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Method of Intelligent Fault Diagnosis of Preload Loss for Single Nut Ball Screws through the Sensed Vibration Signals

Yi-Cheng Huang and Yan-Chen Shin

Abstract**—**This paper proposes method of diagnosing ball screw preload loss through the Hilbert-Huang Transform （HHT） and Multiscale entropy （MSE） process. The proposed method can diagnose ball screw preload loss through vibration signals when the machine tool is in operation. Maximum dynamic preload of 2 %, 4 %, and 6 % ball screws were predesigned, manufactured, and tested experimentally. Signal patterns are discussed and revealed using Empirical Mode Decomposition（EMD）with the Hilbert Spectrum. Different preload features are extracted and discriminated using HHT. The irregularity development of a ball screw with preload loss is determined and abstracted using MSE based on complexity perception. Experiment results show that the proposed method can predict the status of ball screw preload loss. Smart sensing for the health of the ball screw is also possible based on a comparative evaluation of MSE by the signal processing and pattern matching of EMD/HHT. This diagnosis method realizes the purposes of prognostic effectiveness on knowing the preload loss and utilizing convenience.

Keywords**—**Empirical Mode Decomposition, Hilbert-Huang Transform, Multi-scale Entropy, Preload Loss, Single-nut Ball Screw

I. Introduction

BALL screws are widely applied in the linear actuators of machinery and equipment because of their high efficiency, no backlash, easy lubrication, and easy maintenance. Preloading is effective to eliminate backlash and increase the stiffness of ball screw for precision motion concerns. It is obvious that a little sacrifice of efficiency is necessary during machine tool motion [1]. Though applying preload inevitably increases the feed system starting torque, preload loss leads to a lower natural frequency, lower stiffness, oscillatory positioning, and chance of rapid downtime in the manufacturing process. In practical application, a fixed preload value is set when the manufacturer sells the ball screw to the customer. However, the true initial preload condition after a certain time will degrade due to rolling and sliding friction result in wear such as abrasion, adhesion or fatigue. Therefore, the prediction of signals to determine the onset of preload loss for ball screws has recently become an urgent necessity in the industry.

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These signals often require conventional Fast Fourier Transform (FFT), Short Time Fourier Transform or Discrete Wavelet Transform for fault diagnosis in the frequency and time domains [2]. Huang and coworkers [3, 4] developed a new approach to signal analysis to avoid generating unphysical results from the Complex Trace formalism [5]. The Complex Trace formalism defines the concepts of instantaneous amplitude, phase, and frequency such that the original signal can be expressed in terms of a Fourier-like expansion based on these concepts [3]. This process and the definition of instantaneous frequency work well for mono-component signals. In many real applications, however, the signals are multi-component and often corrupted by noise. Researchers have recently used HHT in numerous applications, including fault diagnosis in electrical machines, rolling bearing failure analysis in mechanical engineering, and brain activity signal monitoring in bioengineering [6,7] HHT provides both the time and frequency analysis for many engineering applications.

Multiscale entropy (MSE) analysis [3-4] is a new method of measuring the complexity of finite length time series. This computational tool can be applied to both physical and physiological data sets, and can be used with a variety of measures of entropy. MSE curves are used to compare the relative complexity of normalized time series [6]. As mentioned, a loss of ball screw preload decreases the bandwidth of the frequency response spectrum. Some time-varying and periodic phenomena, energy dispersion should reveal the dynamic complexity or perturbations for the balls of the ball screw with ball nut of the feed drive system. However, there is a lack of literature discussing the diagnosis of the ball screw preload during its operation [2]. Industrial applications demand ball screw life time or diagnosis prediction for such preload loss. Therefore, this study constructs a preload-varied feed drive system and applies FFT, HHT with MSE to perform prognostic experiments for ball screws of machine tool in a signal axis positioning stage. Vibration signals are sensed with accelerometer attached to the surface of the single ball screw nut. Different maximum dynamic preload rating of 2 %, 4 %, and 6 % ball screws were predesigned, manufactured They represent the level of less, standard and more preload setting value for each individual ball screw. One of the great challenges for a ball screw feed system is to know the development or phenomena of preload loss in industrial applications. The importance of this task is highlighted by how to develop diagnosis method to prevent downtime or conduct preventive maintenance.

The black box of preload loss dynamics includes complex synergy of oscillatory motion; undetermined force on wear, temperature rise, and fatigue; and failure ball bearing contact; etc., which degrade health of the ball screw. The extraordinary complexity of a CNC machine in operation is the basis for such unpredicted development of preload loss. Then the vibration signals are acquired and processed for analyzing the preload loss of the ball screw drive system. Different preload levels can be determined and abstracted using MSE. The dynamics development of a ball screw preload loss complexity is related to the larger MSE value.

