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Robust feature design for early detection of ball screw preload loss

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Abstract

The ball screw is a critical device for precision linear motion control that has widespread applications in industrial robots, computer numerical control (CNC) machines, and high-precision leveling systems, among others. Because high-precision positioning is ensured by the addition of a preload to the ball screw system, it is crucial to detect and monitor the loss of preload at the earliest possible stage of degradation. The degradation process of the ball screw can be characterized in two stages: the initial reduction of preload without backlash, followed by a loss of preload with an emergence of backlash. To explore the change of the ball screw dynamics caused by degradation, a novel fixed cycle feature test (FCFT) is implemented in combination with multi-level mass experiments and a run-to-failure (RTF) test. The relationships of the ball screw dynamics with preload, worktable mass, and axis position are investigated, with a focus on the axial natural frequency as an indicator of preload loss. Experimental results validate the axial natural frequency's role as a reliable early detector of preload loss for interventive use in a prognostic system.

Keywords: Ball Screw; Preload Loss Detection; Predictive Maintenance

1. Introduction

In many high-precision manufacturing systems, the functioning of a ball screw can profoundly affect the operational precision and reproducibility of the entire system. For example, imprecision in a robotic arm operation caused by a degraded ball screw can cause expensive damage to wafer products in semiconductor manufacturing processes, and the excessive vibration caused by a degraded ball screw in a CNC machine can result in large manufacturing errors and scrap parts. Therefore, it is critical to develop a prognostic system that can detect the ball screw degradation at an early stage and predict its future degradation for actionable insights.

The major challenge of developing a trustworthy prognostic system for ball screws is the accurate tracking and prediction of preload loss. Preload is an internal force that tightens the screw-nut connection to eliminate backlash and increase both the rigidity of the ball screw assembly and the reproducibility of the linear axis positioning. However, as the ball screw starts to degrade, the wear of the rolling and rotating elements causes the preload level to decrease. Empirically, the degradation of a ball screw can be described in two different stages, as shown in Fig. 1. In stage I, the preload of the ball screw starts to degrade, but no backlash can be observed. In stage II, incipient backlash is observed with an increasing trend, and the rate of preload degradation decreases as the system moves toward a complete loss of preload. Previous work of the authors developed a methodology to monitor the backlash development using inertial sensors [1] but the relationship between preload loss and backlash development still needs more investigation for robust diagnostics.

In addition to preload, the worktable mass and worktable displacement also affect the ball screw dynamics [2]. In this paper, a fixed cycle feature test (FCFT) is designed to be performed in a multi-level mass experiment and a run-to-failure (RTF) experiment to investigate the relationship between three factors (i.e., preload, worktable mass, and worktable position) and the axial natural frequency (ANF) of the ball screw assembly. Therefore, two experiments are proposed and designed in this effort. The first experiment will investigate the ANF shift with changing worktable mass and axis position. By comparing the observed ANF shift with its theoretical shift, we can verify the range of the ANF. Following the first experiment, another RTF experiment is performed by operating a new ball screw with a 100 kg worktable mass to failure (i.e., a fast-rising increase of backlash is observed). In the RTF experiment, the axis travel includes a jittering motion to accelerate the degradation of the ball screw, and a pre-designed FCFT procedure is repeated every 3 days to collect useful inertial data for ball screw backlash assessment.

The main contribution of this work is a novel methodology to assess the ball screw preload loss using transient operation data. The effectiveness of the proposed method is validated in an RTF experiment, in which the analysis indicates a clear downward trend of the ANF as the ball screw degrades. To the best knowledge of the authors, this is the first time that such a ball screw degradation monitoring method is proposed and tested in a RTF experiment.

