A PHM Architecture Based on Hybrid of Model and Data for Electronic Products

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Abstract: According to the current international PHM (Prognostics and Health Management) technology, this paper proposes a PHM architecture based on hybrid of data and model for electronic products. For prognostics, this paper presents a novel fault prediction method based on the hybrid of model and data—based on Bayesian Belief Networks(BBN) hybrid method. The proposed method considers both POF model of components and real-time monitoring data of systems, which makes the prediction result more accurate, more reliable, and more widely applicable. Then, a PHM platform according to the architecture and BBN techniques is implemented through the way of LabVIEW and MATLAB hybrid programming. By taking an elevator door circuit board as an object, the functions of PHM platform for electronic products are demonstrated and tested. The results indicate that the BBN hybrid fault prediction method proposed in this paper and the PHM platform can realize the function of fault prediction and remaining life prediction for electronic products, which lay an important foundation for the development of fault prediction technology for electronic products.

Keywords: PHM, BBN, hybrid, architecture, platform.

1. INTRODUCTION

With the development of science and technology, modern electronic devices are gradually more and more complicated and intelligent. At present, the failure of electronic products has occupied a large proportion of system and equipment failures, and the maintenance and repair processes for electronic products are cumbersome and costly. Traditional periodic maintenance consumes resources and is inefficient, which is no longer applicable for the increasing maintenance requirements of complex systems. Therefore, there is an urgent need to improve fault prediction, diagnosis and maintenance of electronic systems [1]. Prognostics and Health Management (PHM) [2,3] is proposed on the basis of the above requirements. It helps to improve the maintenance efficiency through the fault prediction of electronic products, and realizes “Condition Based Maintenance”. What’s more, it reduces the cost of the whole life cycle, guarantees the system to exert the maximum design ability, and extends its using life.

Recently, PHM technology has gained widespread attention and practical application in military and civil fields [4]. In aerospace, Boeing, Glenn Research, Honeywell and MIT co-developed the Carrier Integrated Health Management Architecture [5], which has been deployed on F/A-18 fighters, DS-1, Earth Observers One satellite X-37 and other carriers [6,7]. In 2011, Neal N. Mc Collom [8] made a more detailed discussion of PHM on the F-35 and described how PHM systems operate in terms of measurement of performance of PHM systems and integration of the assurance chain.
Due to prognostics as a key part of PHM, a variety of relevant literature related to PHM emphasis on the prognostics approaches. Generally, prognostics approaches can be divided into model-based approaches [9] and data driven approaches [10]. The application of a model-based prediction method relies on the understanding of system physics of failure (POF) and underlying system degradation models, which restrict its development. With the advancement of modern sensor systems and data storage and processing technologies, data-driven methods for prognostics have been widely used and

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dominated. Data-driven methods usually require feature extraction, information fusion, statistical pattern recognition, and life prediction. A considerable amount of data processing methods have been studied and used for prediction purposes, such as methods based on regression and classification [11,12], Bayesian estimation, Artificial Neural Networks (ANN) [13], and Ant Colony Optimization(ACO)[14,15], Support Vector Machines (SVM) [16], Grey Model (GM) [17], Particle Filter (PF) [18] and so on.