II. Theoretical Backgrounds

A. Hilbert-Huang Transform

Huang and coworkers [3, 4] recently introduced a new signal analysis technique based on the decomposition of a signal in terms of empirical modes and their representation within the context of the Complex Trace Method introduced by Gabor [5]. This method formulates a signal, X(q),(q representing either time or an spatial coordinate) as the real part of a complex trace, Z(q),

$$Z(q) = X(q) + iY(q)$$

where the imaginary part, Y(q), is the Hilbert Transform.

$$Y(q) = \frac{1}{\pi} \cdot PV \cdot \int_{-\infty}^{\infty} \frac{X(q')}{q - q'} dq' \tag{1}$$

The term PV indicates the principal value of the singular integral. The complex conjugate pair (X(q); Y(q)) defines the amplitude, $a(q)$, and phase $\theta(q)$, as an analytical function of the q-variable:

$$Z(q) = a(q)e^{i\theta(q)} \tag{2}$$

where

$$a(q) = \sqrt{x^2(q) + y^2(q)}$$
$$\theta(q) = \arctan(\frac{y(q)}{x(q)}) \tag{3}$$

with the instantaneous frequency defined as

$$\omega(q) = \frac{d\theta(q)}{dq} \tag{4}$$

As mentioned above, the Complex Trace formalism defines the concepts of instantaneous amplitude, phase, and frequency such that the original signal can be expressed for a Fourier-like expansion. This process and the definition of instantaneous frequency work well for mono-component signals. Huang and coworkers developed an entirely new approach to signal analysis to avoid generating unphysical results. The Hilbert Transform is not directly applied to the signal itself, but to each of the members of an empirical decomposition of the signal into intrinsic mode functions (IMFs). These IMF's are individual, nearly mono-component signals with 'Hilbert-friendly' waveforms, to which the instantaneous frequency defined by Eq. (4) can be applied [7].

The algorithm to create the IMF's contains the process of finding modes $c_j(q)$ and the residue R_n) of the signal trend (i.e., the "time-varying" mean). Thus, the signal, X(q), is given by the sum

$$X(q) = \sum_{j=1}^{n} c_j(q) + R_n \tag{5}$$

Once the IMFs are obtained, the Hilbert Transform can be applied to each IMF to compute the instantaneous frequency and amplitude using Eq. (3) and (4). After applying the Hilbert Transform to each IMF, the signal can be expressed using Eq. (6), where $a_j(q)$ and $w_j(q)$ respectively represent the instantaneous amplitude and frequency corresponding to each IMF $c_j(q)$.

$$X(q) = \mathrm{Re}(\sum_{j=1}^{n} a_j(q) \cdot e^{i\int w_j(q) \cdot dq}) \tag{6}$$

This expression enables the representation of the instantaneous amplitude and frequency as functions of q in a three-dimensional plot or contour map. The time-frequency representation of the amplitude is called the Hilbert-Huang spectrum, H(w,q) [7].

Equations (7) and (8) define the marginal frequency and marginal time for the H(w,q):.

$$h(w) = \frac{1}{T}\int_0^T H(w,q)dq \tag{7}$$

$$h(q) = \int_{-\infty}^{\infty} H(w,q)dw \tag{8}$$

B. Multi-Scale Entropy Method

Multiscale entropy (MSE) analysis [8,9] is a new method of measuring the complexity of finite length time series. This computational tool can be applied both to physical and physiological data sets, and can be used with a variety of measures of entropy. For entropy is using the sample entropy (SampEn) measure [10]. SampEn is a refinement of the approximate entropy family of statistics introduced by Pincus [11].

The MSE method incorporates two procedures:

1. A "coarse-graining" process is applied to the time series. For a given time series (x_i), multiple coarse-grained time series are constructed by averaging the data points within non-overlapping windows of increasing length, τ [12].

Each element of the coarse-grained time series, $y_j^{(\tau)}$, is calculated according to Eq. (9)

$$y_j^{(\tau)} = \frac{1}{\tau}\sum_{i=(j-1)\tau+1}^{j\tau} x_i \tag{9}$$

where τ represents the scale factor and 1≦ j≦ N/τ. The length of each coarse-grained time series is N/τ. For Scale 1, the coarse-grained time series is simply the original time series.

2. SampEn is calculated for each coarse-grained time series, and then plotted as a function of the scale factor. SampEn is a "regularity statistic" that "looks for patterns" in a time series and quantifies its degree of predictability or regularity.

C. Axial Stiffness of a Ball Screw

There are several factors that influence the equivalent axial stiffness of a ball screw drive. These include the stiffness characteristics of the ball screw, the preload nut, the front-end support bearing and the back-end support bearing. The axial fixed bearing ($K_{bearing}$), the screw itself (K_{screw}), and the ball screw-nut (K_{mut})interface contribute to the stiffness of the ball screw within its active length [13] It should be noted that the stiffness of the ball screw itself is dependent on the axial position of the feed drive table (X_{pos}) along the screw. Hence, the equivalent axial stiffness (K_{eq}) is expressed as follows.

$$\frac{1}{K_{eq}} = \frac{1}{K_{bearing}} + \frac{1}{K_{screw(X_{pos})}} + \frac{1}{K_{nut}} \tag{10}$$

The screw's equivalent axial stiffness can be expressed as [13]

$$K_{screw(X_{pos})} = \frac{K}{z + X_{pos}} \tag{11}$$

The *1/K* indicates the unit flexibility per active length of the screw. The *z*, in above, is the distance between the fixed bearing (front-end support, close to servo motor) location and axis home position. The X_{pos} is the table position referenced according to the driver's home position. Hence, the screw's equivalent axial stiffness decreases as the table travel to the simple support (back-end) bearing unit. The lower stiffness affects in preload loss for more mechanical backlash, change of balls contact frequency and self rotating frequency, which renders the oscillatory position error, causes pitted ball trace and wear problems.

