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Prognostics and Health Monitoring of Electronic System: A Review

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Abstract

Miniaturization of electronics, reduction of time to market and new functionalities in the current context of autonomous driving, electrification and connectivity, are bringing new reliability challenges. Prognostics and Health Management (PHM) can be used effectively to address some of the key challenges, in particular new challenges associated with the transfer of consumer electronics to automotive industry. The concept of PHM is not new, but its application to electronic systems is relatively new. It is expected that the PHM demand for electronic systems would continuously increase as autonomous driving is being realized. This paper attempts to summarize the recent studies in the system-level PHM of electronic systems. Condition monitoring (CM) techniques and prognostics methods used for the PHM of electronic systems are reviewed first. Various implementation examples are followed using different system classifications. The findings from this review is expected to offer a technical summary of accomplishments and challenges during the course of applying PHM for electronic systems, and to identify future research tasks to be performed to make the PHM a more viable tool for reliability assessment of electronic systems.

1. Introduction

Functional safety is a key reason for the development of PHM, and it has been widely implemented in avionics and large mechanical systems. Compared to mechanical systems, the degradation of electronics is somewhat difficult to detect due to the geometric scales of components and their complex architectures [1]. Quantification of the degradation and fault progression in an electronic system is even more difficult since not all faults necessarily lead to system failure or functionality loss [2]. In addition, there is an uprising trend in which the industry shifts to increase system availability. This happens because some of the businesses are not selling the product anymore, but lease it or selling the system with the services included.

The electronics industry encounters an ever-increasing demand for cost reduction, short time-to-market, miniaturization, higher density/compactness of components, rapid upgrades, and enhanced customer satisfaction. All of these create numerous reliability problems. In some cases, solutions are available only by allowing trade-offs, inducing loss of profit, time and availability of the product. Implementing PHM on a system level at the design stage [3] as well as the qualification phase [1], can help solving most of the problems. PHM of electronic components and systems can offer competitive advantages as it improves performance, reliability, safety, maintainability and availability [4].

In Telecom, it is called Intelligent Platform Management Interface (IPMI), in aerospace, Integrated Vehicle Health Management (IVHM) [5], in electronics, Prognostics and Health Management [6]. In the maintenance perspective, it is Condition Monitoring (CM) [7]. Implementations may vary in different applications, but the same basic principles are employed. In CM, the system/equipment health is monitored by the sensors and predictive measures are taken right before the incipient failure, whereas in Prognostics and Health Management the Remaining Useful Life (RUL) is calculated at any point in time.

Prognostics has not been applied to electronic systems until recently. It may be attributed to the facts that (1) the time to failure is not readily quantifiable, (2) prognostics techniques are not ready for the complexity of electronic systems, or (3) the safety is not a major issue. PHM for electronics has first been introduced in avionics, followed by automotive, and more recently, in consumer electronics.

Due to the large variety of the techniques used for PHM, it is difficult to study and review all of the exiting techniques. Hence, this study is focused on the most relevant techniques used to integrate PHM in electronic systems and sub-systems, and to highlight the papers that offer a solution to problems of the system level PHM. Basically, PHM is an algorithm or a set of algorithms based on measurements and models, which collect as an input an already known information about the system/structure and data from strategically positioned sensors. Then it subsequently provides as an output different levels of prognostics such as failure detection, diagnostics and prediction. Various levels of prognostics require different strategies/algorithms for successful implementation.

As depicted in Figure 1, a well-implemented prognostic methodology should include the following items:

- Sensors for prognostics
- Data collection, processing, reduction and feature extraction

- Data Security and integrity
- Identification and analyze precursors, Risk and uncertainty analysis
- Health assessment, anomaly detection, fault recognition, fault classification, fault propagation
- Physics-of-Failure (PoF), Damage Models, Reliability testing
- Model Order Reduction, Metamodels, Surrogate Models of Finite Element Methods (FEM) or any oder Physical Model

Methods used for recording relevant loading information include measuring the temperatures [8], [6], installing canary devices [9], collecting data about operational conditions [10] or usage hours [8], using strain gauges to measure the strain on solder joints, using piezoresistive stress sensor inside a system package [11] and detecting when the performance of a system degrades [6].

PHM algorithms performance relies on [1], [2]:

- real-time sensor data which contains relevant structural data
- accurate data collection (limited resources, noise cancellation and so on)
- accurate,robust and effectiveness fault detection algorithm
- reduced false alarms
- accurate models for prognostics

Three approaches of PHM are: (1) data-driven approach, (2) model-driven approach, and (3) fusion approach which combines the first two approaches. Due to the limited availability of the fusion approach, this paper focuses on the first two. The data-driven approach aims at transforming the raw data from sensors into relevant information, which is used to learn models for health assessment and RUL prediction. The model based approach deals with the prediction of the RUL of systems by using numerical models to simulate the physical behavior of degradation mechanisms.

This paper will review the two PHM approaches implemented for electronic systems with an emphasis on the sub-system and system level. The concepts and case studies found in the literature will be presented.

