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Zheng-Xin Zhang
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Data-Driven Remaining Useful Life Prognosis Techniques

Stochastic Models, Methods and Applications

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Xiao-Sheng Si
Department of Automation
Xi'an Institute of High-Technology
Xi'an, Shaanxi
China

Chang-Hua Hu
Department of Automation
Xi'an Institute of High-Technology
Xi'an, Shaanxi
China

Zheng-Xin Zhang
Department of Automation
Xi'an Institute of High-Technology
Xi'an, Shaanxi
China

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Preface

The remaining useful life (RUL) of a system is defined as the length from the current time to the end of the useful life. The concept of the RUL has been widely used in operational research, reliability, and statistics literature with important applications in other fields such as materials science, biostatistics, and econometrics. However, there are many definitions as what is regarded as the useful life. In 'Businessdictionary.com,' it defines the useful life "the period during which an asset or property is expected to be usable for the purpose it was acquired'. However, in accounting, it is defined as 'the expected period of time during which a depreciating asset will be productive." The keyword here is 'usable' or 'productive' which is again upon individual explanations. Clearly the definition of the useful life depends on the context and operational characteristics. In this book we will assume that the definition of the useful life is known to the owner of the asset and the main interest is to investigate the modeling methods for RUL estimation given condition and health monitoring information.

In conventional data-based approaches, estimating the RUL is achieved by evaluating the conditional lifetime distribution given that a system has survived up to a specific time. The obtained RUL distributions from these approaches are generally based on the life characteristics of a population of identical systems and lifetime data are required. However, such data are scarce in reality or even nonexistent at all for systems which are costly or time-consuming to collect the life data. With the advances in CM technologies, degradation data can be obtained from routine CM as feasible and low-cost alternatives to estimate the RUL. These data are usually correlated with the underlying physical degradation process. If they are properly modeled, degradation data can be used to predict unexpected failures and accurately estimate the lifetime of gradually degraded systems. In many situations, such as the drift degradation of an inertial navigation system used in the aerospace industry, it is natural to view the failure event of interest as the result of a stochastic degradation process crossing a threshold level, i.e., to model the hitting time of the degradation as a time-dependent stochastic process. On the other hand, dynamic environments induce changes in the physics of failure.

RUL prognosis is one of the key factors in condition-based maintenance (CBM), and prognostics and health management. It is critically important to assess the RUL of an asset while in use since it has impacts on the planning of maintenance activities, spare parts provision, operational performance, and profitability of the owner of an asset. RUL estimation has also an important role in the management of product reuse and recycle which has strategic impacts on energy consumption, raw material use, pollution, and landfill. The reused products must have sufficient long lives left among others to be able to be reused. This puts the importance of the estimation of RUL beyond CBM and prognostics and health management because of the green issues associated. As a consequence, developing RUL prognosis methods is much desired for health management of degrading systems to prevent sudden failure and reduce the safety risk. In the past four decades, valuable contributions to prognostics in reliability field have been made. This book is intended to summarize the research results studied mainly by the authors in the past decade.

This book introduces the main ideas of data-driven remaining useful life prognosis techniques, with an emphasis on stochastic models, methods, and applications. It gives a thorough survey of new methods that have been developed in the recent years and demonstrates them with examples. To the knowledge of the authors, all major aspects of RUL prognosis are treated for the first time in a single book from a common viewpoint. With the presentation of RUL prognosis methods for degrading systems, the book provides novel materials that have not yet been described in monographs or textbooks.

This monograph consists of four parts:

- **Part I: Introduction, Degradation Data Acquisition and Evaluation**. Advances in data-driven RUL prognosis techniques are reviewed. As fundamental issues for data-driven RUL prognosis, methods of how to acquiring the degradation data and how to evaluate the usability of the acquired data are presented.
- **Part II: Prognostic Techniques for Linear Degrading Systems**. Methods for adaptive RUL prognosis, exact RUL prognosis solution, RUL prognosis with multiple kinds of variability for linear degrading systems are presented and the methods are demonstrated by case studies.
- **Part III: Prognostic Techniques for Nonlinear Degrading Systems**. Methods for nonlinear degradation modeling, adaptive RUL prognosis, nonlinear RUL prognosis under multiple sources of variability, residual storage life prognosis with switching systems for nonlinear degrading systems are presented and the methods are demonstrated by case studies.
- **Part IV: Applications of Prognostic Information**. This part discusses the applications of prognostic information such as mission reliability estimation, condition-based replacement, spare parts forecasting, and joint optimization of spare part ordering and replacement.

