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A survey on life prediction of equipment

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Abstract Once in the hands of end users, such durable equipment as spacecraft, aircraft, ships, automobiles, computers, etc. are in a state of debugging, working or storage. In either state, availability, reliability and super-efficiency are the ultimate goals, which have been achieved through constant monitoring as well as regular, preventive, routine and corrective maintenance. Although some advanced instruments can visualize certain invisible malfunctioning phenomena into visible ones, deeply hidden troubles cannot be found unless monitoring and testing data are addressed using tools that process the data statistically, analytically and mathematically. Some state-of-the-art trouble-shooting and life-predicting techniques and approaches are introduced in this paper.

1. Introduction

In the United States of America, two of the five space shuttles, "Challenger" and "Columbia", disintegrated in midair killing 14 astronauts on board. The trouble rate accounts for 40%! The "Challenger tragedy" occurred in 1986 because the National Aeronautics and Space Administration (NASA) Space Shuttle Program Manager and management of the builder of Challenger's solid rocket motors (SRM) believed it was not possible to predict equipment failures with certainty, so ignored the prediction by the SRM Chief Engineer that the O-rings would fail with certainty if launched well below the SRM's contractual launch temperature. The most susceptible component to fail when launched well below the specified lower launch temperature was the SRM's O-ring seals that failed at the SRM ignition during the lift-off. This was the result submitted to the NASA Headquarters (HQ) Office of Safety and Mission Assurance in the prognostic analysis completed by Losik, the President of Failure Analysis.[1] The "Columbia disaster" happened because the NASA Space Shuttle Flight Manager decided not to wait and analyze the Columbia space shuttle wing's telemetry stored on-board and decided not to inspect the underbelly of Columbia after being informed that a large piece of foam insulation on its external tank broke off and would likely hit Columbia as had happened in other space shuttle launches.[1] Catastrophes dictate us to use data and tools provided to find physical, chemical, mechanical, electric, electronic, or photovoltaic failures in advance and remedy them readily. Meanwhile, the senior U.S. strategic bomber B52 may live as long as 84 years! How do we know this? Because we possess an ability to predict the likelihood of a piece of equipment's life span in probabilistic terms or mean time between failures (MTBF) using probability reliability analysis (PRA) engineering that employs stochastic equations. These stochastic equations provide results in probabilities or likelihood, not certainty. Wikipedia states that

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"a missile system can have a mission time of less than one minute, service life of 20 years, active MTBF of 20 min, dormant MTBF of 50 years and a reliability of 0.999 999", all determined using stochastic equations and PRA.[2]

Due to the influences of storage and working environments, a piece of equipment may degenerate, and even fail, which may lead to an accident, an injury to people and great loss of properties.[3,4] If the life of the equipment can be predicted accurately with certainty in advance, appropriate maintenance and management actions (such as repair and replacement) can be adopted to ensure the reliability and effectiveness of the equipment. Therefore, it is important to predict life of equipment[5] using certainty, and life prediction of equipment has been widely studied in the past decades using probabilistic terms from a PRA.[3–8]

Pecht classified life prediction methods into two types that are mechanism model-based methods and data-driven methods.[3] Si et al. further surveyed data-driven methods, and classify them into monitoring data-based methods and indirectly monitoring data-based methods.[5] Jardine et al. classified life prediction methods into statistics-based methods, artificial intelligence-based methods and model-based methods.[8]

Life prediction of equipment may face at least three engineering problems: (1) how to determine the life of a piece of debugging equipment that has not been put into use yet, (2) how to predict the remaining life of a piece of equipment that has worked for some time known as its normal lifetime, and (3) how to estimate the life of a piece of equipment that is powered off and in (long term) storage. Nowadays, there is no open literature that discusses life prediction of equipment from this kind of engineering point. Any processes that are in use are proprietary and thus not available for public use. As such, this paper tries to discuss the state of the art of the life prediction technology from the above three engineering problems. However, in research, a reliability prediction model can usually be used for life prediction by setting a threshold, so in this paper we do not discuss the difference between reliability prediction and life prediction in detail.

