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# Modeling Approaches for Prognostics and Health Management of Electronics

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**Abstract:** Prognostics and Health Management is an enabling technology with the potential to solve complex reliability problems that are due to complexity in design, manufacturing, and maintenance. There are several different mathematical techniques that can assist in performing prognostics and health management of electronic systems. These techniques can be categorized into statistical reliability, life cycle loads, state estimation, and feature-extraction based models. The selection of the appropriate model depends on the application environment. This paper presents a methodology for selecting the correct model to perform diagnostics and prognostics in electronic systems based on a user's application environment. The model selection method is based on five properties, including usability, accuracy, performance, applicability at the system level, and flexibility of the model. Based on all this information, a comparison is made between the five prognostic models to show the advantages and disadvantages of each. Finally, recommendations are given for selecting the most appropriate model for system fault diagnostics and prognostics of electronics. While this methodology used in this study for analysis of electronic systems, it can be extended to other applications as well.

***Keywords:*** *Electronics, health monitoring, diagnostics, prognostics, data-driven, physics-of-failure (PoF)*

## 1. Introduction

Prognostic and Health Management (PHM) systems have been created to monitor system health, provide early detection of faults, identify failure modes, point out failure precursors, detect degradation, determine remaining useful life, and recommend maintenance/logistic responses [1]. The real-time health assessment of electronics has great importance due to its wide range of applications as components, subsystems, or products that provide functionality to various systems through digital controls. Electronics long life-cycle ensures customer satisfaction and low liability at the manufacturer's end. Electronic system's health management should be considered at par with other system's health management. Because, the airline industry and the heavy vehicle industries new contracting policy, which would be based on the systems availability. Need of higher operational availability, increased warranties, and severe liability due to system failures prompts one to estimate and predict a system's performance in the field.

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Any industry would like to have the maximum operational availability of their products and systems, minimum periodic inspections, a low number of spares, maximum usage life, accurate part-life tracking, and no false alarms. PHM can make such things possible. PHM is an approach that enables real-time health assessment of a system in its actual application conditions by sensing, recording, and interpreting environmental, operational, and performance-related parameters that are indicative of a system's health [2]. Electronics prognostics has been identified as one of the most needed maintenance-related features, and a same view was expressed in the avionics industry [3][4].

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. Often, quantification of degradation and fault progression in an electronic system is difficult since not all faults necessarily lead to system failure or functionality loss. Whereas prognostics refer to the ability to determine operational availability, as well as to accurately determine the remaining useful life (RUL) of a system. The built-in test (BIT) and self-test abilities in a system were early attempts at providing diagnostic capabilities that were incorporated into a system's structure [5]. But the applicability of these capabilities was limited to the failure definition embedded at the system's manufacturing stage, whereas with recent developments in sensor and data analysis capabilities, the implementation of data-driven diagnostic systems that can adapt to new failure definitions is now possible. The no-fault-found situations in electronics system are another issue [6]. Therefore, system's health assessment should include information on in-service uses, operations, and environmental conditions in order to predict failures and provide warnings in advance of catastrophic failure. Different types of sensors are used to monitor and collect important operational and environmental data.

PHM system is developed by processing sensory information by diagnostic and predictive algorithms. These algorithms help in determining the extent of deviation or degradation of a product from its expected normal operating condition (*i.e.*, the system's "health" or reliability). The objective is to : (1) warn of impending failures; (2) reduce unscheduled maintenance, extend maintenance durations, and increase system availability by needed actions when required; (3) reduce life-cycle cost of equipment by decreasing downtime, and inventory; and (4) improve and assist in design and logistic support for systems in service and in the design stage [7]. Few other basic requirements for any algorithm are the ability to insure that the collected data are accurate, consume fewer resources, build system history, and reject noise due to the measurement or operational environment.

Diagnostics is based on observed data, knowledge about the system current operational and environment data. Prognostics is based on the historical data and profiles of future usage and environmental factors. Although the goals of diagnostics and prognostics are somewhat different, studying them separately is not practical. This is because prognostic methods are often built on the results of diagnostic methods. There are number of mathematical models available that have been used for diagnostics/prognostics over the years. Some models are system specific and cannot be extended to other applications. Therefore, there is a need to identify some basic mathematical models, generic in nature that can be used for similar applications. Due to the vast range of mathematical modeling techniques it is difficult to study all of them. Here, the most common models that are used in different engineering applications, but can be used or has been used for electronic systems are studied.

