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A COMPARISION OF MODEL AND SIGNAL BASED CONDITION MONITORING AND MODE SEPARATION FOR PREDICTIVE MAINTENANCE OF FEED DRIVES

Modern production strategies increase the demand for closer monitoring of the machine's condition. Especially wear affects its condition. This paper deals with the methodology of condition monitoring that can be based on different sources of data such as controller NC CNC and additional sensors. Two main methods for assessment are signal analysis based exclusively on measurement data and a model based method. The latter is based on comparing the simulation of the objects behaviour with the acquired data. Ball screw drives are key elements of machine tools. They considerably contribute to the machine's performance. The paper compares two signal-based wear inducing characteristics and discusses the results. Afterwards a model-based approach is discussed.

1. INTRODUCTION

Increasing demands on productivity, quality and output as well as modern production management and flexibility [1] rise stringent demands on machine components and process. For modern production strategies such as Build Operate Transfer (BOT) the ability to monitor the condition and the process is a key factor. Also, higher demand for flexibility calls for assessing the state of the relevant units. Within the DFG's Research Unit 639 ("Gezielte vorbeugende Wartung durch automatisierte Zustandsbeobachtung" FOR 639) monitoring the feed drives condition of wear is investigated by the Institut fuer Werkzeugmaschinen (IfW) of the Universitaet Stuttgart. As a first component a method to investigate drive-inherent data has been developed. D. Maier developed a figure based on both position signals [2].

The method uses positioning data to generate characteristics for describing wear of the mechanical components of the ball screw drive. As input signals the rotatory position and the linear position are used. The rotatory position is taken from the servo motor's encoder the linear position is the machine table's direct actual position. From this data two wear inducing figures are derived. In [3] M. Walther introduces a figure based on the signal energy. In [4] is shown how the operational behaviour of a ball screw drive is analysed. The

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purpose of the analysis is to decompose the signal for identifying the relevant component's specific wear sensitive portion within the signal. After a presentation of these purely signal based figures their methods are compared with a model-based approach.

At the IfW a test stand was realised for the investigation of drive feeds with worn mechanical components (Fig. 1). The test stand consists of a servo motor that drives a ball screw drive via a polymer coupling. All parts used are standard market-based parts as they can be found in any machine. The investigated ball screw drive is a NSK W3210G-17ZY-C5Z10. It has got a nominal diameter of 32 mm a pitch of 10 mm and its ball's diameter is 6.35 mm. Fig. 1 shows the test stand, where the investigated feed drive is pointing away from the point of view. The servo motor can be seen in the foreground.

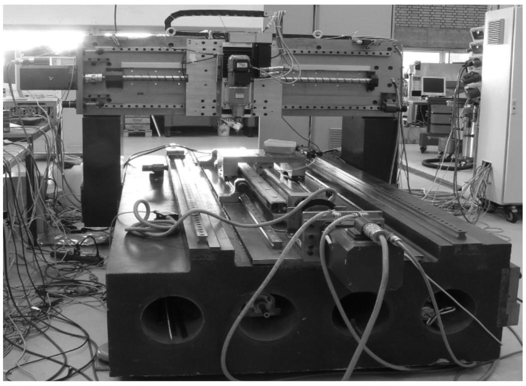

Fig. 1. Test stand for feed drives with ball screws

2. DATA ACQUISITION

For data acquisition of the relevant signals the encoder signals were used. Both signals of the motor and of the linear encoder were fed to a signal acquisition system consisting of two digital counters. One of them also is used for generating a trigger signal by dividing the pulses sent by the motor's encoder. Afterwards the signals are subtracted from each other. Fig. 2 shows the signal flow for generating wear induced characteristics. The characteristics quantify the state of wear.