2. PHM Frameworks/Architectures in electronic systems

In this section several PHM frameworks for electronic systems found in literature are presented. The number of the frameworks far exceeds the number of actual case studies based on electronic system. The reason behind is the large complexity and the non-linearity of the systems that these techniques are to be applied to or the insufficient technological breakthroughs. Also in [12] it is stated that one of the reasons for the lack of progress is the available data on which to apply prognostic algorithms. Even with a lot more possibilities available now, there are few electronic systems equipped with sensors that can support collection of data.

The framework offers PHM guidelines to the research community in this area [13]. This is why it is important to start reviewing several concepts and strategies.

An PHM approach utilizes measurements, models, and software to perform incipient fault detection, condition assessment, and failure progression prediction [14]. PHM can be performed on different completion stages, starting from fault/anomaly detection through diagnostics till fault prediction. A fault is defined as the operation outside of specifications, while failure is defined as the lack of operation [15]. Another advantage of PHM is that it can be implemented in steps, for example in the design, development stage [16], production and released products [17]. A key requirement in any prognostics method is identification of the appropriate parameter(s), which, can be used to asses impending failure. It is usually called precursor parameter selection. Also, a failure precursor is an event that signifies impending failure [10]. Although effective, most approaches to PHM focused on monitoring failure precursor indications which does not require system failures to be deterministic in nature, but does require that the selected precursor has a deterministic link to the actual system failure [18].

One way of identifying and select the precursor parameters is to apply Fault Mode and Mechanisms Effect Analysis (FMMEA) proposed by Pecht et al. [19]. A failure mechanism is defined as the physical phenomena causing the onset of failure. Common examples of failure mechanisms are fatigue, fracture, corrosion, cracking and so on. Failure mode defines how a system or device fail, for example overheating, unexpected shutdown, reduced performance [20], lack of electrical contact. Also, based on FMMEA a decision is made where to place the sensors. It is used along with PoF approach which utilizes knowledge of a product's life cycle loading and failure mechanisms to asses product reliability [21].

In comparison with PHM, CM is the application of the appropriate sensors (data), analysis (knowledge), and reasoning (context) to estimate the health and track the degradation of equipment [14] and in some cases assessing the remaining useful life.

The ultimate goal of PHM is to determine RUL of a monitored system. RUL is typically a time, cycle, or mission-based expression, correctly accompanied by uncertainty bounds. Similarly, RUL may be a range of values, correctly accompanied by a confidence interval. The RUL is a prediction of a component or system functional/operational usage expectancy based on measured, detected, modeled, and/or predicted health state. The RUL is dependent on the intended set of operating conditions or mission to be performed [14].

