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Residual Life Prediction and Optimal Maintenance Decision for a Piece of Equipment

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Foreword

Residual life prediction and predictive maintenance of complex engineering equipment exist as a significant engineering problem demanding a prompt solution. For the applications in aviation, aerospace and other related sectors requiring high reliability and long life, this problem is a very challenging one. In consideration of the high cost and long lifecycle of this kind of equipment, it is difficult to acquire massive failure data or life data of the equipment through tests. As a result, the traditional residual life prediction and optimal maintenance methods based on statistical analysis of failure distribution become unavailable or unfeasible. While performing R&D, type test, storage and operation of the equipment, we have accumulated some monitoring and test data indicating the operation status and performance of the equipment. These data contain abundant information about the residual life of equipment. Unfortunately, the existing residual life prediction methods have not applied these data reasonably. Fortunately, as early as 2002, the author and his research team have begun to explore the comprehensive application of life data and degradation data in equipment history monitoring and inspection information to model the performance degradation rule, predict the residual life and make optimal maintenance decisions. A great number of original achievements, such as the first passage time (FPT) distribution and residual life prediction of nonlinear Wiener degradation process, self-detection of abrupt changepoint, multi-stage degradation modeling and residual life prediction, evidence reasoning degradation modeling and residual life prediction based on subjective and objective information, optimal detection strategy of degraded equipment based on life prediction information and cooperative predictive maintenance of two-component system under limited resources, have been made. These research results have been published on *IEEE Transactions on Reliability*, *European Journal of Operational Research*, *Science China* and other top academic journals in the field and attracted wide attention from peers both at home and abroad. It means that the theoretical results of this book have produced a wide range of international academic influence with superiority, systematization and originality. Meanwhile, the author and his team attach great importance to integrating theory with practice and use the methods proposed in the book to handle the residual life prediction and maintenance decision of aerospace products, such as gyroscopes and platforms, and obtain some prediction and decision results more applicable to engineering practices. This book has strong specific applicability and high reference value. In this sense, it is a rare monograph on equipment residual life prediction and optimal maintenance decision in recent years. The publication of this book will promote the development of residual life prediction and maintenance decision technologies for complex engineering equipment based on degradation modeling and also provide an important theoretical basis for solving major engineering problems related to the residual life prediction and maintenance decision of complex engineering equipment. Moreover, this book is an excellent monograph in the fields of reliability engineering, maintenance engineering and management engineering and brings a significant reference value to numerous scientific workers engaged in the research in related fields.

March 2021

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Preface

Equipment performance degradation and even failure will inevitably occur during equipment operation. Maintenance has been widely applied as an indispensable approach to ensure normal system operations. After years of development, maintenance has evolved from the breakdown maintenance at the earliest stage to the condition-based maintenance at the current stage. In recent years, predictive maintenance based on condition-based maintenance has attracted wide attention from researchers. Life prediction, which is known as the core technology for realizing predictive maintenance, has become one of top priorities for domestic and overseas researchers. Both *the Outline of the National Program for Long- and Medium-Term Scientific and Technological Development* (2006–2020) promulgated by the State Council in February 2006 and the field of advanced manufacturing technology in Program 863 have listed the life prediction technology of major products and facilities as one of the cutting-edge technologies for instant development. The traditional life prediction technology takes class-I products as the research object, and performs statistical analysis on the life data by statistical methods, and then obtains the life distribution. However, this method has ignored the influence of environment and other factors during equipment operation. Therefore, the life distribution obtained by statistical methods cannot accurately describe the life change of equipment, resulting in the unreasonable arrangement of maintenance activities. With the development of science and technology, equipment life is getting longer and longer, and the reliability is getting higher and higher. Therefore, it is difficult to collect massive life data. This fact will inevitably degrade the accuracy of statistical results.

With the development of sensor technology, it is extremely urgent to evaluate the residual life of equipment online through data monitoring, which has attracted the attention of scholars. As a kind of monitoring data, performance degradation data, which contain a large number of reliable and useful key life-related information, can directly reflect the performance degradation process of equipment. Degradation process modeling and prediction using performance degradation data has become an important research in the field of life prediction.

Starting from the practical engineering requirements of residual life prediction and optimal maintenance decision of key missile components, this book systematically discusses the theories and applications of equipment performance degradation rule modeling, residual life prediction and optimal maintenance decision based on historical equipment monitoring data. This book is also a systematic summary of the research results of the author and his team in this field for more than one decade. As early as 2002, the author and his team have started researches on the theories and applications of equipment performance degradation rule modeling, residual life prediction and optimal maintenance decision. However, the research on residual life and predictive maintenance of missiles and other aerospace equipment from this perspective can be seldom found in China, and the related monographs are rare.