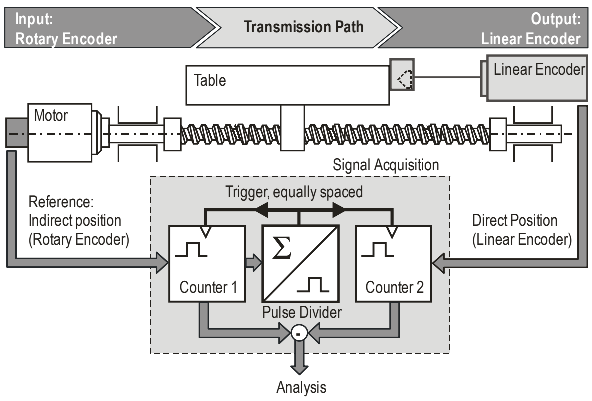

Fig. 2. Signal flow chart for generating wear depicting characteristics

The pulse divider may be set to get the appropriate sample rate. Thus the acquisition's reference input is generated by one of the acquired signals. The reference variable is the rotary position. The setup isolates the mechanical components of the feed drive from their environment by a sensor at its input and another sensor at its output. In this way the mechanical parts represent a transfer path. The resulting characteristic c_1 is based on both positioning signals. By using the position as the reference instead time a sampling method is created that is independent from time. That means that the feed speed may alter during data acquisition. Therefore, the decomposition of the signal for identifying component specific portions may be based on data that has been sampled during altering feed speeds.

Another characteristic c_2 was generated by evaluating only one of them [3].

Fig. 3 shows the scheme for generating the characteristic called "Vibration Energy" as it is presented in [4].

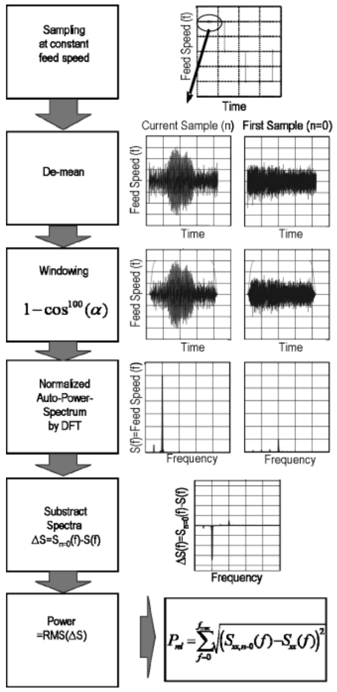

Fig. 3. Scheme for generating the signal based characteristic c2"Vibration Energy" [4]

"Vibration Energy" is generated in six steps. Fig. 3 on the left shows the signals processing, on the right it shows the results. The positional signal of the linear encoder is acquired at constant feed speed. The positioning signal is differentiated to generate a velocity signal. This is first done at the very beginning of the observation (step one) and then at a current given date within the observation. The very first measurement is the reference by which the progression of wear is compared. The signal then is de-meaned (constant part is removed, step 2) windowed (step 3) and Fourier-transformed (step 4). The auto-correlated spectrum of the current date's signal is subtracted from the auto-correlated spectrum from the beginning of the observation i.e. when condition monitoring was started (step 5). Finally the signal energy is calculated as root mean square (step 6).

An experiment was conducted during which a zone of wear in the middle of the drives range was generated by repeated reversing between 200 mm and 400 mm with 9 m/min. For data acquisition the table was moved at a constant speed of 3 m/min between 0 mm and 640 mm (Fig. 4).

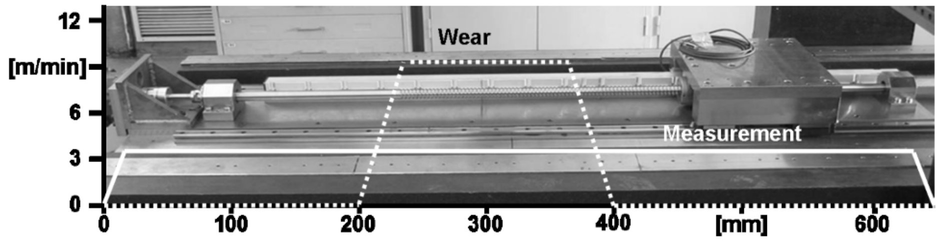

Fig. 4. Velocity cycles for inducing wear on feed drive

The data for both characteristics were acquired at the same time i.e. at the same state of wear. A cycle consisted of 22 reversions in the wear zone followed by 8 reversions over the complete range for data acquisition. In total 274 cycles were performed. In order to reduce time the ball screw nut was treated with grease grinding debris was added to. The purpose was to get a level of steadily increasing wear that was the same for both sets of data during acquisition. There is no physical unit of measurement for wear. Therefore at the moment the absolute values of the characteristics may not be discussed. Therefore, both figures were normalized by their maximum value to make them dimensionless. Fig. 5 shows the behaviour of the normalized characteristics during the observation period. It's clearly visible that the characteristic's behaviours are very different.