As each of the models used requires its own mathematical background and the methods based on these models follow different lines of thinking, the book cannot present the methods for all details. The aim is to give the readers a broad view of the field and provide them with bibliographical notes for further reading. A further reason for the different depth with which the chapters tackle the RUL prognosis problems is given by the status of research. In the introductory parts of all chapters, the problems to be solved are posed in a framework that is familiar to practicing engineers. They describe the new ideas and concepts of RUL prognosis in an intuitive way, before these ideas are brought into a strict mathematical form. Examples illustrate the applicability of the methods. Bibliographical notes at the end of each chapter point to the origins of the presented ideas and the current research lines. The evaluation of the methods and the application studies should help the readers to assess the available methods and the limits of the present knowledge about RUL prognosis with respect to their particular field of application.

Together with four parts, the book is composed of 16 chapters. Chapter 1 is devoted to an introduction to advances in data-driven RUL prognosis techniques. Chapter 2 considers the problem of planning repeated degradation test for degrading products with three-source variability. In Chap. 3, the attention is paid to specifying measurement errors for required lifetime estimation performance so as to evaluate the data usability. A linear degradation model with a recursive filter algorithm and Bayesian updating is presented to estimate the PDF of the RUL in Chap. 4. Chapter 5 derives the exact and closed-form solution of RUL prognosis for linear degrading systems. Chapter 6 presents a Wiener-process-based degradation modeling framework for RUL estimation with three-source variability. In Chap. 7, a diffusion process-based model was presented to characterize the dynamics and nonlinearity of degradation processes, and the corresponding RUL distribution is formulated. The results in Chap. 7 are further extended to an age- and state-dependent case in Chap. 8. In Chap. 9, an adaptive and nonlinear prognostic model is presented to estimate the RUL using the history of the observed data to date. Chapter 10 develops a real-time RUL estimation method based on a state space model considering that the degradation process is hidden and nonlinear. Chapter 11 presents a general nonlinear diffusion process-based model to estimate the RUL with the temporal variability, unit-to-unit variability, and measurement variability. In Chap. 12, the problem of predicting RSL for a class of systems with operation state switches is concerned. Chapter 13 applies the prognostic information to reliability estimation of phased-mission systems. In Chap. 14, a real-time variable cost-based maintenance model is presented based on nonlinear prognostic information. Chapter 15 presents an adaptive spare parts demand forecasting method based on degradation modeling of the CM data. In Chap. 16, a new sequential maintenance and inventory model is developed to consider the effects of both expectation of the maintenance cost and its variability under prognostic information.

In preparing the book, efforts have been made to maintain a balance between the required theoretical and mathematical rigor in the exposition of the methods and the clarity in the illustration of the numerical examples and practical applications. For this reason, this book can serve well as a reference to both reliability and risk analysis researchers and engineers. Furthermore, sufficient references leading to further studies are cited at the end of each chapter. This book will serve as a textbook and reference book for graduate students and researchers in reliability and maintenance. Although the book is self-explanatory, a standard background in probability theory, mathematical statistics, and stochastic processes is recommended.

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Xiao-Sheng Si
Zheng-Xin Zhang
Chang-Hua Hu

Contents

Acronyms

AIC	Akaike information criterion
BM	Brownian motion
CBM	Condition-based maintenance
CDF	Cumulative distribution function
CM	Condition monitoring
CTMC	Continuous-time Markov chain
EKF	Extended Kalman filter
EKS	Extended Kalman smoother
FHT	First hitting time
FPK	Fokker–Planck–Kolmogorov
FPT	First passage time
HMM	Hidden Markov model
HSMM	Hidden semi-Markov model
INS	Inertial navigation system
KF	Kalman filter
ME	Measurement error
MLE	Maximum likelihood estimation
MSE	Mean squared error
MTTF	Mean time to failure
PDF	Probability density function
PHM	Prognostics and health management
PMS	Phased-mission system
RE	Relative error
RSL	Residual storage life
RTS	Rauch–Tung–Striebel
RUL	Remaining useful life
STF	Strong tracking filter
TMSE	Total MSE

Part I
Introduction, Degradation Data Acquisition and Evaluation

Chapter 1
Advances in Data-Driven RUL Prognosis Techniques

1.1 Introduction

Prognosis and health management (PHM) has drawn increasing attention and gained deepening recognition and widening applications during the past decades [1–4]. Actually, the initial health and usage inspection system was fist equipped in the early helicopters of US military and the synthetically health management philosophy was presented for spacecraft in the 1970s. Recently, the comprehensive solution for system performance prognosis and maintenance has been achieved in the Joint Strike Fighter F-35 project [5]. Further, the ability of PHM has already been listed by the Department of Defense (DOD) of United states as one of the essential norms for weapon system purchasing. This shows the significant implication of PHM in military fields. On the other side, industrial practice indicates that PHM technology can effectively reduce the maintenance cost, improve the reliability and guarantee the completion of tasks of the system [6, 7]. Research institutes including NASA [8], University of Maryland [6] and George's University [9], as well as commercial companies such as Boeing have launched a great deal of theoretical and applied research works about PHM technology. The PHM conference has been successfully organized and held by IEEE Reliability Society in Shenzhen, Macau, Beijing, Rome, and Zhangjiajie respectively, Beijing in six consecutive years since 2010.