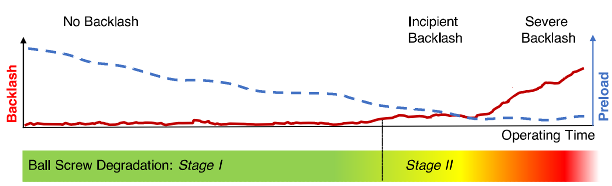

Fig. 1. Degradation of ball screw

The remainder of this paper is organized as follows. Section 2 reviews the existing methods for ball screw degradation monitoring. The proposed methodology, experiments, and analytics are explained in section 3. Finally, section 4 shows the results, and conclusions are given in section 5.

2. Literature Review

The degradation of ball screw performance caused by preload loss can lead to excessive vibration and loss of operational precision [3][4][5]. As such, many studies have focused on monitoring the preload or preload loss for a ball screw assembly. The approach in [6] uses support vector machine learning to classify the severity of preload degradation based on vibration and temperature data. However, it fails to report a continuous trend of preload loss over time that can be leveraged for prediction. In [7], a dynamic model to determine the relationship between ball pass frequency and preload is used. However, it only detects the onset of preload loss while neglecting to quantify the extent of degradation. Methods developed in [8] and [9] use vibration, position, and current information to quantify the continuous relationship between axial natural frequency and preload for real-time reporting, while [10] tracks the peak rotational frequency with respect to changes in the preload. Other experiments have tracked preload loss through the measure of frictional torque, as in [11], or through a thermo-mechanical finite element method-based procedure [12]. To estimate the preload loss of the ball screw, these approaches all use dynamic equations that require prior knowledge of the ball screw's mechanical parameters, such as various stiffness coefficients, Young's modulus, and geometric properties [9].

In addition, some data-driven methods have also been proposed, which extract the degradation-related features from sensory data, such as vibration and torque, and then utilize predictive analytics to diagnose and predict the failure. The study in [13] proposed to use the Hilbert-Huang transform and multiscale entropy to extract degradation-related features. A systematic methodology for ball screw early diagnosis, degradation assessment, and remaining useful life (RUL) prediction is proposed in [4]. The study obtained a smooth degradation trend of the ball screw based on the features from vibration data and the torque signal. Ref. [14] proposed to extract the intrinsic mode functions of the ball screw using the variational mode decomposition (VMD) algorithm for early fault detection and RUL prediction of the ball screw assembly. The study in [15] employed a novel method to predict the RUL of the ball screw based on a hybrid gated recurrent unit (GRU) – particle filter. Even though the data-driven methods are easy to implement, these methods alone cannot reach satisfactory prediction accuracies as the methods can be susceptible to the operation conditions (load and speed changes) and dynamic behaviour of the ball screw.

This work proposes a systematic methodology for the data processing and experimental design for preload loss monitoring that estimates the preload as a function of worktable mass, worktable position, and the first axial natural frequency of the ball screw assembly. The proposed method considers the decreasing trend of preload and the rising trend of backlash at different stages of the ball screw degradation. Through this experimental investigation, the correlation between preload loss and ball screw backlash will be quantified.

3. Methodology

3.1 Preliminaries

The ball screw's preload can be described as a function of worktable mass m_t, axis position x_t, and first axial natural frequency f_a of the ball screw assembly, as seen in Eq. (1), where C_a is the basic dynamic load rating, K is a stiffness parameter provided by the manufacturer [16], d_m is the minor diameter of the ball screw, L is the screw length, G and E are the shear modulus and Young's modulus of the ball screw shaft, β is the transmission ratio of the ball screw, m_s is the mass of the ball screw, m_{nut} is the mass of the ball nut, and $k_{bearing}$ is the stiffness of the support bearing.

$$P = \frac{0.1C_a}{\left\{0.8K\left[-\frac{4x_t}{\pi d_m^2 E} - \frac{32\beta L}{\pi d_m^2 G} - \frac{1}{k_{bearing}} + \frac{1}{(2\pi f_a)^2(m_t + m_s + m_{nut})}\right]\right.} \quad (1)$$