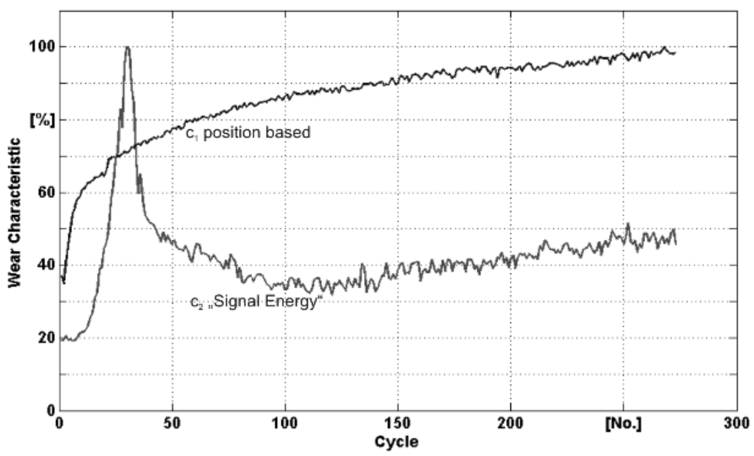

Fig. 5. Behaviour of the wear inducing characteristics during the long term test

The experiment was conducted in a way that one expects constant growth of the characteristics. It is necessary to investigate their usefulness for condition monitoring.

3. ANALYSING THE CHARACTERISTICS IN TERMS OF PREDICTIVE MAINTENANCE

In the presented case lifespan would be remaining cycles until total failure. The objective of a wear depicting characteristic is to be evaluated by quality management. For this it's important that the characteristics somehow react to the increased wear. Simplest the characteristic is proportional to the degree of wear. For maintenance planning it's important to know how much time i.e. cycles is left until the next maintenance measure. Contrary to expectations fig. 5 shows that c_2 decreases after it reaches its maximum. In practise that means that its trend must be observed over a long period to be meaningful. Since the characteristics behaviour is not foreseeable it will be difficult to set the necessary period of observation. c_1 shows a steady grow during the observation. That means fewer samples are meaningful. It is obvious that at some time any sensible characteristic will show a reaction. But that is not sufficient for predictive maintenance. To plan maintenance it is important to know how much a characteristic reacts. If the growth rate is known it can be calculated how much lifespan is left. The growth rate is a characteristic's sensitivity. It is the relation of the alteration of the characteristic versus the alteration of the machines cycles i.e. time:

$$s_i = \frac{dc_i}{dt} \tag{1}$$

Fig. 6 shows the sensitivity of the characteristics trends. The trends were calculated by low-pass filtering. After the wear induction starts c_1 decreases and stays positive. s_1 the sensitivity of c_1 shows that wear progresses continuously. In contrast at the beginning s_2 is sensitive to wear. Further s_2 becomes negative. Afterwards as s_1 it tends to steadiness.

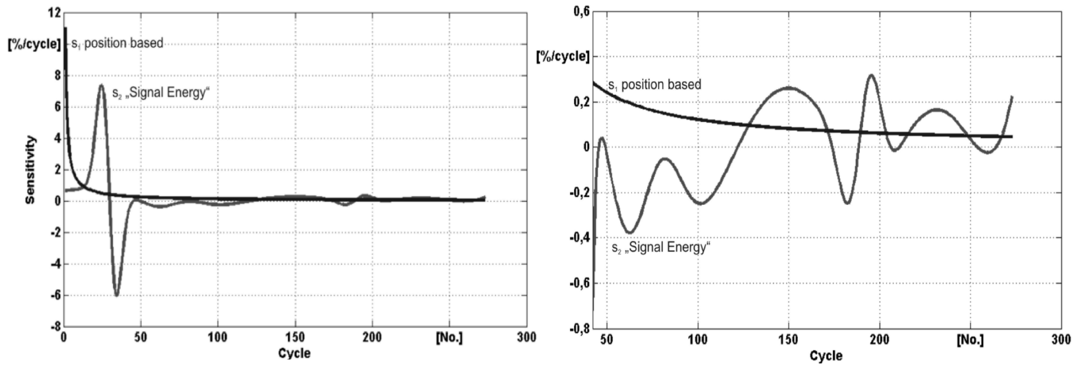

Fig. 6. Sensitivities s_1 and s_2 of the characteristics c_1 and c_2

Fig. 6 shows that c_2 is difficult to evaluate compared to c_1. A more detailed section of s_1 and s_2 is shown right. s_2 is comparatively more unsteady than s_1. This means that c_2's data has to be sampled at a higher rate than c_1's. Also c_2's behaviour to cross zero may mislead to the conclusion that wear is decreasing. The experiment was conducted at constant steady loads. So it is not likely that wear decreases again. c_2 also has to be processed by low-pass-filtering to obtain a meaningful figure. These measures further reduce the characteristic's significance. To evaluate a characteristic's suitability its standard deviation can be used. Fig. 7 shows that the raw data of c_2 is varying more than c_1. The standard deviation is calculated of the recent data sets. For the experimental data the remaining lifespan may be calculated. The characteristics' extrapolations were calculated with a level of prediction accurateness of 95% (right).