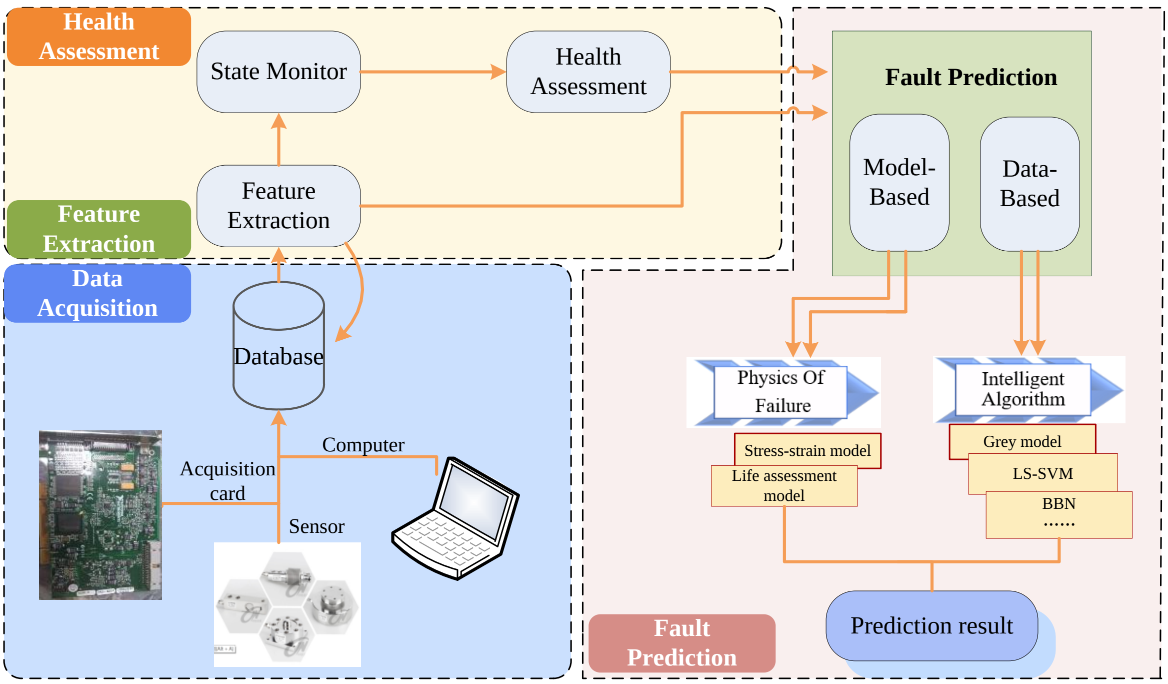
The fault prediction of electronic products involves many components, and the faults between the components are not independent, and the fault mechanism is not completely clear; at the same time, information of complex electronic products and probability of the interaction of various causes to produce results are not easy to obtain. The Bayesian Belief Network (BBN) is a kind of uncertain knowledge representation model based on probabilistic reasoning to solve the problem of uncertainty. It not only has a solid probability basis, but also corresponds well with the expert knowledge structure. There is a great advantage in researching failures caused by uncertainties and relevance of complex equipment.

In view of this, this paper proposes a PHM architecture based on hybrid of data and model for electronic products. For prognostics, a novel method based on Bayesian Belief Networks(BBN) is presented as a kind of method based on hybrid of data and model. On the basis of these, a PHM platform is implemented. Finally, by taking an elevator door circuit board as an object, the functions of PHM platform for electronic products are demonstrated and tested.

2. A PHM ARCHITECTURE OF ELECTRONIC PRODUCTS BASED ON HYBRID METHOD

The paper proposes a generic PHM architecture of electronic products to extract data features from output signals of electronic products, apply statistical data processing techniques, monitor the health states of system and predict its remaining useful life(RUL). For the PHM architecture, this paper proposes a fault prediction method based on the hybrid of model and data—based on Bayesian Belief Networks(BBN) hybrid method.

Figure 1: PHM architecture of electronic products.



The PHM architecture proposed in this paper is shown in Fig.1, which should be divided into four parts: data acquisition module, feature extraction module, health assessment module and fault prediction module. Firstly, signal which needs to be monitored are collected and transmitted to the computer through the data acquisition module to obtain the real-time monitoring data; and then the feature extraction module preprocesses the collected data and extracts the required fault feature parameters. After feature extraction and processing, the data is compared with the threshold to judge the states of system. According to the complexity of the electronic system, failure site, failure mechanism, and so on, the RUL is predicted based on hybrid of model and data approach.

Data acquisition techniques mainly refer to design of hardware equipment. Through the external hardware equipment—mainly data acquisition card, output signal is collected. The data acquisition card can be directly inserted in the host's PCI slot to achieve the connection of external hardware devices and computers, PCI bus is used to achieve data transmission. The software part of the data acquisition module controls the data acquisition card to collect and transmit the data to the computer to realize the combination of the software structure and the hardware structure of the platform.

Feature extraction is to process the original data obtained by data acquisition by the feature extraction method to obtain the feature parameters that can characterize the circuit fault. The signal feature extraction algorithm is different for various signals. At present, the feature extraction techniques include time domain analysis, frequency domain analysis, time-frequency domain analysis methods such as FFT transform, power spectral density, wavelet packet transform, Hilbert transform and so on.