This book consists of 12 chapters. Chapter 1 presents an overview of researches on life prediction and maintenance decision methods. Chapter 2 proposes the real-time residual life prediction method based on Wiener process for the equipment suffering nonlinear degradations. With respect to abrupt changepoints during degradation, Chap. 3 has given the algorithm of abrupt changepoint detection and the real-time prediction method of residual life. In Chap. 4 and Chap. 5, performance degradation modeling and residual life prediction methods based on Gamma process and inverse Gaussian process have been studied, respectively. In Chap. 6, the residual life prediction method based on support vector machine (SVM) is studied for the small sample size of degradation data. Chapter 7 proposes a fuzzy model identification method based on relevance vector machine (RVM) and studies the corresponding performance degradation modeling and prediction methods. The degradation modeling of evidence reasoning and the prediction of residual life based on subjective and objective information are systematically studied in Chap. 8. In Chap. 9, the related algorithms of particle filter are introduced, and an excellent weight selected particle filter algorithm is proposed and applied to the residual life prediction of equipment. Chapter 10 introduces the grey model theory and its application in performance degradation modeling and prediction. In Chap. 11, the optimal detection strategy based on residual life prediction information is studied. In Chap. 12, a cooperative predictive maintenance model is proposed for the equipment with two dependent failure modes.

The publication of this book is supported by the National Defense Industry Press, Springer Verlag and partially supported by National Natural Science Fund under grants 61873273, 61833016, and 61973046. Here, I would like to express my sincere thanks.

Due to my limited knowledge, it is inevitable that there is something inappropriate with the book. Any comment from the readers will be appreciated.

Xi'an, China Changhua Hu
March 2021

Summary

This book is an academic monograph that systematically discusses the residual life prediction and optimal maintenance decision method based on performance degradation modeling. It mainly covers the overview of life prediction and maintenance decision modeling and optimization, real-time residual life prediction based on Wiener process for nonlinearly degraded equipment, performance degradation modeling and remaining life prediction (respectively based on Wiener process with abrupt changepoint, Gamma process, inverse Gaussian process, support vector machine, relevance vector machine fuzzy model, weight selected particle filter and gray prediction model), performance degradation modeling and reliability prediction based on evidence reasoning, optimal inspection strategy of degraded equipment based on life prediction information and cooperative predictive maintenance of two-component system under limited resources.

This book can provide reference for the great majority of scientific and technical personnel engaged in theoretical research or applied research on equipment fault diagnosis and fault-tolerant control, life prediction and maintenance decision, etc. For the great majority of engineering and technical personnel, teachers, graduates and senior undergraduates engaged in reliability engineering, maintainability engineering, management engineering, testing and measurement technologies and instruments, inspection technologies and automation devices, this is a systematic, innovative and practical reference book with cutting-edge knowledge and outstanding theories.

Contents

Chapter 1
Introduction

1.1 Background

With the high-tech development and increasing global competitions, the modern industrialization process intends to be more and more extensive and complex [1]. However, the related equipment in the fields of industrial production, transportation, communication, aerospace and missile weapon system is becoming more and more advanced. Moreover, most of them are becoming more and more complex. The failure of a tiny component may cause a failure to the whole system and even a great disaster. For example, on September 8, 1994, a Boeing 737 aircraft of American Airlines crashed near Pittsburgh due to the non-command deflection of its rudder, and 131 people died [2]. In 2005, due to the blockage of Tower P-102 in the nitration unit of Jilin Petrochemical Company Aniline Plant, a severe explosion occurred, which caused great economic losses [3]. Therefore, it is of great significance to ensure the reliability and security of such complex systems. This also determines the necessity of repairing these kinds of complex equipment. Maintenance can improve the system reliability, availability and safety, thus reducing losses and ensuring personnel safety. But maintenance needs massive financial supports. According to related statistics, maintenance costs account for 15% of total production costs in the manufacturing industry and 40% in the steel industry. In the USA, the annual maintenance cost of enterprises is more than US$ 200 billion [4]. It is estimated that about 30% of the maintenance cost is caused by low-efficiency maintenance methods [5].

In order to keep maintenance as an effective role in ensuring correct system operations with the lowest cost, researchers have accomplished massive studies on maintenance policies. Meanwhile, maintenance has also evolved from the original breakdown maintenance to scheduled maintenance, and then to the widely used condition-based maintenance at present. With the rapid development of sensor technology and prediction technology, the predictive maintenance, as an important solution, has evolved from condition-based maintenance. At present, the scholars both at home and abroad have paid close attention to predictive maintenance. Some foreign

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countries have paid attention to predictive maintenance as early as the end of last century. In China, both *the Outline of the National Program for Long- and Medium-Term Scientific and Technological Development* (2006–2020) promulgated by the State Council in February 2006 and the field of advanced manufacturing technology in Program 863 have listed the life prediction technology of major products and facilities as one of the cutting-edge technologies for instant development [6].