Remaining useful life (RUL) estimation, offering guidance for sequential management involving inspection schedule, maintenance, replacement and spare parts ordering, has been considered as the kernel technology of PHM, and the focus of current research in the field of reliability also. According to Petch's classical monograph about PHM technology [6], methods for RUL estimation can be classified into three kinds: namely physical model-based methods, data-driven methods and their combinations. However, with the development of industry and the continuing extension of human exploring activities, the complexity of a system, together with the diversity and uncertainty of its operating environments, continues to increase, which results in extreme difficulties in constructing physical models capturing the system and its operating circumvents. Meanwhile, data-driven methods, including

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artificial intelligence-based methods and statistical data-based methods have become an effective avenue to evaluate reliability and estimate RUL, especially for vital systems with high reliability and long lifetime. Artificial intelligence based methods can hardly provide a probability density function (PDF) estimate capturing stochastic and uncertain characteristics of the RUL, while this desire is a natural result for stochastic data-driven methods [10]. To address the uncertainty of prognosis, we mean statistic data-driven methods as data-driven methods throughout this chapter. According to the observability of underlying degradation process, Si et al. provided an review on data-driven methods for both direct and indirect observed degradation data, introducing many common methods including Gamma processes, Wiener processes, Hidden (semi-) Markov models, stochastic regression models, stochastic filtering-based models and covariate hazard-based models, from the perspectives of applying procedure, merits and drawbacks [11]. While being satisfactory for RUL estimation under each specific applying condition, these methods exhibit some limits in cases with heterogeneity from the inner states or the external operating conditions of systems.

Heterogeneity is widespread in the inner states of the system and the related working environments. Examples involve that a weapon system may experience various operating conditions, saying storage, inspection, transport, and maintenance during its life cycle due to different tasks; that a manufacture system produces different products under different workloads; and that even systems from the same category may exhibit various degrading paths in the same environment. The performance degradation of a system is a result of interactions of both inner deterioration and working environment of the system, indicating a need for incorporating the heterogeneity into degradation modeling, to achieve a more accurate RUL estimation. For particular heterogeneity, such as the unit-to-unit variability, changing working conditions and periodic tasks, many recent advances in RUL estimation have appeared. However, to the best of the authors' knowledge, there is still no review regarding degradation modeling and RUL estimation for systems with heterogeneity. Therefore, this chapter tries the best to fill this gap.

Toward the end of this chapter, three kinds of heterogeneity are considered consecutively: the unit-to-unit variability for systems from the same category, the variability in time-varying operating conditions, and the diversity of tasks and workloads of system during their life cycles. The first kind of variability describes the differences in degradation processes of units from the same category, while the second represents noninform working conditions related to the degradation, such as the time-varying, multi-state and stochastic working environments or random shocks. The third kind of heterogeneity captures the influence of changes in tasks and management activities involving inspection, maintenance, etc. Accordingly, this chapter classifies methods addressing degradation modeling and RUL estimation with heterogeneity into three kinds, each of which considers one kind of heterogeneity introduced above and consists of some subclassifications. The taxonomy of RUL estimation approaches for systems with heterogeneity is illustrated in Fig. 1.1.

The remainder of the chapter is structured as follows: Section 1.2 summarizes methods considering unit-to-unit variability, saying degradation models with random