The following parts of this paper is divided into four parts, namely life prediction methods for debugging equipment, remaining useful life (RUL) prediction of working equipment, storage life prediction of equipment, and outlook.

2. Life prediction methods for debugging equipment

Prior to the development of model-based and data-driven methods, there were two kinds of debugging equipment. One is equipment improved from existing equipment, and the other is newly designed equipment. For the former, the similar product analogy-based methods are often adopted for life prediction. For the latter, the mechanism analysis-based methods, the component reliability synthesis-based methods, the accelerated life test-based methods and the environmental factor conversion-based life prediction methods can be used. For debugging equipment, the available information includes: (1) the inherited information from a similar product, (2) the mechanism information by analyzing the equipment in the debugging state, (3) the component and structure information, (4) the life information obtained by accelerated tests, and (5) the life information gotten from environmental tests. Therefore, based on the different kinds of information of the debugging equipment, the classification of life prediction methods for debugging equipment is given in Fig. 1. The results from the predictions of life using either of the two kinds are highly unreliable and not generally relied upon, and their unreliable life predictions are the reason that model-based and data-driven methods were developed achieving the accurate life predictions obtained by Losik et al.[9]

2.1. Life prediction methods based on similar product analogy

In these methods, the life of a similar product is assessed according to the prior information gotten from the similar product during a long working process firstly, and then the life of the debugging equipment can be determined by the similar product analogy-based methods. The basic model adopted in these methods is described as follows:

$$h(\lambda) = \rho h(\lambda|H) + (1-\rho)h(\lambda|N) \quad (1)$$

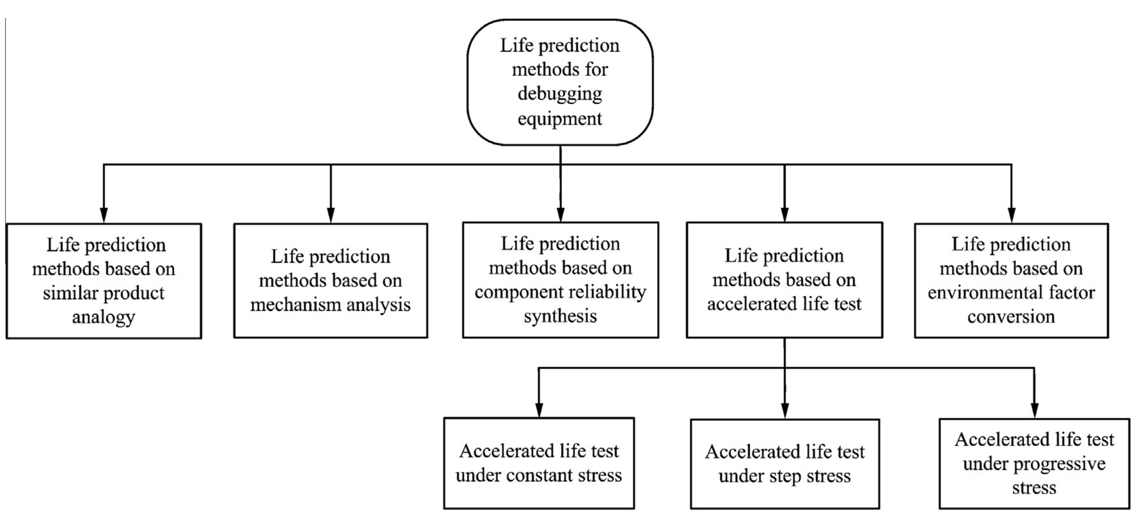

Fig. 1 Classification of life prediction methods for debugging equipment.

where $h(\lambda)$ denotes the complex posterior, ρ an inheritance factor that can reflect the similarity degree between the history products and the debugging equipment, $h(\lambda|H)$ the history posterior, and $h(\lambda|N)$ the innovation posterior of the debugging equipment.

