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Topical Review

Status and prospect of the development of modelling technology for accelerated degradation of CNC machine tool reliability

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Abstract

As a fundamental technology for functionality and performance, studying CNC machine tool dependability is a challenging system engineering undertaking. For the design, analysis, and improvement of CNC machine tools, reliability modelling is crucial, and accelerated degradation modelling is an important subfield that should not be disregarded. This method provides innovative solutions to the problems of attaining high reliability and long life in engineering applications. Performance degradation modelling and acceleration modelling are the two primary categories of accelerated deterioration modelling. Stochastic process models, degradation trajectory models, degradation amount distribution models, and others are often used models for accelerated degradation. Physical, empirical, and statistical acceleration models are the three most often utilized types of acceleration models. This study analyses and discusses the features and application breadth of accelerated deterioration modelling technology for CNC machine tools based on a summary of domestic and international research findings.

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It emphasizes the introduction of cutting-edge artificial intelligence technology and the reliability accelerated degradation modelling approach while taking into account multi-source uncertainty parameter coupling and nonlinear operating conditions. Lastly, accelerated deterioration modelling's future development path is anticipated for industry development requirements and engineering technology application.

Keywords: CNC machine tool, reliability, accelerated degradation modelling

1. Introduction

While the development of high-end equipment and emerging industries continues to accelerate, the country is actively supporting the traditional manufacturing sector to accelerate the transformation and upgrading of the strategic background. In China's manufacturing industry, automated, digital, and intelligent production has steadily risen to the top of the market. Companies urgently need to provide reliable, high-quality products quickly to gain a competitive edge. High-end CNC machine tools, the core machinery of the manufacturing industry, are closely related to the technical capability of a country's equipment manufacturing sector [1]. At present, domestic high-end CNC machine tools are approaching the international advanced level in terms of accuracy, speed, multi-axis connection, composite functions, intelligence, and other aspects. However, the reliability problem is very obvious, the failure rate is high, and the advanced functions are difficult to maintain during operation [2]. Since the reliability test of CNC machine tools is costly and time-consuming, the reliability study approach for electronic equipment faces several practical application obstacles [3].

Researchers have discovered in recent years that the possible performance deterioration of highly dependable and long-lasting mechanical products builds up gradually and ultimately results in failure or malfunction. This discovery has led to the development of the degradation modelling methodology [4]. Degradation modelling evaluates a product's degradation status by fitting the decline trajectory of its performance parameters, rather than testing to full failure, which significantly decreases the time required for reliability testing. However, the CNC machine's intricate and highly interwoven structure results in a very slow degradation process, which means that traditional degradation testing still has issues with lengthy test cycles and expensive costs. In this context, accelerated degradation modelling has steadily emerged as a research hotspot. It considerably reduces the cycle of gathering degradation data and speeds up a product's degradation process by applying a stress level above typical use conditions while maintaining the consistency of the failure mechanism [5, 6]. Since CNC machine tools are complex electromechanical systems with multiple physical fields, their operating conditions are complex and variable. By using a load loading device to simulate the host machine's or functional components' actual operating conditions, the accelerated degradation test (ADT) can accurately reflect the degradation law in real-world use.

In summary, CNC machine tools integrate mechanical, electrical, and hydraulic control into a unified system. The coupling effect and subsystem interactions are substantial, and the precision and efficiency of their work have a direct impact on the quality of the final product. Due to the high value and complexity of CNC machine tools, conducting ADTs is costly and difficult, and the requirements for applicability of their accelerated degradation modelling methods are more stringent than those for ordinary mechanical products. Figure 1 illustrates the methodology flowchart for accelerated degradation modeling.

This study outlines the applicability of accelerated deterioration modelling to CNC machine tools, analyses advancements in accelerated degradation modelling for remaining life forecast and reliability assessment, and then looks at future perspectives for accelerated degradation modelling.

2. Performance degradation model

2.1. Degradation trajectory model

The degradation trajectory model represents one of the earliest and most widely studied approaches in performance degradation modelling. This methodology involves analysing the characteristics of degradation data, selecting appropriate regression curves for data fitting, or establishing degradation trajectories based on failure mechanisms. Subsequently, the model extrapolates the time-to-failure to predict product lifespan under normal operating conditions. For mechanical products with well-established or extensively researched failure mechanisms, models constructed based on intrinsic physical principles exhibit high reliability. Such models provide a robust theoretical foundation for product optimization, as they are grounded in mechanistic understanding rather than purely empirical fitting. Key advantages of this approach include its ability to integrate domain-specific knowledge of degradation processes, thereby enhancing model interpretability and predictive accuracy. This makes it particularly suitable for applications where mechanistic insights are available to guide model formulation. To simulate the performance degradation of bearings, Wang *et al* [7] established a multi-physics field effect coupling model by exploring the failure mechanism of high-speed bearings under impact and friction. In a similar vein, Kim *et al* [8] proposed a degradation model for forecasting the fatigue life of welded joints by integrating the fatigue fracture mechanism into the Gaussian regression procedure. The