## 2. Different Modeling Approaches for Prognostic and Health Management

Prognostics and health management is a combination of three concepts: enhanced diagnostics, prognostics, and health management. While a system performs its intended functions, enhanced diagnostics estimates the system's health condition and provides a high degree of fault detection and fault isolation capability with a low false alarm rate. Prognostics involves the assessment of a system's actual health condition followed by modeling fault progression, health degradation, performance prediction, and remaining useful life determination. Health management provides the capability to make intelligent, informed, and appropriate decisions about logistic actions based on diagnostics and prognostics information, available resources, and operational demand.

Diagnostic techniques for a system are based on observational data taken from the system's performance and its environment, while prognostic techniques are based on historical data, system knowledge, future usage, and future environmental conditions. Although the goals of diagnostics and prognostics are somewhat different, studying them separately is not practical. This is because prognostic methods are often built on the results of diagnostic methods. The following subsection provides a literature review of work related to electronic prognostics and Mahalanobis distance.

The various models and algorithms for PHM are studied and can be grouped into four different categories based on available data type and system information: (1) statistical reliability–based approaches, (2) life cycle load–based approaches, (3) state estimation–based approaches, and (4) feature extraction–based approaches. The following section presents the models and algorithms being used in PHM.

### 2.1 The Statistical Reliability–based Approach

A statistical reliability–based PHM approach is appropriate for systems that have a sensor network that insufficiently monitors health conditions; that have a short life cycle with a low fault rate; are non-critical; and involve low risk. This approach assumes usage and environmental conditions have no effect and that knowledge of failure mechanisms is not required. This approach needs a system's historical failure data and can be used for legacy systems, since failure and/or inspection data for legacy systems are often available in abundance to be used as input for statistical reliability models. However, for new products accelerated testing is required to obtain failure times. Accelerated testing may cause new or different failure modes to evolve under accelerated conditions.

Many statistical distributions that are described by two parameters: scale, which defines the time when a certain proportion of the specimens have failed, and shape, which indicates the spread of data about the scale parameter. The Weibull distribution is the most appropriate statistical distribution for analyzing life data [8]. The lognormal distribution has also been used in many applications to analyze life data [8].

Gebraeel [9] developed a degradation-modeling framework that combined reliability and degradation characteristics of a component's population with real-time sensory information acquired through condition monitoring.

From the past historical data of same or similar system can be used to determine cumulative failure distribution. These models are updated as more data becomes available [10]. The benefit of a regularly updated maintenance database is better estimation of prognostic distance that results in lowering the life cycle cost, as well as a better understanding of the system performance.

### 2.2 The Life Cycle Load–based Approach

The life cycle environment of an electronic product consists of the assembly, storage, handling, and use of the product (application and operational loads), including the severity and duration of these conditions [10]. Various life cycle loads are due to environmental conditions such as temperature, humidity, pressure, vibration or shock, chemical environments, radiation, contaminants, and loads due to operating conditions such as current, voltage, and power. These loads may affect the reliability of the product either individually or in combinations with each other.

Mathew *et al.* [12], presented remaining-life assessment of circuit cards inside the space shuttle solid rocket booster (SRB) based on vibration time history from the prelaunch stage to splashdown in conjunction with damage models. Vichare *et al.* [7][13], performed in-situ health monitoring of notebook computers and estimated the distributions of the load parameters, which were used to estimate damage accumulation and make a remaining life prediction.

In the life cycle load–based approach, damage accumulation models for specific systems and components are formulated considering the usage profile (*e.g.*, fatigue cycle as a function of operating conditions). Damage is often assumed to accumulate at the same rate for a given stress level irrespective of the past, although experimental results have shown that damage can accumulate in a nonlinear manner [14]. As a result, many nonlinear damage theories have been proposed to account for the nonlinearity in damage accumulation. In general, Miner's rule is recommended for its simplicity, versatility, and reasonable accuracy.

### 2.3 The State Estimation–based Approach

State estimation–based techniques take all the information collected by sensors and uses it to determine the underlying behavior of a system at any point in time. It can track the gradual degradation of systems and assist in providing intelligent control, detecting faults, and in predicting future faults. Controls provided by an electronic system require reliable real-time estimation of its present state. The overall approach is to create a model and train the model with the data made available by the health monitoring of a system.