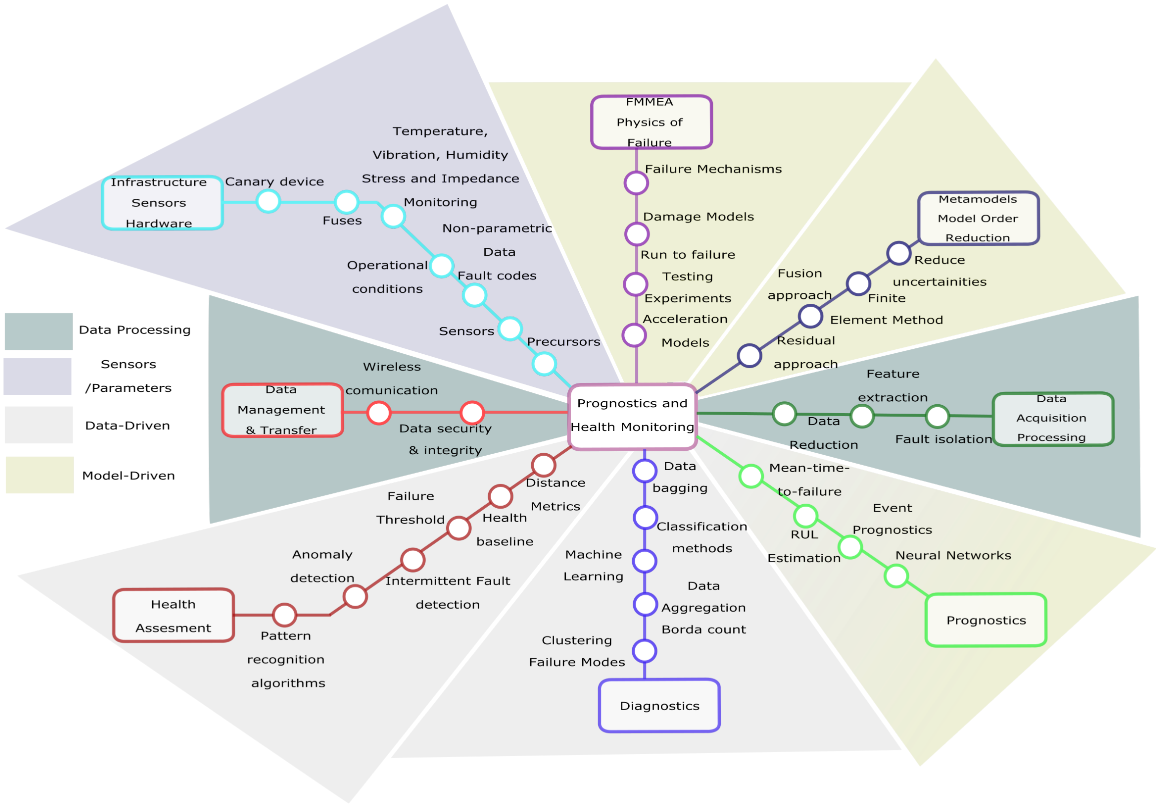

Figure 1. PHM for Electronic Systems Metro-Map.

A. System definition

There is a lot of discussion regarding system classification, definition and what it exactly represents. In case of electronics we can establish different levels of system classification as it follows [10]:

- Device Level (die and metalization)
- Component Level (resistor, capacitor, lead frame)
- Board level (circuit board and solder joints)
- Sub-system (Hard Drive, Electronic Unit)
- System
- System of systems

As previously mentioned this paper is mainly focusing on the PHM methodology implemented on the sub-system and system level.

B. Strategies/Schematics used in implementation

Mishra and Pecht [23] introduced the Life Consumption Method (LCM) for PHM in electronic systems, which basically uses the environmental loads combined with PoF models to assess the life consumed. Based on the same approach Zhang et al. [24] developed an enhanced method adding uncertainty adjusted prognostics. Uncertainties are included to capture the fault evolution as a distribution of the predicted RUL.

CALCE PHM Research Center at the University of Maryland used different approaches including canaries and fuses, precursors feature and PoF models based on life-cycle loads [10].

Amor-Segan et al. [5] focuses on the automotive industry and proposes a new system level approach to manage the faults in a vehicle networked electronic systems. The framework involves different phases - data collection, data analysis, knowledge discovery, diagnostics or prognostics leading to corrective and preventative intervention.

Terrissa et al. [25] described PHM architecture into seven layers:

- Data Acquisition
- Data processing
- Condition assessment
- Diagnostic
- Prognostic
- Decision support
- Human machine interface (HMI)

Braden [1], proposed a framework for development stage for validation and testing the automotive electronics. The proposed techniques are providing the estimation of RUL based on a real time monitoring data during a reliability testing. In Figure 2 a conceptual architecture of PHM is shown, with a focus in diagnostics techniques. Most of the work performed so far reaches different diagnostic stages, implying that the prediction part is not yet mature in electronic systems.

3. Sensor and parameter selection

Every PHM system typically collects the data throughout sensors located strategically and usually measures exterior and interior loading conditions. There is a lot of

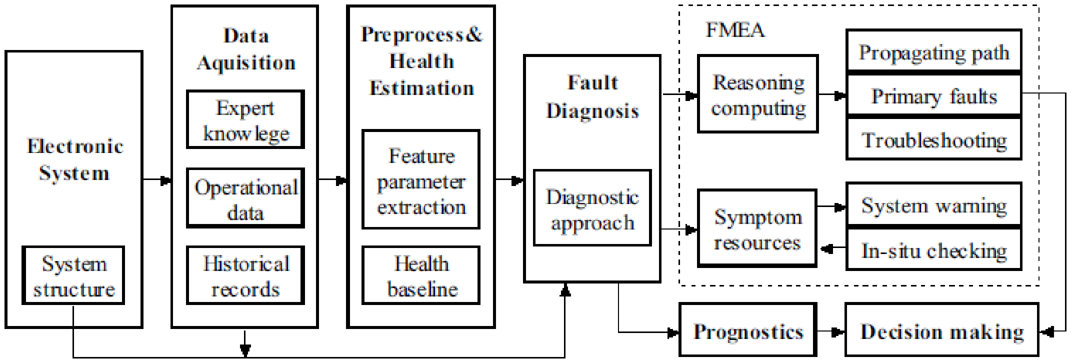

Figure 2. Conceptual architecture of PHM-based fault diagnosis for electronics-rich system. [22]

references regarding sensor and parameter selection for electronic system, although there are not many examples of such devices used especially to handle the system level prognostics. According to [26], monitoring the parameters is a fundamental step in oder to accurately assess the health and to predict the remaining useful life. This section is a brief and general introduction for sensors and parameters used for PHM in electronic system. For More detailed information please check [26].

A. Sensors used in electronic systems and the parameters related to the sensors

Typical parameters that have the potential to be monitoring devices in a PHM system is showed in Table 1.