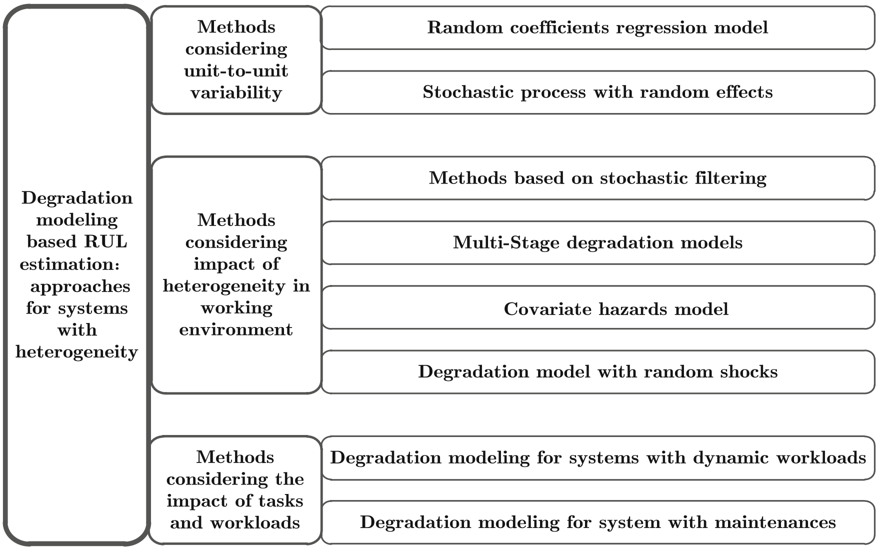

Fig. 1.1 Taxonomy of RUL estimation approaches for system under heterogeneity

effect In Sect. 1.3 methods considering the impact of the working conditions are provided. Methods for incorporating the influence of diversity in tasks and workloads are reviewed in Sect. 1.4. Section 1.5 concludes the chapter and provides several possible directions for future studies.

1.2 Methods Considering Unit-to-Unit Variability

A large number of experiments and engineering phenomena show that systems of the same category, even from one batch degrade differently from one another in performance. This kind of difference in degradation is usually defined as the unit-to-unit variability, due to the variability in inner structures of the considered systems, as well as the diversity in their working environment. Commonly, models with random effects are employed to capture the unit-to-unit variability, when we model the degradation process and estimate the RUL. The most typical way to do so is to specify some parameters of the model as random variables governed by distributions with computing convenience, presenting the individuality in degradation processes from different units and leave the rest of parameters as constants describing the universality in degradation of systems from the same category or batch. In the following, random coefficients regression models and stochastic process models with random coefficients of this kind are discussed, respectively.

1.2.1 Random Coefficients Regression Models

Random effects first appeared in random coefficients regression models. In the most frequently cited paper about degradation modeling and RUL estimate [12], Lu and Meeker described the random coefficients regression model in a general form as

$$X(t_{ij}) = g(t_{ij}; \boldsymbol{\phi}, \boldsymbol{\theta}) + \varepsilon,$$

where $X(t_{ij})$ is the amount of the degradation of the ith device in the jth inspecting time t_{ij}, the fixed coefficients $\boldsymbol{\phi}$ and the random coefficients $\boldsymbol{\theta}$ are, respectively, used to characterize the universality and individuality in degradation of different systems, and is the random noise.

Random coefficients regression models have been extended, developed and applied widely in many areas, in which a series of extended works presented by Gebraeel et al. are included [13–15] Son et al. compared various kinds of RUL estimation method based on random coefficients regression models [16]. Suk and Paul proposed a nonlinear random coefficients regression method for degradation data [17], and applied the model to the degradation of the vacuum fluorescent tube display. To improve the accuracy of parameter estimation, Weaver and Meeker also studied the optimal design of repeated measures degradation studies, and the method to design accelerated repeated degradation studies [18, 19]. A procedure deciding the minimum sample size and the minimum times of systematic sampling for each item to achieve an anticipant accuracy of estimation (large sample approximate variance) has been provided in their works.

However, according to Wang's analysis in [20], the assumptions of random coefficient regression models result in several limitations, involving the need for more historical degradation data from different systems of the same category, the difficulty in capturing the time-varying dynamics of systems and the independency between random noise with time.

1.2.2 Stochastic Process Models with Random Coefficients

Incorporating random coefficients into stochastic degradation process-based models enables both considerations of time-varying dynamics of an individual system, and description of unit-to-unit variability, and thus has been favored by many researchers. Suppose that the degradation of a system is modeled by a stochastic process $\{X(t); t \leq 0, \boldsymbol{\theta}, \boldsymbol{\vartheta}\}$, with constant parameters $\boldsymbol{\theta}$ and random parameters $\boldsymbol{\vartheta}$. Under the concept of first passage time (FPT), the RUL of the system conditional on the observation $X(t_k)$ at time t_k is defined as

$$L_k := \inf\{l_k : X(t_k + l_k) \geq \omega | X(t_k) < \omega\},$$

where is a preset constant failure threshold.

