry, and features of the environmental and operational loads. The environmental and operational loads are monitored in-situ, and features such as cyclic range, mean, and ramp rates of the data are extracted and used in the PoF models to provide estimates of damage and RUL for the system.

Another implementation of the PoF approach is the use of "canary" devices. Expendable devices such as fuses and canaries are examples of devices that have been used as a means for providing protection in electrical power systems to sense excessive current and disconnect power from the concerned part [4], [20]. In the case of PHM, canary devices, also known as prognostic cells, are designed so as to fail at a statistically significant time before the failure of the device of interest for a particular failure mechanism [1], [4], [20]. Typically, canary devices are integrated into the specific system or component of interest during the design stage and are designed to capture the failure mechanisms that occur first in the embedded device [17]. The time-to-failure of the canary is precalibrated with respect to the time-to-failure of the actual system by means of increased stresses on the canary by scaling. Failure of the canary device therefore provides a warning along with a predetermined RUL [1], [4], [20].

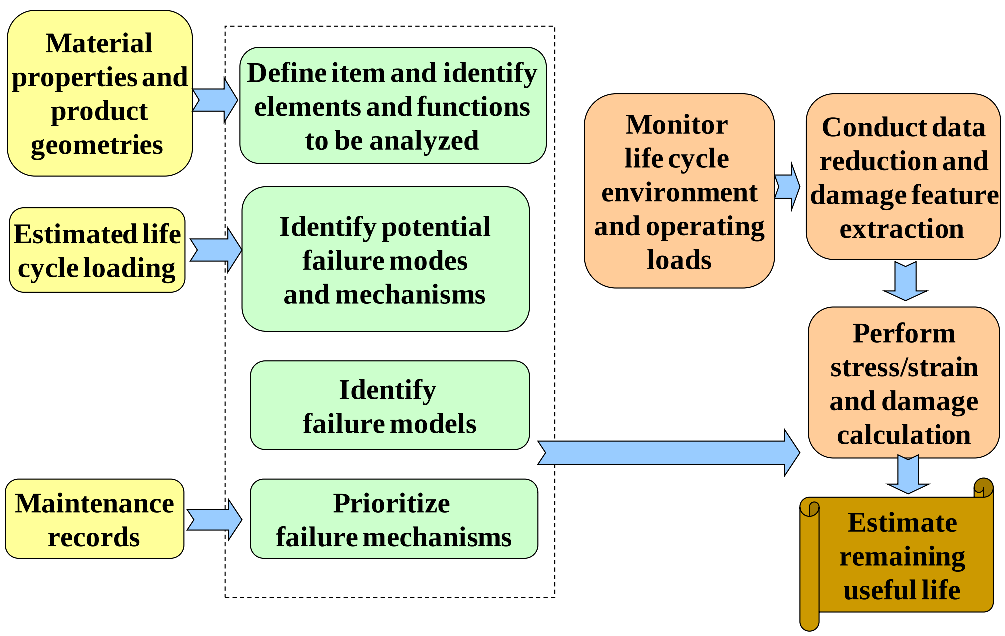



Fig. 2: Steps in Implementation of PoF Approach. [1], [17]

### *2.1.2. <u>Literature Overview</u>*

PoF-based prognostic methodologies have been applied to estimate RUL in a variety of electronic assemblies and components. Pecht and Gu [17] outlined a procedure for the implementation of a PoF-based approach to PHM. The various steps in the methodology include FMMEA, data reduction and feature extraction from life cycle loads as inputs used with PoF models to estimate damage accumulation, followed by assessment of uncertainty. Application of PoF-based prognostics for new and legacy systems was suggested.

Gu et al. [21] developed a prognostics methodology based on the PoF approach to analyze and estimate the RUL of printed circuit boards (PCBs) subjected to life cycle vibration loads. Strain gauges were used to monitor the bending curvature of PCBs as a response to loading in the form of vibration. Finite element analysis (FEA) was used to calibrate an analytical model developed to calculate the strain at interconnects using the measured response (bending curvature). The interconnect strain values were used in a vibration failure fatigue model for damage assessment. Finally, Miner's rule was used to estimate the accumulated damage which was then used to estimate the RUL of the PCBs. The failure times based on resistance readings from the experiments were used to verify the results from the PoF prognostics methodology.

Gu et al. [22] further carried out uncertainty analysis of prognostics for electronics under vibration loading conditions. The various sources of uncertainty were identified and categorized as measurement uncertainty, parameter uncertainty, failure criteria uncertainty and future usage uncertainty. Sensitivity analysis was used to determine the dominant variables that influence PoF model outputs. Using distributions for input parameters instead of single values, a Monte-Carlo simulation was performed to provide a distribution of accumulated damage. Based on the damage distributions thus obtained RUL was predicted along with confidence intervals. A case study demonstrated the uncertainty analysis for an electronic board under vibration loading which showed that the experimentally measured failure time was within the bounds of the prediction from the uncertainty analysis.

Simons and Shockey [23] presented a PoF-based methodology to prognosticate the cycles to failure for a power supply chip on a DC/DC voltage converter. The component considered for the study was a gull-wing lead chip on the converter PWB assembly. The study suggested a two step process which included a three-dimensional finite element analyses to determine the strains in the solder joints of the gull-wing leads due to thermal or mechanical cycling of the component as a first step. The strains were a result of lead bending due to the mismatch in the co-efficients of thermal expansion (CTEs) of the board and chip, the local mismatch in the CTEs between the lead and the solder and the mismatch in CTEs between the board and the solder. It was suggested that in the second step, using a probabilistic model to simulate initiation and growth of cracks in the microstructure of the solder joint and the strains calculated in the FEA for boundary conditions, the growth rate of the cracks in the solder joint could be estimated. Using the crack growth rate, prognosis of the cycles to failure for the electronic component could therefore be carried out.

Studies conducted by Ramakrishnan and Pecht [19], and Mishra et al. [24] evaluated the remaining life using a life consumption monitoring approach. The test vehicle consisted of a PCB placed under the hood of an automobile which was subjected to driving conditions in the Washington, D.C., area. Sensors were used to monitor the temperature and vibrations on the board in the application environment during the drives. Solder joint fatigue was identified as the dominant failure mechanism for the test board under these conditions. Features from the monitored environmental data were extracted using the ordered overall range and rainflow cycle counting algorithms. Appropriate stress and damage models were used along with the Miner's rule to estimate accumulated damage and the amount of life consumed.

Mathew et al. [25] used the PoF-based approach to conduct a prognostic assessment of circuit cards placed within a space shuttle solid rocket booster (SRB). A virtual RUL assessment of the circuit card was conducted to estimate the number of future missions that the circuit card could be used for without failure. Vibration time history for the SRB from the pre-launch stage to splashdown was recorded in order to assess the damage caused due to the vibration and shock loads using PoF models. Using the entire life-cycle loading profile of the SRBs, the RUL of the components on the circuit cards was predicted. The study determined that an electrical failure was not expected within another forty missions.

Nasser and Curtin [26] developed a prognosis software framework for prediction of failure for electronic power supply systems based on material fatigue due to thermal and vibration loads. The power supply was subdivided into its components and analyzed in a hierarchical fashion. Predicted degradation within any single or combination of component elements could be rolled up into an overall reliability prediction for the entire power supply system. Their prognostics 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. [3], [27] provided guidelines for monitoring and modeling of environmental and usage loads in order to implement PHM for electronics systems. Various techniques to analyze and extract features from in-situ data were discussed. In-situ health monitoring of notebook computers was conducted and the temperatures inside the notebook computer experienced during usage, storage, and transportation were analyzed. The statistical analysis proved that the temperatures in the electronics such as the hard drive were higher than the recommended values. This proved the need to collect such data in order to improve the thermal design of the product and to monitor prognostic health. The possibility of using the data in PoF models for estimation of accumulated damage and RUL was also suggested.

Rouet et al., [28] developed a PoF-based tool has been developed for real-time prediction of RUL of PCBs exposed to thermal cycling environments. The on-board methodology for RUL prediction was adapted from an off-board validated methodology. The tool integrates information from sensors and uses data reduction techniques such as the rainflow counting algorithms. Results from experiments and simulation using PoF models were integrated as parameters in the monitoring tool to allow computation of life consumption for an electronic assembly in real time. The methodology was used to monitor an electronic test board and assess its RUL based on component solder joints degradation.

Mishra and Pecht [29] used a precalibrated semiconductor circuit as part of the actual circuit as a prognostic cell. The prognostic cell or canary experiences the same environmental conditions as the actual circuit but the loading conditions are varied in a controlled manner (for example, by increasing the current density).

The idea of using prognostic cells to provide advance warning of failure has been commercialized by Ridgetop Group Inc., at the chip, package and module levels. Prognostic cells for various failure mechanisms such as time dependent dielectric breakdown [30], hot carrier injection [31], radiation effects such as increase in leakage current [32] and threshold voltage [33] in transistors at the chip level are available. At the package level, cells are available to provide early warning of fatigue failure in solder joints of ball grid array components used in field programmable gate arrays [34], [35]. At the module level, for power electronics, the cells are used to detect failure of power supply modules using a "ringing" characteristic [36]. The time to failure of these prognostic cells could be pre-calibrated with respect to the time to failure of the actual product.

An extension of the prognostic cells to board-level failures was proposed by Anderson et al. [37]. The canary components were to be located on the same printed circuit board as the actual components. Two prospective failure mechanisms identified were low cycle thermal fatigue of solder joints and corrosion. Low cycle fatigue was to be assessed by monitoring solder joints of the canary package. Corrosion monitoring was to be carried out using circuits that would be more susceptible to corrosion than the actual product. The environmental degradation of these canaries was assessed using accelerated testing, and degradation levels were calibrated and correlated to the failure levels of the actual system.

Lall et al. [38] proposed a damage precursor–based health management and prognostication methodology to electronic systems in harsh environments, which is similar to the canary approach mentioned above. The framework has been developed based on a development of correlation between damage precursors and underlying degradation mechanisms in lead-free packaging architectures. Test vehicle includes various area-array packaging architectures subjected to single thermo-mechanical stresses including thermal cycling in the range of -40°C to 125°C and isothermal aging at 125°C. Experimental data on damage precursors has been presented for packaging architectures encompassing flex-substrate ball grid arrays, chip-array ball grid arrays, and plastic ball grid arrays. Examples of damage proxies include phase-growth parameter, intermetallic thickness and interfacial stress variations. Damage proxies have correlated with residual life.

### *2.3. Advantages of the Model-based Approaches*

The model-based approaches described in the literature provide a variety of advantages when implemented in PHM systems. These advantages are described in this section.

The first advantage is that using the system or PoF models developed, it is possible to calculate the damage accumulation and RUL for known failure mechanisms using the monitored environmental and operational data from the system under consideration. Therefore, the model-based approaches do not require historical data for the purpose of RUL estimation once models are available.

For systems that are placed in storage conditions (uncontrolled or controlled) or transported, it is possible that the humidity, thermal loads due to diurnal and seasonal temperature cycles, vibrations and shock loads during transportation can cause degradation in the system even as the system is not in operation. The model-based approaches take into account degradation caused by environmental conditions such as thermal loads, humidity, vibrations, and shock. Therefore, they can be used to estimate damage in situations where systems are in a non-operating state such as during storage and transportation.

Model-based approaches are built on the knowledge of the processes and failure mechanisms occurring in the system of concern. This information along with the monitored environmental loads and system parameter data 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 [39], [40]. Identification of the nature and extent of the fault occurring can provide valuable information for root cause analysis and maintenance decisions to be taken.

### 2.4. Limitations of the Model-based Approaches

One of the limitations of the model-based approaches is that development of the system or PoF models requires detailed knowledge of the underlying physical processes that lead to system failure [8]. For example, in complex systems, it is difficult to create dynamic models representing the multiple physical processes occurring in the system [7]. Further, in order to implement a PoF model-based approach, system-specific knowledge, such as geometry and material composition, is necessary. Such detailed information may not always be available.

Intermittent faults are characterized by sudden changes in system parameters that are temporary leading to no-fault found or re-test ok situations in field returned systems. Model-based approaches that use PoF models or graph-based models are not suitable for detection of intermittent system behavior [14] as these approaches are modeled for specific degradation mechanisms or for the diagnosis of specific fault modes respectively. The changes in system parameters are not accounted for in these models and therefore the intermittent faults go undetected.

# Chapter 3: Data-driven Approaches to PHM

Data-driven techniques are used to learn statistical relationships and patterns from sensor data and intelligently provide valuable decision-making information [1]. They are based on the assumption that the statistical characteristics of the system data remain relatively unchanged until a fault occurs in the system. A flowchart that summarizes the steps in implementing the data-driven approach is shown in Fig. 3. 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 anomaly detection followed by prediction of RUL. Anomalies and trends or patterns are detected in data collected by in-situ monitoring to determine the state of health of a system. Anomaly detection techniques are used for diagnostics in order to detect changes in the system that may lead to system malfunction or failure. For prognostic purposes, trends in parameter values, features or changes in probabilities of the system state are then used to estimate the time to failure of the system using prediction algorithms. An important aspect of the data-driven approaches is that they provide capabilities to analyze complex systems which require the use of multiple sensors and multivariate algorithms.