Table 1. Examples of parameters for PHM applications. [27]

Domain	Examples
Mechanical	Length, area, volume, velocity or acceleration, mass flow, force, torque, stress, shock, vibration, strain, density, stiffness, strength, angular, direction, pressure, acoustic intensity or power, acoustic spectral distribution
Electrical	Voltage, current, resistance, inductance, capacitance, dielectric constant, charge, polarization, electric field, frequency, power, noise level, impedance
Thermal	Temperature (ranges, cycles, gradients, ramp rates), heat flux, heat dissipation
Chemical	Chemical, species concentration, gradient, reactivity, mess, molecular weight
Humidity	Relative humidity, absolute humidity
Biological	pH, concentration of biological molecules, microorganisms
Electromagnetic radiation and ionizing radiation	Intensity, phase, wavelength (frequency), polarization, reflectance, transmittance, refractive index, distance, exposure dose, dose rate
Magnetic	Magnetic field, flux density, permeability, direction, distance, position, flow

The sensors suggested above have to be addressed with real-world components that are available in a reasonable size and at a reasonable cost to support use under a cost-benefit analysis [12].

B. Non-physical software parameters

Except the physical parameters that can be monitored throughout the electronic system, also software parameters can be monitored and indicate an impending failure of the system. These parameters are for example software values concerning the performance and the quality of the service. The System Telemetry Harness proposed by Sun Microsystems [15] uses soft variables (given by the operating system regarding hardware performance) and canary variables (given by the software such as quality of the service, number of transactions per minute) for estimating the health of the electronics for computer servers.

Regardless of the fact that the clear indication of the system degradation is given by the physical parameters, these non-physical values can be used to link some physical parameters to the actual system performance. A framework is proposed in [5] regarding Electronic Control Unit (ECU) to use ECU hardware and software data to asses the health. It is using parameters from the ECU such as ECU reset and initialisation statistics, ECU error counts, function activation statistics, network status and performance statistics. Also, FMMEA can indicate software parameters to be monitored such as CPU usage, CPU throttle [21], CPU loading factor [28]. Other examples can be fault codes, scan error, memory usage capacity or queue lengths.

4. An overview of Data-driven approaches

In electronic systems perspective diagnostics refers to the ability to identify deviation from its normal operational profile as well as detect, isolate and diagnose electrical faults [2]. Data-driven approaches, also called model-free, rely on observation data without a priori knowledge about the system [29] and according to [30] they are called also black box. In this section techniques used in data-driven approaches for electronic system are presented. Usually it refers to fault detection, diagnostics and prediction. In most of the cases the first two parts are handled with Data-driven approaches. The prediction part can be also obtained from PoF.

Table 2. Data-driven techniques

Distance Metric	Machine Learning	Statistical	Neural Computation	Stochastic
Euclidean	Fuzzy Logic	Bayesian Methods	Artificial Neural Networks	Markov chain
Mahalanobis	Support Vector Machine	Principal Component Analysis	Deep Learning	Monte Carlo
Bayesian	Kalman Filter	Regression Analysis	Self Organizing Maps	Wiener Process
K-nearest Neighbour	Particle Filter			Gamma Process

In Table 2, a selection of representative methods used in prognostics are shown. These methods are used or have the potential to be used in all necessary steps in prognostics. Improvements of all these methods implemented for different purposes are found in the literature. Also, there are many more other techniques in other fields, which can be transferred to the electronic systems in order to improve the prognostic requirements.

A. Fault detection

Fault detection, also found as anomaly detection in the literature is a fundamental requirement for prognostics. The method should be accurate enough that the false alarm rate is close to zero. So far, the distance metric techniques have been shown the most effective in fault detection. Also, methods like one-class Support Vector Machine and Fuzzy Logic can be used for fault detection.

Canary devices mounted on the actual product can also be used to provide warning of failure due to specific wearout failure mechanisms. The time to failure of these prognostic cell can be pre-calibrated with respect to the time to failure of the actual product. The stresses experienced by the product is applied to these cells as well. Canaries can be calibrated to provide sufficient advance warning of failure to enable appropriate maintenance and replacement activities [31].

B. Fault Diagnostics

Diagnostics monitors determine the current state of health of a system and determine potential problems [15]. Also, [25] diagnostic determines if the health of the system have degraded, suggest fault possibilities and identify the component that has ceased to operate. For electronic systems diagnostics refers to the ability to identify deviation from its normal operational profile as well as detect, isolate and diagnose electrical faults [2]. The first efforts in diagnostic health monitoring of electronics involved the use of built-in test (BIT), defined as an on-board hardware-software diagnostic device to identify and locate faults. It is used as a diagnostic tool, although has a big rate of false alarms [31].

Diagnostic parameters and measures can be generated using the time series [32], Bayesian network approach [22], an advanced remote intelligent diagnostic support system (RIDES) [33], self-diagnostic Automatic Test Equipment (ATE) [7], etc.

1) Fault isolation: This concept normally is used in the systems, where data detected as faulty should indicate from which component or sub-system the faulty signal is coming from. In the literature this is presented mostly as a concept, there were no relevant examples in electronic system where techniques or methods are used to isolate the fault.