Life prediction, which is known as the core technology for realizing predictive maintenance, has become one of top priorities for domestic and overseas researchers [7–11]. The traditional life prediction technology takes class-I products as the research object and performs statistical analysis on the life data by statistical methods and then obtains the life distribution. However, this method has ignored the influence of environment and other factors during equipment operation. Therefore, the life distribution obtained by statistical methods cannot accurately describe the life change of equipment, resulting in the unreasonable arrangement of maintenance activities. With the development of science and technology, equipment life is getting longer and longer, and the reliability is getting higher and higher. Therefore, it is difficult to collect massive life data. This fact will inevitably degrade the accuracy of statistical results.

With the development of sensor technology, it is extremely urgent to evaluate the remaining life of equipment online through data monitoring, which has attracted the attention of scholars. Jardine et al. [12] summarized the main research results of life prediction in recent years. They pointed out that the current researches on remaining life prediction mainly focus on predicting the probability distribution and expectation, involving statistical method, artificial intelligence (AI) and mechanism model. Both statistical method and AI are data-driven methods. Xiaosheng Si et al. systematically reviewed the statistical data-driven remaining life prediction methods in the reference [13]. According to the types of status monitoring data, the obtained data are divided into direct monitoring data and indirect monitoring data. Based on such data classification, the existing methods are divided into direct monitoring data-based methods and indirect monitoring data-based methods. They also described and commented all existing prediction methods from the perspective of remaining life modeling. In this book, the author has made a more comprehensive summary and comment on the life prediction methods in the following aspects, including life determination of newly developed equipment, the remaining life prediction of equipment under working conditions and the storage life of equipment [14].

In particular, the performance degradation path modeling and maintenance decision modeling and optimization are described as follows.

1.2 Equipment Life Prediction

1.2.1 Fundamental Concept of Life Prediction

Residual life (RL), usually called remaining useful life (RUL) and also called remaining service life and remaining life, is the normal operation time of equipment from the current moment. Life prediction refers to the prediction on how much time is left before one failure (or multiple failures) when the current equipment status and historical status data are known. In most cases, remaining life is defined as a conditional random variable [12]:

$$T - t|T > t, Z(t) \tag{1.1}$$

where T is the random variable of failure time, t indicates the current operation time and $Z(t)$ represents the historical monitoring condition up to the current moment.

Since RUL is a random variable, its distribution is very meaningful to gain a full understanding toward RUL. In relevant references, remaining useful life estimate (RULE) is defined in two different ways, including the calculation of RUL probability distribution and the expectation of RUL in some cases [12]:

$$E(T - t|T > t, Z(t)) \tag{1.2}$$

The accurate definition of equipment failure is a significant prerequisite for life prediction based on performance degradation data. It is generally believed that a failure occurs when the performance degradation data reach the preset failure threshold. For example, the equipment suffering fatigue failure is defined as an incident that the fatigue crack data reach the prescribed threshold.

1.2.2 Literature Review on Life Prediction

1.2.2.1 Life Determination Technology for Newly Developed Equipment

There are two types of newly developed equipment, including the equipment upgraded from the existing equipment and the equipment obtained by redesign. For the former type, the available information mainly comes from similar equipment, so the similar product reasoning method is usually used for equipment lifetime prediction. For the latter type, the available information mainly includes mechanism information, component and equipment structure information, information obtained through accelerated life test and life information in environmental test. The corresponding lifetime prediction methods include mechanism analysis, component reliability synthesis, accelerated lifetime test and environmental factor conversion.

However, most lifetime prediction results obtained through the above methods are not reliable. Under such circumstance, it is necessary to study other methods that can realize accurate lifetime prediction. At present, most related researches focus on model-based methods and data-driven methods.

I. Lifetime prediction method based on similar equipment information

This method makes comprehensive use of the prior information obtained by similar equipment in the long-term operation and the information in the lifetime test of newly developed equipment for lifetime prediction. The basic model of this method is shown as follows:

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

where $h(\lambda)$ indicates the posterior information related to the reliability of newly developed equipment, $h(\lambda|H)$ refers to the information obtained in the operation process of similar equipment, $h(\lambda|N)$ represents the new information obtained during the test for newly developed equipment, ρ is inheritance factor and reflects the similarity of reliability between new equipment and old equipment and can be determined by test information or experts and $1 - \rho$ represents update factor and reflects the uncertainty caused by the new equipment when improving the old equipment.