III. Experimental setup

The experiments in this study used an experimental platform designed and assembled in-house (Fig. 2).This apparatus was fabricated as the industrial standard for a single-axis feed drive system of a tapping machine. Some key specifications of this table are as follows: Delta Electronics© 2 kW servo motor ECMA-C11020ES with a rated speed of 3,000 rpm and maximum of 5,000 rpm; LNC-M310i-V Numerical Controller; feedback sensor with a Heidenhain© Encoder Strip with a resolution of 0.25 μm, Hiwin© Ball Screw R-36–16(K3)-FSC-C1–527–855–0.006-H with a single ball nut and Hiwin© Linear Guide way of HGH30CA2R760ZASPII.

The fabricated machine tool bed has the accuracy of 5 μm with repeated accuracy of 2 μm. The maximum positioning speed is 45 M/min with acceleration of 1.5 G at a motor speed of 3,000 rpm. The design platform can carry a maximum load of 50 kg.

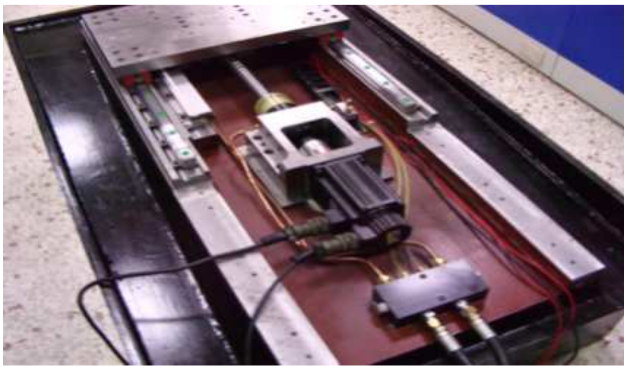


Fig. 2 The in-house single axis platform

The table has a traveling distance of 270 mm and achieves reciprocating movement by varying motor speed from 300 rpm to 3,000 rpm. The device is driven by a servomotor followed by a coupler and single nut ball screw with different preloads. The standard ball screw preload force is determined by 4 % of its maximum dynamic force of 3,750 kgf. Its maximum static force is 9,542 kgf.

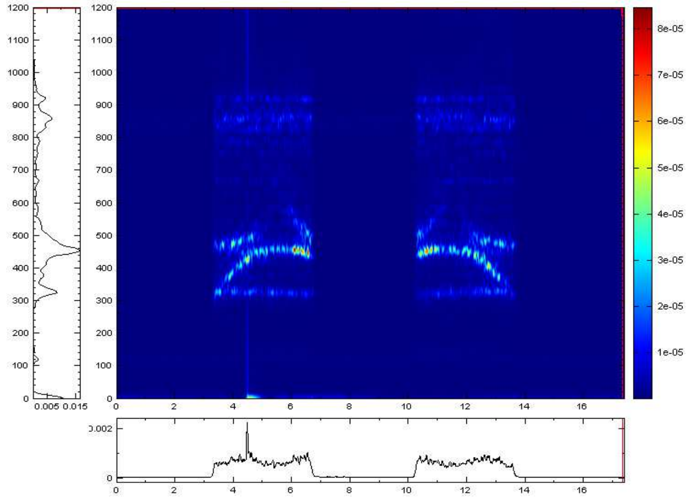
The specification of ball screw preload for a CNC feeding table is generally chosen when the positioning accuracy is determined a priori. In this study, 4 % preload was used as the standard preload for usual precision motion by industrial design purpose. Therefore, 2 % preload indicates a preload loss situation in which preload loss should exhibit more mechanical backlash, pitted ball trace, lower stiffness, and oscillatory position problems.

IV. Experimental Results

A. Characteristics of 4% Ball Screw Vibration Dynamics

The ball screw was installed in the test bed by fixed and simple supported bearing-fit status. Pretension for each ball screw was 5 μm . The preload force was designed and determined by different ball sizes inside the ball screw race and nut. An accelerator was attached to the ball screw nut with an outside recirculation ball race flow. The balls running inside the ball race periodically changed the stiffness of the feed drive system when the table moved forward and backward. The stiffness of the feed drive system changed when the table was in different positions, and the vibration signals in the radial and axial directions of the ball screw changed as the table moved. Fig. 3 shows the Hilbert Huang Spectrum (HHS) for vibration signals in radial and axial directions, and plots the marginal time and marginal frequency of the H(w,q) under and on the left side of HHS, respectively. Feature extraction of Fig. 3(a) shows the acceleration and deceleration patterns of the table in radial direction. These patterns relate to the rich frequency excitation caused by installing the ball screw with fixed and simple supported bearings when the table travel forward and backward. Frequency features of Fig. 3(b) at 320 Hz and 850 Hz appear in marginal frequency significantly. Value of marginal frequency and marginal time in Fig. 3 (b) is larger than those of Fig. 3(a). This details the major vibration modes of this ball screw drive system in axial direction. Since the axially fixed and support bearings unit, the screw itself, and the single ball screw-nut interface contribute to the stiffness of the ball screw within its length. In [13], classification of a double nut preloading variance was discussed by using integrated sensor system for measuring the internal forces. It mentioned, the periodic variations of the preloading have an effect on the local force distribution within the double nut. Fig. 4 shows the frequency response of the vibration signals for different ball screw positions. The significant feature of the frequency at approximately 320 Hz moves slightly as the feed drive table moves. It is interesting to note that the structure dynamic response of the feed drive ball screw system is highly related to the vibration response when the CNC machine table is traveling. Consequently, the characteristics of the preload feature (series stiffness in the axial direction) are focused on the frequencies at approximately 320 Hz and 850 Hz, as follows.