By combining the parameters, Eq. (1) can be simplified and rearranged as Eq. (2) and Eq. (3), where $\boldsymbol{\Theta} = \{a, b, c, d\}$ is the set of mechanical parameters that vary over individual ball screw units due to manufacturing and assembling errors.

$$P = \frac{1}{\left[a \cdot x_t + b + \frac{c}{f_a^2 \cdot (m_t + d)}\right]^3} = f(x_t, f_a, m_t, \boldsymbol{\Theta}) \quad (2)$$

$$f_a = \sqrt{\frac{c}{\left[\left(\frac{1}{P}\right)^{1/3} - a \cdot x_t - b\right] \cdot (m_t + d)}} = g(x_t, P, m_t, \boldsymbol{\Theta}) \quad (3)$$

Based on Eq. (3), the axial natural frequency f_a can be estimated as a function of x_t, P, and m_t. The relationship between the axial natural frequency and each factor can be plotted as shown in Fig. 2. The axial natural frequency decreases as the preload decreases and as the mass and position of the worktable increase.

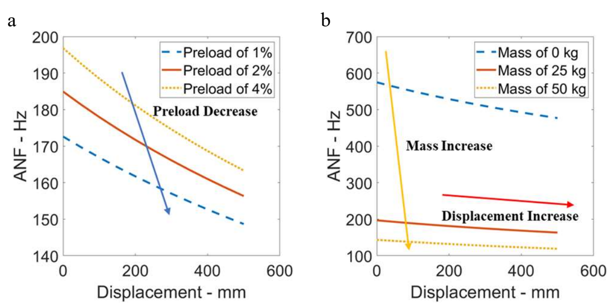

Fig. 2. Theoretical trend of axial natural frequency (ANF) versus axis position (displacement) as a function of (a) preload or (b) worktable mass

In practice, the preload cannot be measured directly during the operation. However, the axial natural frequency can be identified as a peak in the frequency response function (FRF). Fig. 3 shows an example of the location of the axial natural frequency in the FRF when the worktable mass is 100 kg and the axis position is 0 mm. Thus, if the theoretical trend of the axial natural frequency over preload loss can be validated through experiments, then this process can be viewed as a virtual metrology (VM) of the preload and be used for in-situ preload loss detection.

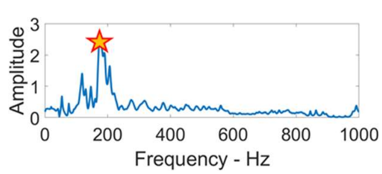

Fig. 3. Axial natural frequency identification (the star) in frequency response function

3.2 Fixed Cycle Feature Test

Over extended periods of operational use, the balls within the ball screw assembly are subject to wear, leading to the gradual development of backlash and a loss of axis positioning precision. At the beginning of the ball screw life cycle, a preload will be applied to the ball screw by utilizing oversized balls. The stiffness of the ball screw system is high at this point and there is no backlash between the balls. Then, as the ball screw assembly degrades, an incipient backlash will occur at some point after continuous loss of the preload, which finally leads to a severe backlash and the loss of position control precision. To validate that the axial natural frequency is a good indicator for the preload loss, experiments should be conducted at different stages of degradation throughout the life cycle of the ball screw. Therefore, a fixed cycle feature test (FCFT) is designed to be performed during a multi-level mass experiment and a run-to-failure (RTF) experiment.

The FCFT will collect data at a set of fixed locations of the ball screw shaft. As shown in Fig. 4, the worktable can approach the designed axis position x_t from a positive direction or a negative direction in an acceleration manner or deceleration manner, leading to four possible conditions: positive/deceleration (PD), positive/acceleration (PA), negative/acceleration (NA), and negative/deceleration (ND). Only two of the four conditions exist for the start and end positions of the axis travel, while all four conditions exist for all other axis positions, as seen in Table 1.