Lawless proposed a Gamma process-based model containing the covariates and random effects, and applied it to degradation modeling and RUL estimation [21]. When fitting the semi-parametric Gamma process to degradation data, Ye et al. also took the random effects into consideration. Further, the unit-to-unit variability was captured using random parameters following some particular distributions in recent degradation models based on Inverse Gaussian process [22, 23]. The same specifications addressing differences in the degradation process of systems from the same category were used in the application of Inverse Gaussian process for systems with monotonous degradation by Wang [24] and Ye et al. [25]. For nonmonotonic degradation processes with fluctuations, Wang proposed a Wiener degradation model with random effects [26]. Si et al. presented a degradation path-based RUL estimation method with exact closed form solution of the estimated PDF of the RUL in linear and exponential cases, which also incorporated the random effects. Peng and Zeng analyzed the misspecification of linear degradation model in the framework of Wiener process with random drift coefficient [26]. Similarly, Si et al. [27] and Wang et al. [28] set some parameters in their methods as normally distributed random variables, when modeling nonlinear diffusion degradation process and additive hybrid degradation process, respectively. From results in the existing literature, stochastic process models with random effects can effectively improve the estimation accuracy and extend the applications of the initial degradation models, in both cases of monotonous and nonmonotonous degradation processes no matter linear or nonlinear.

In the industrial applications, the main flaw of degradation models with random effects is the complexity in computation. Therefore, the primary concern choosing the random parameters and their distribution models is the convenience of calculation. Normally distributed random variables are with high frequency in the related literature. For example, in Tseng and Yu [29], Lu and Meeker [12], Gebraeel [13], Si [30], all selected models with random variables following Normal distribution to characterize unit-to-unit variability. As for some particular degradation models, parameters subjected to special forms of distributions are preferred. Wang utilized Gamma distributions to mode the drift and diffusion coefficients in the Wiener degradation model [26], and Ye el al. also used gamma distributed parameters when constructing semi-parametric Gamma degradation process. These choices are made due to the purposes of computing convenience. The misspecifications of such distributions are considered by some researchers and some nonparametric distributions based on observations are recommended [31–34]. However, explicit results of the estimated RUL can hardly be derived when nonparametric distributions are used. Besides, the corresponding computation is always complicated, which makes it inadequate for real-time RUL estimation. Therefore, it is a challenge to reasonably choose random parameters and their distributions that cannot only capture the unit-to-unit variability but also benefit computation, when using degradation models with random effects.

1.3 Methods Considering Impact of Heterogeneity in Working Environment

1.3.1 Methods Based on Stochastic Filtering

As early as 1979, Sarma et al. estimated health state of aerospace engine using Kalman Filter (KF) technology, and achieved a maintenance decision optimization based on the estimated results [35]. Afterwards, Wang and Christer [], Batzel and Swanson [], proposed different state evaluation and RUL estimation methods, applied successfully to electromagnetic induction smelting furnaces, aeronautical batteries and other industrial systems, based on the construction of state-space models. As for the nonlinear and nonGaussian state-space models, Extended KF, Benes Filter, Multiple Model Filter and Particle Filter based methods for health state and RUL estimation, have been successively proposed [36–40]. When the impact of heterogeneity is incorporated into stochastic filter-based methods, two kinds of sub methods can be referred to, namely semi-stochastic filter based methods and adaptive parameter based methods.

Ability to handle unobservable degradation is an advantage of stochastic filter based methods, while the failure threshold of the unobservable degradation can hardly be specified. In this connection, the lifetime of a system is directly defined as a state in the state-space model by Wang and Christ, and the length of time interval between two consecutive inspections is treated as the decrease of the lifetime. As such, RUL estimation method based on stochastic filter was proposed in [20] through constructing a stochastic relationship between the condition monitoring data and the lifetime of the system. This original method has been extended to cases where the operating environments are considered, by establishing the stochastic relationship between lifetime with the condition monitoring information and the operating environments simultaneously [41].

In another class of approaches for degradation modeling, some important parameters are expanded as state of a state-space model, which is utilized to describe dynamics in parameters. These parameters are adaptive to the changing environmental variables and updated jointly online with the healthy state of the system. As a result, the updated states and parameters are substituted to obtain a new estimation of RUL. Wang and Mattgew set the drift coefficient in Wiener process as an adaptive parameter, which will be updated through KF technology once new observations are available [42]. Inspired by [42], Si et al. proposed a Wiener degradation model with nonlinear drift coefficient function, which also makes some parameter adaptive to the observed data [43, 44]. In this chapter concerning models for RUL estimation under three sources of variability, the drift coefficient was also treated as an adaptive parameter and expanded to a state in the state-space model describing the degradation of the system, and was updated with the degradation level on-line [45]. The successful application of this method in the RUL estimation of an inertial navigation system has shown much superiority of such method.