2) Fault identification: It is the process of identifying the cause of a failure at various points in a system. Fault identification is the key concept of diagnostics. Recently, classification methods were used to mitigate the fault identification such as machine learning techniques [34], [35]. For example :

- Random Forrest - is an ensemble classifier that consists of many decision trees and outputs the class that is the mode of the classes output by individual trees
- Voting - Given a class of learned models, voting or majority response could be used to determine the response of the overall PHM system.
- Support Vector Machine - It is based on boundary optimization problem of an already known failure data

C. Fault prediction

The data driven approach can realize predictions for RUL through statistical and probabilistic methods [4]. Models built for prognostics are focused on building computation models that learn a specific or holistic behavior of the system based on empirical sensor data. Examples of data-driven techniques used for fault prediction [36] are:

- Ensemble Learning - such methods use multiple models to obtain better predictive performance
- Neural Networks - This creates a linear RUL model based on the historical sensor data of the system till failure
- Stochastic - These methods employ probabilistic methods to handle system level prognostics

Prognostics is possible for system modeling through Markov chains, stochastic methods and time series analysis, considering the Shannon‘s principle which states that the physical processes in the past will remain in the future.

D. Case studies

Lopez et al. [15] used Sequential Probability Ratio Test (SPRT) and the Multivariate State Estimation Technique (MSET) for computer servers soft variables, canary variables and physical variables to implement prognostics. Also, Urmanov [30] uses an approach to implement prognostics for computer servers. He added empiric models such as Wiener process with a drift in the process.

An unique hybrid prognostics and health management methodology combining both data-driven and physics-of-failure models is proposed in [21] for fault diagnostics and life prediction of a computer system. First a FMMEA was conducted and parameters as fan speed, CPU temperature, motherboard temperature, videocard temperature, %CPU usage, and %CPU throttle were established to be monitored. Fault detection was performed using Mahalanobis Distance (MD) and a Projection pursuit analysis was performed to show which variables vary the most. These parameters can be matched to a PoF damage model to assess damage.

In [37] it is described the nonlinear Wiener process with a time drift for degradation process and the Proportional hazard model for RUL. Also methods such Gamma process, and continuous-time Markov chain can be used for degradation process.

In [38] failure prognostics of an electronic system is performed by Fast Relevant Vector Machine based on Fruit Fly Optimization algorithm. It does not provide a concrete example, the procedure is a general approach.

Hirohata et al. [28], monitors the cooling performance degradation and load history of a Printed Circuit Board (PCB) in digital equipment. A hierarchical Bayes model based on Computer-aided Engineering results of thermal stress simulation and experiment data from actual measurements is used. The case study is a notebook PC on which the temperature and deformation distribution from monitoring variable by using Bayes model can be estimated. Based on the monitored data such as device load factor and revolution number of cooling fan it can estimate the temperature and the deformation distribution of the PCB. This linking is provided by the FEM simulation obtained parameters, such as thermal dissipation of the device and thermal boundary condition using the hierarchical Bayes model. The term Health Distance was developed calculated between two signal D1 and D2 as a shift on an angle. This angle is computed as the inverse of cosinus between the sum of all dot product and the product of each euclidean norm of D1 and D2. When the angle is 0 the signals are the same and when the angle is pi the signals are totally different.

In [29] and improved approach was presented, that makes it possible to extract and analyze the power systems eigenvalues, which are related to the frequency of the power system that determine correlations between extracted features and state of health. The goal is to provide correlation information such as SOH using pattern analysis with real-time data from a non-intrusive smart power sensor. The test vehicle represents the electronic power systems (e.g. switched mode power supply).

A data-driven approach presented in [32] is applied to electronic systems and uses methods such as pattern recognition (SVMR), signal processing and Markov chain techniques. In [32] it is stated that building analytical models for even rudimentary on-board systems from the component models is virtually impossible due to the high level of complexity and non-linearity. The methodology consists of four main stages: (1) Mahalanobis Distance to generate healthy baseline, (2) Noise suppression and conversion to generate symbolic time-series, (3) A Markov state model and (4) Diagnostic and prognostic parameters and measures to be generated using the time series and neural network techniques. A wavelet transformation was performed on a MD time series to remove noise from the signal, and to extract features from the data. This data was partitioned into eight regions, each being represented by a symbol. Based on this a Markov state model is generated to provide the parameters and measures for health condition monitoring and prognostics.

In [22], Diagnostic Bayesian network based on PHM is proposed to perform available and efficient fault diagnostics for electronic system. The numerical data is gathered based on a set of radar indicators on avionics system. The algorithm uses the Bayesian approach and the basic idea is a formula which is used to calculate the condition probability of occurring fault B when a fault symptom A appears. The monitored data is voltage or current and it is used to define the fault symptoms.

Jin et al. [7], proposes a model to monitor the degradation of electronic equipment and further to predict the RUL based on the self-diagnostic data. The degradation precursor, characterized by voltage or current signals, is modeled as a Non-stationary Gaussian process with time-varying mean and variance. The algorithm is periodically executed to collect the system health information using voltage and current signals as failure precursors for the healthy index. This model is based on a Statistical signal degradation based on the shift of the mean or the change of the variance, or both.