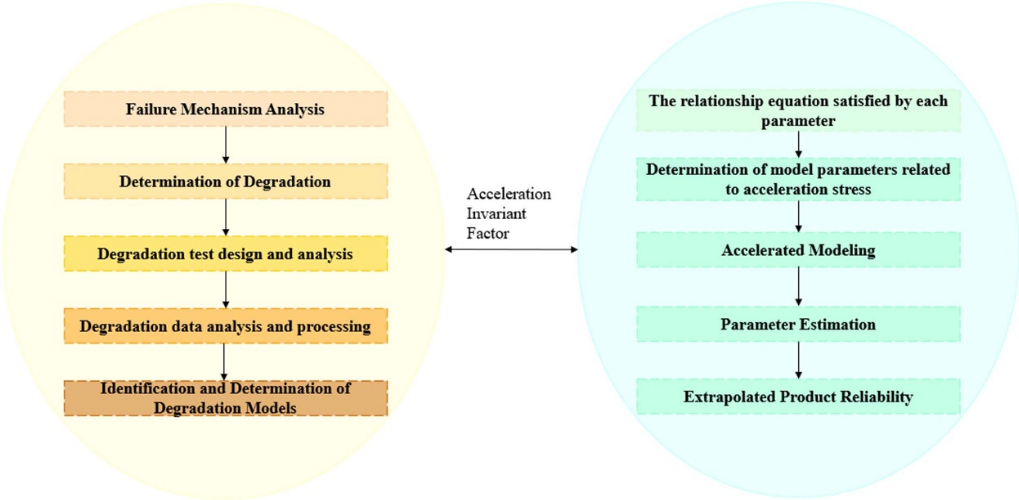

Figure 1. Flowchart of accelerated degradation modelling approach.

identification of the primary mechanism of failure in mechanical products constitutes the foundation of constructing a failure physical model. However, given the complexity of the failure principle of CNC machine tools, it is challenging to directly produce a failure physical model for them. Consequently, researchers typically utilize the deterioration of associated mechanical components to infer the degree of degradation of critical functional components of CNC machine tools. For instance, Luo *et al* [9] developed a radial error motion degradation model of the electro-spindle based on the Hertz contact theory and Archard wear theory, taking into account the fluctuation of the degradation law of the electro-spindle under various loading situations.

Mechanism analysis is a challenging method; yet empirical regression fits the data to the deterioration trajectory, allowing for quick reliability modelling. It is also uncomplicated, easy to use, and has a wider range of applications. As the study went on, researchers discovered that the majority of mechanical goods had nonlinear degradation routes, even though the majority of the early models of deterioration trajectories fitted the degradation data using linear models. Li *et al* [10] established the corresponding degradation model by fitting the accuracy degradation data of a gantry boring and milling machine induced by beam creep using a normal distribution. Kim *et al* [11] developed a mixed-effects degradation trajectory model to describe the nonlinear degradation of mechanical goods and showed that it outperforms alternative models regarding goodness of fit. Sun *et al* [12] established a generalized degraded trajectory model based on the concept of nonlinearity by also incorporating the mixed factors of individual product variability and the external environment. To better determine the degradation trajectories, Kong *et al* [13] created a thorough residual life prediction framework that not only accounts for measurement errors and random shocks but also chooses the best degradation model from several candidate models and validates its applicability using data from milling machines. Data on CNC machine tool degradation is more limited than that of other mechanical goods because of the high costs of downtime and the difficulty of measuring data in the real production environment. Based on this, Duan *et al* [14] used a machine learning approach to create a degradation trajectory model with a small sample of data. They then used multivariate regression analysis to examine the degradation trajectories of several parameters of a joint CNC machine tool to achieve the reliability assessment of CNC machine tools. To estimate the remaining life, Fan *et al* [15] used a degradation path approximation model. The model's prediction accuracy was incredibly high, and its suitability for CNC machine tool goods was further confirmed.

The limited accuracy of traditional degradation trajectory models has been addressed through various methodological improvements; however, model performance remains susceptible to noise and missing data. In the case of CNC machine tools, degradation trajectory models often involve multiple unknown parameters, significantly complicating parameter estimation. While this approach is effective for modelling nonlinear degradation processes, its applicability depends on high-quality data inputs. Consequently, degradation trajectory modelling is best suited for mechanical systems under continuous or periodic monitoring, where data integrity and completeness can be ensured.

2.2. Degradation volume distribution model

The performance degradation modelling approach based on the distribution of degradation quantities has significant advantages in the following two cases due to the unique modelling idea. One is that mechanical products'performance degradation trajectories vary greatly, and it is challenging to estimate the parameters of the performance degradation model with any level of precision using the first two modelling approaches. Second, it is impossible to test a product's performance degradation data frequently, and modelling the degradation process of each specific product is difficult. For example, certain products' measurement procedures are destructive, therefore, each product only receives one performance deterioration data point [16]. Methods based on the distribution of degradation volumes model the total degradation volume of the sample rather than the degradation trajectories of individual goods. Jin *et al* [17] assumed that the degradation data obeyed a normal distribution, used the degradation amount distribution method to establish reliability models for several hydraulic components under a single failure mode, and fused these models through a competitive failure model to examine the degradation process of fluid contamination. Likewise, Zi *et al* [18] applied the method based on the distribution of degradation quantity to the reliability assessment of electric spindles, thus demonstrating that this approach shortens test time and improves assessment accuracy, which is of some significance to the reliability study of long-life products.

By simulating the product's degradation distribution law at each measurement point, the degradation distribution approach achieves reliability assessment. Despite significant research, the degradation distribution model still has flaws. First, there is a strong probability that the degradation distribution model will differ from the real scenario, since the quantity of deterioration of a CNC machine does not always follow the same distribution at each detection point. Second, models of degradation distribution typically include the glaringly unrealistic assumption that degradation at various measurement points is independent. Moreover, the degradation volume distribution model is only helpful for characterizing basic degradation processes because it is hard to expand and cannot account for a range of stochasticities, including measurement mistakes. Therefore, to better serve the reliability assessment of long-life and high-reliability products, the researchers must thoroughly analyse and improve the degradation distribution model, which is currently still a mathematical model with an imperfect structure, to explore its potential in the field of degradation modelling.