The best advantage of such stochastic filter based RUL estimation methods lies in that the parameters and the accordingly RUL estimation can be updated with the newly observed condition monitoring information. Furthermore, the dynamics in the degradation process and the probable measurement errors are taken into consideration, which makes it suitable for indirectly observable degradation process. However, these methods have a premise in common that an explicit state-space model must be constructed, which may be impossible in some cases. Another limitation is that the RUL estimation is obtained without consideration of the possible future changes in the degradation. In addition, the assumption in the semi-stochastic filter based method that there is a deterministic equal relationship between the reduction of lifetime and the inspection interval may not hold in many cases, especially when there are changes in the operating environments of the workloads of the system.

1.3.2 Multi-stage Degradation Models

Multi-stage degradation models are proposed to handle the period differences existing in the degradation process. In Wang's two stage degradation model, the degradation data after the defect point were used to estimate the parameters in the degradation model and predict the RUL of the system [46]. In order to evaluate the remaining storage lifetime of a system, Feng el al. proposed a multi-stage Wiener degradation model in [47], where some related works were listed. These works include the nonhomogeneous Poisson process which can be used to analyse time-varying failure rate of software, the nonlinear model with random coefficients which is applied to the multi-state nonmonotonic degradation process of hardware, the multi-stage linear regression model, the multi-stage linear stochastic process model, and so on. Li and Pham studied the reliability modeling problem of multi-state degrading systems, under the interaction of multi competing failure modes and random shocks [48]. The common shared by these models is the presence of change points, such as the defect point in two-stage model and the starting/finish points of each stage. Generally, the unknown locations of these change points have to be determined by selecting appropriate detection methods before model identification and RUL estimation. This problem has been considered as highlight but also aporia. Currently, the maximum likelihood estimation, stochastic filtering, and control charts are the most popular methods to estimate the change points in multi-stage degradation models. Thus, the accuracy of change points estimate has direct influence on the accuracy of the RUL estimation. Another popular multi-stage degradation process for RUL estimation is the Markovian model. To model the hidden degradation process, Hidden Markovian Model (HMM) was first introduced to RUL estimation and condition based maintenance (CBM) [49]. On this basis, Dong et al. proposed the RUL estimation framework by using Hidden semi-Markov Models (HsMM), which extends the exponential assumption of state sojourn time to more general situations [50]. He and Dong extended the work in [50] and obtained RUL estimation through a comprehensive consideration of sojourn time in each state which has been modeled by a single HsMM [51]. Prognosis of both performance and RUL were achieved in [52] by a combination of HsMM and AR model for time series data. Giorgio, Guida and Pulcini considered the age- and state-dependency of the degradation process in the framework of Markovian degradation model [53, 54]. A very good result was obtained when the proposed models were applied to the degradation process of marine engine cylinder.

The proposition of these models improves the accuracy of degradation modeling, and enriches the selections of models for different degradation processes. However, almost all multi-stage degradation models face the problem of determining the number of degradation stages, and a large amount of training data as well as a complex computation procedure are needed for parameter estimation. Further, instead of a derivable analytical solution to the PDF estimate of the RUL, a time-consuming simulation based methods have to be executed. In addition, the RUL estimation in multi-stage degradation models is based on the information since the latest change point. Such an estimation of RUL is accurate if there will be no change occur in the future time of the system. In more practical situations with possible change points in the future, severe bias will be introduced into the RUL estimation if using such estimation mechanism, i.e., ignoring the possible change points in the future. To tackle this problem, the possible change points in the future should be considered in multi-stage degradation processing modeling and RUL estimation.

1.3.3 Covariate Hazards Model

Factors that affect degradation in performance of systems are defined as covariates in engineering pactive. The classical model for lifetime analysis, named proportion hazards model, is the most widely used ones in the fields of RUL estimation, reliability analysis/evaluation, decision-making and optimization on maintenances, etc. The existing works related to hazards models have been reviewed in [55]. The description of the system failure rate is the core of the proportional hazards model, and also the key for reliability assessment and RUL estimation. Failure rate in the proportional hazards model usually consists of the product of a reference failure rate function $h_0(t)$ and the covariate function $\psi(\boldsymbol{\beta} \boldsymbol{z}(t))$,

$$h(t|\boldsymbol{z}(t)) = h_0(t)\psi(\boldsymbol{\beta} \boldsymbol{z}(t)),$$

where $\boldsymbol{z}(t)$ are the covariate variable, $\boldsymbol{\beta}$ are the regression coefficients which can be estimated using historical lifetime data or censored lifetime data of the system from the same category. Proportional intensities model and proportional covariates model, developed from the proportional hazards model, are also popular models for RUL estimation [].

In heterogeneous working environments, the failure rate of the system will be affected. Ye et al. studied the influence of heterogeneity in the working conditions on the estimation of the RUL, based on the analysis of accelerated life test [56].