Anomaly detection techniques can be broadly categorized as supervised, semi-supervised and unsupervised learning techniques based on their requirements of labeled historical data for training [41]. Supervised learning involves the use of labeled healthy and faulty data to train the algorithms for detection purposes. These methods therefore can be used only if data representing both, the healthy and faulty states, of the system are available. One of the disadvantages of the supervised learning technique is that obtaining accurate labels for both the classes of data is usually challenging [41]. When data for only one class, such as the healthy state of the system, are available, then the semi-supervised approach is used. The semi-supervised techniques are more widely applicable as data from only one class, either the healthy or the faulty class is required. In general, due to the availability of healthy data, semi-supervised techniques are more commonly 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. In general the assumption made in the unsupervised techniques is that healthy data instances occur more frequently than anomalies in the monitored data [41], [42]. 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 models built on the training data, and unreliable training data can lead to errors in detection leading to increased false and missed alarms.

In addition to detection, an important aspect of data-driven approaches for PHM is prognostics. Although not as fully developed as diagnostics, prediction of failure has been accomplished using a variety of techniques. The most important techniques amongst these are Markov chains, neural networks, stochastic processes, time series analysis (for example, using autoregressive moving averages and symbolic time series analysis) and fuzzy logic. These techniques use past or historical information of the system to infer its future state and continually update the prediction of RUL. Some of these techniques such as Markov chains can also be used to provide an estimate of the uncertainty associated with the process of predicting the system's RUL.

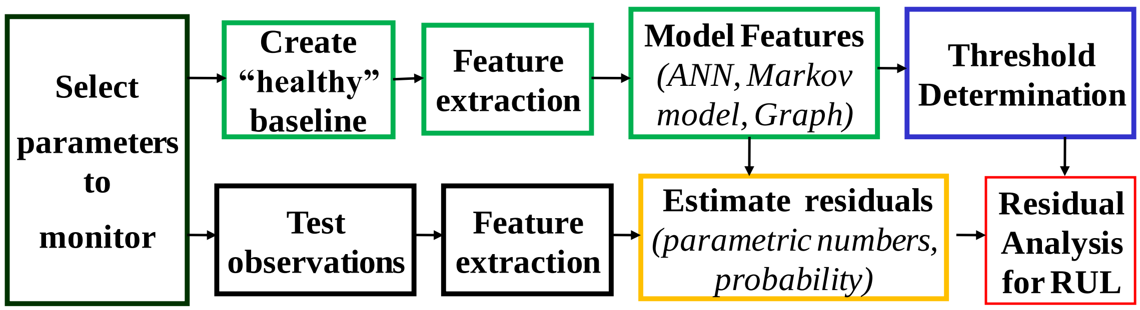



Fig 3. Implementation of Data-Driven Approach to PHM

*3.1. Literature Review*

Data-driven approaches have been used for diagnosis and prognosis of a variety of systems. Brief explanations of various anomaly detection techniques that can be used for diagnostics can be found in [41], [43], [44]. Although the techniques described have been applied in a variety of fields such as intrusion detection and credit card fraud, they can be adapted for use in a PHM framework to accomplish diagnostics. This section first summarizes studies on diagnostic techniques followed by studies in the area of prognostics.

A technique for health monitoring and diagnostics of computer servers was demonstrated in a study by Lopez [45]. The various server signals were continuous monitored using a system known as the continuous system telemetry harness (CSTH). The analysis of signals obtained by the CSTH is carried out using pattern recognition algorithms. Multivariate state estimation technique (MSET) was used for the purpose of estimating the values of the server signals using past and current observations. The residuals (difference between the MSET estimates and the observations) were then input to the sequential probability ratio test (SPRT), a statistical hypothesis testing technique. Deviations of the system operational data from estimated values implied changes in system health or degradation in system performance and were detected as anomalies. Using SPRT, any anomalous behavior in the residuals that represented faults or anomalies in the server was detected.

Kwon et al. [46] demonstrated a technique for early detection of interconnect degradation by in-situ monitoring of RF impedance using SPRT. Mechanical fatigue tests were conducted on a surface mount component and DC resistance and the time domain reflection coefficient as a measure of RF impedance were measured in-situ. SPRT was used to detect changes in the RF impedance and the DC resistance measurements. The RF impedance provided detectable failure precursors, while the DC resistance remained constant with no precursors. A second test was performed in which testing was stopped at the instant that SPRT detected a change in the RF impedance. Failure analysis was then performed to reveal that the change in RF impedance resulted from a crack in the solder joint. The results indicated that this approach involving the use of failure precursors (RF impedance) coupled with data trending techniques (SPRT) therefore provides a means to detect early degradation before component failure.

Namuburu et al. [47] demonstrated the use of a data-driven technique to detect faults and estimate their severity levels in automotive engines. A Simulink model of a Toyota Camry engine with its engine control unit is simulated under several operating conditions. Data is collected before and after the occurrence of the fault for eight engine faults with different severity levels. Analysis of the data was carried out using hypothesis testing techniques for fault detection. Wavelet-based preprocessing and pattern recognition techniques were used to classify the faults and estimate their severity. The results demonstrated that diagnostic accuracy and fault severity estimation were possible with pattern recognition based techniques such as support vector machines.

Kumar et al. [48] presented a Mahalanobis distance (MD) based diagnostic approach for electronic systems. The approach employed a probabilistic technique to establish diagnostic thresholds in order to classify the state of health of a system. Detection of trends in system health was carried out by constructing control charts using diagnostic thresholds for the MD values. Faulty parameters were isolated using a residual MD value based approach. The entire approach was demonstrated using a case study on notebook computers.

Wang and Vachtsevanos [49] proposed an architecture for prognosis using dynamic wavelet neural networks (DWNN). The proposed methodology was tested using vibration data from a fault seeded experiment that used a cracked bearing. An initial crack was seeded in the bearing and vibration data recorded during that period. The set-up was then stopped and the crack size was increased followed by a second run. This procedure was repeated until the bearing failed. The crack sizes were organized in an ascending order while time information was assumed uniformly distributed among the crack sizes. A training data set relating to the crack growth was thus obtained.

Dong and He [50] provided a diagnostic and prognostic methodology for multi-sensor equipment diagnosis and prognosis which was tested for hydraulic pumps. In this paper, the health states of components were modeled using state transition probability, state duration probability and observation probability using a hidden semi-Markov chain (HSMM). A modified forward–backward algorithm for HSMMs was used to estimate the parameters of HSMMs. Information from multiple sensors was fused using discriminant function analysis to determine the weight of each sensor. For prognosis of remaining life, a state duration model-based prediction calculation procedure was provided.

Kumar and Pecht [51] developed a methodology for prognostics of notebook computers using Mahalanobis Distance (MD) and Markov state models. MD was used to reduce the various monitored parameters from the notebooks into a univariate time series and to capture correlations between monitored performance parameters. Symbolic time series analysis was then used to discretize the MD time series and create a symbolic representation of system dynamics to distinguish healthy and unhealthy system states. The state transition probabilities and transition times were then predicted using a non-linear dynamic Markov state model. Using this methodology and historical fault data, the times and probability of the fault occurring in the notebook could be determined.

Saha et al. [52] applied a data-driven technique using the particle filter algorithm for prognostics of insulated gate bipolar transistors (IGBT). The IGBTs were subjected to accelerated ageing tests wherein thermal-electrical stress was applied on the devices. In-situ monitoring of various parameters such as the steady state voltages and currents, electrical transients, and thermal transients was carried out during accelerated aging tests on the IGBTs. The state and measurement equations that described the collector-emitter current during semiconductor aging were determined using regression analysis from the monitored experimental data. The model was input into the particle filtering algorithm which then provides estimates of RUL based on comparing predictions of the system state over time against an assumed end-of-life threshold.

Other applications in electronics where data-driven approaches have been used for RUL estimation include global positioning systems [53], avionics [54], and aircraft electrical power systems [55], [56].

### 3.2. *Advantages of the Data-driven Approach*

Implementation of data-driven approaches provides a variety of advantages in comparison with the model-based approaches. This section summarizes the advantages of the data-driven approaches for PHM purposes.

Data-driven approaches learn the behavior of the system purely from features of the monitored system data and do not require system-specific knowledge for modeling purposes. As a result, the data-driven approaches can be used as black-box models to enable diagnostics and prognostics even in the absence of 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 using multivariate techniques. 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.

### 3.3. *Limitations of the Data-driven Approach*

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. The requirement of training data to make decisions therefore is one of the limitations of data-driven approaches. Further, techniques such as Markov models and time series analysis require historical data until system failure while regression (trending) based techniques and particle filter algorithms require a pre-defined failure threshold for the system in order to estimate RUL.

It is not only important to prognosticate failure but also provide the information required to troubleshoot the system in order for an effective PHM implementation. This requires information that can help in the identification of failure mechanisms causing system failure. Data-driven approaches for PHM do not take into account any system-specific information and hence cannot provide such information regarding failure mechanisms.

# Chapter 4: Fusion Prognostics

Fusion prognostic methodologies combine the strengths of the model-based and data-driven approaches, in order to provide better estimates of RUL. The various advantages and limitations of implementing the model-based and data-driven approaches were described in Chapters 2 and 3. A solution that can overcome these limitations is to incorporate (or fuse) information from the model-based approaches with the data-driven techniques.

Previous studies have suggested the incorporation of information from various sources. While a number of studies have been carried out on fusion approaches in PHM, the emphasis in the work has been on fusing RUL estimates from different algorithms or models [57], [58], fusing data from different sensors [59], fusing information from various system parameters or features of data using algorithms [60], [61]. The papers reviewed in this section deal with the fusion approach as a framework for combining model-based or PoF based approaches and the data-driven approaches from the beginning of the PHM implementation to the estimation of RUL step.

Kumar et al. [62] provided a hybrid framework for prognostics of electronics products that uses data-driven techniques for anomaly detection and PoF models for the estimation of RUL based on isolation of component degradation. They also suggested the use of data-driven feature trending techniques for RUL prediction for cases where PoF models were not available. A case study using notebook computers was used to demonstrate the anomaly detection using Mahalanobis distance and parameter isolation using projection pursuit analysis. Prediction of RUL was suggested as future work.

Jaai and Pecht [63], [64] presented the fusion prognostics approach as a current research area that can help with the challenges faced in implementing PHM for electronics. The study in [63] provided a preliminary explanation of the approach along with a demonstration of prognosis of RUL for PCBs. The approach and the demonstration were further explained in detail in [64] as a part of the roadmap for PHM of information rich systems. The fusion prognostics approach was proposed as an approach to cope with the challenges in implementing PHM for information rich systems. The approach is explained in detail in Section 4.1 and the case study using printed circuit board assemblies is presented in Section 4.2 of this thesis.

Cheng and Pecht [65] implemented the fusion approach to prognostics for determining the RUL of multilayer ceramic capacitors subjected to temperature-humidity bias tests. In the paper, an FMMEA showed that the potential failure mechanisms were silver migration and degradation of the dielectric leading to the choice of capacitance, dissipation factor and insulation resistance were monitored. MSET and SPRT were used for anomaly detection. Lack of PoF models for the identified failure mechanisms led to defining a failure model using the Euclidean norm of the MSET residuals. A failure threshold was obtained from the failed capacitors in order to carry out prognostics.

The fusion prognostics approach provides a framework for information exchange between the two approaches in order to provide the capability to detect intermittent faults using data-driven techniques, use system-specific information from the model-based approaches for defining failure thresholds to enable RUL estimation using data-driven techniques and also to help in identification of failure modes and mechanisms.

Fusion prognostic methodologies therefore 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, enable RUL estimation using data-driven techniques and identify the potential processes causing system failure along with an estimation of the extent or severity of the fault for effective maintenance strategies. A fusion approach to PHM is illustrated in Fig. 4.

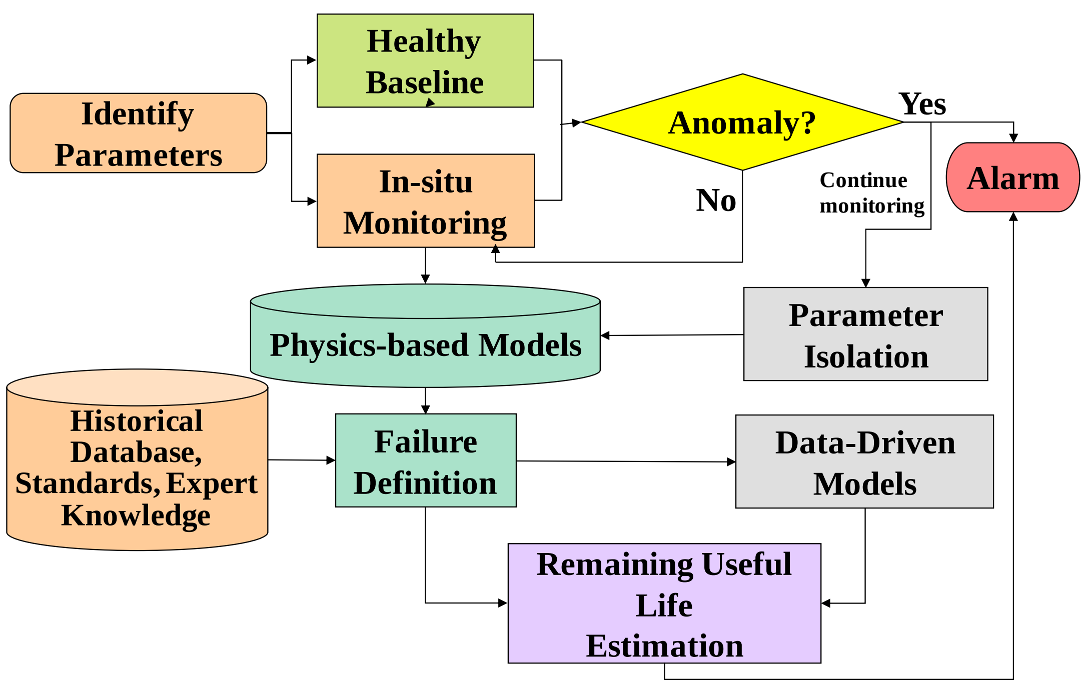



Fig. 4: Fusion Prognostics Approach

### 4.1. *Implementation of Fusion Prognostics Approach*

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. These parameters may include operational and environmental loads, system parameters such as voltages and currents as well as performance parameters. Both, environmental and system parameter data are required to be monitored to enable diagnosis and prognosis of a system's health in real time. A systematic analysis of the processes that lead to system failure using physics based tools such as FMMEA can aid in the process of identifying the parameters to be monitored. Along with FMMEA, virtual simulations, information from maintenance records, qualification tests, and expert knowledge can be used for such systematic analysis. These techniques help identify the parameters that are required in order to assess the state of health of a system and identify parameters that can be used as potential indicators of system failure. Understanding the physical processes occurring in the system helps in identifying critical components, possible failure sites, failure mechanisms, and their effects on the system. These techniques also help in determining the relevant physics based models for estimation of RUL for the system and its components.