The preload, axis position, and worktable mass are the controlling factors in the experiments. The FCFT in the multi-level mass experiment varies the mass, follows the set FCFT pattern to vary the axis position, and keeps the preload as a constant, which explores the axial natural frequency shift over worktable mass and position. In contrast, the FCFT in the RTF experiment keeps the worktable mass constant and investigates the axial natural frequency shift during the continuous process of ball screw preload loss. During each FCFT, the following data will be collected for analysis: 1) the 3-phase motor current signal measured by an add-on current sensor, 2) the high-resolution torque signal from the ball screw motor controller, 3) the vibration signal at the screw-nut measured by add-on triaxial accelerometers, and 4) the worktable position measured by the high-resolution encoder from the ball screw motor controller.

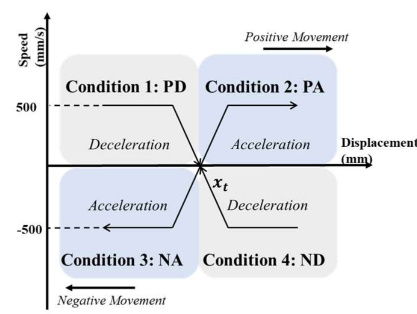

Fig. 4. Operation conditions for arbitrary axis position (displacement)

Table 1. List of conditions for specific axis positions

x_t = Axis Position in the Design of Experiment		
x_t = **Start**	x_t = **End**	**Start** < x_t < **End**
Condition 2, Condition 4	Condition 1, Condition 3	Condition 1, Condition 2, Condition 3, Condition 4

3.3 Data Processing Methodology

The data collected in each FCFT includes the transient data and steady-state data, but only transient data will be used for this analysis. Fig. 5 shows examples of data segments for speed, torque, and vibration signals, respectively, of the ball screw under PA and ND conditions.

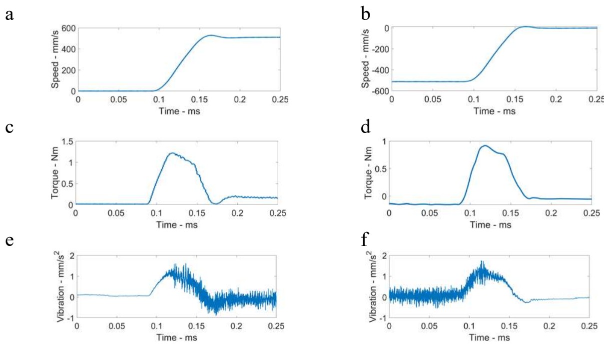

Fig. 5. Data segments: (a)(c)(e) speed, torque, and axial vibration signal for positive/acceleration; (b)(d)(f) speed, torque, and axial vibration signal for negative/deceleration

The data processing methodology is shown in Fig. 6. The transient segments of vibration and torque signals are truncated to remove the steady-state signals. Subsequently, a Hanning window is applied, which is followed by zero-padding and the fast Fourier transform (FFT). By correlating the system torque input and the vibration response at the screw nut, the FRF can be obtained from which the axial natural frequency f_a can be estimated. To reduce the experimental noise, 30 repetitions are collected for each setting of a FCFT, and the FRFs are averaged before the identification of the axial natural frequency.

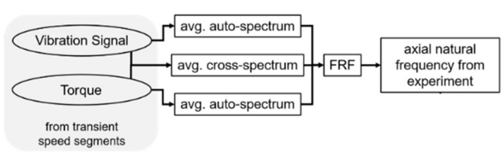

Fig. 6. Proposed data processing methodology

4. Design of Experiments

Fig. 7 shows the setup of the ball screw testbed. The ball screw is driven by the motor, and the worktable with a steel mass moves on the guideways in the axial direction, which is denoted as the X-axis direction. The steel mass is loaded on the worktable of the ball screw in the plumb radial direction which is denoted as the Z-axis direction. The horizontal radial direction is denoted as the Y-axis direction. Two triaxial accelerometers are installed on a side of the ball nut. All the signals are collected at the sampling rate of 12.8 kHz.

