

Erratum

Erratum to “Remaining Useful Life Prediction of Ball Screw Using Precision Indicator”

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In [1], citations in the following sentences were incorrect. The correct citations and references are as follows.

I. INTRODUCTION

EMERGING edge computing (EC), cyber-physical systems (CPSs), and Industrial Internet-of-Things (IIoT) technologies have been vigorously promoting the automation level of enterprises, which puts forward higher requirements for the reliability of the machinery [2]–[5]. As a key step in predictive maintenance (PdM), remaining useful life (RUL) prediction not only provides effective decision support for maintenance strategies but also avoids catastrophic failures and casualties [6]. Therefore, RUL is a hot issue that has been attracting more and more attention in recent years [7].

At the same time, the ball screw, as a high-precision transmission component that converts rotary motion into linear motion, acts a pivotal role in maintaining the normal operation of machine tools [8].

The precision and reliability are constantly threatened by degradation problems, such as grinding, pitting, and cracking [9].

The precision decreasing, as well as the stiffness decreasing of ball screws, will cause the instability of the servo controller and damage the quality of machine parts [10]. Similar to the concerns for other motion components, such as guide rails or bearings, the existing studies on the prognosis of ball screws mainly focus on their abrasion [7], [8].

Therefore, most of the physical-driven methods and data-driven methods are not sufficient to capture the nonlinearity and stochasticity of the degradation process from the limited data in less than one life cycle [11].

The particle filter (PF) is suitable to deal with this issue since it combines the acquired data with the expert knowledge in empirical models [12], which will be applied to reveal the precision degradation process of the ball screw.

B. Related Works

Data-driven methods, e.g., artificial neural networks (ANNs) [13], [14], the Gaussian process regression (GPR) [15], [16], and support vector machine (SVM) [17], [18], leverage data mining to establish the correlation between the acquired data and RUL. To cope with the complexity and uncertainties in prognostics, Cheng *et al.* [19] proposed a novel ensemble long short-term memory neural network (ELSTMNN) model. Verl *et al.* [20] proposed the sensorless automated condition monitoring algorithm based on the signals from the control drive (e.g., position, speed, current, and so on) to monitor the wear status of the ball screw. Li *et al.* [21] conducted in-depth research and experimental analysis on the sensor-less and sensor-rich strategies and used GPR to predict the RUL of ball screws. Mao *et al.* [22] utilized Pearson's correlation coefficient to divide the state of bearings and then applied the least-squares SVM (LSSVM) to establish the RUL prediction model for the fast-degradation state. Data-driven methods rely on historical data throughout the life cycle, while the new machinery lacks historical data to train the model and infer its degradation curve [23].

Physical-driven methods aim to establish a mathematical or physical model to capture the changes in physical properties induced by the deterioration of the machinery [24]. For instance, through monitoring the change of ball pass frequency, Tsai *et al.* [25] detected the preload loss of the ball screw caused by long-term operating. Feng and Pan [26] established a mathematical model of the ball screw and diagnosed the preload variation by the slide of peak frequency and the magnitude of the peak frequency. Xi *et al.* [27] developed a multi-mass model to simulate the frequency shift of the machine axis dependent on wear.

Hybrid methods leverage the advantages of both data-driven and physical-driven methods to perform RUL prediction [28]. Wang *et al.* [29] obtained different representative data through the data-driven method and established the exponential model to extrapolate the degradation curve. Ahmad *et al.* [23] selected the appropriate regression model through the growth rate of the health indicator. To achieve better performance in accuracy and convergence, Baptista *et al.* [30] integrated data-driven methods with Kalman-based models for RUL prediction. Skordilis and Moghaddass [31] proposed a hybrid state-space model to describe the evolution of the system's operating status and its degradation over time.

C. Contributions of This Article

Investigation reveals that the backlash generated by wear is considered to be a significant indicator reflecting the precision degradation status of the ball screw [10], [27].

Manuscript received July 20, 2021; accepted July 20, 2021. Date of current version August 10, 2021. (Corresponding author: Zheng Sun.)

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Digital Object Identifier 10.1109/TIM.2021.3099188

II. THEORETICAL BACKGROUND

In low-power mechanical systems, the backlash phenomenon will interfere with the accuracy and stability of the position loop in the control system, whereas, in high-power systems, they are likely to excite impulse torque, which will further aggravate the growth of cracks and the increase in wear area [32].