Zhang et al. defined an inherited factor that describes the similar degree between the similar equipment and the debugging equipment. Thus, the inherited factor is adopted to fuse the life assessment of similar equipment and debugging one.[10] Yang et al. utilized this method to evaluate the reliability and predict the life of airborne electronics, and the result indicated that this method can not only take full advantage of historical information, but also reflect the characteristics of new products.[11,12]

2.2. Life prediction methods based on mechanism analysis

In these methods, the relationship between the life and the physical change that is named as mechanism model is built, and then the life of the equipment is predicted. The advantage of these methods is that the life of the equipment can be predicted more accurately. Tanaka and Mura proposed a mechanism model to describe that the fatigue crack initiates along a slip band inside a crystal.[13] Brückner-Foit and Huang applied the mechanism model to simulate the micro-crack initiation of martensitic steels' each crystal.[14] Mu and Lu further built a 3-D simulation model to describe the initiation of the fatigue crack, and a life prediction method based on the simulation is proposed.[15] However, in engineering, for some complex equipment, it is difficult to obtain the inner mechanism and build the mathematical model further, which limits the application of these methods.

2.3. Life prediction methods based on component reliability synthesis

In these methods, the reliability relationship or simulation model between the reliabilities of the equipment and a component is built firstly, and then the reliability of the equipment can be obtained by reliability synthesis or simulation according to the reliability of the component that is usually given by the handbook of the component or the reliability prediction handbook of the American military standard. The general model can be described as follows:

$$F(t) = \Psi(F_1(t), F_2(t), \ldots, F_n(t)) \tag{2}$$

where $F(t)$ denotes the joint distribution of the life and $F_i(t)$ (i = 1, 2,..., n) the marginal distribution of the life with n being the total number of components.

Ref. 16 presented a method for reliability assessment and life prediction based on reliability competition relation, and reported the application of the method to reliability assessment and life prediction of some circuits. Chen et al. further improved this method and used it for reliability assessment and life prediction of an aviation power circuit.[17] The method firstly identifies the key unit circuits by sensitivity or principal component analysis. Then the failure probability distributions of the key units can be obtained by statistical or failure physical analysis. Finally, the life of the equipment can be assessed by reliability synthesis based on the reliability relationship between the equipment and its unit circuits. However, this method requires that the relationship between the equipment and all the components can be built, which is not applicable for some large-scale complex equipment.

2.4. Life prediction methods based on accelerated life test

In these methods, the life distribution and the accelerated factor are determined firstly according to the life data obtained from an accelerated life test, and then the life information in the accelerated environment is converted to the normal working environment. Based on the assumption that the failure mechanism does not change, the life data can be obtained during a shorter time through raising the testing stress. These methods have been widely applied in the fields of aerospace, aviation, and so on.[18] According to the difference of accelerated stress, an accelerated life test can be classified into the following three sub types.

(1) Accelerated life test under a constant stress

In these methods, under a constant stress that is higher than the normal level, the life test of a piece of equipment is carried out until the test reaches a given time or failure number, and then the life is assessed by analyzing the data gotten from the test. These kinds of methods are widely applied in engineering. The disadvantage of these methods is that it may need a long time. Four national standards about this kind of methods have been published in China.[19–22]

(2) Accelerated life test under a step stress

Compared with the accelerated life test under a constant stress, the testing stress level is raised step by step in these methods. When statistical analysis is carried out in a step stress-based test, the complexity and non-process of the algorithm are the main problems that increase the difficulty of engineering applications of step stress-based tests and software programming cannot be realized easily. As early as in 1961, Dodson and Howard at Bell Labs proposed a method of step temperature stress test in reliability analysis and life prediction of a semiconductor product.[23] In 1980, Nelson presented statistical models and methods for analyzing accelerated life-test data from step-stress tests, and they adopted the maximum likelihood method for providing estimates of the parameters of such models.[24] In 2005, Zhao and Elsayed proposed a generally accelerated life model for step-stress testing and presented a general likelihood function formulation for step-stress models. Their model can also be applicable to any life distribution in which the stress level only changes the scale parameter of the distribution, and be extended to multiple-stress as well as profiled testing patterns.[25]