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 monitored data in anomaly detection techniques. Knowledge of the processes taking place in the system and the relationships between the various parameters can help in choosing the appropriate data-driven techniques for diagnosis and prognosis. For example, for a linear system one can choose to use the Kalman filter algorithm which cannot be used for non-linear transitions. Knowledge of the system dynamics can further be used to create system models that can be used with the Kalman filter for diagnosis.

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. In this semi-supervised learning approach, it is assumed that data representing all the possible healthy states of the system are available a priori. The collection of parameter data that represents all the possible variations of the healthy operating states of the system is known as the healthy baseline. The baseline data is collected during various combinations of operating states and loading conditions when the system is known to be functioning normally. It is also possible for the baseline to consist of representative threshold values based on features extracted from the healthy data, specifications and standards. For example, Mahalanobis Distance can be used to reduce multivariate data and create control charts that can serve as a baseline for comparison with test data [48]. 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 extracted from multidimensional data. In addition projections and filtering of the data can also be used to extract features from the data. Distinctions between normal and anomalous data instances are made using assumptions such as the normal instances are more similar (using a certain similarity measure) to a majority of the data sequences, than anomalous data. Detection can also be carried out using assumptions regarding the frequency of occurrence of normal versus anomalous data or assuming that the normal instances follow a particular distribution, deviations from which are declared anomalous. 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 as 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), partial least squares, independent component analysis, and fisher discriminant analysis. Based on the information from the parameter isolation step, the critical parameters are used to select appropriate models from the database. Isolating of parameters also helps to identify the root causes of the failure. 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. Features such as cyclic range, cyclic mean, ramp rate and dwell time of parameters such as temperature and vibration are used as the primary inputs of the physics-based models to calculate the damage of the product [17].

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 for 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 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. The fusion approach therefore provides a framework for information exchange between physics based analysis and the data-driven approaches from the first step of parameter identification to establishing failure thresholds to enable estimation of RUL.

### *4.2. Application of a Fusion Approach to an Electronics System*

The fusion prognostics approach was implemented on an electronics system consisting of a printed circuit card assembly. The assembly consisted of representative components such as ball grid array (BGA) packages, quad flat packages and surface mount resistors that are commonly found in circuit cards (shown in Fig. 5). The fusion approach implemented involved the selection of parameters required for diagnosis and prognosis using FMMEA analysis. These parameters were then used with a regression based residual analysis technique for detection of anomalous behavior. The technique also involved the use of sequential probability ratio test (SPRT) algorithm for diagnostics. After the anomaly detection, features of the isolated parameter were used in the relevant PoF model for failure prognosis. A failure threshold was obtained from standards in order to enable a trending based RUL estimation for each component. The case study is described in detail in this section.

The circuit cards containing eight BGA components with 256 I/Os, eight BGAs with 144 I/Os, 4 QFPs and 40 surface mount resistors were subjected to accelerated temperature cycling tests in order to evaluate the effect of thermal cycling on the reliability of the components. During the thermal cycling, the printed circuit boards were subjected to a maximum temperature of 185˚C and minimum temperature of -40˚C. The ramp rate was 3.5 ˚C/ minute and the cycle time was 159 minutes with a dwell time of 15 minutes at both extremes.

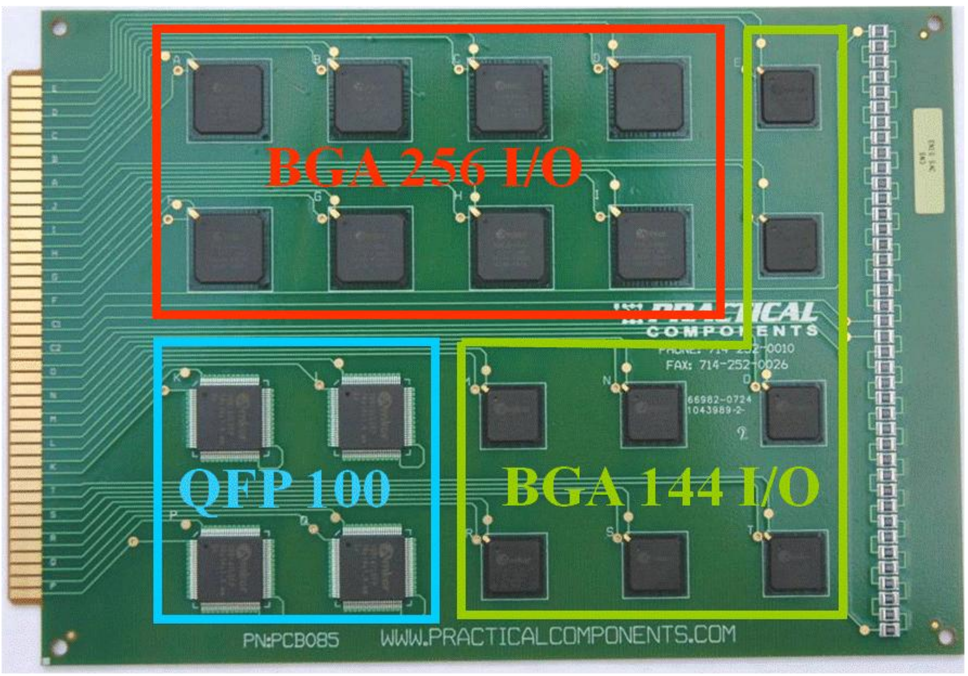



Fig. 5: Components of Printed Circuit Assembly used in Case Study

An FMMEA analysis was carried out on the circuit cards in order to determine the critical modes and mechanisms affecting the assembly due to thermal cycling. The critical failure mechanism was found to be interconnect fatigue and the failure mode was an open circuit which would result in an increase in resistance of the components. The BGAs were identified as the weakest components in the system. Temperature and resistance parameters therefore were critical to detect system failure for the given loading conditions and hence were chosen to be monitored. As the BGAs were identified as the weakest components, in-situ monitoring of the BGAs' resistances was carried out along with measurement of the board temperatures. Each BGA was provided with one daisy chain in order to carry out resistance measurements. Thermocouples were placed on the board to measure the temperatures during the experiment. The measurements were recorded once every minute. The resolution of the resistance monitoring equipment was in the $10^{-3}$ range.

The resistance, temperature data was then used in the anomaly detection step. Anomaly detection was carried out using a data-driven residual analysis technique described below (see Fig. 6 for illustration of the approach).

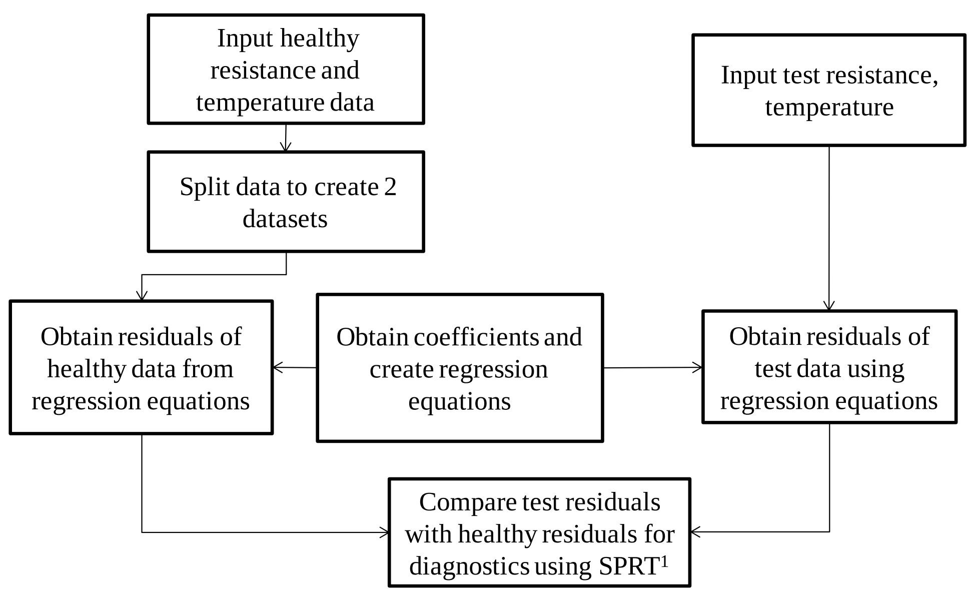



Fig. 6: Flowchart Summarizing Residual Based Anomaly Detection Technique

The required training data (baseline) to model the healthy states of the system was created using ten cycles of in-situ data from the beginning of the test. 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. Figure 7 shows 5 cycles of the BGA resistance versus temperature that was used as training data.

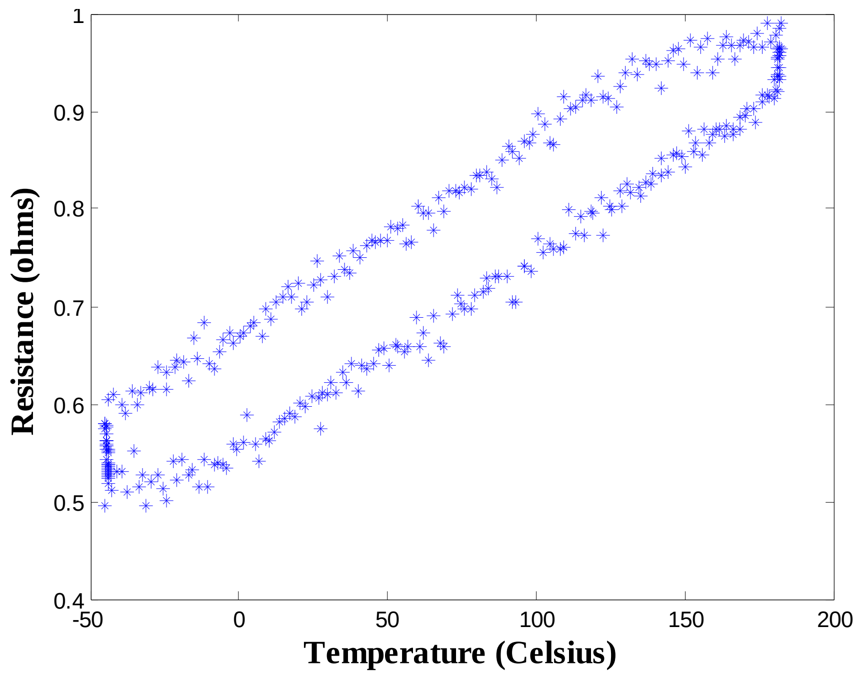


Fig. 7: BGA Resistance vs Temperature Data

The regression model used for the estimation of the resistance is shown in equations 1 and 2. Two equations were used as a result of the distinct resistances shown in Figure 7 during the temperature cycling.

$$\mathbf{R_{inc}} = 0.002*\mathbf{T} + 0.567 \tag{1}$$

$$\mathbf{R_{dec}} = 0.002*\mathbf{T} + 0.724 \tag{2}$$

where $R_{inc}$, $R_{dec}$ are the resistances during the increasing and decreasing parts of the temperature cycling respectively, and T is the temperature.

The regression model was used to estimate component resistance for every observed board temperatures using the thermocouple readings. The differences between the regression model estimates and the observations of resistance were used to obtain a 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 signals alarms when it detects that the system is statistically deviating from its normal state by choosing between two or more statistical hypotheses [45], [46], [66], [67]. SPRT is based on the assumption that the data follow a Gaussian distribution. The null hypothesis, $H_0$, represents the healthy state of the system with the data following the Gaussian distribution with mean equal to 0 and standard deviation equal to $\sigma$. Four alternate hypotheses are formulated that represent the degraded state of the system. The hypothesis $H_1$ is when the mean of the data has shifted to +M with standard deviation $\sigma$. $H_2$ is when the mean of the data has shifted to –M with the standard deviation $\sigma$. $H_3$ and $H_4$ are hypotheses in which the mean remains zero but the standard deviation has increased to $V\sigma$ and decreased to $\sigma/V$, respectively. The parameters M and V are predetermined disturbance magnitudes. These are system-specific and are determined based on system behavior. Figure 8 shows a pictorial representation of mean changes and standard deviation changes that SPRT can be used to detect (Figure at the top shows the mean shift hypotheses and figure at the bottom shows the hypotheses for change in standard deviation).