Chinnam *et al.* [15] presented an approach based on the Hidden Markov Model (HMM) for autonomous diagnostics as well as prognostics. Camci *et al.* [16] used HMM for health-state forecasting. Pattern recognition algorithms, such as the multivariate state estimation technique (MSET) and sequential probability ratio test (SPRT), are used to identify signal degradation and provide a preliminary indicator of failure in servers. Lopez [17] used electronic prognostics consisting of a continuous system telemetry harness with SPRT and MSET algorithms for electronics prognostics.

In the state estimation–based approach, by minimizing error between an estimate obtained from a model and measurement, future states can be predicted. The state estimation–based approach has been used successfully as a product maintenance strategy, but it has not been widely used for electronics prognostics.

### 2.4 The Feature Extraction–based Approach

Feature extraction–based PHM approaches derive features directly from routinely monitored systems' operational data (*e.g.*, calibration, power, vibration and acoustic signal, temperature, current, and voltage). These approaches assume that the data features are relatively constant unless a malfunctioning event occurs in the system. These approaches are based on the theory of pattern recognition and can be implemented at the system level or at the subsystem level. Generally, these techniques work for assessing system-level degradation, since a performance loss typically results from the improper functioning of multiple components and their interactions. These approaches require the availability of sensor information to assess the current health condition of a system or sub-system.

Vichare *et al*. [13] monitored a time-load signal and processed it to extract the cyclic range ($\Delta s$), cyclic mean load ($S_{mean}$), rate of change of load (ds/dt), and dwell time (tD). These outputs are used in fatigue damage accumulation models. Vichare *et al.* [18] suggested embedding the data reduction and load parameter extraction algorithms into a sensor module to reduce on-board storage space, lower power consumption, and provide uninterrupted data collection over longer durations.

Wu *et al*. [19] proposed an autoregressive integrated moving average (ARIMA) modeling and forecasting approach based on the Box-Jenkins model to predict the future health status of a machine. Brown *et al*. [20] used a principle feature of a device to define a healthy profile under temperature cycling testing, and later used that profile for remaining useful life prediction. Certain distance measures are also used to classify a system into different groups. Some of the distance measures that have been used quite often are the Euclidean distance, the Mahalanobis distance, and the Bayesian distance. Nearest neighbor algorithms are used to combine two closest groups in a new group and are based on distance measures.

## 3. Assessment of Different Modeling Approaches

Prognostics approaches focus on estimating the remaining time to failure of the component, or system. Other prognostic measures include time to failure, remaining useful life, probability of occurring failure before next maintenance, and probability of premature system seizure before maintenance can be estimated for different applications. Remaining time to failure requires a precise definition of failure and failure criteria but the other measures are probabilistic in nature and can be of equal in importance for decision makers.

A number of different techniques used for development of prognostic models are discussed in the last section. Each of these methods has its own merits and limitations. It is often not easy to decide which technique is most suitable for a particular application. However, there are number of features a model should possess in order to qualify for applicability in electronics diagnostics and prognostics at system, subsystem or component level.

Development of an accurate model takes a lot of resources in terms of time, money and human effort. The developed model should be generic in nature; otherwise it would be waste of resources if such models could not be transferred to other applications or systems. Prognostic models that may survive such transfer are known as robust: slight changes to the environment in which a prognostic model is employed, or slight changes to its content will not have a major effect on its level of performance.

Techniques that allow frequent incorporation of explicit domain knowledge yield robust models. These models can be transferred to other applications or systems. Prognostic models should also be easy to use and understandable by users. An electronic system is comprised of several components, which might influence each other's performance. Therefore, we need a model which takes into account these interactions.

Statistics based reliability models are time dependent [8]. These models work well provided significant amount of failure data is available. These models may give approximate results because models do not consider the usages and environmental conditions.

State estimation based models are computationally expensive and need a better understanding of the system [21]. Determining system states and transition probability requires a lot of historical data. Since system behaviors are dynamic in nature, efforts to update system states and transition probability would be computationally intense and expensive. State estimation models are system specific in nature and have to be redefined for other systems.

Life cycle based models consider actual usage of system but these models are very specific to particular load conditions and cannot be used under different usage conditions [11]. Each loading condition initiates and propagates damage in different forms. Damage models considered in electronic systems are more at component level rather than a system level. This model is good for individual components assessment but does not consider the interaction and combined effect of these individual components at system level. Usually Damage models are considered linear in nature, which seems to be a tradeoff between computational effort and the residual life estimates for components.