The health assessment module evaluates the states of the current product and reflect the product in which stage of the life cycle in time. The health status evaluation module mainly evaluates the current health status of the product by comparing the current time feature parameters with preset threshold values of each status feature parameter. According to the current measurement, the health status is divided into four levels, which are good, normal, recession, failure. Different products correspond to different thresholds, by comparing the measured value of the product running information with a threshold to determine the current health status of the product.

The main function of fault prediction module is to predict the trend of future development of feature parameters by using prediction algorithms based on the current feature parameters and historical data, and then to make early warning of the fault and estimate remaining life of products. The key part of the fault prediction module is the embedding and invocation of different fault prediction algorithms. The paper proposes prognostics approaches using BBN hybrid method, which is illustrated in detail in the next section.

3. PROGNOSTICS TECHNIQUES USING BBN HYBRID METHOD

3.1. BBN Related Theory

BBN is a kind of probability network. It is a specific probability distribution graphical modeling tool based on Bayesian formula using directed graphs and related probability tables. The BBN is defined as a directed acyclic graph $G=(V,E,\theta)$. The node pointed from the parent node to the child node, and its set is $V=\{x_1,x_2,...,x_n\}$; The node directed edge set E represents the dependency relationship between variables, and the edge of each node represents the dependent probability of the relevant random variable; The model parameter θ represents conditional probabilities of each state of a node, that is, for each node $x_i \in V$, $P(x_i \mid Pa(x_i))$,where $Pa(x_i)$ represents the set of parent nodes of variable x_i, and prior probabilities are used for expressing information if there is no parent node. So, the joint probability distribution is expressed as:

$$P(x_1,x_2,...,x_n)=\prod_{i=1}^{n} P(x_i \mid Pa(x_i)) \tag{1}$$

The establishment of BBN mainly includes the following three steps:

a. Determine network nodes

The nodes in the BBN correspond to the various variables in the system. Node variables can be abstractions of any problem, such as product test signals, failure modes, and observed phenomena. Nodes can be used to represent uncertain and probabilistic events and to reason about incomplete or uncertain knowledge or information. Various nodes in the Bayesian network are determined by analysis of products.

b. Determine network structure

The determination of the network structure refers to determination of causal relationships between BBN nodes. There are two main methods for determining the structure. One is constructing a causal relationship between nodes according to the fault tree, and then converting the fault tree to BBN; The other is through data collection and parameter learning to construct BBN structure.

c. Determine network parameters

Network parameters refer to conditional probabilities of BBN nodes, which can be obtained through parameter learning. Assuming a fixed unknown parameter θ, under the given topology *S*, priori information is used to obtain the parameter value of θ with the maximum posterior probability, which can be obtained by Bayes theorem.

$$P(\theta \mid D,S) = \frac{P(D \mid \theta, S)P(\theta \mid S)}{P(D \mid S)} \tag{2}$$

Where $P(D,S)$ is the prior probability of the parameter θ under topology *S*. Considering the polynomial parameter is $\theta_1, \theta_2, ..., \theta_n, \sum_i \theta_i = 1$, the Dirichlet distribution consists of a set of hyperparameters $a_1, a_2, ..., a_k$. When $P(\theta \mid S)$ satisfies the Dirichlet distribution, its posterior probability is:

$$P(\theta \mid D,S) = Dir(\theta \mid a_1, a_2, ..., a_k) = \frac{T(a)}{\prod iT(a)} \prod_i \theta^{a-1} \tag{3}$$