(3) Accelerated life test under a progressive stress

Compared with the accelerated life test under a constant stress, the testing stress level is raised continuously in these methods. These methods can stimulate the failures of testing samples as quickly as possible. However, it is complex to analyze testing results, and special devices are needed to generate the progressive stress. Kimmel tried to assess the reliability of an electronic product using the progressive stress test.[26] Yin and Sheng gave the life distribution of a product under the progressive stress test, and discussed the life assessment when the acceleration equation satisfies the inverse power law and the progressive stress is directly proportional to time.[27]

2.5. Life prediction methods based on environmental factor conversion

In these methods, the data gotten from different environmental tests are converted into the data that we concern firstly, and then the life is predicted based on the available data. The premise to apply these methods is that the failure mechanism of equipment keeps unchanged under different environments, and the key is how to determine the environment factors of different environments. These methods enlarge available data sources, but it is necessary to know the type of life distributions. In engineering, the lives of electronic equipment and mechanical equipment are often assumed to obey the exponential distribution and the Weibull distribution, respectively. Pan discussed the reliability assessment-based environmental factor of ammunition storage based on environmental factor and Bayesian method, and his result showed that through the conversion of the reliability data under different environment, we can take full advantage of the testing data and reduce the testing cost.[28] Under the assumption that the shape parameter of the Weibull distribution is invariant, Li et al. gave a method to estimate the environment factors between the ground test and the space, and then used this method for the life test of an aerospace engine.[29] By the proportional hazards model, Hong et al. described the relation between the environmental factor and reliability parameters, proposed a method to estimate the environmental factor, and used this method to analyze the stress influence of a continuous current dynamo.[30]

3. RUL prediction methods for working equipment

RUL prediction of a piece of working equipment means that after the equipment has worked for a period of time, some information can be obtained up to current time instant and is used to predict RUL. Usually three types of information are available for working equipment, which are historical working information, similar equipment's life information and information obtained from an accelerated life test. These three types of information are mainly composed of failure data and degradation data. The current RUL prediction methods include failure data-based methods, degradation data-based methods and multi-source information fusion-based methods. Fig. 2 shows the detailed classification of these methods.

3.1. RUL prediction methods based on failure data

Based on the failure data, the life distribution of the equipment is determined by the statistical inference, and then the RUL is predicted according to the life distribution. In these methods, there are four steps: (1) collection and pretreatment of the failure data, (2) selection of the life distribution, (3) parameters estimation of the life distribution, and (4) prediction of the RUL. The key of these methods is how to choose an appropriate life distribution, and the usual distributions include the exponential distribution, the logarithmic distribution, the normal distribution, the Weibull distribution and the uniform distribution. For example, electronic equipment and mechanical equipment usually follow the exponential distribution and the Weibull distribution, respectively.[31,32] Marshall and Olkin summarized the common life distribution functions, and discussed the methods for estimating the parameters of the distribution functions.[33] However, these methods describe the general life distribution of a product, so it is usually used to reflect general degradation.

3.2. RUL prediction methods based on degradation data

Based on the historical working information, the model of the performance degradation path can be built. Then the time