II. Lifetime prediction method based on mechanism analysis

When this method is adopted, it needs to analyze the physical and chemical factors that lead to equipment failure. The relationship between equipment failure and physical and chemical factors, such as component wear, is established through physical factor analysis, and physical and chemical factor analysis, thus acquiring the lifetime evolution rule and predicting the equipment lifetime. This method has the advantage of predicting the equipment lifetime more accurately. Tanaka and Mura have proposed a mechanism model that can describe fatigue cracking along slip band [15]. Mu and Lu further established a three-dimensional simulation model to describe fatigue cracking and performed lifetime prediction based on the model [16].

However, most engineering equipment is very complex. It is difficult to obtain the mechanism model, thus restricting the application of this method.

III. Lifetime prediction method based on component reliability synthesis

In this method, the reliability relationship between equipment and its components is established at first. Then the reliability of the whole equipment is evaluated and analyzed according to the reliability of components. Reference [17] proposed a reliability evaluation and lifetime prediction method based on reliability competitions and applied this method to reliability evaluation and lifetime prediction of some circuits. Chen et al. improved the method in Reference [17] and applied it to reliability evaluation and lifetime prediction of aviation power circuits [18].

This method has the disadvantage of establishing the relationship between equipment and all its components. It is difficult to establish such relationship for some very complex equipment.

IV. Lifetime prediction method based on accelerated lifetime test

If the failure mechanism of equipment under different stress levels remains unchanged, the lifetime test can be performed at the stress level higher than the normal, and the lifetime test data can be obtained in a short period of time. The lifetime distribution and environmental factor of equipment under the environment of accelerated lifetime test can be obtained by analyzing the lifetime data and converted into the lifetime distribution under normal environment. This method has been widely used in aerospace and other fields [19].

The main difficulties in using this method are as follows: first, how to ensure the consistency of failure mechanism between accelerated lifetime test and normal status; second, how to extrapolate the result of accelerated lifetime test to normal status. It is also difficult to create the model of relationship between accelerated lifetime test and normal status.

V. Lifetime prediction method based on environmental factor conversion

In this method, it needs to convert the test data in different environments into the test results under the same environment and use the data for reliability prediction. Like the method based on accelerated lifetime test, keeping the failure mechanism under different environments unchanged is a premise of using this method. The determination of environmental impact factors under different environments plays a decisive role in this method. The test data under different environments can be converted, which has expanded the source of available data. However, this method has the disadvantage that the type of lifetime distribution must be known. In practical engineering, it is generally assumed that the lifetime of electronic equipment and mechanical equipment follows exponential distribution and Weibull distribution, respectively. Based on final products and failure products, Wengeng Pan [20] discussed the data processing of sampling test for ammunition storage reliability by using the environmental factor method and performed evaluation before and after conversion by Bayesian method. According to the result of comparison with classical methods, the data after conversion can improve the status of ammunition storage and avoid waste. Dongpao Hong et al. [21] used the proportional risk model to describe the relationship between reliability and environmental factor and gave a method of determining environmental conversion coefficient based on the comprehensive use of variable environmental test data.

1.2.2.2 Research Status of Residual Lifetime Prediction of Working Equipment

The residual lifetime prediction of equipment under working conditions refers to the RUL prediction of equipment based on relevant information after the equipment has been operated for a period of time. The aforementioned relevant information includes historical information during aforementioned operation period, lifetime information of similar equipment and lifetime information obtained during accelerated lifetime test. Furthermore, the aforementioned three types of information are mainly divided into failure time data and performance degradation amount. Accordingly, the remaining lifetime prediction method can be divided into remaining lifetime prediction method based on failure time data, remaining lifetime prediction method based on performance degradation amount and remaining lifetime prediction method based on multi-source information fusion. Detailed division is shown in Fig. 1.1.

I. Residual lifetime prediction method based on failure time data

If the failure time data of the equipment are obtained, the parameters of equipment lifetime distribution can be estimated by using statistical inference method based on the assumed equipment lifetime distribution, and then the remaining lifetime distribution of the equipment after being operated for a period of time can be obtained. The commonly used lifetime distribution form includes exponential distribution, normal distribution and Weibull distribution. The suitability of the equipment lifetime distribution directly affects the accuracy of lifetime prediction results. Marshall and Olkin [22] summarized the commonly used lifetime distribution functions and discussed the method of estimating the parameters for the corresponding distribution functions;