Life cycle model uses Physics based models of component [22]. These models are based on the test data that are collected from the study of specially designed boards. These models can only be extended for system modeling if the relationship between component and system are well defined. Defining such relationship may not be accurate for real time applications, which is a major disadvantage of model based techniques. Development of physics model requires good understanding of the failure mechanism involved. These types of models are more suitable for component or assembly level but are hard to be applied at system level.

Feature based models are very popular in all kinds of research, probably due to their simplicity and the long period of time they have been around. They do not need to have an insight into underlying failure mechanisms. It is suitable for detection and classification of systems. It can be used for real time prognostics to determine remaining life provided it a system is modeled using failure data. One advantage of the feature-based approach is that it works well for products that have a large number of monitored parameters. The Feature based approaches can reduce the dimensionality of the problem by detecting the parameters that are critical in classifying the state of the product. Analysis of the critical parameters reduces the problem to a lower dimension, and easier to make future inferences about the test data. Further, the strength of feature based approaches arises from modeling the correlation between parameters, providing the capability of accounting for interactions between subsystems and environmental parameters. Modeling the behavior of the product as a result of these interactions is possible.

A data feature such as distance measures are most suitable for the multivariate systems. All performance variables are incorporated into one distance measure making them easy to monitor. These methods can be used as first cut for system analysis. Specific parameters and other trending methods then can be applied to analyze individual parameters. The distance measure with time can also be used for approximate remaining life estimation. Other technique such as artificial neural net provides better results on failure detection but does not give any insight on performance parameters. Neural net has the problem of over fitting and is not accurate for predicting at time much longer than the training data-duration. Also the effect of outlier data points is not prominent. Bayesian belief network is hard to construct and assign dependencies since they are more subjective in nature. However, it retains uncertainties associated with parameters but is very expensive computationally.

The data-driven approach can be used in complex products where PoF models are not available or when product specific knowledge is limited. The data-driven approach is advantageous as it does not require knowledge of the physics of the product. This approach can also be used to detect sudden changes in product parameters caused by intermittent faults or subtle changes due to factors such as product aging or gradual degradation. Data-driven approaches are capable of using parameter data collected around the time of occurrence of intermittent faults towards the prediction and assessment of product health. The approach integrates information from separate sources, for example, the hardware and software components of a product to improve the overall health assessment. This is important in today's products as performance is affected not only by faults in the hardware components but also by problems within the software embedded in the product.

The prognostic aspect of data-driven approaches is not as developed as detection, but prediction is feasible, and there are many flavors to it. Prognostics is possible by system modeling through Markov chains, stochastic processes and time series analysis, which use the past history to infer the future, and their accuracy is continually updated and associated with predictable variation (uncertainty). This information makes the data-driven approach very useful for online monitoring of the product health.

However, one of the limitations of the feature based approach is that it cannot be implemented when the product is not in an operational state since product parameter's data are required. Another limitation of using data-driven approaches lies in the requirement of sufficient and reliable training data. Insufficient data may lead to false alarms and greater uncertainty in predictions from the algorithms. Further, some techniques require complete historical information about the product from initial operation until failure to enable the estimation of remaining life. There is also a lack of a standard approach in defining thresholds through which precursors and faults can be detected or predicted. Also, since the approach does not take into account failure modes and mechanisms, identification of the root cause of anomalous behavior is difficult.

Some of the questions user should ask before selecting a model includes: What kind of data is available? From which part of the system data is available? At which system level are prognostics required? How accurate results are needed which can be derived from the system criticality? How many performance parameters he can capture in system monitoring? How much flexibility he needs in terms of applicability to similar system, at other locations and different operating environmental conditions? Who are users of these models? What is objective in terms of decision making? The user can consider many more factors and rate them on the same scale. Scores for models can be calculated either by summation of ratings assigned to these factors. Summation can be done by giving equal weight to each factor or different weights (user defined but based on their application nature) to factors. The model with the highest score should be selected for application.

In order to identify a mathematical model to be used for a consumer product, which fails in different modes, it is needed to identify the failure type and cause. Failure could be in the form of intermittent, degradation or total functionality loss. The failure can arise due to error in hardware or/and software, user abuse or change in environmental condition.