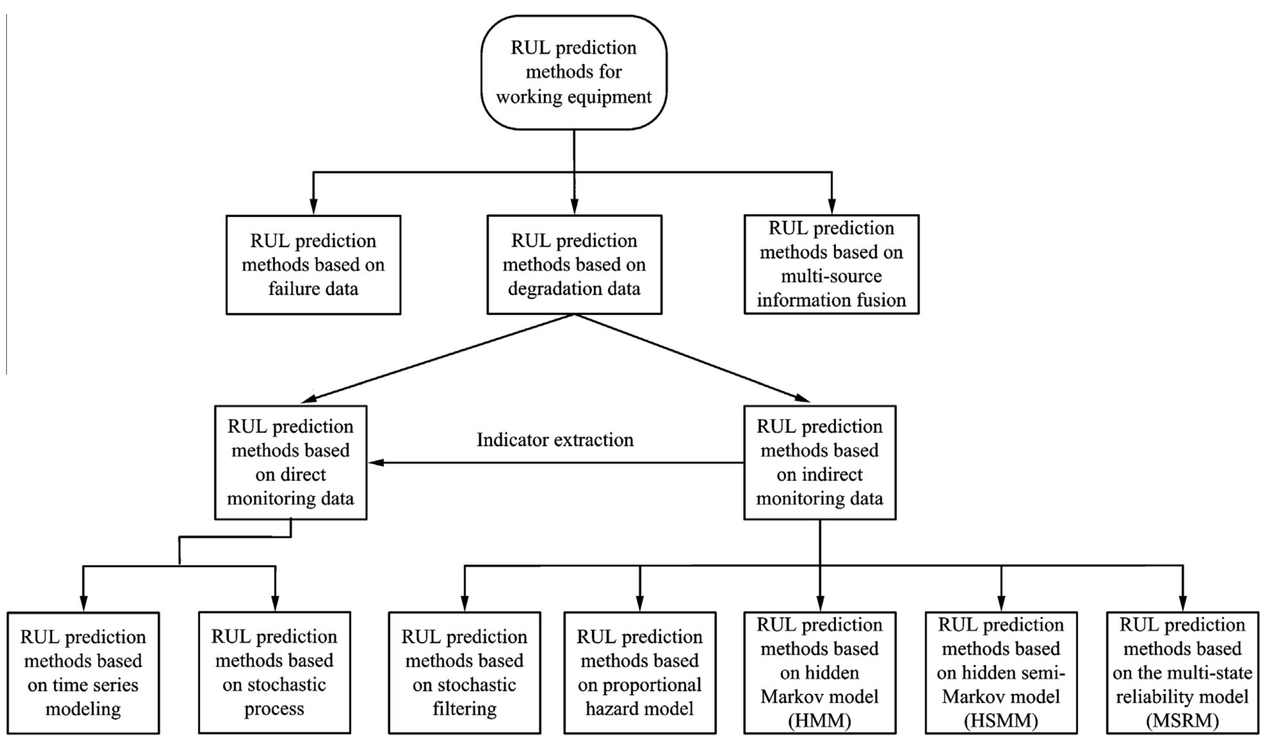

Fig. 2 Classification of RUL prediction methods for working equipment.

instant is determined when the degradation exceeds the failure threshold. Thus, the RUL can be predicted. These methods include direct monitoring data-based methods and indirect monitoring data-based methods. Moreover, not only the individual degradation but also the overall degradation can be modeled by these methods.[5,7,10]

3.2.1. RUL prediction methods based on direct monitoring data

Direct monitoring data refers to data that can directly reflect the performance or health state of a piece of equipment, such as wear, fatigue crack data, and so on. Direct monitoring data-based methods include time series modeling-based methods and stochastic process-based methods.[5,7]

(1) RUL prediction methods based on time series modeling

In these methods, the degradation data is regarded as a time series firstly. Then the time series model is used to establish the model of the performance degradation path. Finally, the time instant is determined when the degradation exceeds the failure threshold. Thus, the RUL can be predicted. The models used in these methods usually include the autoregressive-moving-average (ARMA) model,[34] the gray model,[35] the artificial neural network (ANN),[36] the support vector machine (SVM),[37] and the combination forecasting model,[38] and these methods are applied in RUL prediction of relay, bearings and gyros. Although these methods have been widely used for RUL prediction,[34,38] the forecasting result is a fixed value, which cannot reflect the uncertainty of RUL prediction effectively.

(2) RUL prediction methods based on stochastic process

In these methods, it is assumed that the degradation process obeys a certain stochastic distribution firstly. Then the models of the performance degradation path and the life distribution are established, respectively. Finally, the time instant is determined when the degradation exceeds the failure threshold. Thus, the RUL can be predicted.[5] These methods are proposed under the probabilistic framework, and the forecasting result is a probability distribution. As mentioned previously, the RUL should be uncertain, so this kind of methods is more appropriate for the engineering. These methods include the random coefficient regression-based methods, the gamma process-based methods, the inverse Gaussian process-based methods, the Wiener process-based methods, the Markov chain-based methods, and so on.[5,7]