Lall et al [34] [35] uses different data-driven techniques. In [34] prognostic framework for electronic systems has been developed with neural network based self organizing maps with multiple failure modes. Unsupervised learning of the neural net has been used to train the neural net for identification of individual failure modes. Transient strain is measured during the drop-event by digital image correlation. In addition FEM models are constructed to which different failure modes are imposed. Prognostic framework is studied with neural network self organizing maps. Fault-mode isolation and mode classification is conducted by Artificial Neural Network approach. The test vehicles are two PCBs test boards of JEDEC Standard.

In [35] a new technique has been developed for health monitoring and failure mode classification based on measured damage precursors. The Karhunen Loeve Transform has been used for feature reduction and de-correlation of the feature vectors for fault mode classification in electronic assemblies. Euclidean, and Mahalanobis, and Bayesian distance classifiers based on joint-time frequency analysis, have been used for classification of the resulting feature space. The system approach is to determine throughout the drop-test all the failure modes such as solder inter-connect failure, inter-connect missing, chip delamination or chip cracking in packaging architectures. The monitored parameters are the transient strains recorded during the drop-event using digital image correlation. The test vehicles are two PCBs with various components mounted on them. A feature vector is created by analyzing the transient strain signal with time frequency technique. Karhunen Loeve Transforms is used to de-correlate the feature space of damage progression. The same failure modes are simulated with explicit FEM and the same transient strain data is extracted. On the decorrelated feature space containing data from both experiments and simulation dominant directions are extracted with MD and PCA to represent each failure mode. Doing so a clustering of the failure data is made.

A method based on the simulation-before-test (SBT) technique to quantitatively assess the health of an electronic system is presented in [39]. The case study is an analog state variable filter circuit. A circuit-centric approach assessing the health on an electronic system is highlighted, which enables an electronic system to be decomposed into individual critical circuits from which local results can be merged to obtain a system level health indication. Thus, by monitoring few nodes within the circuit and estimating and combining HIs for the critical circuits, one could obtain a health indicator for the whole system. The proposed approach involves three stages: system decomposition, off-line testing and on-line testing. The off-line testing is mainly represented by simulations-before-test to understand the circuit behavior under healthy and failure conditions, hence various faults are seeded into critical components. To asses the health, an index or +1 healthy and -1 faulty is considered. A function is used to consider the state between these two values. This function is the same as in the case of SVM and LS-SVM. Another circuit-centric example is also presented in [40].

An example of applying PHM at the design stage to enhance reliability is presented in [3]. It introduces failure precursors and investigates their impact on product real failure to improve accuracy of reliability prediction in design phase. Hard disk drives are selected as a case study. A failure precursor is used such as scan error from Self-Monitoring Analysis and Reporting Technology (SMART) which can be caused by bad sectors (damage on hard drive sectors) on hard disk or malfunction of magnetic head. These failure precursors are selected and their statistical distribution of time-to-failure-precursor are obtained. The calculation shows that mean-time-to-failure for drives with failure precursor is 49 times shorter than mean-time-to-failure for drive with no failure precursors. Also it shows that PHM applied at 3 months, 6 months and 1 year of operational hours have different results in RUL calculations. The one calculated at 1 year is getting more closer to the real drive failure occurrence.

Niu et al. [41] presents a novel approach for health monitoring of electronic products using MD and Weibull distribution. The MD value is used as a health index and the Weibull distribution is used to determine health decision metrics. A case study of a notebook computer health monitoring system is carried out. First FMMEA is used to select effective performance parameters, and then a normalization process is performed on the data. The failure mode contains rotation failures of the fan, head crashes in the hard disk drive and electrical short on the memory card with the corresponding measurable variables, such as temperature of the fan, hard disk drive and memory usage capacity. The scale parameters are extracted from the distribution. Additionally the distribution and the mean is calculated. Weibull distribution is used because not always MD values follows a Gaussian distribution.

5. An overview of Model-driven approaches

Data-driven approaches can be very effective for electronic systems, considering that the capability of realizing complex physical models for system is reduced. However, in most of the cases the parameters monitored have no connections to the real fault/failure. This fact is demanding for a method to link the actual failure with the monitored parameters. Using physical models can easily make this link and have the benefit to be more accurate.

A. PoF description and FMMEA

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 [31]. A prognostic feature or failure precursor provides advanced warning of impeding failure that in turn may predict RUL. Essential to any predictive system are the careful selection of prognostic product feature that correlate damage accumulation with known failure modes [1]. The PoF approach includes several steps, mainly FMMEA, feature extraction and RUL estimation. Further, failure models or graph-based models are not suitable for detection of intermittent system behavior as they are modeled for specific degradation mechanisms. Sudden changes in system parameters that characterize intermittent fault are not accounted in these models [19]. Model-based approach uses prior knowledge of the system to develop mathematical models to process and evaluate the current data [29]. These mathematical representation incorporate a physical understanding of the system, and include both system modeling and PoF modeling. 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 are then used to detect, isolate and predict degradation [19]. PoF approaches to model electronic system reliability have shown that time-to-failure for electronic parts and interconnects can be predicted within quantifiable bounds of uncertainty. [16]