B. Basic Theory of PF

In PF, a dynamic system can be characterized through the state-space model comprising the following state transition and measurement function [33]:

$$\begin{aligned} x_k &= f_k(x_{k-1}, v_{k-1}) \\ y_k &= h_k(x_k, n_k) \end{aligned} \quad (1)$$

where x_k is the system state at time k , v_{k-1} stands for the process noise at time $k-1$, $f_k(\cdot)$ is a nonlinear function describing the correlation between x_k and x_{k-1} , n_k is the measurement noise, y_k is the observed value, and $h_k(\cdot)$ represents the measurement function.

However, the analytical solution for (2) and (3) is intractable due to the nonlinear and non-Gaussian systems [33].

A. Backlash Acquisition

Given the inconsistent contact surface characteristics at different positions, the backlash varies slightly at different measurement locations [10].

B. Physical Model Construction

The inherent randomness in manufacturing and operation leads to the stochastic degradation process [34], which can be represented with the following state-space model:

$$\begin{aligned} x_k &= x_0 + \theta t_k^\eta + \sigma B(t_k) \\ y_k &= x_k + n. \end{aligned} \quad (12)$$

C. Data-Driven Methods for Initial Parameter Estimation

Existing studies assume that the initial value is 0 to characterize a perfect state without any degradation [7], [34].

If (15) is appropriately deformed, the optimal value of can be easily acquired, i.e., invert (15) and then apply the quasi-Newton algorithm to acquire the optimal initial parameters [35]:

$$\hat{\Phi} = [\hat{\mu}_\theta, \hat{\sigma}_\theta, \hat{\eta}, \hat{\sigma}^2, \hat{\tau}^2] = \arg \min_{\Phi} \left\{ -\ln L\left(\Phi | \mu_y, \sum_y\right) \right\}. \quad (16)$$

D. RUL Prediction Process

In the online prediction process, observations are used to estimate and update unknown parameters as a form of the PDF, which is expressed by the following form [24]:

$$p(\Theta|y) \propto L(y|\Theta)p(\Theta) \quad (17)$$

where $\Theta = [\Phi, x]$ denote the unknown parameters, y is the observed data, $L(y|\Theta)$ is the likelihood function conditional on the given Θ , and $p(\Theta)$ is a prior function for Θ .

IV. EXPERIMENT AND DISCUSSION

A. Introduction to the Experimental System

2) In the real industrial environment, the wear speed of the guide is much lower than that of the ball screw [21].

In the precision transmission process, the backlash above 10 μm is generally considered that the ball screw is in the fault state [21], [36].

D. Method Comparison

In order to demonstrate the effectiveness of the proposed method, the prediction results are compared with the data-driven approach in [21], the widely used physical-driven approach in [24], where the parameters are selected manually, and the hybrid approach in [29].

Two score functions are used to comprehensively evaluate the prediction results. The first type of the evaluation function is expressed as follows [37]:

$$\begin{aligned} \text{Score1} &= \frac{1}{3} \sum_{i=1}^3 A_i \\ A_i &= \begin{cases} e^{-\ln(0.5)\frac{\text{Er}^i}{5}}, & \text{Er}^i \leq 0 \\ e^{\ln(0.5)\frac{\text{Er}^i}{20}}, & \text{Er}^i > 0 \end{cases} \end{aligned} \quad (22)$$

where $\text{Er} = 100 \times (\text{RUL}_{\text{true}} - \text{RUL}_{\text{predicted}})/\text{RUL}_{\text{true}}$.

In [21], GPR is applied for ball screw RUL prediction. In the physical-driven approach [24], the initial parameters for the stochastic model are selected manually.

As shown in Table III, the prediction accuracy of [21] and [24] is relatively low, where the values of Score1 are the same, which is 0.0008, and the values of Score2 are 225.333 and 333.3333, respectively.

In [29], a hybrid prognostic method is proposed, in which a data-driven method is used to determine the fitting curve, and the exponential model is constructed to characterize the degradation process.

Compared with the prediction results in [21] and [24], the prediction results in [29] have been improved, where the values of Score1 and Score2 are 0.3012 and 50.6667, respectively.

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