Based on the system description mentioned earlier the first and foremost requirement of a model is its flexibility. The model should be applicable to various system levels; this gives flexibility to utilize the same model to analyze components, assemblies, subsystems, and a system. The model should be capable of analyzing multiple operational and environmental parameters, which defines system domain and its functionality. Uncertainties is associated with each parameter, therefore, total uncertainties associated with a result obtained through multivariate approach would be larger compared to univariate approach. But if the model used is mathematically simple, uncertainty propagation would be less, in comparison to complex models. Thus, one of the requirements for model selection is its easy to use or low complexity. A mathematical model should be less complex such that less number of experiments would be required to validate it. The validation process should not be very time consuming *i.e.*, experiments should not take much time. Therefore, it can be said that models have two constraints: resources and time. Model should also be robust enough to ignore inherent variations in products due to manufacturing.

Different modeling techniques were assessed based on literature surveys in a variety of fields, not just electronics. Subjective judgments were made in consultation with other personnel involved in other research areas. Based on the discussion it is apparent the selection of models for prognostic is not a one step process. It depends on prognostics or diagnostics and which system level we are interested in. A rating criterion can be adopted for model selection. This will assist in determining modeling techniques for a specific application and level of interest. Few model criterion that can use used for model rating include are easy of use, accuracy, performance parameters, applicability at system level, and flexibility in terms of applications on a scale of 1- 3 where 1 is low, 2 is medium and 3 is high, a rating was assigned to each attribute of the modeling method. Equal weight is assigned to each factor. Preliminary comparisons of modeling approaches are shown in **Figure 1**. The rating used here is based on the author's modeling requirement and understanding. These rating and weighting criteria do not represent the general view for the selection of modeling techniques. These can be different for different user or systems. Prognostic modeling is widely used in financial sectors, decision analysis and statistics.

A large number of specific prognostic models are being developed in electronics too. However, many of these prognostic models are not in practice. A model based approach to prediction and prognosis, as advocated in the data driven section, may offer advantages in this respect, by offering more natural and intuitively attractive tools for decision support.

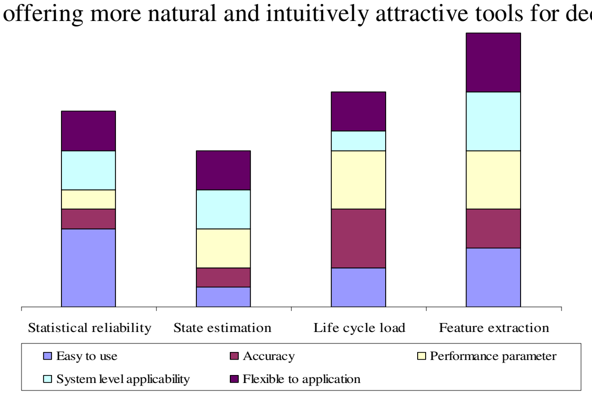


**Figure 1:** Comparative analysis of models

The construction of prognostic models is usually carried out using information extracted from systems performance databases. Unfortunately, electronics performance databases of sufficient size and reliability, filled with data from various environmental and usage conditions, are not widely available.

Based on preliminary comparison, one can select a data driven approach over life cycle load approach for diagnostics/prognostics of electronics products under consideration. If further consideration is given for a specific modeling approach the distance based approach should be chosen since it is flexible, can be used for other applications, is multivariate, can be used at any system level, is reasonably accurate, is easy to use and does not need a lot of historical data. It can be stated without reservation that performance based electronics reliability will increase significantly. As a consequence the roles of prognostic models and of systems that aid in prediction of prognosis are expected to increase in the near future.

## 4. Conclusions

In this paper, various modeling approach for PHM are studied and these models can be grouped into four different categories based on available data type and system information: (1) statistical reliability–based approaches, (2) life cycle load–based approaches, (3) state estimation–based approaches, and (4) feature extraction–based approaches. It is recommended that before selecting a PHM model one should determine the type of available sensory data, the system level at which health assessment would be made, the number of system's performance parameters available for monitoring, and the ability to monitor system's environment and operating conditions. A methodology is proposed for selecting the appropriate model that utilizes information from the previous step. The methodology evaluates each prognostic model in terms of their characteristics such as its usability, accuracy, performance, applicability at the system level, and flexibility. For electronic systems, we conclude that the most appropriate models for conducting system fault diagnostics and prognostics are the data driven model, which includes statistical, state-based, and feature-based models, because it draws its capability from mathematics, computer science, and engineering to actively learn about the system and its dynamics, faults, and failures. The life cycle-based (*i.e.*, physic-of-failure) model are used for developing life consumption model. The data-driven model is best to be used at the system level because it can not only process the increasing complexity of system information, but is also a more general methodology that can adapt to changes. The life cycle-based model is best used at the component level because it uses the material properties and the structure geometries of products and the environmental loads.

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