2.3. Stochastic process models

In practice, the degradation process of CNC machine tools frequently manifests significant randomness. This randomness can be attributed to various factors, including minor variations in raw materials, dynamic fluctuations in the operating environment, random errors in measurement processes, and potential inherent defects. However, the prevailing assumption in the field is that degradation trajectory models presuppose an underlying degradation path and subsequently fit degradation data based on this path. This assumption represents a significant simplification of the actual situation by ignoring the dynamic stochasticity of the degradation process [19]. Stochastic process models have great potential to capture stochastic dynamic properties, and thus degradation analysis and remaining life estimation based on stochastic modelling have been favoured by many researchers [20]. Three conditions need to be met when stochastic process models are used for modelling degradation processes: first, they can reasonably explain the physical mechanisms of product degradation processes, second, the models should be clear and intuitive, which is convenient for researchers to understand and use, and third, the models should be of good mathematical properties, and be able to flexibly incorporate the information of covariates, random effects, and so on. After much research, the Wiener process, the Gamma process, and the inverse Gaussian process have become the most commonly used stochastic process models for modelling degradation.

The most common and extensively researched model in the subject of degradation modelling is the Wiener process. Originally developed to characterize thermal noise in electronic devices—that is, random fluctuations in voltage brought on by the movement of charge loads [21], the Wiener process was later applied to the reliability modelling of mechanical systems after researchers discovered that cumulative fatigue in mechanical products displayed a similar randomness [22]. To improve the model accuracy, Li *et al* [23] constructed a generalized Wiener process model by introducing time variability and measurement error into the traditional Wiener process. Li *et al* [24] further considered nonlinearity, uncertainty, and incomplete maintenance to establish a comprehensive accuracy degradation model for key CNC machine tool components. High-end CNC machine tools frequently work in dynamic environments in real-world engineering applications, and time-varying stress has a substantial impact on how well they function. By avoiding the drawbacks of linearization or incremental modelling, Jiang *et al* [25] presented an adaptive Kalman filter (UKF)-based RUL prediction method that improves RUL prediction accuracy by directly describing the dynamics and nonlinearity of the degradation process through a nonlinear state space model. Cheng *et al* [26] investigated the ball screw mechanism's accuracy deterioration process while taking load operating conditions and time-varying motion into account. They also suggested an accuracy degradation analysis framework. A deep state space model framework was developed by Tanzeem [27] for sensor-driven modelling and monitoring of intricate dynamic degradation systems functioning in various operating environments. Valis *et al* [28] assessed and forecasted the drill tool system's degradation using the state space model and the stochastic diffusion process. The model outperforms the Wiener process with drift in terms of prediction accuracy. Measurement errors in the ADT are due to reasons such as insufficient accuracy or improper operation of the measuring instrument, and have a high degree of uncertainty. Ge *et al* [29] and Li *et al* [30] both addressed the characterization of measurement errors during degradation. In past studies on the Wiener model, the unknown parameters are usually considered independent, but the degradation rate of the actual product is affected by the material properties and the fluctuation of temperature and humidity in the working environment. The correlations of the model's unknown parameters were included in the proposed degradation model by He and Tao *et al* [31] and Yan *et al* [32]. When modelling the degradation process of CNC machine tools, multiple indicators characterizing their performance degradation are usually used, and there are correlations among these indicators. Yang *et al* [33] established a multivariate degradation model for rotary encoders based on the Wiener process theory. They expressed the association between various degradation features using a

Copula function. The D-vine Copula approach, which is superior to the Copula method in modelling effect, was used to represent multivariate dependencies in the generalized Wiener process put out by Sun *et al* [34]. Additionally, a multi-stage degradation process is caused by the interactions between the CNC machine tool subsystems. Yan *et al* [35] created a physical model and a two-stage Wiener model to describe the fatigue degradation process in spinning machinery. Wang *et al* [36] looked into a two-stage degradation model based on the degradation angle to precisely pinpoint the transitions between the various stages of degradation.

To model the accelerated degradation of CNC machine tools, it is worthwhile to establish degradation models with the coupled influence of multiple error sources. This is due to the fact that the degradation of such high-precision products as CNC machine tools is primarily related to high-speed operation, temperature and humidity changes, and heat generated by friction. This results in reduced machining accuracy and thermal deformation errors of the machine tool.

The wear and fatigue crack propagation of mechanical products is a constant, cumulative process; that is to say, the degradation process changes monotonously. In such circumstances, it is more appropriate to use the same monotonous Gamma process for modelling. Zhang *et al* [37] used a multi-objective optimization technique to optimize the Gamma process-based accelerated deterioration test. Similar to this, the Gamma process has outstanding mathematical qualities. In order to represent the heterogeneity across various goods, Duan and Wang [38] created an accelerated deterioration model based on a non-smooth Gamma process and took random influences into account. The degradation process of CNC machine tools exhibits temporal variability, with the degree of degradation varying across its various positions due to the influence of material properties and the working environment. Oumouni *et al* [39] proposed a spatiotemporal stochastic model based on the Gamma process to evaluate the impact of this temporal and spatial variability on the degradation process of mechanical structures. By introducing stochasticity on a spatial scale, this model can more accurately predict the degradation paths of mechanical products. In addition, Dai *et al* [40] examined a conditional bivariate Gamma model for the wheel wear degradation process and integrated it with a Bayesian hierarchical model to greatly enhance the model's predictive power. By assuming that the rate of degradation is altered at random, Ling *et al* [41] suggested a two-stage degradation model based on the Gamma process, which makes the model more adaptable to the degradation process. Sudden modifications to the deterioration process.