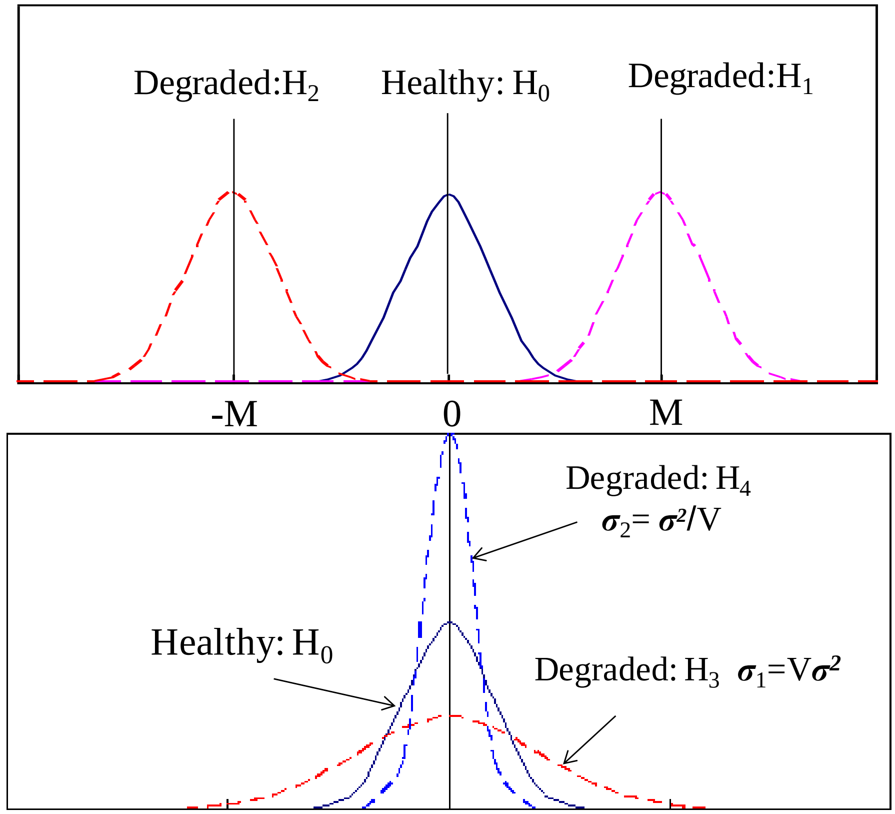



Fig. 8: Hypothesis Testing using SPRT

SPRT analyzes observations sequentially to determine whether or not the test data is abnormal. Then the SPRT index, which is the natural logarithm of the likelihood ratio, is calculated for each of the alternate hypotheses using equation (3).

$$B \le \ln\left[\prod_{i=1}^{n} \frac{\Pr(x_i \mid H_j)}{\Pr(x_i \mid H_0)}\right] \le A \tag{3}$$

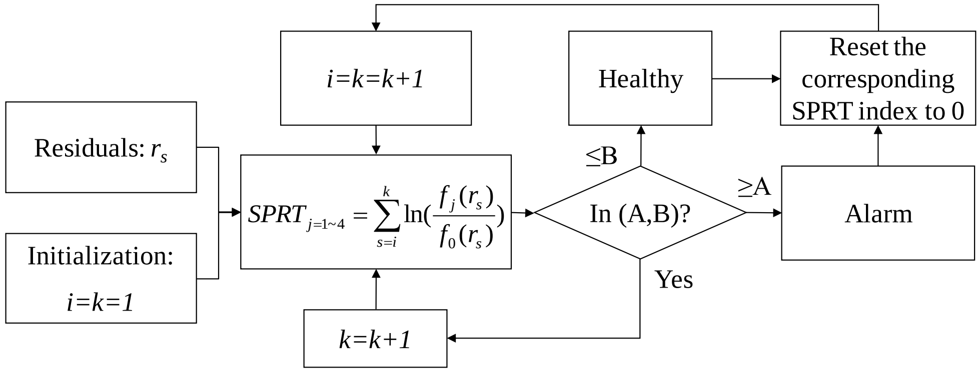
where

$$\ln\left[\prod_{i=1}^{n} \frac{\Pr(x_i \mid H_j)}{\Pr(x_i \mid H_0)}\right]$$
$$= ln\frac{probability\ of\ sequence\ \{X_n\}\ given H_j\ is\ true}{probability\ of\ sequence\ \{X_n\}\ given H_0\ is\ true}$$
$$= SPRT\ index$$

and $A$ and $B$ are the reject and accept thresholds defined using the false and missed alarm probabilities, $\alpha$ and $\beta$ as sown below.

$$A = ln\frac{1-\beta}{\alpha} \; and \; B = ln\frac{\beta}{1-\alpha}$$

If the SPRT index is less than or equal to $B$, then the null hypothesis is accepted and the system is considered to be healthy. The SPRT index is reset and the next test residual is input. If the index is between $A$ and $B$, no decision is made as there is not enough information. In this case the next test residual is input without resetting the SPRT index. If the SPRT index is greater than or equal to $A$, then the alternate hypothesis is accepted. SPRT sets off an alarm and the system is said to be degraded. The SPRT index is again reset and the next test residual is input. Figure 9 illustrates the steps in implementing SPRT for diagnostics.




$$SPRT_{j=1\sim4} = \sum_{s=i}^{k} \ln\left(\frac{f_j(r_s)}{f_0(r_s)}\right)$$

$SPRT_j$ is called SPRT index

$f_j(r)$ is the pdf of the distribution of $H_j$

$f_0(r)$ is the pdf of the distribution of $H_0$

$$B = \ln\left(\frac{\beta}{1-\alpha}\right), \quad A = \ln\left(\frac{1-\beta}{\alpha}\right)$$

A and B are the threshold values.
$\alpha$ is the false-alarm probability
$\beta$ is the missed-alarm probability

Fig. 9: Procedure to Implement SPRT for Anomaly Detection

The remaining five cycles of training data were used in the regression model to calculate healthy residuals. The healthy residuals were then used to train SPRT for anomaly detection (see Figure 10 for histogram of healthy residuals calculated from the remaining training data).

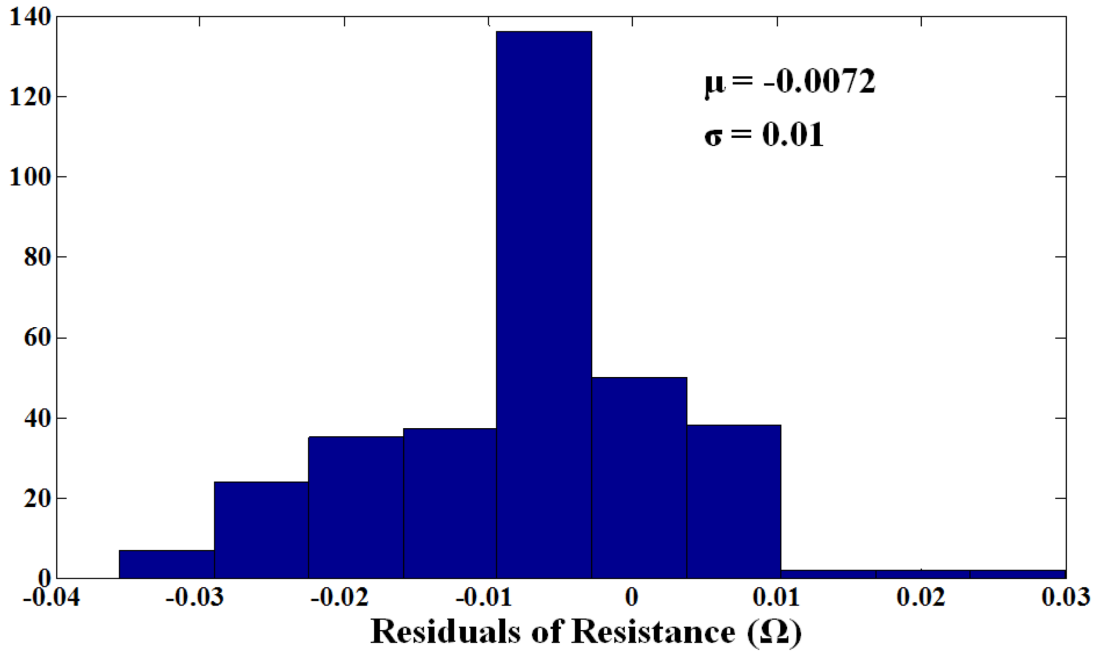


Fig. 10: Histogram of the residuals of the remaining training data

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. The false and missed alarm probabilities were chosen to be 0.005 (0.5%) each to calculate the SPRT thresholds. Figure 11 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. Figure 12 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. The results for this component (No.1) and the remaining 7 BGA components (256 I/Os) that were part of the tested assembly are shown below in Table 1.

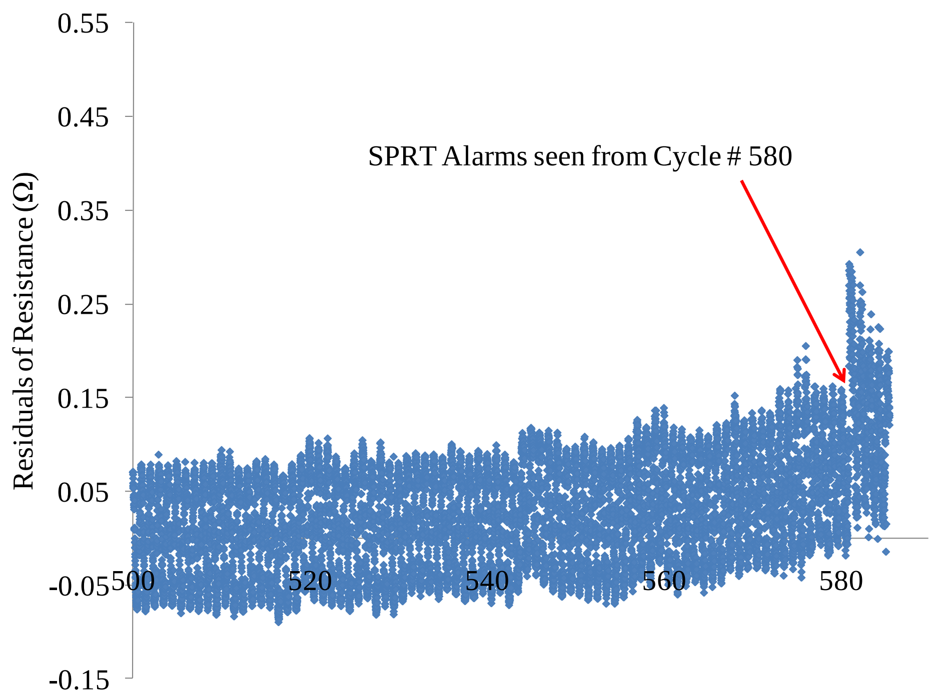



Fig. 11: SPRT Alarms at 580th Cycle Due to Increase in the Mean of the Residuals of Resistance (The red crosses indicate that SPRT has detected anomalies at the 580th cycle).

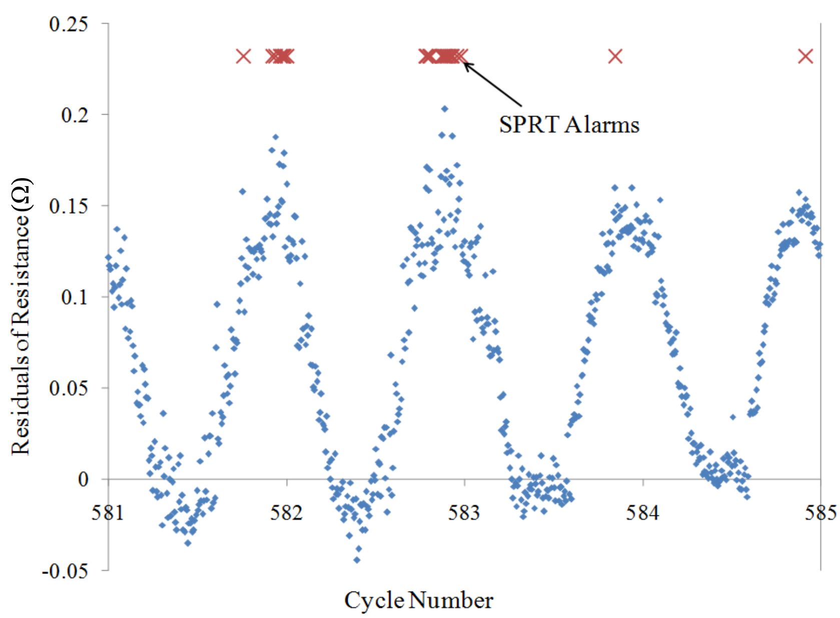



Fig. 12. Zoomed in View of Fig. 8 from cycle 581 to 585 to Show Residuals of Resistance and SPRT Alarms.

| Component | First Alarm from SPRT | Cycles to Failure |
|---|---|---|
| 1 | 580 | 693 |
| 2 | 623 | 725 |
| 3 | 738 | 1139 |
| 4 | 650 | 1095 |
| 5 | 632 | 741 |
| 6 | 716 | 1274 |
| 7 | 698 | 1036 |
| 8 | 703 | 927 |

Table 1: Detection Time based on Alarms from SPRT

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 behavior due to an increase in resistance was detected. Knowledge from the physics of failure analysis determines that 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 [68] was selected to calculate the RUL. A model of the PCB was created with information regarding the BGA and the various parameters such as the package dimensions (17mm*17mm*1.56mm), package interconnect pitch (1mm), substrate material (BT-epoxy), BGA span (15mm*15mm) with a full array, die dimensions (9.5mm*9.5mm*0.4mm), BGA ball diameter (0.5mm), solder material (SAC 305), solder joint height (0.25mm), stand-off height (0.65mm) and solder joint bond area (0.5mm$^2$) from the datasheet. The solder material used in the assembly was $Sn_{96.5}Ag_{3.0}Cu_{0.5}$. The damage to the components and time to failure due to the thermal cycling on the components were calculated. The mean cycles to failure for the 256 I/O BGAs was calculated to be 1038 cycles (2750.7 hours). The estimate for 10% cycles to failure was obtained as 817 cycles and for 1% cycles to failure was obtained as 760 cycles using Monte-Carlo analysis. The Monte-Carlo analysis was carried out by adding a triangular distribution with 10% variation for the solder joint height, stand-off height and the solder joint bond area. 10,000 iterations were performed in order to calculate the 10% and 1% cycles to failure for the BGAs. 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. Further, the result from the PoF model reflects the average failure cycles to failure for all the BGA components (256 I/Os) as they have similar geometry and material properties.