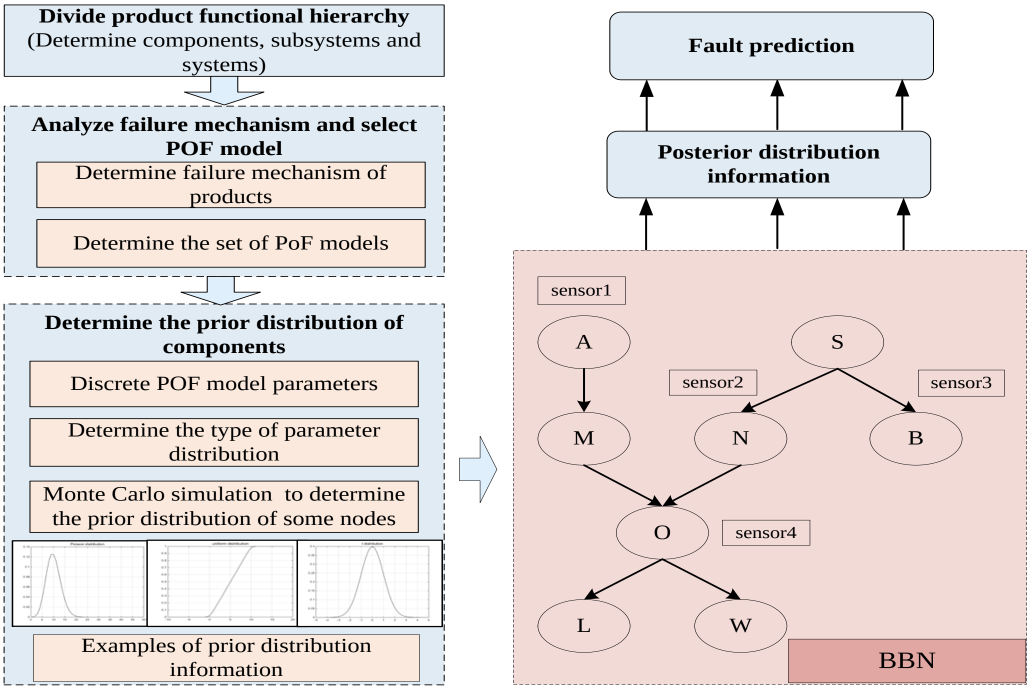
The parameter estimate is calculated by Eq. (4):

$$\theta_{v|u} = Dir(a_1 + N(x_1, u), ..., a_{vk} + N(v_k, u)) \tag{4}$$

3.2. The Proposed BBN Hybrid Method

The proposed BBN hybrid method for prognostics in this paper is a hybrid prediction method based on model and data. First, the functional structure level of products is divided and components, subsystems, and systems of the product are determined. Then, physical of failure (POF) models of components are determined by analyzing the failure mode, mechanism of components, model parameters are combined with Monte Carlo simulation to determine the prior distribution information of components; Second, the prior information and sensor real-time monitoring information are input into the BBN, and Bayesian inference is used to obtain the posterior information of components, subsystems, and systems, finally achieving fault prediction. The concrete flow of proposed BBN hybrid method for prognostics is shown in Fig.2.

Figure 2: The concrete flow of proposed BBN hybrid method for prognostics.



a. Acquisition of prior information of components

According to structure and function of systems, functional level of products is divided, specific causal logic relationship between components, subsystems and systems is determined. And component variables representing health and performance states of systems are determined. The failure of system components is affected by many factors, including intrinsic factors and external factors. Intrinsic factors include manufacturing processes, materials, and structures. External factors include temperature, humidity, and mechanical vibration. Considering these factors, appropriate POF model is chosen.

$$F = g\left(x, s, m, C, k\right) \tag{5}$$

Where, F is a feature parameter of products related to failure mechanism, x is a geometric parameter, s is an environmental load, m is a workload, C is a model constant, and k is a material parameter.

Next, combining the reliability test and expert experience, distribution types of model parameters are determined, the Monte Carlo simulation is used to determine the prior distribution information of components. Among them, the specific acquisition process of the priori information of components is as follows: First, the POF model parameters related to failure mechanism of components are discretized; then, the distribution type of model parameters is determined, the sample values of the POF model parameter are obtained through Monte Carlo sampling and are taken into the POF model to obtain sample values of the model; finally, sample values of the model are used to fit the fault distribution curve of components to obtain the prior distribution information of products.

b. BBN modeling and fault prediction

The main objective of the BBN-based prediction is to combine new observations and related knowledge of the parameters, update the parameter values to obtain posterior information of parameters, and finally realize fault prediction.