The independent increment of the Wiener process is found to adhere to a normal distribution. This distribution can be simplified by standardization methods, thereby significantly reducing the complexity of the model. Conversely, the Gamma distribution of the independent increments in the Gamma process is intricate and challenging to operate, resulting in elevated model complexity, which considerably restricts the scope of its application. This is especially evident in the context of reliability analysis of CNC machine tools, where the failure process frequently involves multiple degradation feature quantities, necessitating the construction of multivariate and multi-stage degradation models, resulting in a substantial increase in computational demands. The interconnection of multiple degradation modes within CNC machine tools poses a significant challenge to the Gamma degradation model, further restricting its applicability. In addressing these challenges, Jin *et al* [42] proposed a comprehensive Wiener model and a Gamma model. The Gamma process is strictly monotonic; however, the CNC machine tool's accelerated degradation process increases the probability of sudden failures due to the chain reaction between the various subsystems. The hybrid model has been developed to address these limitations by encompassing the features of multiple performance indicators and thereby providing a more comprehensive assessment of system reliability. It is anticipated that this hybrid approach, which combines the benefits of the two, will be crucial in future, more realistic applications and is better able to manage the reliability analysis of CNC machine tools under challenging operating situations.

In addition to the Wiener and Gamma process models, the inverse Gaussian process model is another natural choice for analysing the degradation data, which also provides monotonic degradation paths [43]. Although Wang *et al* [44] looked at an ideal design approach for ADTs of step stresses based on the inverse Gaussian process, this study's degradation data handling is still statistical. He *et al* [45] applied the objective Bayesian method to the parameter estimation of the accelerated degradation model based on the inverse Gaussian process and proved that this method is more scientific and reasonable compared with the traditional statistical method. Taking into consideration the skewed normal distribution of the random effects and the measurement error, Hao *et al* [46] expanded the conventional inverse Gaussian model to better fit the degradation data and bring it closer to the real degradation process of mechanical products. Zheng *et al* [47] further incorporated the unit heterogeneity and nonlinear parameter stress relationship into the degradation model and proposed a two-step parameter estimation interval estimation method. Facing the situation that there are multiple performance degradation characteristics of CNC machine tools, Fang *et al* [48] established a multivariate inverse Gaussian degradation model, so that the model can more accurately deal with multidimensional degradation data.

The inverse Gaussian process has been demonstrated to be a highly effective model for the analysis of mechanical products characterized by monotonous degradation paths. However, its application in the context of accelerated degradation modelling of CNC machine tools is not without its limitations. However, the current research on the inverse Gaussian model largely ignores the effect of measurement error, which raises the data demand for modelling using the inverse Gaussian process. The degradation process is frequently non-monotonic when some parts of the CNC machine tool undergo sudden failure, and at this time, the inverse Gaussian process is no longer applicable. Additionally, the multi-stage, multi-variable degradation model based on the

Table 1. Comparison of the scope of application of the three stochastic processes.

	Applicable degradation patterns	Typical parts for CNC machine tools
Wiener process	Typically used to characterize random degradation with drift	Electric spindles, guideways, spindle bearings, gearboxes, etc.
Gamma process	Suitable for modelling strictly monotonically increasing degradation processes, but with limited applicability to complex degradation features.	Tool wear, guides, screws, etc.
Inverse Gaussian process	Suitable for modelling parts with defined failure thresholds	Lubrication systems, seals, etc.

inverse Gaussian process needs to be further investigated. The application comparison of the three aforementioned stochastic degradation models is shown in table 1.

2.4. Other performance degradation modelling

One of the main problems faced in improving the accuracy of degradation modelling of CNC machine tools is the lack of degradation data, and a single type of data source cannot fully describe the degradation process of complex products. The small sample problem can currently be solved in two ways. In order to create a more accurate reliability model with a limited amount of data, the first way involves fusing the reliability data of CNC machine tools at different phases. Zhang *et al* [49] created a reliability model based on the Wiener process by fusing the multi-stage degradation data of a CNC system's servo drive unit using a Bayesian technique. Traditional Bayesian methods in reliability modelling usually rely on empirical *a priori* distributions to determine model parameters, and such *a priori* assumptions based on subjective perceptions may lead to significant deviations between the modelling results and the actual working conditions. To address this issue, Chen *et al* [50] suggested a small-sample reliability modelling technique based on Bootstrap-Bayes and confirmed that the findings of this technique are more accurate by simulating the machining centre spindle. The second approach addresses the issue of inadequate sample size by extending the degraded dataset with small samples using machine learning, artificial intelligence, and other approaches. Using generative adversarial networks and learning with limited examples, Ma *et al* [51] suggested a way to expand the degraded dataset. In order to create virtual samples, Cai *et al* [52] combined the Bayesian neural network (BNN) and differential evolution algorithms with MTD techniques. They also built a reliability assessment model based on BNN, which increases sample generation accuracy and effectively addresses the small sample problem. In order to obtain an accurate reliability assessment, Sun *et al* [53] employed the Worm Wasserstein generative adversarial network learning approach, which is based on the expansion of small-sample time series data and does not require any *a priori* knowledge or assumptions.