A system may experience fixed, time-varying, and even stochastic environmental conditions and the corresponding covariates may also be constants, time-varying or even random variables. In order to characterize the influence of random covariates on the failure rates in the proportional hazard models, researchers have considered using some stochastic process to model the time-varying covariates, and incorporating the modeled covariates into the proportion hazard models. For example, Markov chains, which can naturally describe the operating process of a system, are the most frequently used process to model the changing procedure of covariates [57–59]. A HMM with a known state transition law was utilized to model the stochastic degradation process, and the formula to calculate the mean RUL was derived in [60]. Lu and Liu studied the relationship between failure rates and the dynamic working environment [61]. In their research, the changing covariates were modeled by a two states (normal/severe) Markov Chain, as such, failure rate functions are changing with operation function, and the lifetime of the system can then be determined by its working conditions.

Although their strong explanatory property makes covariate hazard models dominant both in theory and application researches, this kind of method does have some inborn limitations, which have been summarized by Si et al. in [11]. Furthermore, some difficulties should be solved before the practical applications of this kind of methods. First, with the development of high reliability and small amount systems, the lifetime data required for estimating parameters $\boldsymbol{\beta}$ and reference failure rate function $h_0(t)$ are difficult and expensive to obtain. Second, it is hard to determine the form of covariate function when systems become complex.

1.3.4 Degradation Models Involving Random Shocks

During the degradation process, a system may suffer various kinds of shocks, which will impact the performance of the system as well as its underlying degradation process. Typically, there are five different types of random shock models existing in the literature [62]: (i) extreme shock model: the system fails when the size of a shock is beyond a specified threshold value; (ii) cumulative shocks model: a system fails when the accumulated damage of shocks is beyond a critical level; (iii) m-shock model: a system failures after suffering m shocks whose sizes are greater than a critical level; (iv) run shock model: failure occurs when there is a series of n consecutive shocks that are greater than a threshold; and (v) shock model: a system experiences failure when the inter-arrival time of two sequential shocks is less than a threshold. As for reliability modeling and RUL estimation under random shocks, there have been a number of studies including [63, 64] to which we can refer. Random shocks, whose influences on the performance of a system are addressed in this section, are regarded as heterogeneity in the working environment. In general, failure is a result from the interaction and competition of the performance degradation and external random shocks [65–67]. Poison process (homogeneous/nonhomogeneous) [68], Markov Chains [69], and the phase-type distribution [70, 71] have all been used to describe the arriving process of random shocks. Models for degradation processes with random shocks can be divided into two categories here, according to the existing of interdependency between the continuous degradation processes with random shocks.

Degradation processes and random shocks are supposed to be independent of the first type of models. Klutke and Yang first proposed an availability model for the system under interaction of degradation and random shocks [65]. Afterward, Huang and Askin analyzed and constructed a reliability model for systems under the competing impact of the degradation process and sudden failure [72]. Li and Pham proposed a reliability model for a system suffering two types of degradation and a type of random shocks [73]. Chen and Li assumed that from the external environment the degrading system may experience two types of random shocks, i.e., fatal or nonfatal [74]. An optimal maintenance strategy was proposed under a further assumption that system's tolerance of the total number of nonfatal shocks decreases subjected to the times of maintenance. A common underlying assumption of the works in [65, 72–74] is that degradation processes causing softer failures and random shocks leading to hard failures are independent from each other, and no mutual influence between degradation and shocks exists.

The interactions between shocks and degradations are considered in the second type of models. When studying the reliability and maintenance model for the system under competing degradation process and random shocks, Wang and Pham supposed that fatal shocks caused a direct failure of the system while nonfatal shocks resulted in abrupt increases in the degradation level [75]. The interdependency of soft failure caused by degradation and the hard failure caused by random shocks was included in Peng's work about reliability modeling [76]. Liu et al. considered the relationships between the failure rate of a system with age, degradation level and their interactions in the degradation model [64]. Recently, Koosha studied the influence of various types of random shocks on the degradation processes of the system and supposed that the level of degradation process jumped once a shock came while the degradation rate changed only after a particular type random shock [62]. A reliability model for dependent competing failure processes with changing degradation rate was then proposed based on this dependency of degradation process on random shocks.

The primary drawbacks of using such kind of methods are the following: (1) Lots of existing works incorporated random shocks to the linear degradation process, while degradation processes of actual systems are often nonlinear. To be more practical, the influence of random shocks on nonlinear degradation processes should be considered, which has seldom been done except [76, 77]. (2) As for discretely inspected system, the time and influence amplitude of random shocks can hardly be measured directly, which may introduce extreme difficulties in model identification and parameter estimation. (3) In cases where the dependency between degradation processes with random shocks is considered, attention has been focused on the influence of random rocks on (levels and rates) degradation process, while researches about impact of degradation on random shocks and the interdependency between each other are rarely reported except for [77, 78]. (4) Random shocks in degradation models are assumed to be negative, causing the increase in degradation level and even the failure of the system. However, there exist some shocks improving the system's performance, e.g., the state-of-health regeneration phenomena in lithium-ion battery systems. As such, this kind of shock should be further considered into the degradation process in the future.