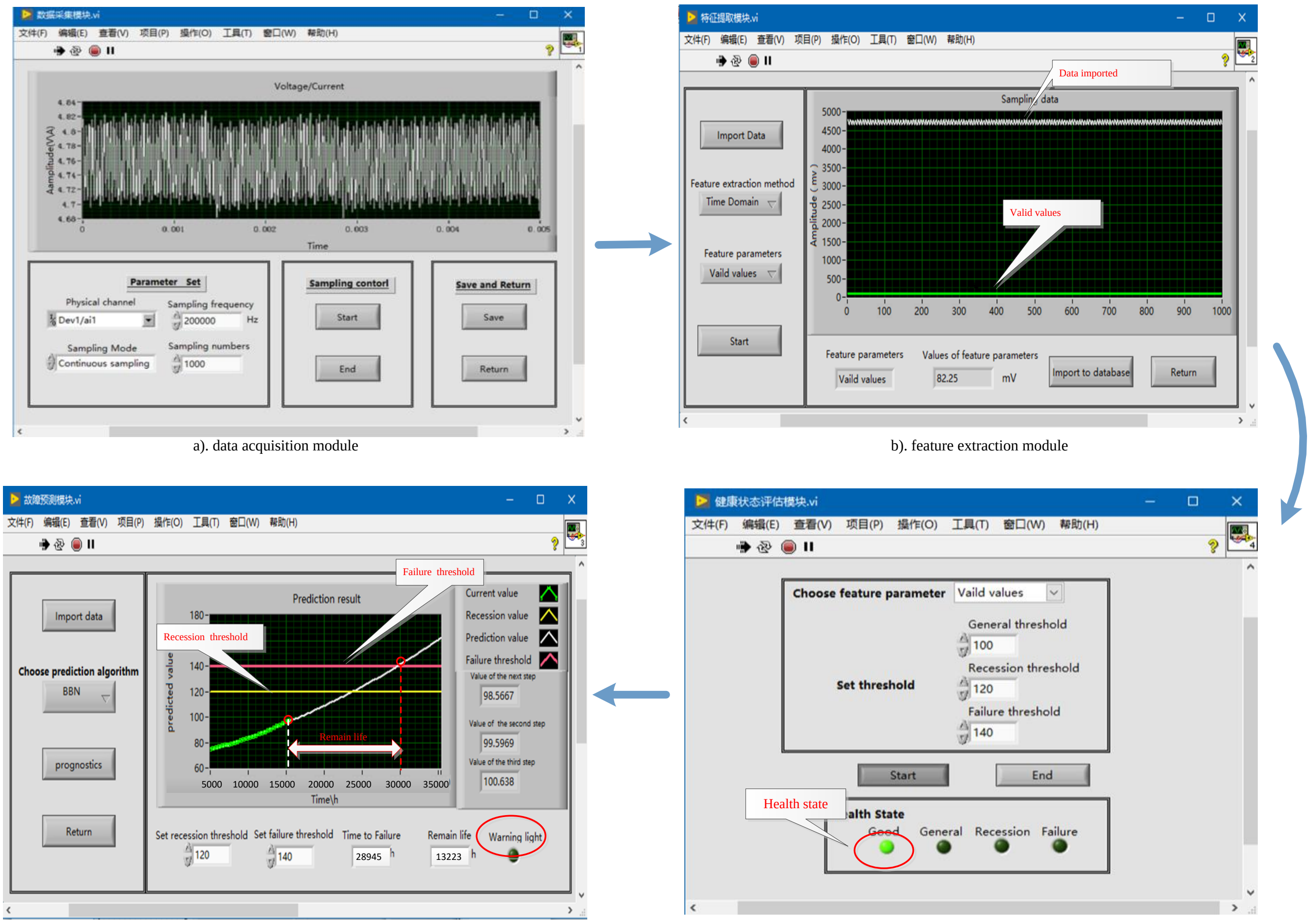
This process begins with the identification of failure modes, failure mechanisms, and mechanistic models of the system. First, the logical algorithm (fault tree) is selected to represent the logical relationship between components, subsystems, and systems in a complex system. Then the Bayesian belief network of the system is constructed, the structure of the BBN is determined, and the conditional probability table of BBN node is determined through parameter learning and expert experience, then complete BBN parameters are determined.