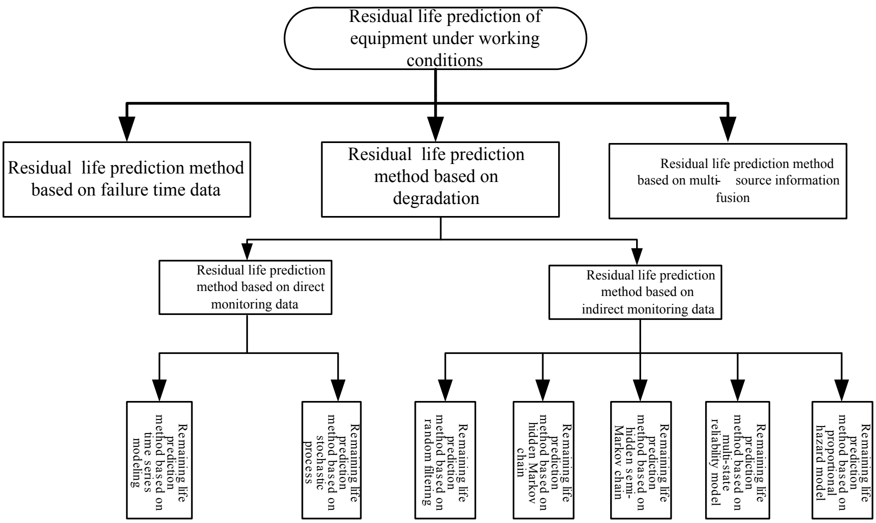

Fig. 1.1 Residual lifetime prediction of equipment under working conditions

however, this method only applies to the overall lifetime distribution of equipment and fails to consider the equipment degradation information during the operation period. Consequently, it cannot well reflect the remaining lifetime distribution of the equipment after being operated for a period of time.

II. Residual lifetime prediction method based on performance degradation amount

According to the historical operation information of the equipment, the performance degradation path of the equipment can be established. On this basis, the time when the equipment performance degradation amount exceeds the failure threshold can be determined, and then RUL of the equipment can be determined. This method can be divided into the remaining lifetime prediction based on direct monitoring data and the remaining lifetime prediction based on indirect monitoring data.

(I) Residual lifetime prediction method based on direct monitoring data

Direct monitoring data mainly refer to monitoring data that can directly reflect the performance or health status of the equipment. The commonly mentioned performance degradation amount such as wear and fatigue crack data fall into this category. Therefore, the remaining lifetime prediction based on direct monitoring data is to predict the time when the monitoring data reach the failure threshold for the first time. The remaining lifetime prediction method based on direct monitoring data can be divided into the remaining lifetime prediction method based on time series modeling and the remaining life prediction method based on stochastic process.

1. Residual life prediction method based on time series modelling

The direct monitoring data obtained at the monitoring time constitute time series. Therefore, the equipment performance degradation rule can be established by applying the remaining life prediction method based on time series modeling, and finally, the time when the equipment performance degradation amount reaches the failure threshold for the first time can be determined on this basis, so that the remaining life of equipment can be obtained. The commonly used time series model includes auto-regressive moving model, gray model, artificial neural network, support vector machine (SVM) and their combined prediction model. The remaining life prediction method based on time series modeling has been widely used to predict the remaining life of bearings, gyroscopes and other equipment; however, such method cannot reflect the uncertainty of prediction results well since it can only obtain the amplitude of remaining life instead of the distribution form of remaining life.

2. Residual life prediction method based on stochastic process

Based on this method, it is considered that the equipment performance degradation rule can be described by applying stochastic process, and then the distribution of the time when the performance degradation amount reaches the failure threshold for the first time can be determined, so that the remaining life distribution of equipment can be obtained. Different from the remaining life prediction method based on time series modeling, this method provides the equipment life under the probabilistic framework. Therefore, the probability distribution is obtained, which can well reflect the uncertainty of prediction results and provide convenience for subsequent maintenance decision. Specifically, the stochastic process model commonly used in this method includes random coefficient model, Gamma process, inverse Gaussian process, Wiener process and Markov chain.

The random coefficient model is one of the models early used in performance degradation amount modeling. In 1993, Lu and Meeker [23] firstly proposed the random coefficient regression model, and then Lu [24] and Tseng [25] developed and applied such model into the modeling of semiconductor industry and LED brightness degradation. Wang [26] and Bae [27] respectively studied the remaining life prediction of the same type of equipment with common characteristics under the modeling and the nonlinear degradation conditions. On this basis, Gebraeel [28–31] et al. further proposed the remaining life prediction method based on Bayesian update and used such method to describe the variation in brake pad thickness. Park [32] et al. analyzed the remaining life prediction based on the accelerated degradation model. If the failure threshold of the equipment is known, then the random coefficient regression model of the equipment can be easily obtained. The random coefficient regression model and the statistical analysis method, which are relatively simple, have been widely applied in industry and chemical fields.

Gamma process is a stochastic process model commonly used for the remaining life prediction of the equipment. This process is usually used to model the degradation path of monotone data, such as metal wear and crack growth. In 1975, Abdel-Hameed firstly proposed and used Gamma process to model the continuously monotonous degradation amount [33]. In 2000, Wang et al. applied Gamma process in the research of remaining life for large pumps [34]. In 2000, Bagdonavicius incorporated the impact of dynamic environment into the degradation model and proposed a remaining life prediction method based on Gamma process which considered dynamic environment [35]. In 2004, Lawless and Crowder considered the parameters in the Gamma process as random variables [36]. In 2009, Noortwijk summarized the relevant research and application of Gamma process in the field of life prediction over recent years [37].