Table 3. Standard failure mechanisms in electronic systems [22], [42]

Failure Mechanisms	Failure sites	Relevant loads
Fatigue	Wire-bond,solder leads, bond pads, traces, vias, interfaaces	ΔT,$T mean$,dT/dt,dwell time,ΔH,ΔV
Corrosion	Metalization	M,ΔV,T
Electro-mitigation	Metalization	T,J
Conductive filament formation	Between metalization	M,∇V
Stress-driven diffusion voiding	Metal traces	s,T
Time-dependent dielectric breakdown	Dielectric layers	V,T

where: Δ: Cyclic range; ∇: Gradient; V: Voltage; T: Temperature; M: Moisture; J: Current density; s: Stress, H: Humidity.

B. Models used

There are several mathematical techniques that can provide prognostics measures for electronic systems. PoF models used in electronics:

- Fatigue - Coffin - Manson, Merkle
- Corrosion - Howard
- Electromitigation - Black
- Conductive filament formation - Rudra
- Stress driven diffusion voiding - Okabayashi
- time dependent dielectric breakdown - Fowler - Nordheim

According to [2], there are four main models used in PHM such as:

- Statistical reliability based approaches. Developed for non-critical systems. Weibull distribution is the most used method.
- Life cycle load-based approaches. Damage accumulation models based on environmental data are used.
- State estimation-based approaches. It can track the gradual degradation of the system.
- Feature extraction-based approaches. Feature extracted from the monitored data.

These models used in electronics are mostly suitable for components, because they do not consider the interactions between components in a system. A much better approach for models can represent the adoption of FEM, reduction techniques for FEM, meta-models or surrogate models to reproduce the entire system behavior.

C. Case studies

Gu et al. [44] proposed LCM to be applied to a electronic component-board assembly placed under the hood of an automobile and subjected to normal driving conditions in the Washington DC area. Solder joint fatigue was identified as the dominant failure mechanism. Vibrations were measured in-situ and used to estimate the LCM using the environmental data. Then acceleration data recorded from vibration loading was analyzed for remaining-life prediction.

Zhang et al. [24], used PoF to calculate RUL of a PCB with different Ball Grid Array packages mounted on it. They used daisy chain resistance as monitoring parameters input for LCM and Uncertainty Adjusted Prognostics methods.

Gu and Pecht [10], analyzed the electronic products with FMMEA and they developed a prognostic approach to estimate the remaining useful life using PCB strain data. Prognostics was performed by using the stress data extracted at the component solder joint.

Fault mode effect analysis (FMEA) is applied in [43], identifying the root cause of failure, probability of occurrence and system-level effects on a GPS system. Failure criteria are the deviation in primary feature value by 30dB below the initial value. A prognostic feature provides an advanced warning of impeding failure to predict RUL.

In [18] prognostics methods are applied to a Line Replaceable Unit (LRU), this can be a engine controller for a jet engine. Discrete event simulation is used to follow the life of individual socket instances from the start of their field life to the end of their operation and support. This can be an alternative for continuous monitoring. The input for such simulation model is a stochastic analysis based on a Monte Carlo simulation.

Pecht et al. [19] proposed a FMMEA analysis, which determined the critical modes and mechanisms affecting the assembly due to the thermal cycling resulting in open circuit. Temperature and resistance were found to be critical to detect system failure for the given loading conditions. FMMEA can be used for PHM for electronic systems because it can track all the failure modes and mechanisms in a system on a given loading condition. The anomaly detection was performed using a data-driven residual analysis technique and the healthy baseline creation was based on ten-cycle data. A regression model was created based on component resistance in function of temperature. The residual between the model and the observed data was used for SPRT algorithm to detect anomalies. SPRT is a statistical likelihood ratio test for anomaly detection. When an anomaly is detected, the parameters causing the anomaly are identified and then used in physics-based models. For example in this case what was causing the anomaly is the resistance change due to thermal fatigue was identified. Hence a Coffin-Manson model was used to calculate RUL. This approach is also capable of detecting intermittent failures.

Ramakrishnan and Pecht [45] used PoF based prognostics to assess RUL of an electronic component board placed under the hood of an automobile and subjected to normal driving conditions. The test board incorporated surface-mount leadless inductors soldered onto an FR-4 substrate using eutectic tin-lead solder. Temperature and vibration were measured in situ on the board in the application environment. Using the monitored environmental data, stress and damage models were successfully used to estimate consumed life.

The uncertainties in prognostics have an effect on its applicability and the quality of prognostics results. Monte Carlo method is the most common method for uncertainty analysis. In [46] the prognostics uncertainty analysis method based on stochastic response surface method has been proposed. The case study is a board-level electronic product of a strain tester (it measures resistance strain test signal). The SRSM constructs the response surface based on the Hermite polynomial to approximate the random response function, which can guarantee the convergence in probability. Here, PoF-based method is used to calculate RUL of the electronic products.A solder fatigue model such as Coffin-Manson, plate through hole thermal fatigue model (PTH), electro-mitigation model (Black) is chosen. A predictive linear cumulative damage models and failure mechanism competition model is constructed to deal with different failure mechanisms.