The iterative upgrading of information technology has resulted in the development of intelligent modelling techniques that are driven by big data. These techniques are profoundly changing the research paradigm in the field of degradation modelling. To illustrate this, the health management of mechanical products is used as a case study, and it is demonstrated that deep feature mining and fusion processing of heterogeneous data from multiple sources can yield significant benefits. Wang *et al* [54] established a stochastic degradation model based on the Wiener process and used empirical mode decomposition to extract the drift increment. They then learned the device degradation law through the LSTM network to predict the drift increment. Guo *et al* [55] processed the data by combining adaptive noise and kernel principal component analysis with a transformer to construct a new type of health indicator, which realized the comprehensive utilization of the information content in the degraded data. The foundation for analysing the defect evolution process of CNC machine tools is degeneration modelling. Conventional fault detection techniques primarily rely on probability statistics and expert experience, both of which are limited and simplistic and are unable to handle complicated and high-dimensional test data. Early fault detection has made extensive use of deep learning because of its potent feature extraction and pattern recognition capabilities. Luo *et al* [56] achieved early failure identification of CNC machine tools under time-varying operating settings using dynamic feature recognition and automatically selected the shock response from long-running machine vibration data using a deep learning model. Through data fusion approaches, Wang *et al* [57, 58] combined data from several sensors, which can more accurately reflect the system's operating status and increase the accuracy of problem prediction.

The desire for complicated system modelling has caused graph structure data to expand at an unprecedented rate. Graph neural networks (GNNs), the most advanced deep learning technique, have quickly taken the machine learning world by storm [59]. The issue that traditional RUL prediction algorithms rely on sensor time series data and ignore device structure information is resolved by Wang *et al* [60] proposal of hierarchical GNNs that combine sensor-level and module-level structural information. Xiao *et al* [61] presented a heterogeneous graph representation-driven multiple aggregation GNN to more thoroughly capture the bearing deterioration mode. Other models already in use are to blame for this model's prediction accuracy. Habibollahi Najaf Abadi and Modarres [62] suggested a dual neural network framework that can adjust to the circumstance of data scarcity and incorporated the physical degradation mechanism into the neural network. Another significant area of artificial intelligence technology, deep reinforcement learning (DRL), has progressively demonstrated special benefits in the areas of RUL prediction and degradation modelling. In order to address the issue of manufacturing system deterioration, Paraschos *et al* [63] employed reinforcement learning for the first time to optimize production, maintenance, and quality control procedures in tandem. Zheng *et al* [64] suggested a DRL-based rolling bearing RUL prediction approach to address the issue of classic deep learning techniques ignoring the time correlation between data. Dai *et al* [65] introduced concept neurons into the DRL-based model to improve the interpretability of the strategy while ensuring that the model performance is not reduced. Furthermore, by combining physical models and data-driven techniques, digital twin technology enables the dynamic mapping of the whole life cycle of mechanical equipment. This technology is progressively being used in the field of degradation modelling. Luo *et al* [66] constructed a high-fidelity digital twin model based on physical models, real-time sensing data, and historical operation data to realize the virtual mapping of physical equipment, and applied it to the remaining life of a CNC machine tool prop prediction. Yang *et al* [67] predicted the accuracy degradation of CNC machine tool transmission units using multi-physical field simulation of a digital twin model and machine learning algorithms of sensor data.

Deep learning and machine learning in degradation modelling are boosting the development of multidimensional fusion and engineering applications. On the one hand, the complexity of the interconnections between the factor systems, as well as the limited number of studies on the degradation modelling of the entire CNC machine tool, makes it impossible to explain adequately using the standard single modelling method. Embedding physical mechanism constraints into an artificial intelligence-based degradation modelling technique can significantly improve the model's interpretability and generalization ability, and this approach, which combines the accuracy of the physical model with the adaptability of the data-driven model, may be an effective means of dealing with the difficult problem of degradation modelling of the entire machine of CNC machine tools. On the other hand, artificial intelligence technology is deeply integrated into the degradation modelling, which realizes the online monitoring of degradation data and real-time updating of model parameters through the online learning framework and dynamic self-adaptive mechanism, to better reflect the dynamic degradation process of CNC machine tools. Furthermore, by automatically extracting complicated features and modelling nonlinear interactions, deep learning further optimizes the degradation model's accuracy and efficiency, resulting in more precise predictions and decision assistance for equipment health management.

3. Acceleration model

The accelerated life test (ALT) was initially used for mechanical products to assess the dependability of long-lasting and high-quality products. ALT focuses on product failure. To estimate the product life under normal stress levels, ALT first assumes that the product's failure mode and mechanism are the same as those under normal stress. Then, it tests the samples under stress levels higher than those found in real-world working conditions and uses the stress-life relationship to extrapolate the samples' life information from the high stress level to the normal level [68]. Table 2 lists common faults and degradation indicators of CNC machine tool subsystems. However, even when stressors above normal are applied, it is challenging to get enough failure data for CNC machine tools, and the ALT technique cannot describe how complex dynamic environments and subsystem correlations affect CNC machine tool dependability. By applying loads greater than the actual operating circumstances, the ADT rapidly induces product failure or degradation in order to quickly gather information on product life and reliability. In theory, ADT is not all that different from the ALT; nonetheless, it compensates for the shortcomings of the ALT, which lacks failure data, by recording the product's degradation information under severe stress. The accuracy of accelerated modelling, which serves as the foundation for extrapolating ADT observations to product dependability data under typical use circumstances, has a direct impact on the extrapolation's accuracy [69, 70]. As a key part of reducing production costs and shortening the test cycle, the optimization design of ADT has become the focus of research. Wang *et al* [71] proposed the M-optimal criterion for constant ADT by using the minimum and maximum allowable stress two-level design. Wang *et al* [44] proposed the optimal test scheme of step-stress ADT (SSADT) under IG process with the constraint of total test cost, and proved that the ADT with two stress levels has the best balance between cost and accuracy, which is suitable for engineering application. Ma *et al* [72] first proposed the ALT and ADT mixed experimental design, and the accuracy of the mixed design is better than that of ALT or ADT alone when the sample and cost are limited. Zhao *et al* [73] solved the ADT optimization problem of non-cubic test area under three-stress coupling of motorized-spindle. Guo *et al* [74] proposed a multi-objective optimization method to solve the problem that single-objective optimization cannot meet the demand in practice, and verified it by motorized spindle test. In the field of ADT optimization of CNC machine tools, although significant progress has been made in research, how to achieve the optimal balance between stress level and sample size is still a key bottleneck for practical engineering challenges such as multi-stress coupling, limited sample size and high-test cost. The optimization design of traditional single objective constraint is easy to lead to redundant sample size or high stress level, and the construction of multi-objective optimization model is an important means to solve this problem. In the face of the uncertainty of stress coupling, dynamic adjustment strategy can be adopted, including dynamic adjustment of stress level by using early data, or dynamic allocation of sample size by hybrid experimental