The basic idea of inverse Gaussian process is to describe the degradation process based on the variation in increment by assuming that degradation is strictly monotonous and that the increment of degradation follows an inverse Gaussian distribution. Inverse Gaussian process was firstly proposed by Wasan [38] in 1968; however, it was not until 2010 that the inverse Gaussian process was firstly applied in equipment degradation modeling by Wang [39]. Inverse Gaussian process was used to describe the monotonous degradation process. Owing to the connection between the inverse Gaussian distribution and the Wiener process with linear drift, inverse Gaussian process can be derived and implemented mathematically in an easier way and is more flexible and applicable compared with Gamma process.

The remaining life prediction method based on Wiener process is mainly applicable to non-monotonic equipment performance degradation process. By this method, the mathematical models in the forms shown below are mainly used to describe the degradation process.

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

Wherein: x_0 refers to the initial performance degradation amount; $\lambda(t)$ refers to the drift parameter; σ refers to the diffusion coefficient; $B(t)$ refers to the standard Brownian motion. After the equipment performance degradation model is obtained, the remaining life distribution of the equipment can be calculated by using the given failure threshold and the Wiener process-related theory. In order to realize accurate and real-time remaining life prediction of the equipment, generally, the remaining life prediction results can be updated from time to time based on the real-time monitoring information of the equipment. Gebraeel et al. [28] firstly established the equipment degradation model based on Wiener process with linear drift (or linearizability) and realized the online update of random drift coefficient by assuming that the drift coefficient followed normal distribution and applying the degradation amount observed in a real-time way and Bayesian inference method. Gebraeel method has a great influence on the field of life prediction and health management for the equipment; however, the remaining life prediction results obtained by applying Gebraeel method are only applicable to the linearly degraded equipment or the equipment of which the performance degradation amount can be directly linearized. Moreover, the Brownian motion term in the degradation model utilized in this method is only considered as an observation error. Consequently, the remaining life distribution obtained is not an accurate solution in the sense of first passage time. Therefore, with regard to the shortcomings of Gebraeel method, a performance degradation modeling and remaining life prediction method based on Wiener process with nonlinear drift is studied in Chapter 2 herein, so as to carry out the remaining life prediction of the nonlinearly degraded equipment.

The remaining life prediction method based on Markov chain is often used for the modeling of degradation processes which are characterized by continuous-time discrete states. It involves two assumptions. In one assumption, the future degradation state is only depending on the current degradation state (namely, memoryless); in the other assumption, the monitoring data of the system can reflect the operating state of the system [40]. In the remaining life prediction method based on Markov chain, the first passage time can be defined as the time when the degradation process reaches failure state for the first time, and the remaining life can be calculated based on the first passage time. From 2003 to 2012, Kharoufeh carried out a series of studies on this method and proposed a degradation model based on Markov chain which considered environmental impact [40–43]. In 2010, Lee et al. incorporated Markov property of degradation process into remaining life prediction based on regression model [44].

(II) Residual life prediction based on indirect monitoring data

Indirect monitoring data mainly refer to monitoring data that can only indirectly or partially reflect the performance or health status of equipment, including vibration analysis data, oil analysis data, etc. The remaining life prediction methods based on indirect monitoring data include random filtering, proportional hazard model (PHM), hidden Markov model, hidden semi-Markov model, etc.

1. Residual life prediction based on random filtering

This method has become a hot spot in current research and attracted the attention of many researchers. This method is usually applied to the equipment that has not been maintained or replaced and has been degrading. In addition, the performance degradation data of equipment should show a certain trend. The model usually used in this method is as follows

$$\begin{aligned} x_t &= \alpha x_{t-1} + \varepsilon_t \\ y_t &= \beta x_t + \eta_t \end{aligned}$$

where x_t, y_t are the actual performance degradation and performance monitoring data of equipment at t; ε_t, η_t are corresponding noises; α, β are parameters related to the model. According to expert knowledge and indirect monitoring data, Wang and Zhang predicted the remaining life of bearings by using random filtering method [45, 46].

2. Residual life prediction based on proportional hazard model

The proportional hazard model was proposed by Cox in 1972, which was used in the medical field at first. The proportional hazard model was introduced into the field of reliability in 1980s and has attracted the attention of researchers since then and has been widely used in the field of life prediction. Generally, the proportional hazard model can relate the failure rate function of working equipment with the overall failure rate function and performance monitoring data of the equipment and then calculate the remaining life distribution of the equipment according to the failure rate function of the equipment [47]. On the basis of this model, Jardine studied the problem of condition-based maintenance decision and determined the optimal replacement time of equipment [48].