(a)



(b)

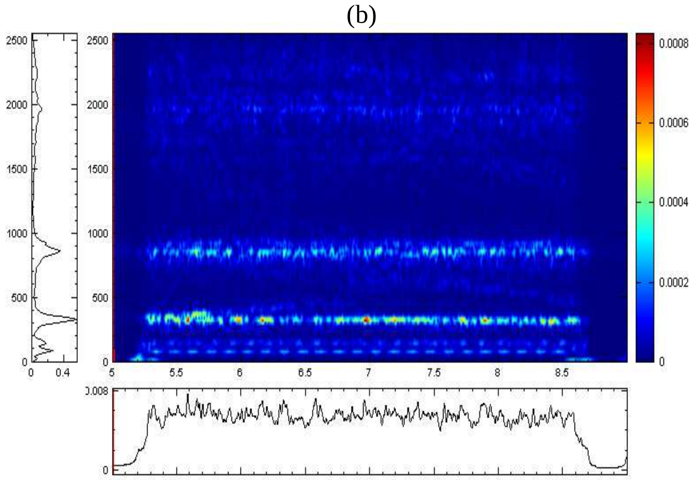


Fig. 3 HHS of the ball screw in (a) the radial direction and (b) the axial direction with reciprocating movement at a motor speed of 300 rpm

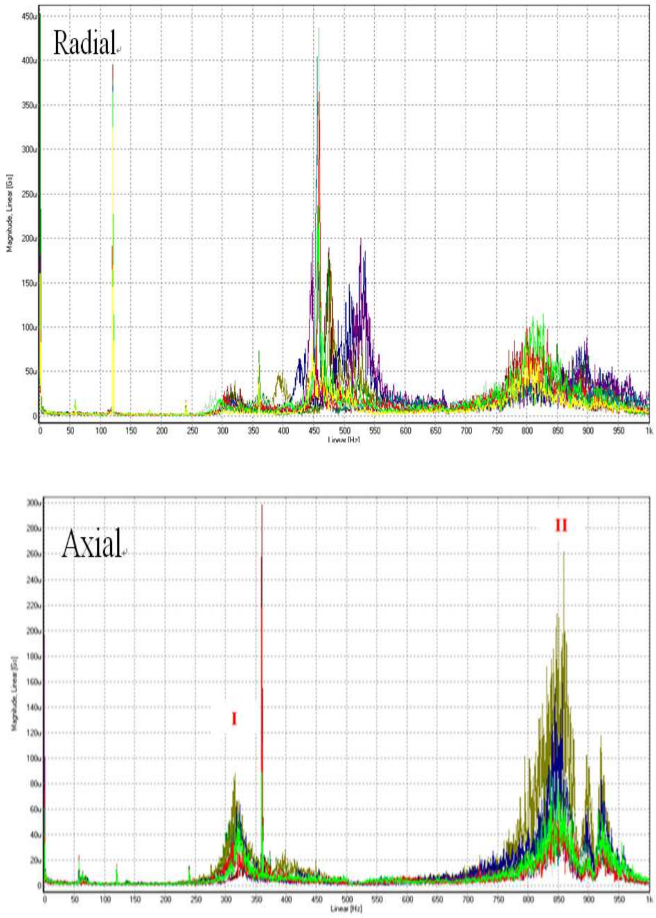
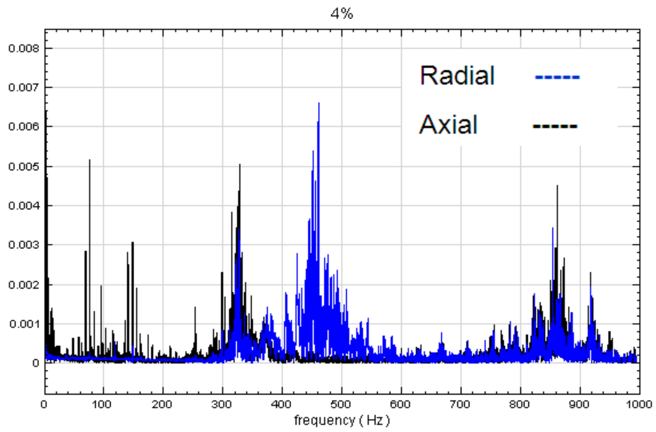


Fig. 4 The modal test responses of ball screw with different positions

B. Frequency response of 2%, 4% and 6% Ball Screws

Two 1-D accelerators were attached near the ball nut and the acquired signals were processed using a spectrum analyzer. Fig.5 shows the frequency spectrum of 2 % and 4 % preload ball screws both in axial and radial dynamic mode.