1.4 Methods Considering the Impact of Tasks and Workloads

1.4.1 Degradation Modeling for Systems with Dynamic Workloads

Due to the diversity and randomness in the operating environments and workloads of systems, the characteristic of degradation varies with age throughout the whole lifetime cycle. If the dynamic operating model of the system's workload is constructed scientifically and incorporated into the degradation model reasonably, a more accurate estimation of the RUL will be achieved.

During the industrial applications, some systems change their working state in several different working modes, corresponding to which are the different workloads and various degradation processes. For example, a missile weapon system with an extremely long storage before being launched may experience different working states involving storage, transportation, inspection and maintenance during its service. Studies have shown that, due to influences of temperature, humidity and human factors in the storage conditions, the performance of gyroscopes installed in an inertial navigation system (INS) exhibit some decreasing trends, which will be accelerated by each electrifying inspection, after some time of storage [79]. Moreover, the states switching of the system is a stochastic process, because of the uncertainty in the coming of different tasks or missions A continuous-time Markov model (CTMM) with finite state is a natural selection to describe such a stochastic operating process [80, 81]. In literature, CTMM was used to capture the time-varying random working conditions of a system in Jeffrey and Steven's stochastic models for degradation-based reliability [82]. Si el al. also utilized two-state CTMM to represent the states switching process between storage and usage, and the operating model was successfully applied to estimate the remaining storage life (RSL) of gyroscopes in INS [83]. Hawkes proposed a reliability assessment model based on the CTMM modeling of working condition switches. Huynh modeled changing working conditions using CTMM and incorporated the results into the decision-making framework for adaptive CBM decisions [84]. Another focus when the dynamics of the workloads are of concern is to establish the relationship between the operating conditions and the degradation process of the system. This relationship is usually supposed to be totally known or at least particular functions with unknown parameters which can be estimated by using the observations of both operating conditions and degradation process. Jeffery pointed out that this relationship varies case-by-vase and should be determined according to the specific characteristics of the device [82]. When Wiener process was used as the degradation model, Si el al. assigned different drift coefficient values for the system in the state of usage and storage, respectively [83]. Besides, Arrhenius model and Eying model are frequently used to represent the relation between the degradation and working environments for electromechanical systems.

It is worth noting that the existing methods suffer some limitations. On one hand, the primary limit of CTMM is that the sojourn time in each state is exponentially distributed, which may be incompatible with the facts in practical applications in industry. To overcome this shortcoming, a semi-Markov model can be employed. Besides, when the operating information cannot be recorded directly, the according HMM and HsMM should be used to model the operation process of the system. On the other hand, with more and more complex structures of systems, the relationship between the degradation with operating conditions can be neither characterized by the simple existing laws, nor constructed through physical analysis, which may restrict the application of this kind of methods.

1.4.2 Degradation Modeling for System with Maintenances

Maintenance is an effective way to remove faults, reduce failure rates and improve the reliability throughout the lifetime of the system. Scientific and reasonable maintenance schedule can efficiently reduce the operating costs and the risks of the system, which also works for degrading systems [85]. Degradation modeling and maintenance activities of systems are closely related. On the one hand, the results of reliability evaluation and RUL estimation based on the degradation data offer the health evaluation information required for scheduling maintenance activities. On the other hand, maintenances improve the performance of the system and thus change the degradation path. To extend the application of the degradation model and improve the accuracy of RUL estimation, the influence of maintenance on degradation should be taken into consideration.

There are plenty of studies addressing preventive maintenance and optimal inspection based on degradation modeling [86–88], and some relate to the effects of maintenances on systems' performance [89, 90]. Popular models include the 'repair as new' model and the 'repair as old' model [91]. Both kinds of models assume that the performance of the system will be improved by maintenances, and the hazards functions are used to describe the effects of maintenance activities. In the 'repair as new' model, the system can be restored to the original state after a perfect maintenance, usually corresponding to the hazard increasing model [92]. The 'repair as old' models assume that maintenances on a system are imperfect so that the performance of the system recovers to a level worse than that of new system [93] Besides, the system degrades until the next maintenance or failure whichever comes first. Recently, Wang et al. employed a renewal-reward process perturbed by a diffusion, which is also defined as a Wiener process with random jumps elsewhere, to model