Sensors and related test equipment are arranged at different nodes of the BBN to obtain health information of systems. The data monitored by sensors are preprocessed and input into the BBN network. Combined with historical data and prior information of BBN nodes, the posterior distribution information of the nodes is obtained, and then Using BBN inference to obtain the posterior information of subsystems and systems, finally realize fault prediction of systems.

4. CASE STUDY AND IMPLEMENTATION OF PLATFORM

This section takes an elevator door circuit board as the test object, implements the PHM platform of electronic product by embedding the proposed BBN hybrid method. The final output voltage of the elevator door is about 5V. Usually, when the MOS full bridge works normally, a P MOS and a N MOS turn on respectively. Under normal circumstances, the turn-on voltage drop is 140mv. When the voltage exceeds 140 mv, that product is failure. By communicating with the designer, the lifespan of the elevator door is about 3.5 years (30660h), so the lifespan of the elevator door is assumed to be about 30660h. The interface of each module during the operation of the platform is shown in the Fig.3.

Figure 3: The interface of each module during the operation of the platform.



a). data acquisition module

b). feature extraction module

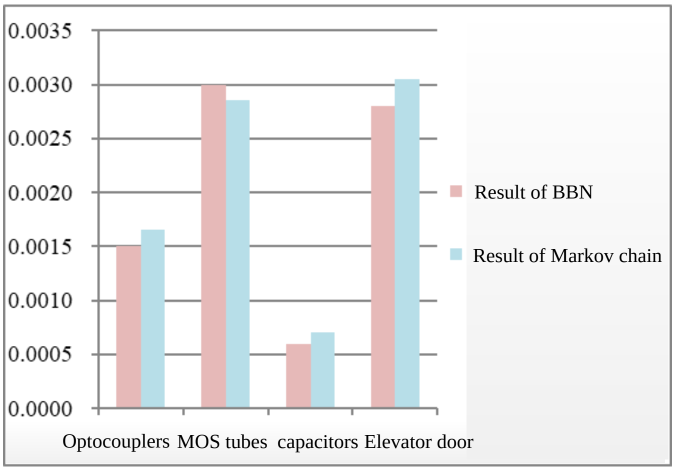
d). fault prediction module

c). health assessment module

First, output voltage signal of the elevator door is collected by building a hardware device, after that, choose time domain analysis as feature extraction method, valid values as feature parameters, to process the raw data and save the result into database. Next, in the health assessment module, set the threshold for each state, including good state, normal state, recession state and failure state. From the indicator light for state, we can see health state of elevator door is "good" at the moment, then enter the fault prediction module, which shows the final time to failure is 28545h, the RUL of the product is 16223h and the prediction error is 6.9%.

To Compare the Markov chain-based fault prediction method proposed in [19] with the BBN hybrid method studied in this paper, taking key components of elevator doors, including optocouplers, MOS tubes, capacitors, and the entire elevator door system as examples, and failure rate prediction results of failure rate in the fifth year are used. It can be seen that the prediction results obtained by the two methods are basically the same, and the comparison results are shown in Fig.4. However, for BBN-based fault prediction method studied in this paper, the amount of computation is greatly reduced. In the BBN, only the conditional probabilities of neighbour nodes are considered, which are transferred layer by layer. The speed of calculation is fast and the information storage is small. In addition, the BBN hybrid method visually describes the state of each node of systems through the failure rate, eliminating the need for additional analysis of systems, and also reducing workload and operating time.

Figure4: The comparison results between BBN and Markov chain.



5. CONCLUSION

According to the current international PHM technology, this paper proposes a PHM architecture based on hybrid of data and model for electronic products, consist of data acquisition module, feature extraction module, health assessment module and fault prediction module. What's more, a fault prediction method based on the hybrid of model and data—based on Bayesian Belief Networks(BBN) hybrid method is presented. On the basis of the PHM architecture and the BBN techniques, PHM platform based on hybrid of data and model for electronic products is initially realized. By taking the elevator door circuit board as an object, the functions of PHM platform for electronic products are demonstrated and tested. The results indicate that the BBN hybrid fault prediction method proposed in this paper and the PHM platform can realize the function of fault prediction and remaining life prediction for electronic products. Next, we will expand the types of data acquisition terminals, such as various types of acquisition cards and sensors, to meet various needs of different users.

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