(a)



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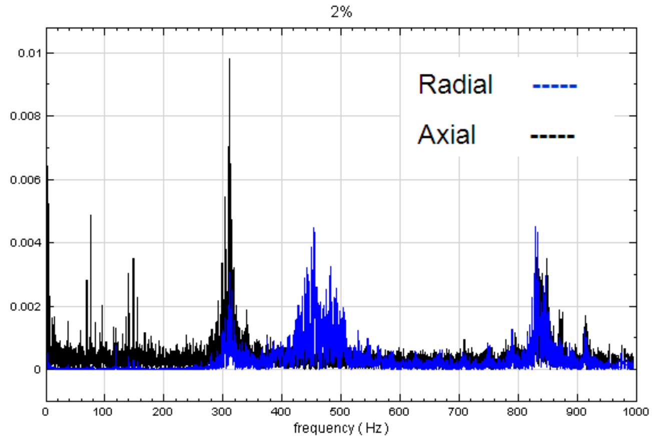
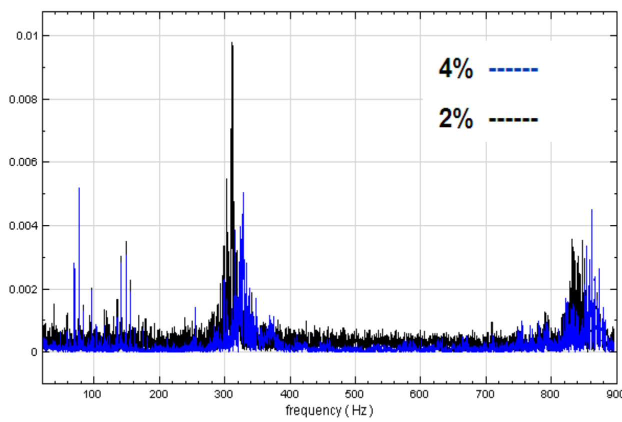


Fig. 5 The axial and radial dynamic spectrum of the ball screws: (a) 4 % (standard) (b) 2 % (less preload)

The major radial vibration signals appearing at pproximately 450 Hz for 2 % and 4 % preload ball screws (Fig. 5 (a) and (b)). In Fig. 8(a) and 8(b), the frequency response shifts when the 4 % preload ball screw changes to 2 % one. The dominant frequencies shift simultaneously at approximately 320 Hz and 850 Hz. However, the frequency response of radial vibration signals for 2 % and 4 % ball screws at 450 Hz has the same profile in Fig. 6(b). In Fig. 7, the dominant frequencies at 320 Hz and 850 Hz remain almost unchanged both in radial and axial directions when the preload ball screw changes from 4 % to 6 %. These experimental results suggest that the bandwidth for the eigen-frequency of the ball screw increases as the preload increases. However, the bandwidth becomes saturated when the preload reaches a certain value [12], indicating that the frequency response of the spring-mass-damped ball screw system depends on the preload value. Consequently, the characteristic frequencies in this study are approximately at 320 Hz and 850 Hz. These frequencies disclose the preload loss syndromes and can be used for analyzing as follows.

(a)



(b)

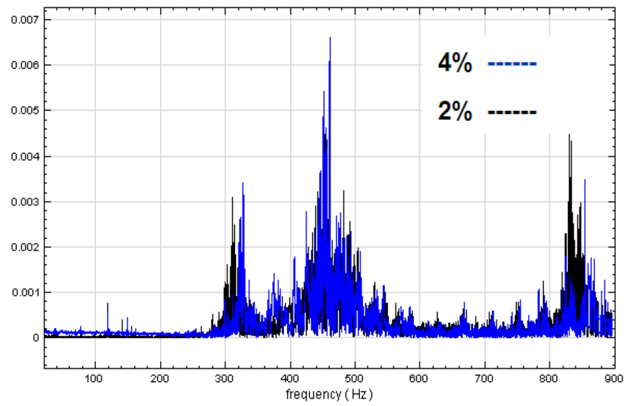
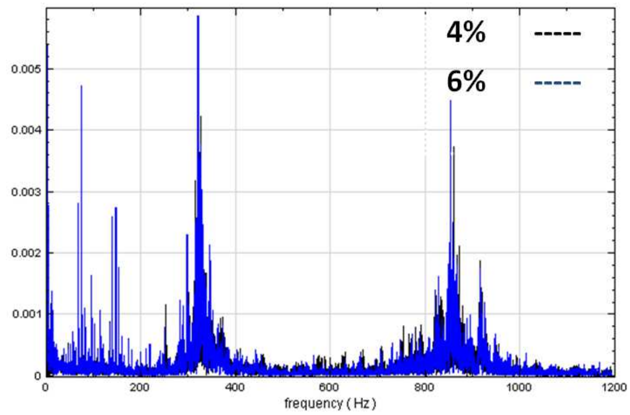