The random coefficient regression method is firstly proposed by Lu and Meeker[39] and the basic model adopted in this method is described as follows:

$$X(t) = h(t; \phi, \theta) + \varepsilon(t) \tag{3}$$

where $X(t)$ is the degradation process at time t, ϕ the fixed parameter, θ the stochastic coefficient, and $\varepsilon(t)$ the noise items at time t. Gebraeel et al. proposed an improved random coefficient regression method based on the Bayesian method.[40] Park and Bae further analyzed the RUL prediction problem of the random coefficient regression method under the condition of an accelerated stress.[41]

van Noortwijk reviewed the theoretical development and engineering application of the gamma process.[42] The model adopted in this method is described as follows:

$$f(\Delta x; \alpha\Delta t, \beta) = \frac{\beta^{-\alpha\Delta t}}{\Gamma(\alpha\Delta t)} \Delta x^{\alpha\Delta t - 1} \exp\left(-\frac{\Delta x}{\beta}\right) I_{(0,\infty)}(\Delta x) \tag{4}$$

where Δx denotes addition of the degradation process, Δt the time interval, α the shape parameter, β the scale parameter, $\Gamma(\bullet)$ gamma funtion and $I_{(0,\infty)}(\Delta x) = \begin{cases} 0 & \Delta x < 0 \\ 1 & \Delta x \geqslant 0 \end{cases}$. Lawless and Crowder studied the uncertainty and difference of the degradation based on the gamma process. Nowadays, the gamma process-based methods have been deeply developed and widely used in engineering.[43] The gamma process and inverse Gaussian process-based methods are only applicable in the cases when the degradation data is monotonic.

The inverse Gaussian process has been used for RUL prediction in recent years.[44,45] Wang and Xu studied the parameter estimation of a class of inverse Gaussian process describing the degradation process based on the expectation maximization (EM) algorithm.[45] Ye and Chen discussed the applicability of the inverse Gaussian process as a degradation model, and illustrated that the inverse Gaussian process is much more flexible and attractive through comparing it with the gamma process.[46]

The Wiener process-based methods are appropriate in the cases when the degradation process is non-monotonic. The model adopted in these methods is described as follows:

$$X(t) = x_0 + \int_0^t \lambda(t)\mathrm{d}t + \sigma B(t) \tag{5}$$

where x_0 is the initial value, $\lambda(t)$ a defined drift parameter, σ a diffusion coefficient, and $B(t)$ the standard Brownian motion. Because most of the degradation process is non-monotonic in engineering,[5,47,48] the Wiener process-based methods have been deeply studied and widely used. Recently, Si et al. presented a nonlinear Wiener process for RUL estimation and proposed several nonlinear degradation models, which were applied into gyros' RUL estimations.[49] The analytic solutions of RUL are firstly obtained by using the nonlinear model.[49]

The Markov chain is often used to describe the degradation process with continuous time and discrete state. Kharoufeh applied the Markov chain to describe wear degradation caused by an environmental load.[50] Kharoufeh[51] and Lee[52] et al. studied how to use the Markov chain to predict RUL according to environmental and degradation data. For the Markov chain-based methods, the key problem is how to model the deterioration of a condition. However, the Markov model is based on the assumption that constant transition probabilities are irrespective of how long an item has been in a state, which may be unreasonable for some cases. In order to solve this problem, the semi-Markov model is proposed. Black et al. introduced how to build a semi-Markov model by using observed condition data and then used this method for life prediction of switchgear oil.[53]

3.2.2. RUL prediction methods based on indirect monitoring data

Indirect monitoring data refers to data that can only indicate the performance of a piece of equipment partially. For example, data obtained by monitoring the vibration or oil of mechanical equipment belongs to indirect monitoring data. There is an indirect relationship between monitoring data and equipment life.[5,48] Indirect monitoring data can be transformed into direct monitoring data. RUL prediction methods based on indirect monitoring data include stochastic filtering, the proportional hazard model, the hidden Markov model (HMM), the hidden semi-Markov model (HSMM) and the multi-state reliability model (MSRM).