To calculate an estimate of RUL dynamically using data-driven techniques, a failure threshold of 300Ω for the resistance parameter was obtained from the IPC-9701A standard [69]. 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 for component 1 (shown in Figure 13). 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 (No. 1) was observed after 693 cycles.

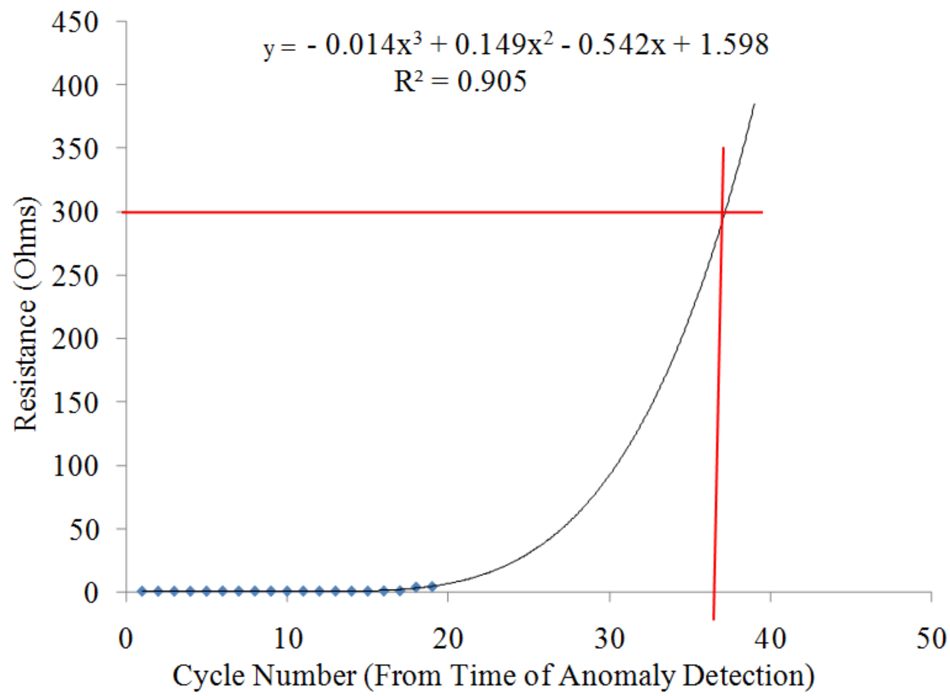



Fig. 13: Trending of Peak Resistance for Data-driven RUL Estimation

This case study showed a step-by-step implementation of the fusion approach to PHM. For component 1, 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. Results for the remaining 7 components are shown in the appendix of this thesis. Table 2 provides the results of the data-driven prediction for all of the eight components.

| **Component** | **Predicted TTF (cycles)** | **Actual TTF (cycles)** | **%Time between Prediction and Failure** |
|---|---|---|---|
| 1 | 620 | 693 | 10% |
| 2 | 642 | 725 | 11% |
| 3 | 830 | 1139 | 27% |
| 4 | 707 | 1095 | 35% |
| 5 | 657 | 741 | 11% |
| 6 | 766 | 1274 | 39% |
| 7 | 980 | 1036 | 0.5% |
| 8 | 923 | 927 | 0.004% |

In the case study presented, SPRT which is a statistical tool to determine mean shifts and changes in other statistical parameters such as the variance, kurtosis and so on was used for anomaly detection. The fusion approach in this case study helped in the exchange of information between the techniques to establish which parameters to monitor and to determine thresholds for the data-driven RUL step from the PoF based standards. While the case study presented involves the analysis of a system wherein 2 parameters (i.e, temperature and resistance) were monitored, analysis of more complex systems that are multivariate would involve the use of techniques such as principle components analysis to determine the parameters that are contributing to the anomalous behavior of the system. The isolation of such parameters would then lead to determining which PoF models should be used for the estimation of RUL. The information from the PoF models and standards could then be used for RUL estimation using data-driven techniques.

The fusion approach provided a number of advantages such as 1) determination of the parameters (resistance and temperature) for in-situ monitoring using FMMEA analysis, 2) 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 3) 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.

# Chapter 5: Contributions and Future Work

This thesis developed a fusion approach to prognostics that integrates the data-driven and model-based approaches in order to overcome the current limitations in PHM implementation. The fusion approach provides a framework to enable information fusion within the PHM system that uses the different tools of the model-based and the data-driven approaches to provide a variety of benefits such as

1) Providing a systematic method to identify the parameters for in-situ monitoring using FMMEA and virtual simulation tools,
2) Enabling detection of intermittent faults using anomaly detection techniques which helps in reducing the no-fault found errors,
3) Isolating the parameters contributing to system failure leading to information regarding the potential component that is failing within the system and information that can be used to identify the failure mechanism that is causing system failure, and
4) Providing method for determination of failure threshold or failure description from the model-based approaches (using models or from standards) to enable estimation of RUL using data-driven techniques.

Suggestions for future work include

1) Analysis of uncertainty in prognostic estimates: 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. 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.

1) Fusion of RUL estimates: A second area of research is investigating techniques to fuse or combine estimates of RUL from the various sources such as the data-driven and model-based estimates to provide single fused RUL value. 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 weighted 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.

# Appendix

This section documents the results of the analysis for the remaining 7 BGA components that were used in the case study. The analysis was carried out in the same way as for component 1. The required training data (baseline) to model the healthy states of the system was created using ten cycles of in-situ data from the beginning of the test for each component. Five cycles were used to create the regression model and the remaining five cycles were used to create residuals for training SPRT. A mean shift of 0.3 was used as the alternate hypothesis with false and missed alarm probabilities of 0.005. After the anomaly detection step, the peak resistance from each cycle was trended to get an estimate of the RUL. The results for each component are provided below:

**Results for component 2:**

The regression equations were found to be:

$$\mathbf{R}_{\mathbf{inc}} = 0.002^{*}\mathbf{T} + 0.576 \tag{A1}$$

$$\mathbf{R}_{\mathbf{dec}} = 0.003^{*}\mathbf{T} + 0.710 \tag{A2}$$

Figure A1 shows the histogram of the residuals of the healthy data that was used to train SPRT followed by Figure A2 which shows the residuals of the resistance for component 2 when anomalies were detected by SPRT.

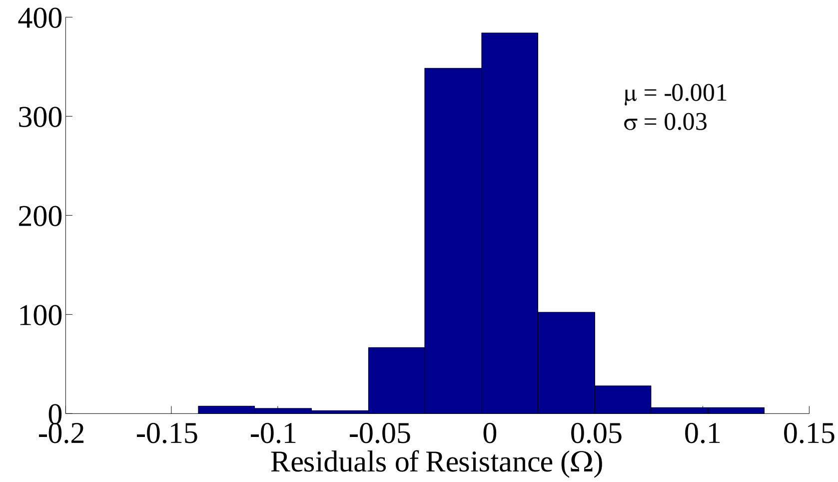



Fig. A1: Histogram of the Residuals of the Remaining Training Data

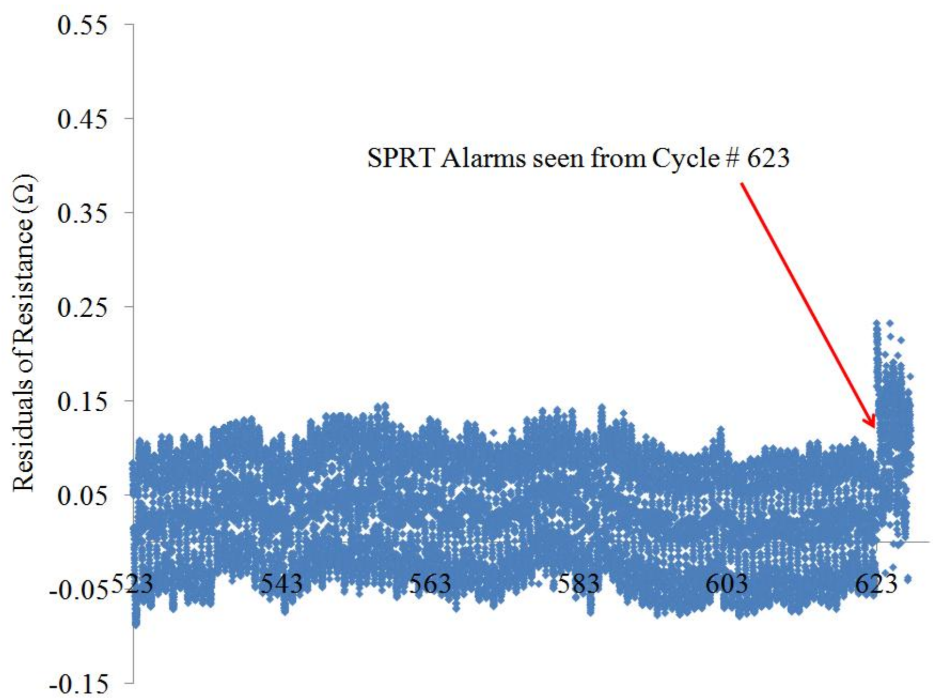



Fig. A2: SPRT Alarms at 623rd Cycle Due to Increase in the Mean of the Residuals of Resistance (The red arrow indicates the cycle from which alarms were seen from SPRT).

The peak resistance from the time of the anomaly was trended to get an estimate of the RUL (shown in Figure A3). The regression equation is also shown in the figure. The cycles to failure was calculated at the 633rd cycle to be 642 cycles for component 2. The actual cycles to failure for component 2 according IPC-9701A standard was found to be 725 cycles. The RUL prediction was 83 cycles (~11% of the total life) before the actual cycles to failure

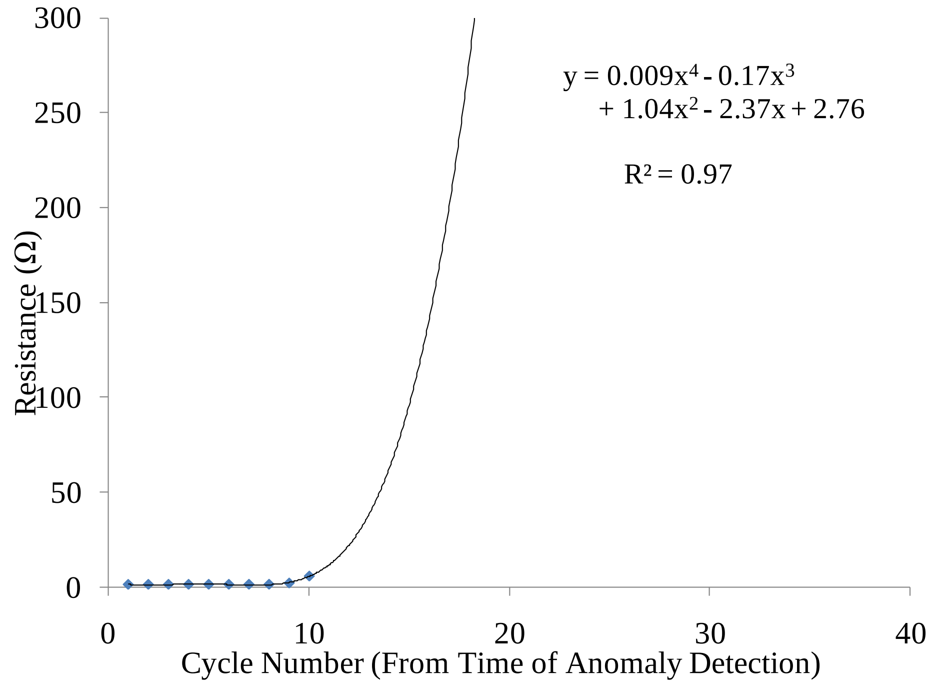



Fig. A3: Trending of Peak Resistance for Data-driven RUL Estimation

**Results for component 3:**

The regression equations were found to be:

$$\mathbf{R_{inc}} = 0.002*\mathbf{T} + 0.642 \quad \text{(A3)}$$

$$\mathbf{R_{dec}} = 0.003*\mathbf{T} + 0.750 \quad \text{(A4)}$$

Figure A4 shows the histogram of the residuals of the healthy data that was used to train SPRT followed by Figure A5 which shows the residuals of the resistance for component 3 when anomalies were detected by SPRT.