Fig. 6 Frequency response of 2 % and 4 % ball screws in the (a) axial direction and (b) radial direction

(a)



(b)

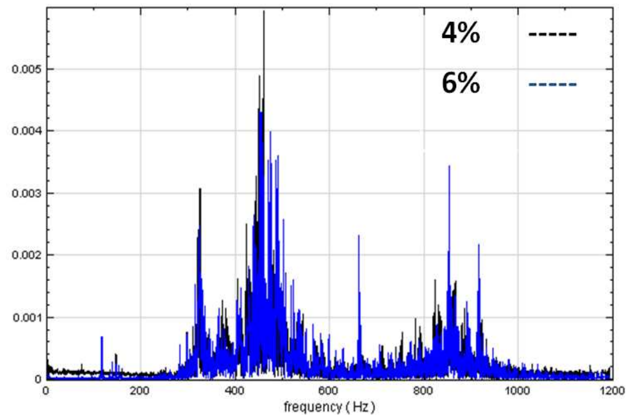
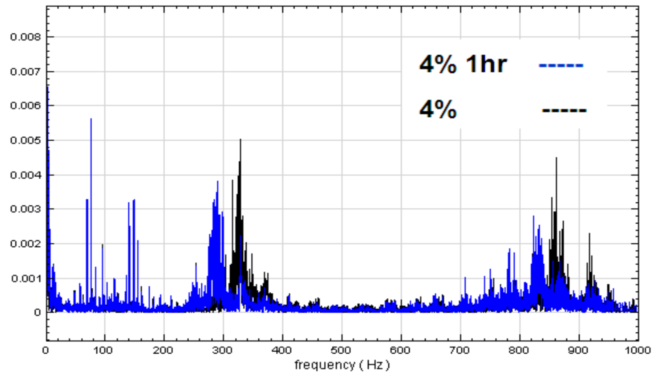


Fig. 7 Frequency response of 4 % and 6 % ball screws in the (a) axial direction and (b) radial direction

Fig. 8 shows the frequency response of the 4 % and 2 % ball screws in the axial direction. When the stage is operated under a reciprocating movement for one hour, the resulting temperature increase can cause a stiffness loss and which decreases the bandwidth of the frequency responses. The traveling time for 270 mm by motor speed of 300 rpm is 3.6 seconds. Experimental results show that the characteristic frequency at approximately 320 Hz and 850 Hz moves toward a lower frequency when the machine is operated for a long time, for example, one consecutive hour.

(a)



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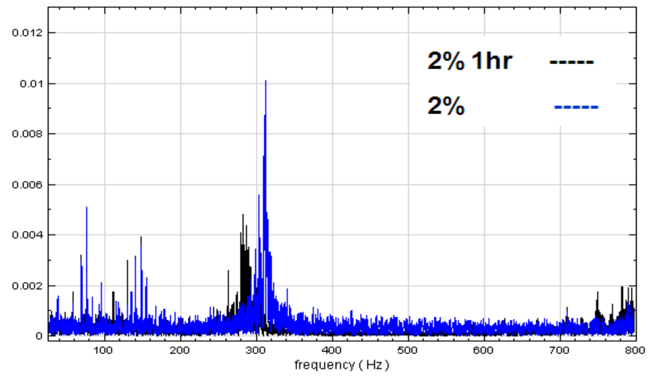


Fig. 8 Frequency response of one reciprocating movement compared with frequency response for one consecutive hour of operation (a) 4 % (b) 2 %

C. Features of the Ball Screw Vibration Signals by EMD

Fig. 9 shows the vibration signals in the time domain of the 4 % ball screw traveling 270mm. It shows that the vibration signals oscillate due to frictional force and starting inertial force when motor speed increases from 0 rpm to 300 rpm and returns to 0 rpm. Fig. 10 shows the IMF 1-IMF 10 from the time domain of Fig. 9 as processed by EMD into several intrinsic mode functions. Taking the first three IMFs of Fig. 10, the HHS associated with the left-hand side of marginal frequency shows significant patterns for 320 Hz from IMF 3 and 850 Hz from IMF 2 in Fig. 11. The significant features of marginal frequency correlate well with the inclusion of signal profiles as indicated in experimental frequency responses of Fig. 4 at approximately 320 Hz and 850 Hz.