In [47] the case study is a laptop computer by implementing FMMEA using a software called MADe. FMMEA is applied to divide the system into subsystems. However, the software does not include all the possible mechanisms that may occur in assemblies. This software can be used to model the entire system and identifies the failure mechanisms in the selected subsystems.

6. Summary and recommendation

The existing PHM examples are usually using the current and voltage of the systems as monitoring parameters. It would be more desired if parameters representing the actual physical quantities linked to failures could be identified. This would require development of new sensors as well as new PHM strategies. Based on the literature reviewed in this paper, it can be stated that the data-driven approaches are more suitable for system monitoring since the physical models are usually developed to analyze components or failure mechanisms. Regarding model-driven approaches, efficient model reduction techniques and advanced statistical uncertainty propagation techniques would be needed to be able to tackle complicated and expensive system modules. The concept of surrogate models can be combined with simulation models in order to alleviate the burden of computational cost. Further advances are expected to be added to PHM applied to electronic systems.

7. Conclusions

Prognostics and Health Monitoring for electronic systems is not a mature subject and requires further work to be performed in several areas. The most important

Table 4. Challenges in PHM for Electronic Systems

Conceptual	Technical	Economical
Systems Complexity	System design	Warranty issues
Time to market, size and cost	Precursor selection	PHM Benefits in product value
Higher loads, longer functionality time	Intermittent Failures	Development Extra Cost
Maintenance Culture	System Physical Models	

tasks involve development of sensors and their location throughout the system, transferring data-driven techniques already developed for different PHM applications to electronic systems. It would be interesting if in the context of Big data/Deep Learning just one algorithm could be used to reach all the levels of prognostics based on the input size and quality. This could simplify all the necessary methods to be used in a chain, but also can be very costly computationally. Nevertheless, the current advancement in Artificial Intelligence techniques will play a key role in the next generations of PHM systems in any type of fields. Clearly, the fusion between data-driven approaches and the model-driven approaches is a key in the performance of the PHM system.

The future trend should be focused on developing smart electronic components with embedded sensors, which contain sensing cells and the logic part in the system-on-chip and have wireless communication and ultra-low power consumption.

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Table 5. Case Studies

Methods	Parameters	Test Vehicle	References
• Mahalanobis Distance - Healthy Baseline • Noise suppression, time series, signal processing - Data Handling • Markov state Model - Generating prognostics parameters	• System Specs usage, Environmental Loads • Fan Speed, CPU Usage, Temperature	Personal Computers	[32]
• Mahalanobis Distance - Healthy Index • Weibull Distribution	• Memory Usage Capacity • Temperature of the fan, Hard Disk Drive	Notebook Computers	[41]
• Reliability Mean-Time-to-Failure	• Scan error	Hard Disk Drive	[3]
• Support Vector Machine • Least Square - Support Vector Machine	• Resistance and Capacitance	Analog State Variable Filter Circuit	[39]
• Karhunen Loeve Transform • Euclidean, Mahalanobis and Bayesian Distance • Finite Element Methods • Principal Component Analysis • Neural Networks, Self-Organizing Maps	• Transient Strains	PCB	[35], [34]
• Empirical Methods • Multivariate State Estimation Technique, Sequential Probability Ratio Test	• Temperatures, Humidity, Vibration • Voltages, Current • CPU and Memory Loads, Fan Speed, Queue Lengths	Computer Servers	[30], [15]
• Physics-of-Failure	• Temperatures, Humidity, Vibration • Voltages, Current,Power	PCB	[45]
• Non-Stationary Gaussian - Analytical Model	• Voltages, Current		[7]
• Bayesian Network - Fault Identification	• Voltages, Current		[22]
• Mean-Time-between-Failures • State of Health	• Voltages	Power Supply	[29]
• Hierarchical Bayes Model • Finite Element Methods	• CPU Loading Factor, Fan Rotation Speed	Note PC	[28]
• Life Consumption Methods • Physics-of-Failure	• Acceleration Data	PCB, Line Replaceable Units	[44], [18]
• Physics-of-Failure	• Signal Strength	RF system, GPS	[43]
• Life Consumption Method • Uncertainty Adjusted Prognostics Fusion	• Resistance	PCB	[24]
• Failure Modes and Mechanisms Effect Analysis Software	• Software identifies the parameters	Laptop	[47]
• Markov Theory • Stochastic prediction model	• Thermal failure rate • Repair rates • Mean time between thermal failures	DC frequency Conversion conditioning	[48]
• Ferni-Dirac Health description • Quantum mechanics analogy • Back-propagation Neural Network remaining useful life model	• Voltage	PCB Power Conversion Board	[49]
• Finite Element Methods • Mahalanobis Distance, Singular Value Decomposition, Support Vector Machine	• Mechanical Stresses	Outer Molded Electronic Control Unit	[11]