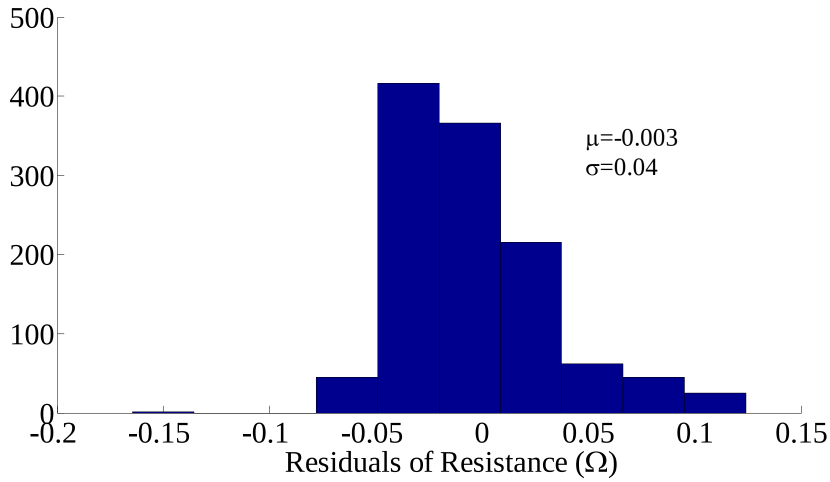



Figure A4: Histogram of the Residuals of the Remaining Training Data

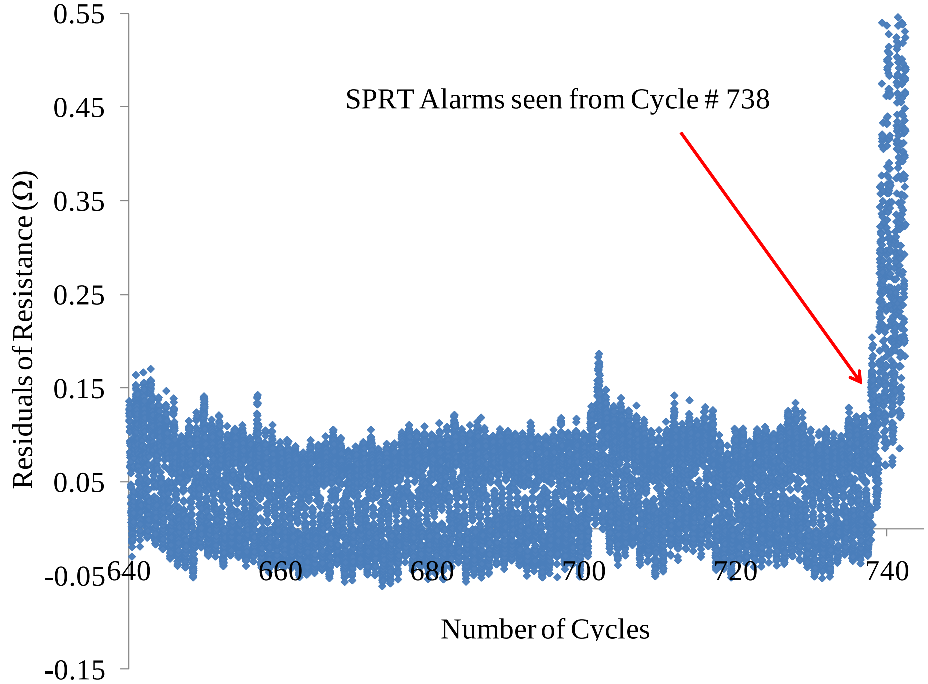



Fig. A5: SPRT Alarms at 738th Cycle Due to Increase in the Mean of the Residuals of Resistance (The red arrow indicates the cycle from which alarms were seen from SPRT).

The peak resistance from the time of the anomaly was trended to get an estimate of the RUL (shown in Figure A6). The regression equation is also shown in the figure. The cycles to failure was calculated at the 778th cycle to be 830 cycles for component 3. The actual cycles to failure for component 3 according IPC-9701A standard was found to be 1139 cycles. The RUL prediction was 309 cycles (~27% of the total life) before the actual cycles to failure

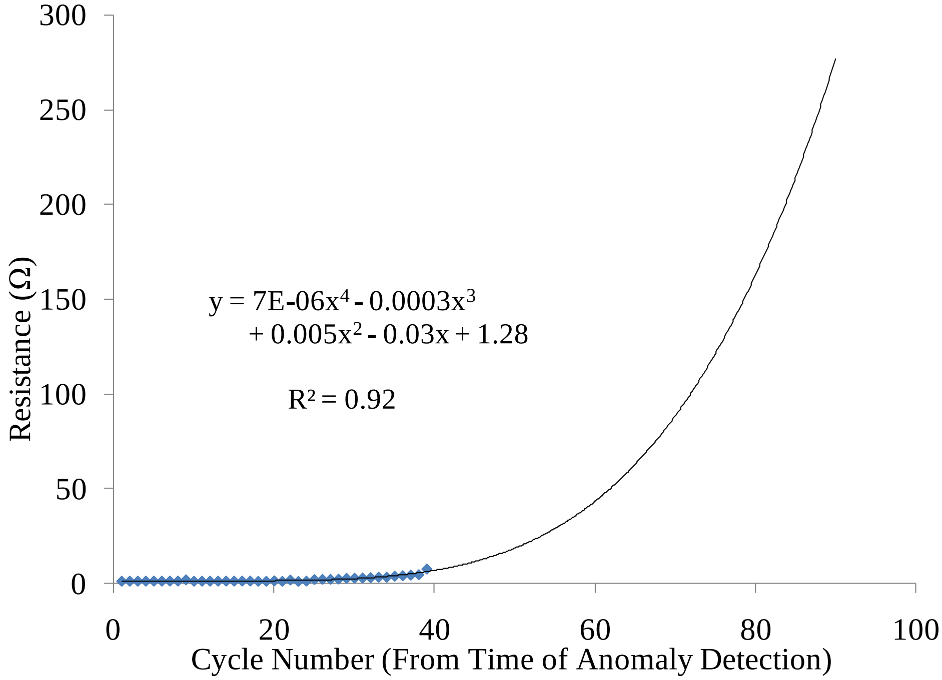



Fig. A6: Trending of Peak Resistance for Data-driven RUL Estimation

**Results for component 4:**

The regression equations were found to be:

$$\mathbf{R_{inc}} = 0.002*\mathbf{T} + 0.641 \quad \text{(A5)}$$

$$\mathbf{R_{dec}} = 0.003*\mathbf{T} + 0.796 \quad \text{(A6)}$$

Figure A7 shows the histogram of the residuals of the healthy data that was used to train SPRT followed by Figure A8 which shows the residuals of the resistance for component 4 when anomalies were detected by SPRT.

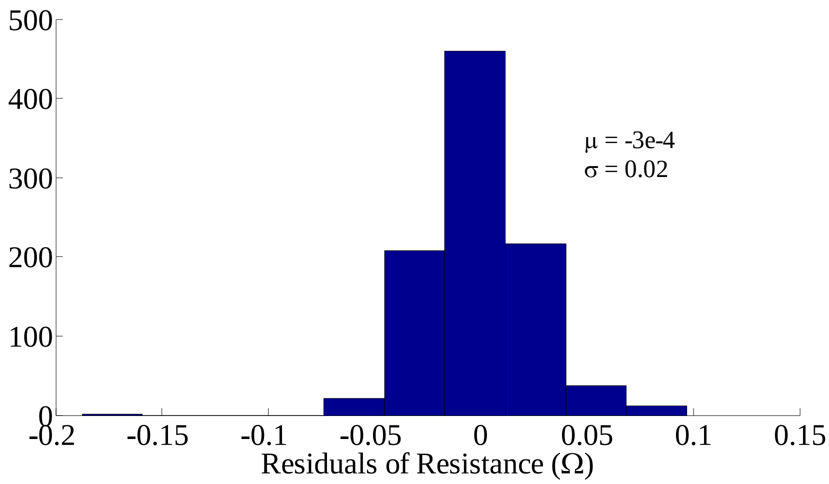



Figure A7: Histogram of the Residuals of the Remaining Training Data

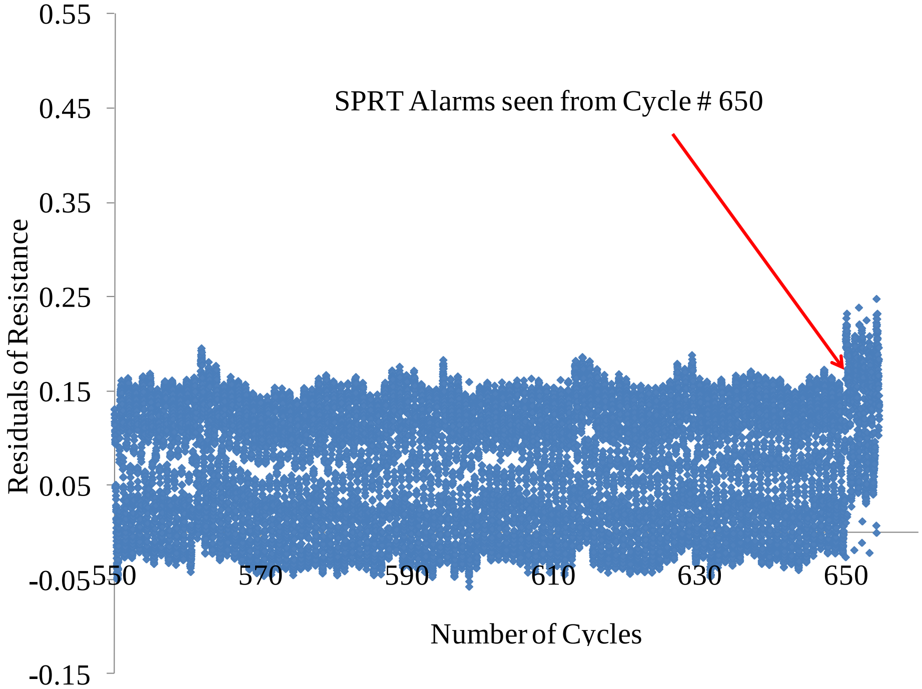



Fig. A8: SPRT Alarms at 650th Cycle Due to Increase in the Mean of the Residuals of Resistance (The red arrow indicates the cycle from which alarms were seen from SPRT).

The peak resistance from the time of the anomaly was trended to get an estimate of the RUL (shown in Figure A9). The regression equation is also shown in the figure. The cycles to failure was calculated at the 670th cycle to be 707 cycles for component 4. The actual cycles to failure for component 4 according IPC-9701A standard was found to be 1095 cycles. The RUL prediction was 388 cycles (~35% of the total life) before the actual cycles to failure.

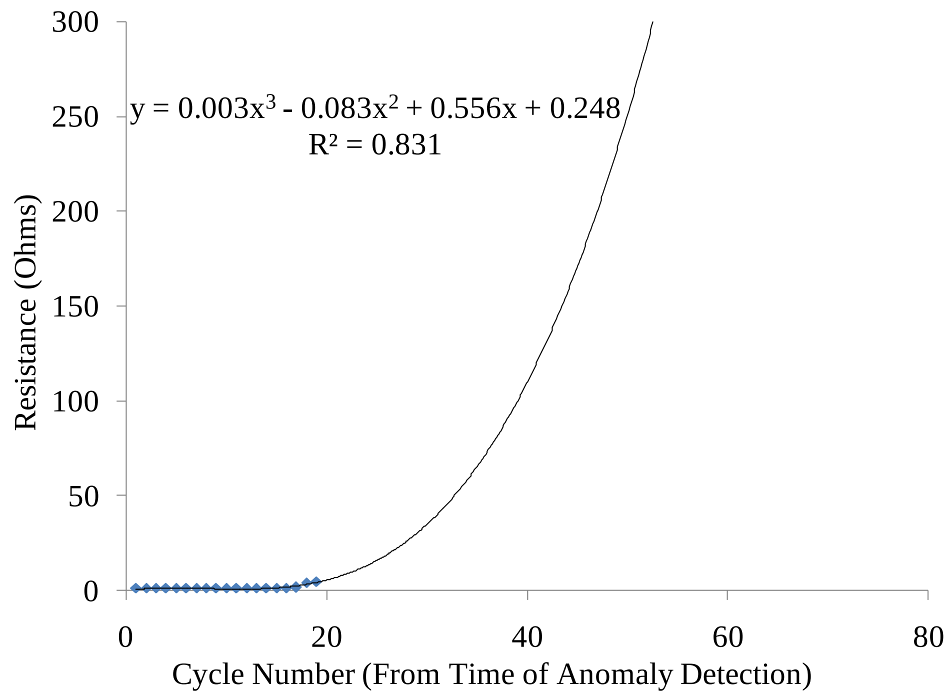



Fig. A6: Trending of Peak Resistance for Data-driven RUL Estimation

**Results for component 5:**

The regression equations were found to be:

$$\mathbf{R_{inc}} = 0.001*\mathbf{T} + 0.495 \quad \text{(A7)}$$

$$\mathbf{R_{dec}} = 0.002*\mathbf{T} + 0.597 \quad \text{(A8)}$$

Figure A10 shows the histogram of the residuals of the healthy data that was used to train SPRT followed by Figure A11 which shows the residuals of the resistance for component 5 when anomalies were detected by SPRT.