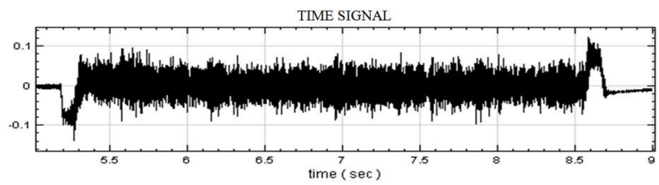


Fig. 9 Vibration signals of the 4 % ball screw traveling 270 mm

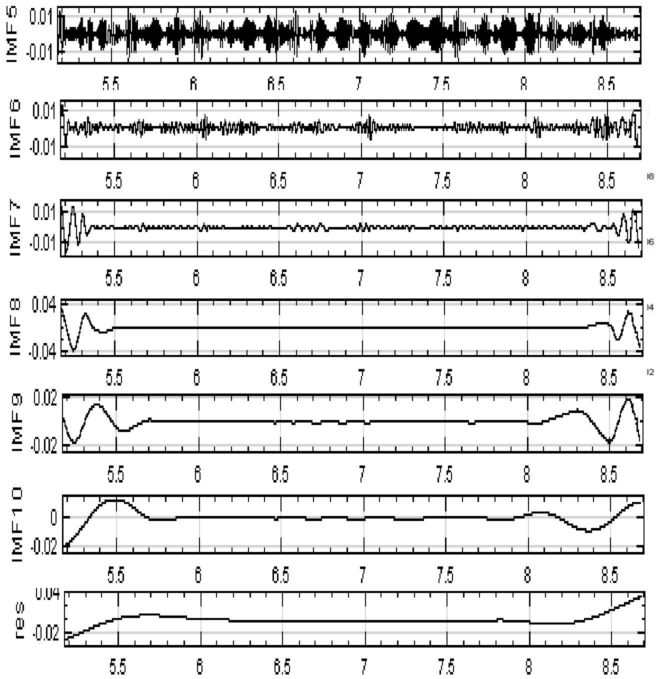
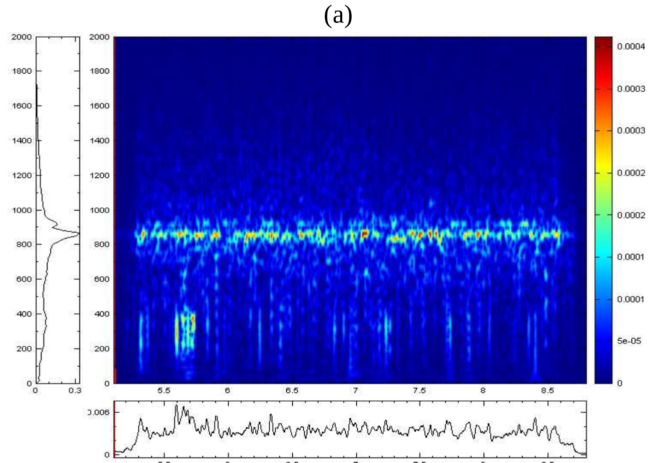


Fig. 10 All the IMF plots of Fig. 11 by the EMD process

(a)



(b)

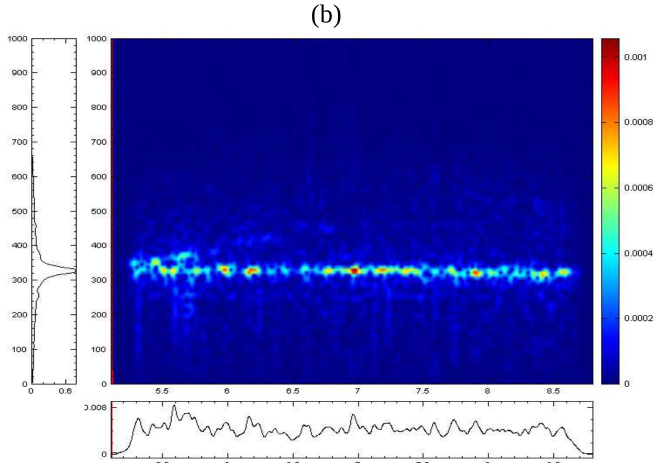


Fig. 11 HHS,marginal time and marginal frequency plots of IMF 2 (a) and IMF 3 (b) in Fig. 10

D.Diagnosis of Ball Screw Preload Loss by MSE

A framework to study the biological systems by a statistical physics approach is introduced via MSE that derived useful measures to quantify the dynamical complexity. Thus, the development symptom of preload loss was mimicked here to determine and abstract via the MSE method based on complexity of mechanical concept. Fig. 12 displays the MSE results calculated by different preloads of ball screws. The sample entropy values indicate that a 2 % preload plot is more irregular than the 4 % and 6 % preload conditions. The entropy value continues to increase after scale factor 2. This seems relatively promising because the increasing complexity (entropy) value corresponds to the fault diagnosis of a preload loss situation. A higher MSE value indicates the high entropy with irregularity followed by the phenomena of preload loss leading to a high complexity index. Once the complexity trend can identify clearly by calculating the increase of entropy value, the development of preload loss should presumably be confirmed. Observation of this fashion is presumably suitable for considering the dynamical complexity of preload when the ball screw is in operation. Fig. 13 shows that using the IMF 3 signals, namely the data reflected from one of the structural vibration modes, facilitates effective analysis for preload loss when the machine in operation. This corresponds to the mechanical complexity hypothesis associated with meaningful structural richness. As the preload loss presents, the balls within the ball nut and race of the ball screw create more rolling contact, random vibration motion, and irregularities.