Table 2. Common failure modes and performance indicators of key functional components of CNC machine tools.

Key functional components for CNC machine tools	Common failure modes	Performance indicators
Spindle	Spindle misalignment, bearing damage, loosening of locking parts, damage to components, exceeding the working accuracy, etc.	Spindle vibration speed, radial runout of shaft end
CNC tool holder	Damage to the servo drive motor, damage to the servo driver, inability of the tool disk to operate, inability of the tool disk to be loosened or locked, positioning accuracy exceeding the standard, etc.	Tool holder cutting process vibration, repetitive positioning accuracy
Chain tool changer	Knife drop by robot, abnormal vibration of robot, motor damage, wrong stop position of knife chain, abnormal vibration of knife chain, wrong position of robot, knife stuck by robot, etc.	Robot vibration, knife bin vibration, motor temperature
Rolling linear guideways	Large backlash, unstable movement, ball screw jamming, ball screw vibration, ball screw rotation difficulties, screw bending or deformation, etc.	Preload drag force, top travel parallelism, guideway rigidity

design. In addition, the introduction of transfer learning technology and the use of historical similar product data through domain adaptation methods can effectively reduce the demand for test sample size. The above methods provide a diversified technical solution for the ADT optimization problem in resource-constrained scenarios.

Acceleration models can be classified into three categories: physical acceleration models, empirical acceleration models, and statistical acceleration models.

3.1. Physical acceleration model

Physical acceleration models, which are based on the physical mechanism of product failure, are used to forecast a product's life or reliability under typical use situations. The Arrhenius model and the Eyring model are the two most commonly used physical acceleration models. Researchers introduced the Arrhenius model into the ADT of electronic devices after it was developed for the study of glucose chemical reactions [75]. Since most electronic component failures also involve chemical reactions like electrolysis, they modified the original Arrhenius model [76] to make it more applicable to the mechanical field. The Arrhenius model has been widely used to describe the relationship between temperature stress and product life. For instance, Zheng *et al* [77] used the Arrhenius model to explain how temperature stress level and metal film resistor degradation rate relate to one another. Liu *et al* [78] used the Arrhenius equation to determine the link between temperature and device degradation rate, taking into account the impact of temperature on the preload relaxation of spacecraft joining and disconnecting devices. The Eyring model, which was based on quantum mechanical theory and was put forth by Henry Eyring [79], was used to explain the connection between longevity and temperature stress. As researchers continue to expand it, the Eyring model is gradually able to handle a combination of temperature, humidity, pressure, load, and other stress conditions. CNC machine tools are often subjected to multiple stresses in the actual working environment, based on which researchers have explored various multi-stress acceleration models. Lin *et al* [80] selected temperature, relative humidity, and electric current as the acceleration stresses, and proposed a model for reliability assessment of multi-stress accelerated tests considering heterogeneous samples. Suhir Suhir and Stamenkovic [81] investigated the joint effects of temperature and mechanical stresses on the life of a product. And assessed the reliability of the product by constructing the Boltzmann–Arrhenius–Zhurkov dual stress model. The Eyring model only takes into account independent stress acceleration and overlooks the coupling relationship between the stresses, even though it can explain the multi-stress acceleration of mechanical products. Pan *et al* [82] presented a multi-stress coupled acceleration model that took into account the competitiveness between failure modes and the correlation of different stressors. It was based on the reliability evaluation approach. While the Eyring model can predict life under multi-stress conditions, it has a more complicated parameter estimation process and more experimental design requirements than the Arrhenius model, which has a simpler form and requires less computing effort to estimate parameters.

3.2. Empirical acceleration models

The empirical acceleration model is based on a summary of engineers' long-term observations of product performance. Typical empirical acceleration models include the Coffin–Manson model, the inverse power law model, and others. For instance, the link between product life and stressors like pressure or voltage is described by the inverse power law model.

The link between temperature cycling stress and product life is provided by the Coffin–Manson model [83]. Klemenc and Nagode [84] described the link between fatigue life and stress level using an inverse power law model. They also used several real-world examples to confirm that the model was effective in calculating the parameters of the fatigue life curve. Allegri and Zhang [85] investigated the suitability and constraints of accelerated fatigue testing under broadband Gaussian random loading using an inverse power law model. Although Shohji *et al* [86] did not use the modified Coffin–Manson model for accelerated testing, they did develop a temperature cycling test and study the acceleration factor and activation energy. Zhao *et al* [87] proposed a modified Coffin–Manson model in order to establish the relationship between temperature cycling and product life. Nevertheless, the Coffin–Manson model is rarely used with CNC machines and is only relevant to particular mechanical fatigue and heat loads.