3. Residual life prediction based on hidden Markov model

The hidden Markov model (HMM) is developed on the basis of Markov chain, which is often used to predict the life of equipment with hidden performance degradation. Bunks et al. [49] proposed a remaining life prediction method based on HMM and expectation maximization algorithm. In order to model complex systems better, Baruah and Chinnam [50] combined HMM with dynamic Bayesian network and used it to predict the remaining life.

4. Residual life prediction based on hidden semi-Markov model

The hidden semi-Markov model (HSMM) is an improved hidden Markov model, which assumes that the residence time of equipment in a degradation state follows arbitrary distribution, such as normal distribution. Dong and He [51, 52] applied this model to the life prediction of equipment and achieved good results. Liu et al. [53] described the degradation state transition probability of equipment and the residence time of each state by using HSMM and then predicted the remaining life of equipment based on sequential Monte Carlo simulation.

(III) Residual life prediction based on multi-source information fusion

In the life test of equipment, usually only a part of equipment fails within the specified time, while the other part of equipment can still work normally. At this time, the data obtained include not only the failure time data of equipment but also the performance degradation data of non-failed equipment. Although the overall life distribution of this kind of equipment can be obtained only by using the failure time data, if the performance degradation data can also be used, a more accurate remaining life prediction result can be obtained. Therefore, making full use of failure time data and performance degradation data to predict the remaining life of equipment is mainly considered in the remaining life prediction method based on multi-source information fusion. By using the characteristic that the first passage time distribution of Wiener process was inverse Gaussian distribution, Pettit and Young [54] integrated the failure time data and performance degradation data in Bayesian framework and predicted the remaining life distribution of equipment. Lee and Tang [55] further estimated the parameters in the model proposed by Pettit and Young by using EM algorithm and applied them to predict the remaining life of LED.

1.2.2.3 Research Status of Equipment Storage Life Prediction

As early as 1950s, the USA conducted many storage tests for missiles and obtained a large number of failure time data and performance degradation data of missiles [56]. In 1980s the Soviet Union also conducted many accelerated life tests for missiles and improved the missiles so that the missiles could be used normally within ten years without test [57].

Two aspects of information can be used for equipment in storage. One is the failure time data of the equipment; the other is the performance degradation information obtained during the periodic inspection of equipment. With the development of science and technology, there is equipment with high reliability and long life, especially missiles, whose storage life is generally long, which makes it difficult to obtain enough storage life data in a short time. Therefore, it is often necessary to use accelerated storage life test or accelerated degradation test to shorten the test time to obtain storage life data or performance degradation data. According to the different types of data obtained, the current storage life prediction methods can be divided into two categories: one is the storage life prediction method based on failure time data; the other is the storage life prediction method based on performance degradation data.

I. Equipment storage life prediction based on failure time data

By statistically analyzing the failure time data of equipment during storage, the storage life distribution form of equipment can be obtained. Due to the long life of some of the equipment, it is difficult to obtain enough failure time data in a short time through field storage test. Therefore, the problem that it is difficult to obtain failure time data can be solved through accelerated storage life test. Accordingly, this kind of method can be divided into: the field storage test-based method and the accelerated storage life test-based method.

(I) Field storage test-based method

Store the equipment under normal conditions until it fails. By analyzing these failure time data, the life distribution of equipment during storage can be obtained. The equipment life obtained by this method is very close to the actual life. Therefore, this method was widely used to predict the storage life of military equipment in the twentieth century. However, due to slow performance degradation during storage, it takes a lot of time to obtain enough test data.

(II) Accelerated storage life test-based method

In view of the shortcomings of the field storage test method, people consider using accelerated storage life test to obtain failure time data and then predict the storage life of equipment. This method tests the storage life of equipment under the stress level exceeding the normal storage environment conditions. Since the test environment of equipment becomes harsh, which accelerates the degradation of equipment, shortens the test time and reduces the cost, this method has been widely used. For mechanical equipment, van Dorp [58] studied the statistical properties of equipment when failure data follows exponential distribution and Weibull distribution. Furthermore, Xiufeng Zhou et al. [59] proposed a new method to predict the storage life of electronic communication equipment. It should be pointed out that the research object of accelerated storage life test can be equipment with degradation failure mode or equipment with sudden failure mode, but the test mainly records the failure time data of equipment, not the performance degradation data.