The FCFT is designed as a full factorial design with three design factors, i.e., preload, mass, and position. Meanwhile, the working conditions, i.e., PA, PD, NA, and ND, are considered for each of the combinations of factors. In the multi-level mass experiment, the preload level is fixed around 4% and the steel mass is adjusted from 0 kg to 50 kg. In the RTF experiment, the ball screw experiences the degradation from a preload level of roughly 4% to 0% when the ball screw fails completely due to a loss of preload. During the entire RTF experiment, the mass is fixed at 100 kg. For both experiments, the axis position varies from 0 mm to 450 mm, and data are collected for all possible conditions around each fixed axis position.

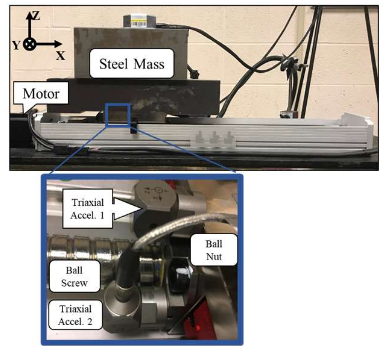

Fig. 7. Ball screw test bed and sensor installation

5. Results and Discussion

5.1. Multi-Level Mass Experiment

Fig. 8 shows the FRF results for different mass levels of the multi-level mass experiment at two axis positions undergoing the negative/deceleration condition. The first resonant axial frequencies are marked by the yellow stars. For the same worktable position, the first resonant frequency generally decreases as the worktable mass increases. Also, for the same mass level, the first resonant axial frequency decreases as the worktable position increases.

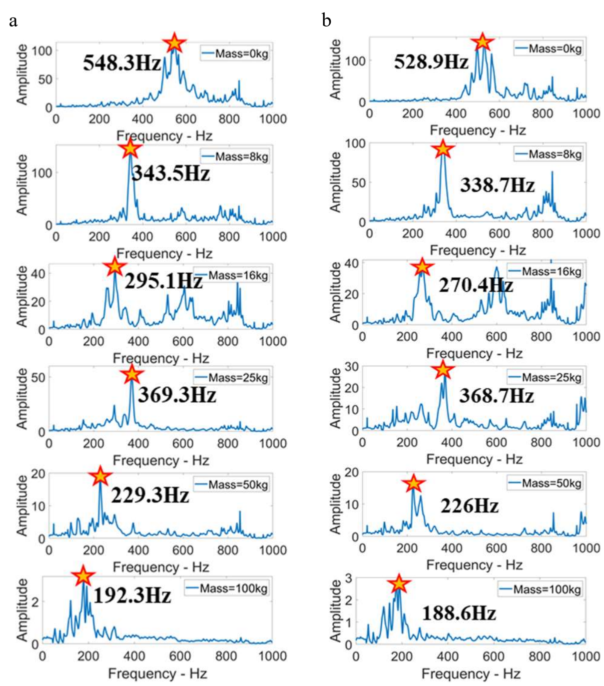

Fig. 8. FRF with identified axial natural frequency (the star) for the ND condition at (a) 0 mm and (b) 90 mm as the worktable mass increases

The first axial resonant frequency of the ball screw can be identified in the same way for all the other conditions. The experimental and theoretical frequencies are compared when the worktable mass is fixed at 0 kg for various axis positions (Fig. 9) and when the axis position is fixed at 0 mm for various worktable masses (Fig. 10). The experimental observations show fairly good agreement with the theoretical analysis for both cases, thus validating the general experimental identification of the axial natural frequency.