3.3. Statistical acceleration model

Statistical acceleration models are derived from statistical analysis methods and are frequently utilized to analyse data that is challenging to explain through physicochemical methods. The proportional risk model, a statistical acceleration model, was proposed by Cox. Initially applied to survival analysis in the medical field, it was later introduced to the reliability field [88]. The Cox model is capable of accounting for both the internal system characteristics of the mechanical equipment and the influence of external factors such as the environment in which the equipment operates, the load conditions, and the historical operating data on the life of the equipment. A two-fold Weibull proportional risk model was proposed by Zhang *et al* [89] based on condition monitoring data and used for machine tool reliability maintenance. Pham *et al* [90] merged the ARMA identification model, Cox's PHM, and SVM into a toolkit to predict remaining life and measure health degradation based on a machine's typical operating conditions. Furthermore, a combined modelling framework for estimating the remaining service life was suggested by Man and Zhou [91] and is based on the proportional risk model and the Wiener process. The proportional risk model has been shown to successfully correlate failure times with degradation signals. Another widely applied acceleration model for mechanical products is the accelerated failure time (AFT) model, which scales the time axis to represent the degradation pathways under accelerated conditions. Compared to the Cox model, the AFT model is easier to understand because it examines the regression relationship between the covariates and the logarithmic survival time. Its form is similar to that of the general linear regression equations, and the regression coefficients are interpreted similarly. The model is straightforward, understandable, and intuitive. Yin *et al* [92] used a hybrid ML-EM technique to assess the model parameters after studying the generalized AFT vulnerability model. Based on the idea of AFT, Zhai *et al* [93] suggested a Wiener process model in which the unit-specific random effects in the deterioration route are treated as stochastic acceleration effects, resulting in a random scaling impact on the time axis. The generalized log-linear acceleration model has been widely used in the field of reliability because it combines the advantages of the Cox model and the AFT model. Wang *et al* [94] and Zhao *et al* [95] described the relationship between the parameters of the degradation model of an electro-spindle and the impacts of composite stressors, such as mechanical and electrical stresses, using the generalized log-linear acceleration model. Additionally, Gong *et al* [96] used an exponential model in conjunction with an ADT to examine the deterioration law of the ball screw sub-preload force. Although statistical acceleration models often assume that product failures are independent, in real-world applications, there may be some correlation between products. In addition, the majority of statistical acceleration models are linear, which results in significant error when used to represent mechanical products with variable stresses and intricate external surroundings.

4. Parameter estimation

The classification of acceleration models and degradation models is shown in figure 2. The parameter estimate of the performance degradation model and the acceleration model constitute a critical stage in the statistical analysis of the ADT data. The accuracy or inaccuracy of this estimate has a direct influence on the model's accuracy. The great likelihood method is the most widely used parameter estimation technique. In a seminal study, Ye *et al* [97] proposed a great likelihood estimate approach for the Wiener process model parameters, taking into account measurement error. Li *et al* [23] calculated the parameters of an extended Wiener process model using the great likelihood estimation approach and then used a genetic algorithm to identify the optimal parameter solution. Zhang *et al* [98] calculated the parameters of a degenerate process model based on fractional Brownian motion by combining the great likelihood estimation with the discrete binary wavelet transform technique. The great likelihood technique is suited for the scenario where the probability density function of the parameters is explicit; however, in uncertainty theory, there is no probability density but just a distribution function, hence the great likelihood method is no longer applicable. Lv *et al* [99] employed the eigenfunction approach to estimate the parameters in the hybrid model, eliminating the necessity to directly solve the complex likelihood function by evaluating the stochastic process's eigenfunctions. The expectation maximization (EM) approach is a useful means of coping with the problem of missing data for hidden variables in complex degenerate models. Song and Cui [100] created a bivariate degenerate model based on the Gamma process and employed the EM technique for parameter estimation. Furthermore, a two-step approach can be utilized to estimate several unknown parameters in a multi-stress model, as Liu *et al* showed [101].

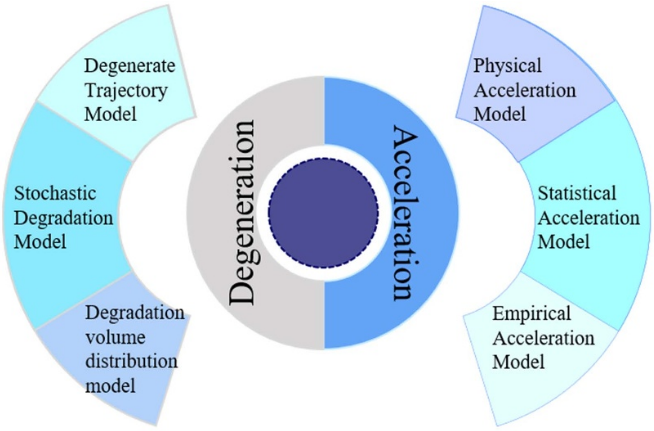

Figure 2. Classification of accelerated degradation models.

5. Summarizing and looking forward

Accelerated degradation modelling constitutes a pivotal component within the domain of reliability engineering, particularly in the context of long-life, high-reliability products, such as CNC machine tools. The theory, technology, and engineering practice of accelerated degradation modelling are reviewed in this work. Researchers and practitioners in this sector can benefit greatly from the systematic summary of this technology's features, methodologies, and adaptability in CNC machine tools. Even if the accelerated deterioration model of CNC machine tools has improved significantly in terms of precision and adaptability, there are still certain issues and difficulties.