(1) RUL prediction methods based on stochastic filtering

Currently, these methods attract more attention in the field of RUL prediction. There are two assumptions about these methods. One is that there are no repair and replacement, and the equipment degenerates all the time. The other is that the monitoring data of the equipment degenerates at some trend. The basic model adopted in these methods is formulated as follows:

$$x_t = \alpha x_{t-1} + \varepsilon_t, \quad y_t = \beta x_t + \eta_t \tag{6}$$

where x_t and y_t are the condition monitoring data and the real degradation data at time t respectively, ε_t and η_t noises, and α and β the parameters of the state. Wang and Zhang proposed a RUL prediction method based on stochastic filter according to expert knowledge and indirect monitoring data, which is used to predict the RUL of a bearing.[54,55]

(2) RUL prediction methods based on the proportional hazard model

In these methods, the RUL of equipment is predicted according to the ratio relationship between the monitoring data and the failure rate of equipment. Cox proposed a RUL prediction method based on the proportional hazard model, which is taken to be a function of the explanatory variable and unknown regression coefficient multiplied by an arbitrary and unknown function of time.[56] Based on Cox's model, Jardine et al. developed the optimization theory of condition-based maintenance decisions.[57] Ghasemi et al. studied how to build the proportional hazard model and predict the average RUL under the condition of missing data.[58]

(3) RUL prediction methods based on the HMM

This kind of methods is developed from the Markov chain model, but they are mainly used to predict the RUL of equipment under the condition that the degradation is a hidden process. Bunks et al. proposed a RUL prediction method based on the HMM and the expectation maximization (EM) algorithm.[59] Baruah and Chinnam proposed a model for obtaining the accuracy result from sample size.[60] Camci and Chinnam developed the HMM by combining the dynamic Bayesian network and then applied it into RUL prediction, which can model complex systems better.[61]

(4) RUL prediction methods based on the HSMM

The HSMM is an improved HMM. Compared with the HMM, the HSMM supposes that the state duration of the equipment obey some distribution, such as the normal distribution. Dong and He applied the HSMM to predict the RUL of the equipment.[62,63] Liu et al. applied the HSMM to describe the transition probabilities among health states and the state durations, and then predicted the RUL of the equipment based on the sequential Monte Carlo simulation.[64]

(5) RUL prediction methods based on the MSRM

The MSRM is usually utilized to describe a multi-state system and further evaluate the reliability or predict the RUL of the system. In order to describe the multiple states of the system, the Markov process, the semi-Markov process and the non-homogeneous continuous Markov process are usually adopted, as in Refs. [65,66]. However, some degradation processes may be non-Markovian. In order to solve this problem, Li et al. proposed a stochastic Petri net representing the multi-state degradation process and applied this method into alloy dissimilar metal weld degradation.[67]

3.3. RUL prediction methods based on multi-source information fusion

In these methods, a degradation model is built based on failure data and degradation data, and then the RUL is predicted according to the degradation model. Pettit and Young built a Wiener model-based on failure data and degradation data of a piece of equipment, and the model parameters were estimated by a Bayesian method.[68] Moreover, Lee and Tang applied the EM method to estimate the parameters of the model proposed by Petti and Young, and apply the method to predict the RUL of a light emitting diode.[69] Si et al. proposed a RUL estimation method with an exact and closed-form solution by using the EM algorithm and the Bayesian rule.[70]

4. Storage life prediction methods of equipment

When a piece of equipment is in storage, two kinds of information can be obtained. One is the failure data, the other is the performance data obtained by regular checks. Because the degradation of the equipment is slow during the storage, an accelerated test is usually adopted to shorten the testing time. Nowadays, there are two kinds of storage life prediction methods. One is the storage life prediction methods based on failure data, and the other is the storage life prediction methods based on accelerated test data.

As early as in 1950s, many storage experiments about missiles have been carried out by USA, and a great deal of failure data and degradation data are obtained about the missiles, which is important to determine the reliabilities and lives of the missiles' equipment.[71] In 1980s, many accelerated storage experiments about missiles have been carried out by Soviet Union, and a conclusion that the missiles can be put into use without measurement within 10 years is drawn.[72]

4.1. Storage life prediction methods of equipment based on failure data

Through the statistical analysis of failure data, the life distribution of equipment can be determined and then the RUL can be predicted. There are two kinds of methods to obtain the failure data of equipment in storage. One is on-site storage test, and the other is accelerated storage test.