II. Storage life prediction based on performance degradation data

The storage life of equipment with degradation failure mode can be obtained by analyzing the performance degradation data. However, under normal storage conditions, the performance degradation process of equipment is very slow, and the performance degradation data do not change obviously, so it is difficult to use them to predict the storage life. In order to solve this problem, accelerated degradation test came into being. The purpose of accelerated degradation test is to study the performance degradation rule of equipment, determine the performance degradation path of equipment and obtain the storage life information of equipment by extrapolation. This method has been developed rapidly because it does not need a large number of test samples and does not need to test the equipment until it fails. Nelson first studied the accelerated degradation test [60]. Padgett et al. extended this method to equipment such as LED, logic integrated circuits and power supplies [61].

1.3 Maintenance Decision of Equipment

1.3.1 Fundamental Concept and Classification of Maintenance

Maintenance refers to "all technical and management activities, including monitoring, carried out to maintain or restore the state in which the product is capable of performing specified functions." Maintenance is short for service and repair [62]. Service refers to all activities taken to keep the system in good working condition when the system still works normally, including cleaning, wiping, lubricating, oiling, etc. Repair refers to activities taken after system failure, such as fault detection, troubleshooting and repair. Researchers began to pay attention to this problem in 1950s and proposed a large number of maintenance models to solve the maintenance problems of different systems. Until now, there are still a large number of references related to maintenance every year, which shows that maintenance decision modeling and optimization are still hot and difficult points at present.

Maintenance can be divided into corrective maintenance (CM) and preventive maintenance according to the timing of maintenance.

Corrective maintenance, also known as failure maintenance, was the main maintenance method before 1940s, which mainly involved repairing the system after it has failed. Obviously, this kind of maintenance was driven by failure events, which made people mistakenly think that breakdown maintenance was a cost-saving maintenance method [5]. Later, people gradually realized that the maintenance cost needed would be higher than that of arranging relevant maintenance operations before failure if minor faults were allowed to develop until failure. This was because the system needed to be maintained immediately after failure, which would interrupt the normal production plan and bring losses. Moreover, since there was no prediction method at that time, the management personnel could not know when the failure would occur, which led to the sudden occurrence of failure events and made the enterprises unable to prepare the materials, tools and maintenance personnel needed for maintenance in time, which would increase the losses caused by failure to a certain extent [63]. These shortcomings of breakdown maintenance promoted the emergence and development of preventive maintenance policy. However, due to the uncertainty of the failure process, failure usually occurred during the operation of the system. Therefore, breakdown maintenance was considered in the policy formulation process in the maintenance theory developed later.

Preventive maintenance refers to finding fault symptoms through inspection and detection on the premise that the system can still work normally, and taking appropriate maintenance actions to eliminate possible faults in the future. According to the types of information used in maintenance decision, maintenance methods can be further divided into scheduled maintenance (SM) and condition-based maintenance (CBM). Recently, on the basis of condition-based maintenance, predictive maintenance has gradually attracted the attention of researchers.

Scheduled maintenance refers to the arrangement of maintenance activities by management personnel according to the characteristics such as failure rate or life distribution obtained based on the statistics of failure time data. After the World War II, there was a shortage of materials and personnel. In order to improve the material supply capacity, highly automated equipment has been put into use one after another. Meanwhile, the urgency of war required that the production equipment must be shut down as little as possible, so the maintenance of the equipment became important. However, since the traditional failure maintenance was driven by failure events, maintenance operations aimed at restoring the specified functions of the system could be carried out only after the system has failed. Obviously, this maintenance method could no longer meet the needs at that time. In order to prevent the occurrence of failure, the researchers proposed the idea of preventive maintenance in 1950s [64], that is, carry out maintenance operations on the system according to predetermined intervals or specified criteria, so as to reduce the probability of system failure or prevent the function degradation. It should be pointed out that preventive maintenance at this time actually referred to the maintenance arranged according to the time, that is, time-based preventive maintenance (TBPM), also known as scheduled maintenance. At that time, China also introduced the scheduled maintenance system from the Soviet Union and applied it to the power industry [65]. Compared with the failure maintenance, this maintenance method has the advantage of improving the system reliability, reducing the frequency of fault and increasing the productivity through a series of maintenance operations (inspection, repair, replacement, cleaning and lubricating, etc.).

However, the introduction of scheduled maintenance not only improved the reliability and availability of equipment but also increased the maintenance cost of enterprises. According to the survey, domestic enterprises in the USA spent nearly USD 600 billion to maintain their key equipment in 1981, and the number doubled over 20 years [64]. Germany spent 13–15% of its GDP on maintenance, while the Netherlands spent 14% [66, 67]. Specifically, 15–70% of enterprises' total expenditure was spent on the maintenance of production equipment [68]. More notably, one-third of the high maintenance cost was wasted in the maintenance implementation process [5]. Main reasons are described as follows. First, in the implementation of scheduled preventive maintenance, the maintenance interval is mainly determined by statistical analysis of the failure time data of the same type of system, without considering the actual performance of the system during operation, resulting in that the maintenance