(1) The harmony between increasing model correctness and the key challenge of solving parameters. Nonlinearity, measurement error, individual variability, and other sources of randomness all affect the degradation process of CNC machine tools. Therefore, it is necessary to expand the model to accommodate a variety of uncertainties in order to increase the model's accuracy. However, doing so also makes the model more complex, which causes dimensional catastrophe or convergence issues for traditional numerical methods.
(2) The failure mechanism in normal working conditions and the accelerated test are consistent. The accelerated test is predicated on the idea that the CNC machine tool or its essential functioning components should consistently fail under test conditions. However, single stress loading does not satisfy the requirements of simulating the actual working conditions due to the characteristics of CNC machine tool multi-stress coupling, and it is also challenging to express how the machine tool works in the random changes in dynamic stress. Therefore, it is necessary to improve the accuracy of accelerated testing of CNC machine tools.
(3) The internal coupling relationship of CNC machine tool subsystems is hard to characterize precisely. It is frequently challenging to utilize mathematical models to represent the interaction between CNC machine tool subsystems since these relationships are typically nonlinear and time-varying. Even if a model can be developed, it must be predicated on some simplified assumptions. However, the great reliability of CNC machine tools results in a lack of data, which is necessary for an adequate definition of the coupling relationship.
(4) Multi-source uncertainty parameter coupling and nonlinear propagation modelling difficulties. When material parameters, environmental loads, measurement errors and other multi-source uncertainties interact, the traditional model solving method faces the curse of dimensionality, and there may be sudden changes near the inflection point of the degradation process. The traditional modelling method cannot effectively deal with the nonlinear relationship and capture the sudden changes in the degradation process.

This paper summarizes the theoretical innovation and engineering application value of the research on the future application of accelerated deterioration modelling technology in the field of CNC machine tools, which aims to address the aforementioned issues.

(1) Study of the modelling approach for accelerated degradation for various stressors and performance metrics in dynamic operating environments. Because internal stress and external environmental elements vary when CNC machine tools are utilized for various processing jobs, their actual working conditions are subject to frequent temporal variations. In addition, the deterioration of CNC machine tools is caused by a combination of mechanical, thermal, and other stressors, some of which may have intricate interactions with one another. Furthermore, it is challenging to completely describe the deterioration process of a single performance degradation index due to the variety of reasons why CNC machine tools fail. However, the modifications in the product degradation process brought on by dynamic working conditions have not yet been taken into account in the present research on multivariate and multi-indicator degradation modelling techniques. Thus, the future focus will be on how to describe the correlation between multiple stress factors and multiple degradation indicators, how to optimize the ADT protocols for the multi-stress multivariate degradation process, and how to establish a multi-stress, multi-indicator accelerated degradation model taking time-varying operating conditions into consideration.
(2) Studying feature extraction techniques for degradation modelling in multi-source time series data. By using sensing technologies, the obtained degradation data now includes multiple dimensions, like temperature, humidity, and current, rather than just one vibration signal. While multidimensional data enhances the available data sources for deterioration modelling, it also presents additional difficulties. To create a more thorough and precise degradation model through information fusion, the

fundamental process of multi-source time-series data feature extraction entails mining complementary information from various sensors or data sources and extracting important features from these intricate multi-dimensional degraded data. In the past, data degradation and feature extraction were typically accomplished using algorithms like principal component analysis and multi-objective optimization. However, as machine learning has advanced, deep learning-based techniques for data degradation and feature extraction have progressively emerged as a new area of study. To fully exploit numerous data sources and increase the accuracy and robustness of the model, more effective multi-source information fusion techniques for deterioration modelling of small-sample data are urgently needed.

(3) Research on the selection techniques for accelerated deterioration models. Conventional approaches use historical data or engineers' expertise to choose models that describe the deterioration of mechanical products, but these experience-driven approaches have clear drawbacks. First, the method's theoretical foundation is insufficient to guarantee that the chosen model and the real deterioration process match; second, the model's misspecification can have a substantial impact on the reliability assessment's accuracy. The establishment of an accurate accelerated degradation model will be aided by the creation of a thorough model selection framework, a methodical analysis of each model's benefits and drawbacks regarding product characteristics, and the gradual screening and exclusion of inappropriate models.

(4) Research on modelling methods considering various uncertain factors and their propagation paths. In practical engineering, uncertainties exist widely, such as changes in environmental conditions, individual differences in products, inconsistencies in measurement standards, and instability of manual operations. These factors will have a significant impact on the use and degradation process of products. Therefore, when establishing an accelerated degradation model, fully considering the uncertainty factors can make the model more comprehensive and reasonable, so as to more accurately reveal the degradation law of the product. In the face of the complex situation that many uncertain factors coexist in the actual working conditions of CNC machine tools, a single modelling method is often inadequate. By combining the probability model with the non-probability model, a hybrid model can be constructed to describe the influence of uncertain factors on product reliability more comprehensively. Probabilistic models can effectively deal with random uncertainties, such as describing the fluctuation of environmental conditions through probability distribution. Non-probability models can deal with uncertainties that are difficult to describe by probability, such as fuzziness or incomplete information. In addition, analysing the propagation path of uncertainty can better quantify its cumulative effect, so as to optimize the construction and application of the model. This hybrid model can better capture the propagation process of uncertain factors, and then provide a more scientific basis for product design, maintenance and life prediction.

(5) Investigation into the accelerated deterioration test's design and optimization process. Several steps must be done to increase the accuracy of the mapping between the bench acceleration test and the real working conditions. In order to get closer to the service performance of CNC machine tools under test settings, the damage accumulation model first optimizes the load spectrum output in the actual working environment. Second, in order to achieve automatic test parameter updating and guarantee that every parameter is constantly in the optimal combination state, hence optimizing the test gain, the active learning technique from deep learning is incorporated into the optimization design of ADT. Lastly, it is worthwhile to investigate the possibility of developing an error compensation model to bridge the gap between the complex workshop environment and the test environment's parameters.

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