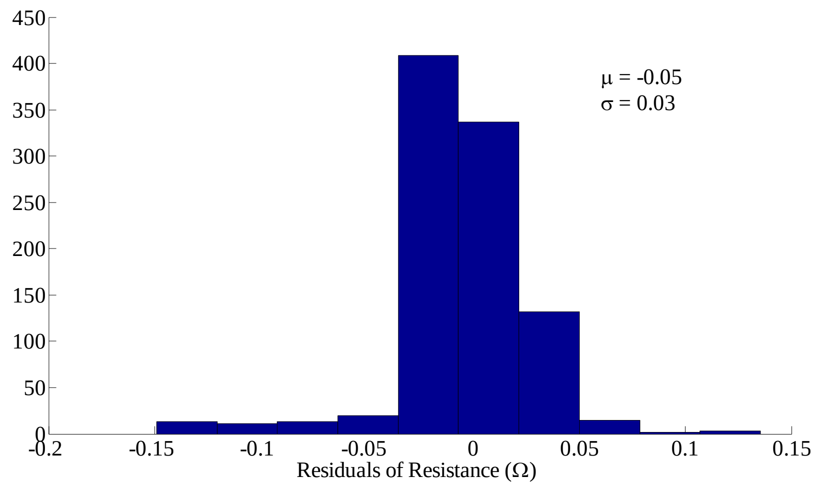



Fig. A10: Histogram of the Residuals of the Remaining Training Data

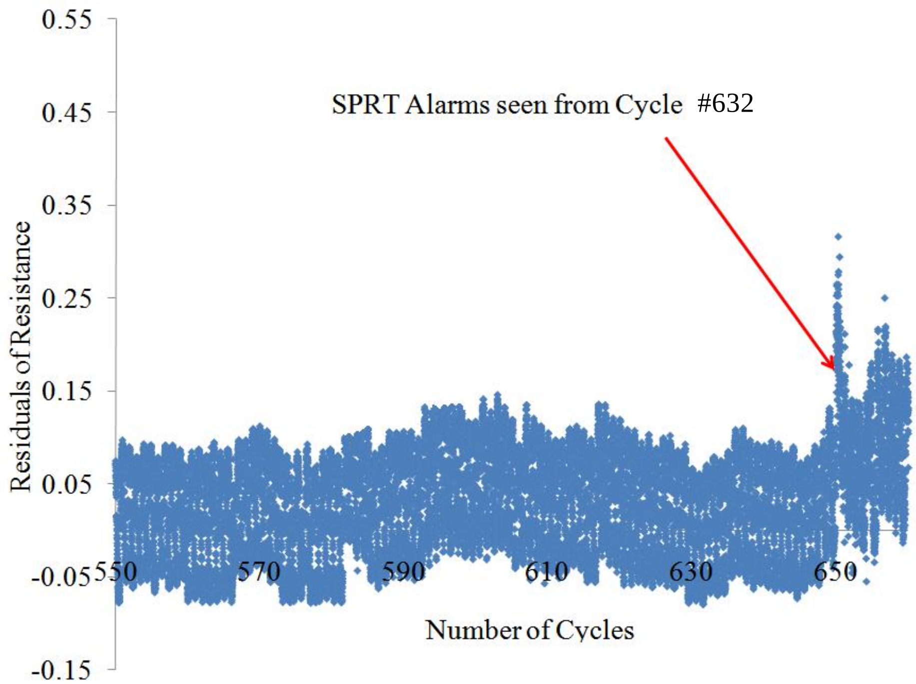



Fig. A11: SPRT Alarms at 632nd Cycle Due to Increase in the Mean of the Residuals of Resistance (The red arrow indicates the cycle from which alarms were seen from SPRT).

The peak resistance from the time of the anomaly was trended to get an estimate of the RUL (shown in Figure A12). The regression equation is also shown in the figure. The cycles to failure was calculated at the 648th cycle to be 657 cycles for component 5. The actual cycles to failure for component 5 according IPC-9701A standard was found to be 741 cycles. The RUL prediction was 84 cycles (~11% of the total life) before the actual cycles to failure.

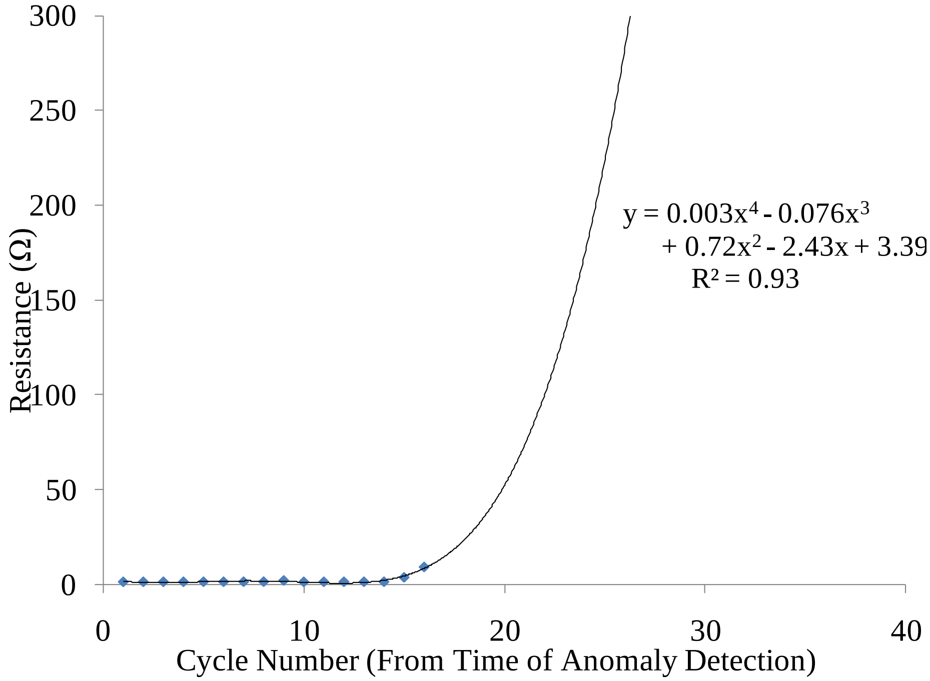



Fig. A12: Trending of Peak Resistance for Data-driven RUL Estimation

**Results for component 6:**

The regression equations were found to be:

$$\mathbf{R_{inc}} = 0.001*\mathbf{T} + 0.503 \quad \text{(A9)}$$

$$\mathbf{R_{dec}} = 0.002*\mathbf{T} + 0.630 \quad \text{(A10)}$$

Figure A13 shows the histogram of the residuals of the healthy data that was used to train SPRT followed by Figure A14 which shows the residuals of the resistance for component 6 when anomalies were detected by SPRT.

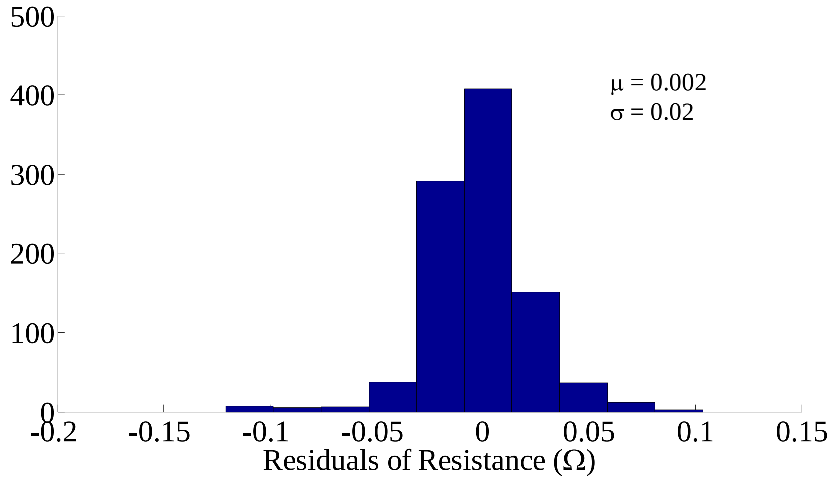



Fig. A13: Histogram of the Residuals of the Remaining Training Data

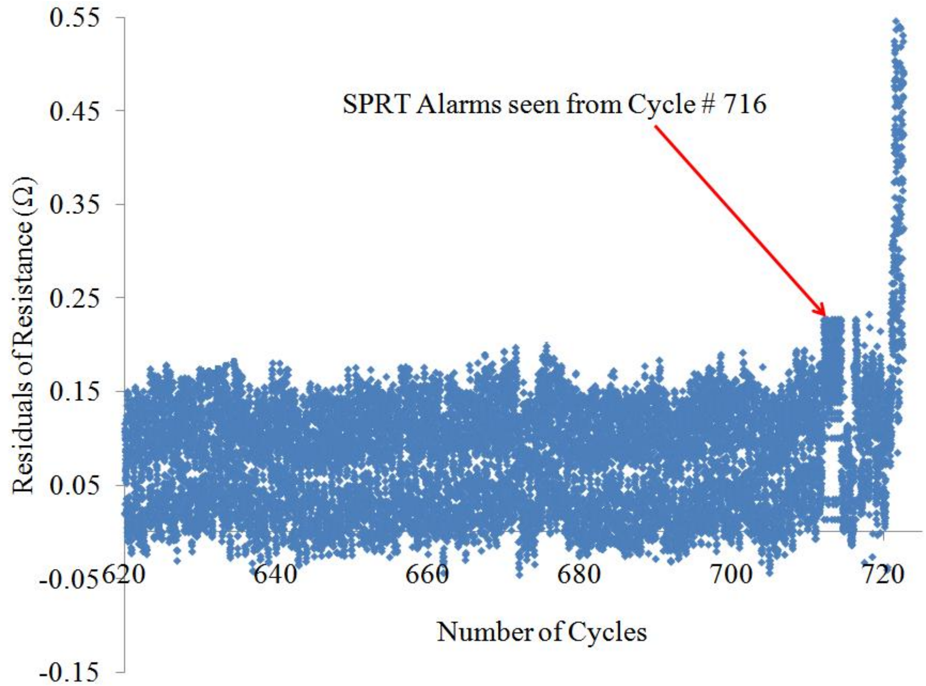



Fig. A14: SPRT Alarms at 716th Cycle Due to Increase in the Mean of the Residuals of Resistance (The red arrow indicates the cycle from which alarms were seen from SPRT).

The peak resistance from the time of the anomaly was trended to get an estimate of the RUL (shown in Figure A15). The regression equation is also shown in the figure. The cycles to failure was calculated at the 735th cycle to be 766 cycles for component 6. The actual cycles to failure for component 6 according IPC-9701A standard was found to be 1274 cycles. The RUL prediction was 508 cycles (~39% of the total life) before the actual cycles to failure.

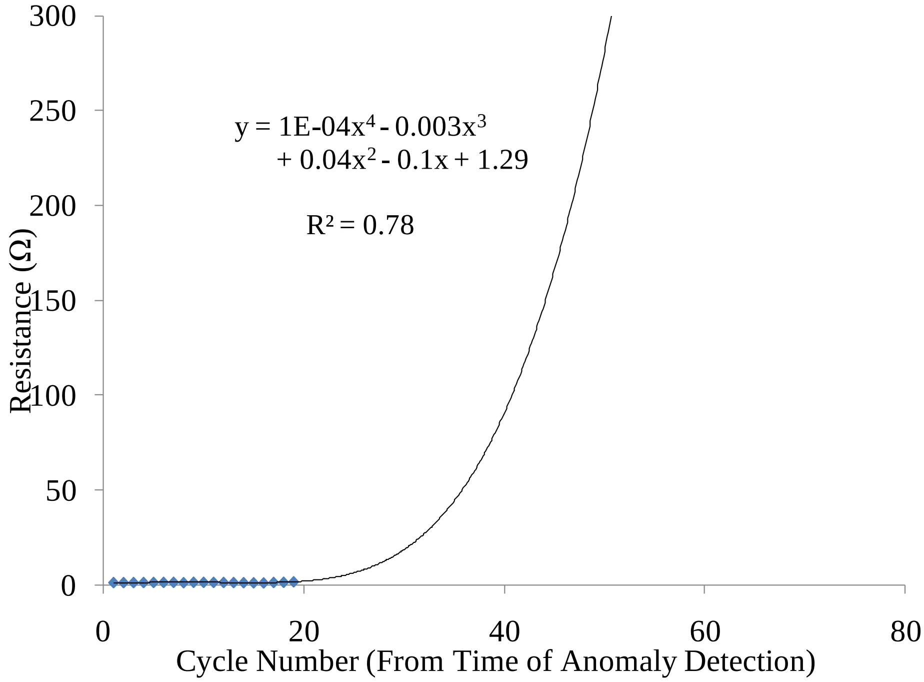



Fig. A15: Trending of Peak Resistance for Data-driven RUL Estimation

**Results for component 7:**

The regression equations were found to be:

$$\mathbf{R_{inc}} = 0.002*\mathbf{T} + 0.527 \quad \text{(A11)}$$

$$\mathbf{R_{dec}} = 0.003*\mathbf{T} + 0.665 \quad \text{(A12)}$$

Figure A16 shows the histogram of the residuals of the healthy data that was used to train SPRT followed by Figure A17 which shows the residuals of the resistance for component 7 when anomalies were detected by SPRT.