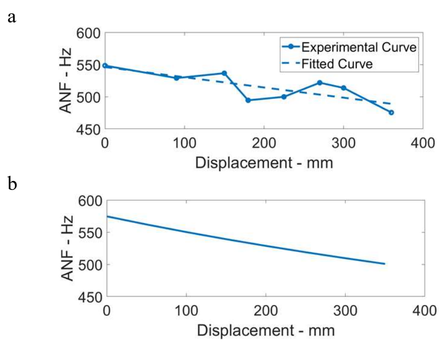

Fig. 9. Axial natural frequency versus axis position (displacement) based on (a) experimental data and (b) theoretical analysis

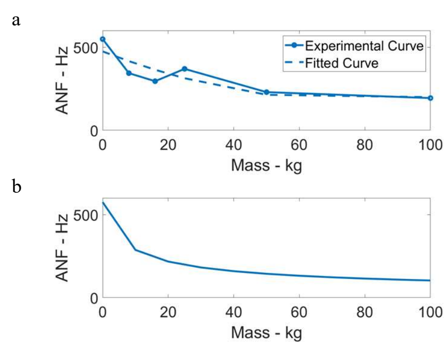

Fig. 10. Axial natural frequency versus worktable mass based on (a) experimental data and (b) theoretical analysis

However, in Fig. 9 and Fig. 10, one can still observe clear differences between the ANFs from the experimental data and the theoretical analysis. This is partly because the dynamic model used for the ANF calculation assumes a 2-point contact (upper and lower) between the ball nut, while the ball screw used in the experiment has a 4-point contact. We will modify the dynamic model as necessary in the future to consider this difference.

5.2. Run-to-Failure Experiment

In the RTF experiment, the preload is set initially at around 4% and the ball screw fails after 80 days as the ball screw simulates a realistic, but accelerated, operational profile. During the accelerated life test, the ball screw degrades due to component wear, leading to a decrease in the system stiffness and the preload. Fig. 11 shows the color spectrum of the FRF from day 0 to day 80. The color of the spectrum represents the amplitude of the FRF. It can be observed that the axial natural frequency decreases as the experiment proceeds, which indicates the positive correlation between the preload and the axial natural frequency of the ball screw assembly.

Throughout the RTF experiment, the backlash of the ball screw is measured with a commercial capacitive displacement sensor. Fig. 12 shows the backlash and the axial natural frequency versus the total operating time of the ball screw for the entire RTF experiment. The axial natural frequency decreases gradually as the backlash increases from 0 μm to 0.4 μm, which justifies the use of the axial natural frequency as an indicator to detect the incipient preload loss.

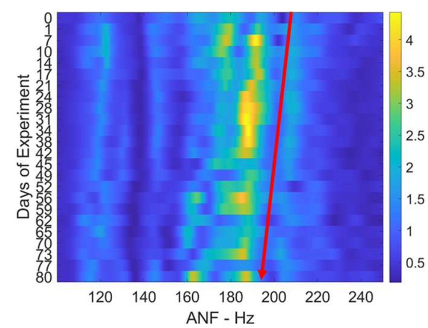

Fig. 11. Axial natural frequency shift with preload loss

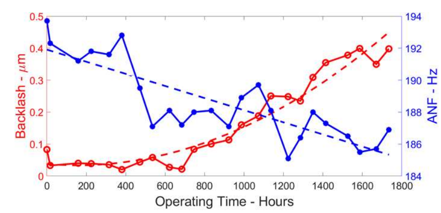

Fig. 12. Backlash and axial natural frequency versus total operating time

6. Conclusion

The feasibility of an early detection prognostic system for ball screw degradation was successfully demonstrated based on monitoring the first axial natural frequency. Such an approach is vital for the maintenance of high-precision manufacturing systems that depend on ball screws. Through a series of experiments, including the run-to-failure test and the innovative fixed cycle feature test, the study verifies the continuous degradation trend of ball screws and solidifies the axial natural frequency as a robust indicator of preload loss. In the future, more experiments will be performed and a location-specific preload prediction model can be established, which will have the potential to significantly reduce the risk of operational imprecision and lead to enhanced efficiency and reliability in manufacturing processes.

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