The results in Fig. 12 reveal an evidence of a preload loss segregation pattern. To summarize, it is possible to drive the ball screw, perform the data acquisition, and calculate the comparative evaluations of the proposed method before manufacturing. Thus, the machinery status of preload loss can be identified before operation. The experimental results of this study are extremely promising for prognostic monitoring on preload loss in industrial applications. The use of this technique for diagnosing a ball screw preload loss through the vibration signals is solid and successful. The results above are suitable for the future wireless sensor framework for future manufacturing processes, and a module for smart-sensing the health of ball screws is available.

Fig. 14 shows the MSE value trend of one reciprocating movement for one consecutive hour operation. A complexity value rises for each 2 % and 4 % preload after an hour temperature effect. This corresponds to the mechanical complexity hypothesis associated with meaningful structural dynamic richness, such as thermo stress, disturbed ball refeeding collision, random contact force between balls within the running race, and greater irregular force between the balls and ball nut when the machine tool is in operation.

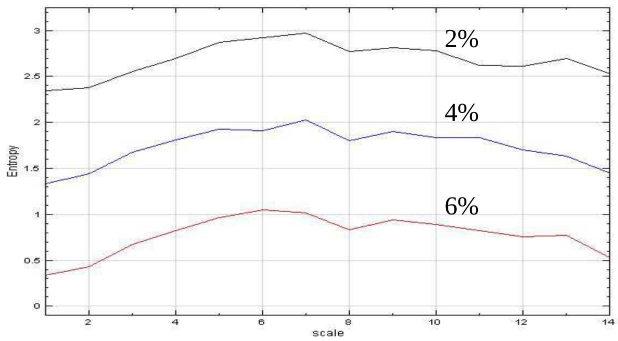


Fig. 12 MSE analysis of different preloads at 300 rpm with one reciprocating movement

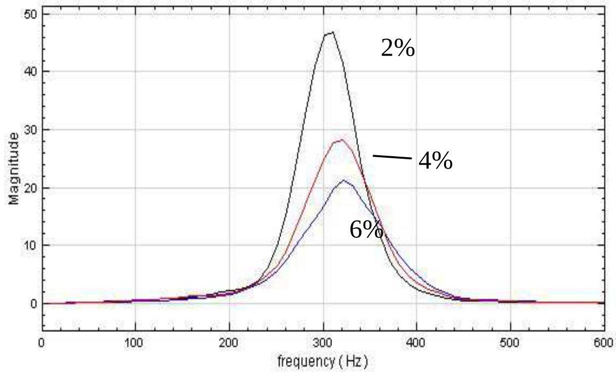
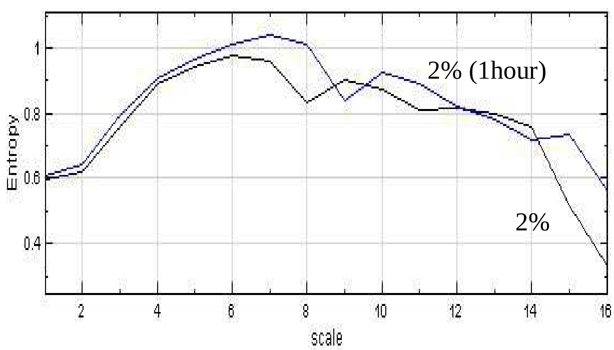


Fig. 13 Marginal frequency analysis of different preloads at 300 rpm with one reciprocating movement

(a)



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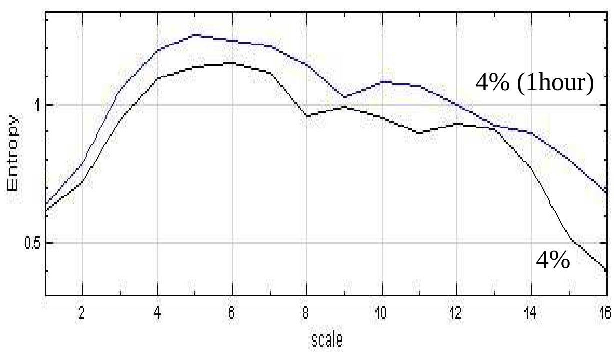

Fig. 14 MSE analysis of one reciprocating movement compared with one consecutive hour of operation (a) 2 % preload (b) 4 % preload

V. Conclusion

This study examines a new signal analysis technique to detect machinery states. Both of the highly nonlinear processing EMD/HHT and MSE methods are suitable for detecting the complexity of a ball screw preload loss system. A computational measure of MSE was used to quantify the ball screw dynamical complexity and identify the irregularity of preload loss. Experimental results reveal evidence of a preload loss segregation pattern for 2 %, 4 %, and 6 % of a ball screw feed drive system. Experimental results also show a clear complexity inclination once preload loss is developed. It has been successfully demonstrated that the preload loss of a ball screw can be prognostic by the vibration signals sensed at the ball nut. The procedures for ball screw preload loss diagnosing are to drive the ball screw, perform the vibration signals acquisition, and calculate the MSE evaluations by proposed method during operation. Thus, the machinery status of preload loss can be identified after a certain time. Experimental results successfully show that the proposed methodology can determine the machinery state when the ball screw is in operation. Applying two new signal analysis techniques of EMD/HHT and MSE achieves the purposes of diagnostic effectiveness and useful application.

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