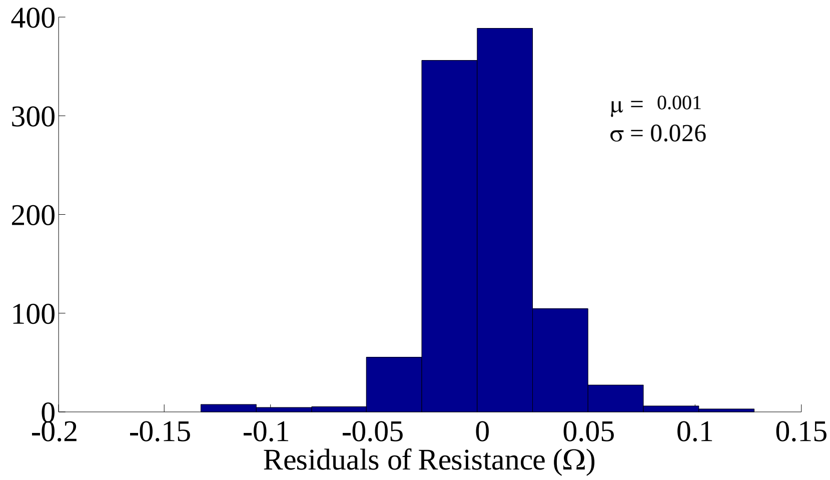



Fig. A16: Histogram of the Residuals of the Remaining Training Data

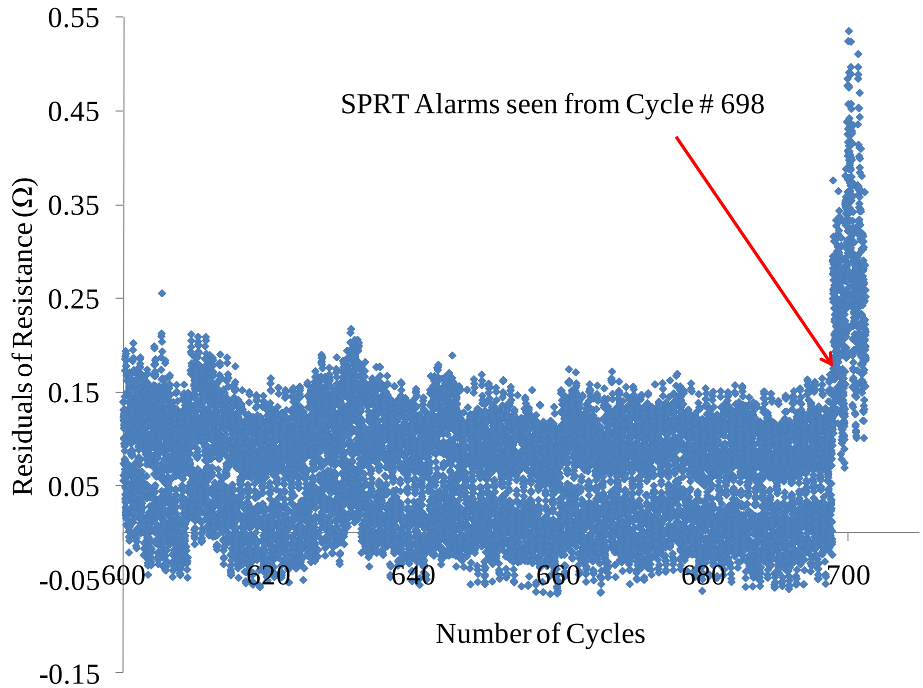



Fig. A17: SPRT Alarms at 698th Cycle Due to Increase in the Mean of the Residuals of Resistance (The red arrow indicates the cycle from which alarms were seen from SPRT).

The peak resistance from the time of the anomaly was trended to get an estimate of the RUL (shown in Figure A18). The regression equation is also shown in the figure. The cycles to failure was calculated at the 813th cycle to be 980 cycles for component 7. The actual cycles to failure for component 7 according IPC-9701A standard was found to be 1036 cycles. The RUL prediction was 56 cycles (0.5% of the total life) before the actual cycles to failure.

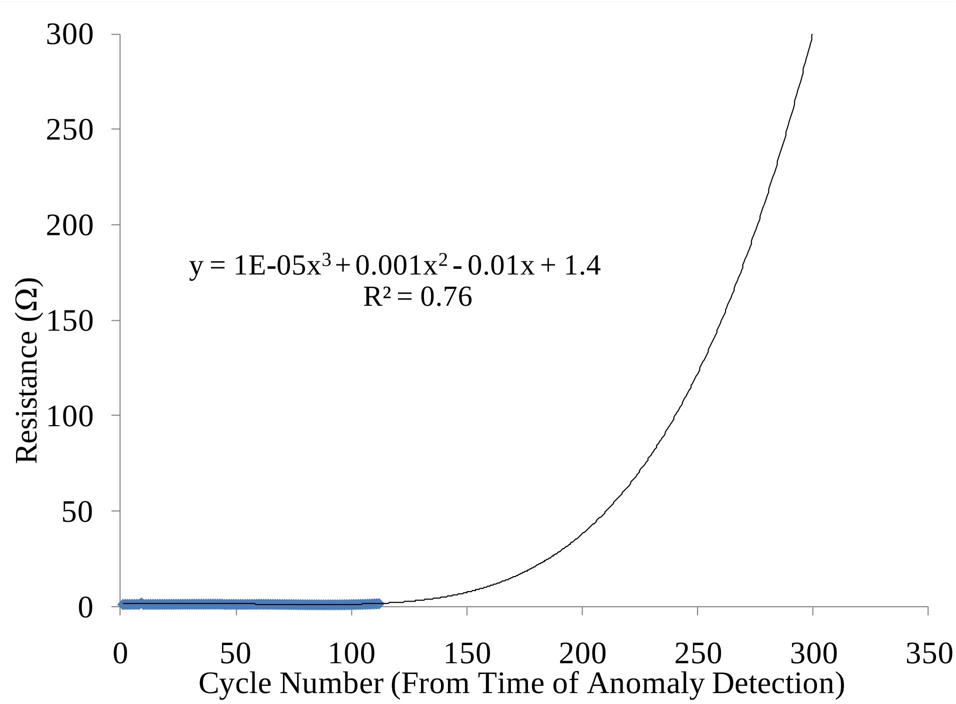



Fig. A18: Trending of Peak Resistance for Data-driven RUL Estimation

**Results for component 8:**

The regression equations were found to be:

$$\mathbf{R_{inc}} = 0.002*\mathbf{T} + 0.568 \quad \text{(A13)}$$

$$\mathbf{R_{dec}} = 0.003*\mathbf{T} + 0.771 \quad \text{(A14)}$$

Figure A19 shows the histogram of the residuals of the healthy data that was used to train SPRT followed by Figure A20 which shows the residuals of the resistance for component 8 when anomalies were detected by SPRT.

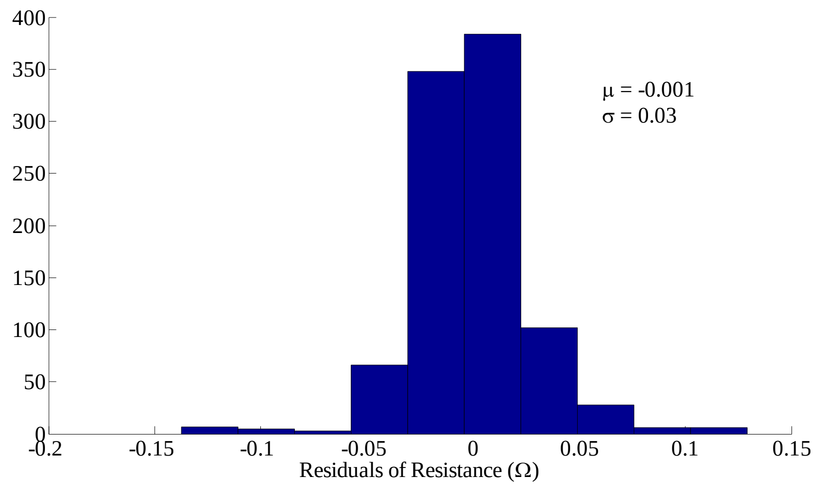



Fig. A19: Histogram of the Residuals of the Remaining Training Data

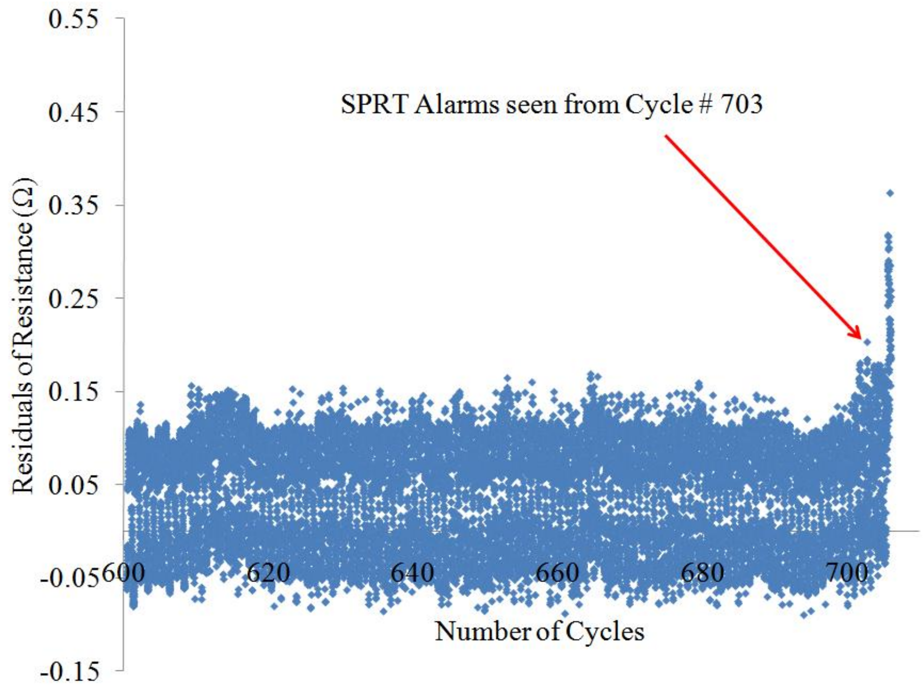



Fig. A20: SPRT Alarms at 703rd Cycle Due to Increase in the Mean of the Residuals of Resistance (The red arrow indicates the cycle from which alarms were seen from SPRT).

The peak resistance from the time of the anomaly was trended to get an estimate of the RUL (shown in Figure A21). The regression equation is also shown in the figure. The cycles to failure was calculated at the 780th cycle to be 923 cycles for component 8. The actual cycles to failure for component 8 according IPC-9701A standard was found to be 927 cycles. The RUL prediction was 4 cycles before the actual cycles to failure.

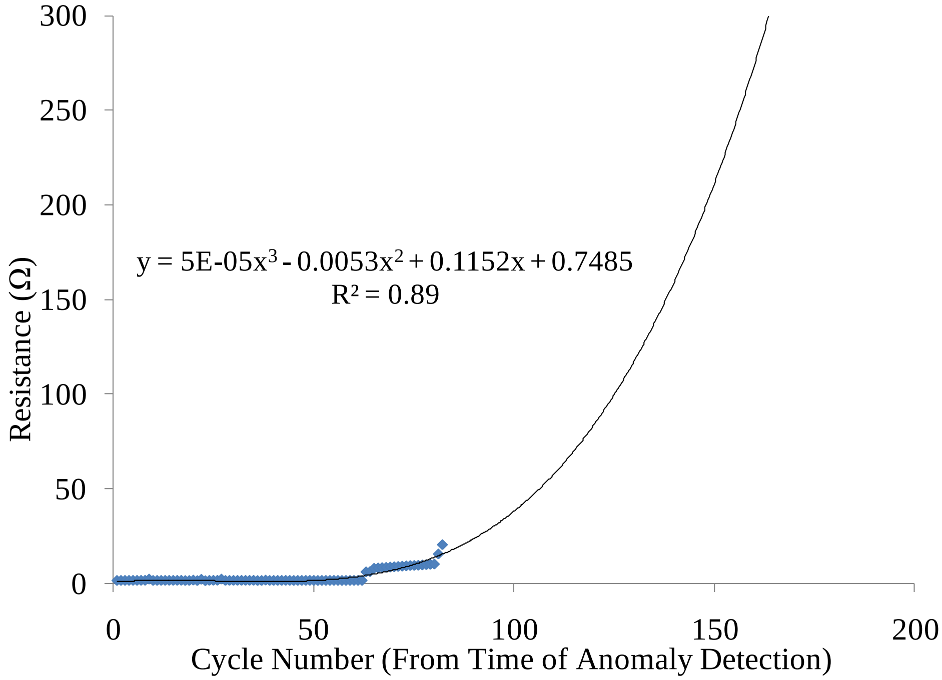



Fig. A21: Trending of Peak Resistance for Data-driven RUL Estimation

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