4.1.1. Storage life prediction methods based on on-site storage test

In these methods, a piece of equipment is stored in an environment that is equivalent to the working environment firstly. Then the performance degradation data and failure data can be obtained by regular checks. Finally the storage life is predicted through analysis of degradation data or life distribution. The forecasting result generated by these methods is close to the actual value and the forecasting precision is high, so these methods have been widely used in the storage life prediction of military equipment in the last century.[73] However, these methods require a long period of time. In order to obtain accurate forecasting results in a relatively short period of time, an accelerated storage test is needed.

4.1.2. Storage life prediction methods based on accelerated storage test

In these methods, the degradation or failure process is accelerated by increasing the stress load. Thus the failure or degradation data is obtained in a relatively short period of time. Then the lifetime distribution or degradation model can be established based on the data obtained. Because these methods need short time and low cost, they have been widely studied and applied. Moreover, the corresponding standards have been developed in component-level equipment such as pyrotechnics.[74–76] In the tests of machine level, van Dorp et al. study the statistical properties of equipment when failure data or degradation data obeys the exponential distribution and the Weibull distribution.[77] Furthermore, Zhou et al. proposed a novel method and applied it in the communication equipment of an electronic machine.[78]

4.2. Storage life prediction methods based on accelerated degradation test

The degradation process is accelerated by increasing the stress level in these methods.[79,80] Nelson studied the accelerated degradation test firstly.[81] Padgett et al. made an extension about the application in light-emitting diodes, logic integrated circuits, power supply, carbon film resistors and other equipment.[82,83] As an important kind of methods for predicting the storage life of equipment with high reliability and long service life, storage life prediction methods based on the accelerated degradation test are developing very fast.[83]

There is no clear standard for selecting a method between the accelerated life test and the accelerated degradation test. In this paper, according to practical engineering experience, the cost of equipment and the testing time are used as the basis for selection. Compared with the accelerated life test, the accelerated degradation life test needs less testing samples and does not need the equipment to run till failure, so it is appropriate for storage life prediction of equipment with high reliabilities and long service lives. On the contrary, a lot of testing samples are needed in the accelerated life test and it can reflect the lives of all the samples. Therefore, these methods are appropriate for equipment with low costs and a lot of experiments can be carried out.

5. Outlook

5.1. Life prediction of equipment with a state switch

In engineering practices, a piece of equipment may not always be in the same working environment and there will be a switch between different states. For example, the equipment may be converted from the working state to being shut down and may also be converted from the storage state to the working state. In the current methods of life prediction, in order to reduce the modeling difficulty, only the degradation in a major state is considered and the degradations in other states are ignored, which is different from the practical case and an inaccurate forecasting result may be generated. There are few studies to focus on this problem. Si et al. studied life prediction when the storage and testing states are switched to each other.[84] Firstly, the storage and testing states are considered as two different states. Then the hidden Markov chain is used to describe the switch between two states. Finally a multi-stage Wiener process is used to model these two states. It is significant to study the degradation modeling and the life prediction problem of equipment when the states are switched to each other.

5.2. Life conversion between different states

As mentioned above, there are multiple states such as storage, working and accelerated test. Obviously, in order to accomplish the life conversion between different environments, it is an important problem to build the conversion relationship function of life between different states. For example, the normal working state could be regarded as the accelerated form of storage, so the storage life could be treated as the function of the normal working life and the stress. If the life function and the stress could be determined, the normal working life can be converted to the storage life. However, it is hard to see life prediction methods that adopt this idea.

5.3. Life prediction fusing qualitative knowledge and quantitative information

So far, quantitative information such as monitoring data and failure data is mainly used. In the current methods for life prediction, because in engineering, for expensive equipment (such as some key equipment in aerospace and missile weapon systems), a lot of experiments could not be operated and it is difficult to obtain enough quantitative information, some qualitative information such as expert experience knowledge may be obtained. Zhou et al. have used a belief rule base and an evidential reasoning approach to predict failure fusing quantitative and qualitative information, but the proposed method has not been used in life prediction.[85] There are few literatures to report the life prediction methods based on the quantitative and qualitative information.

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