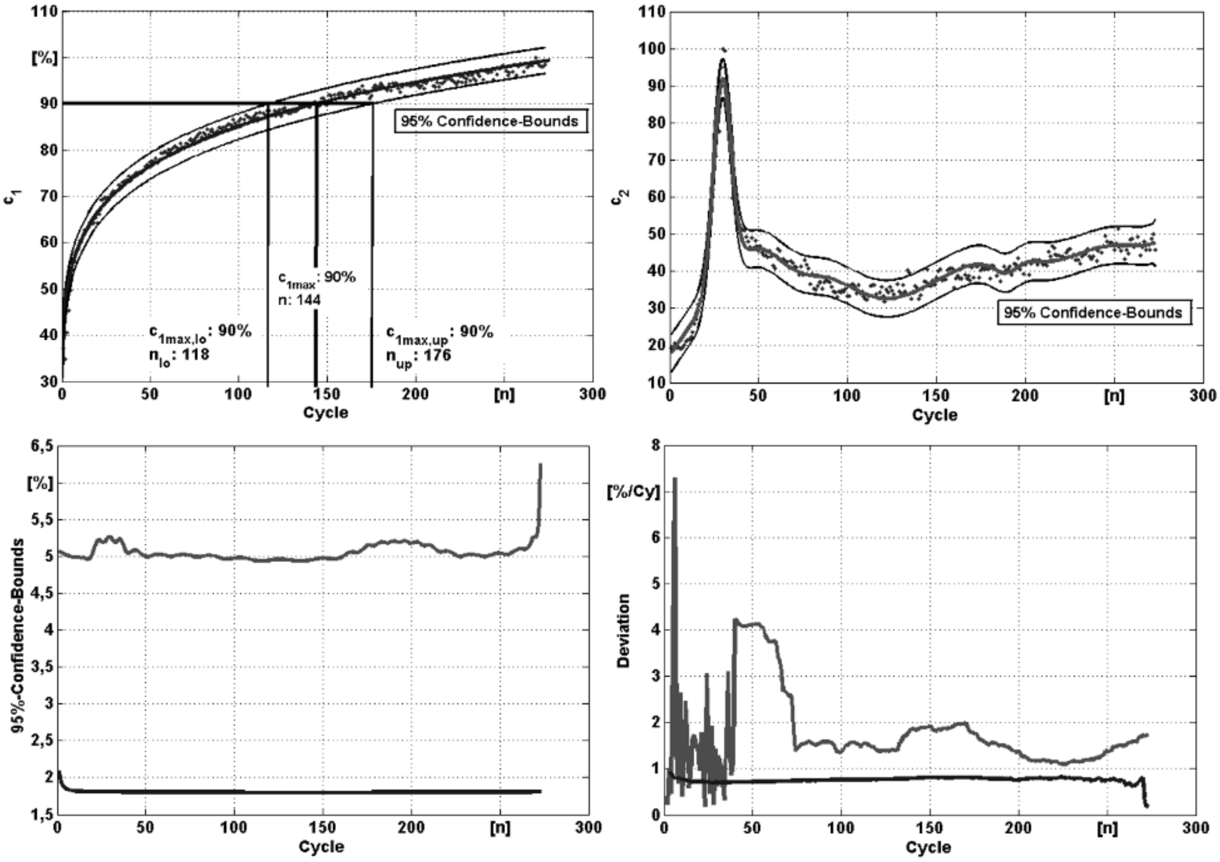

Fig. 7. Characteristics c_1 and c_2 confidence bounds and standard deviations σ_i of the sensitivities

This also influences the characteristic's sensibilities s_1 and s_2. Since the time limits for maintenance are derived from the sensitivities it's important to know the sensitivities standard deviations (fig. 7 below right). Maintenance planning is guided by different objectives. On one hand the availability of a device probably is best, when it is serviced as soon as possible. So the due date will be set to the calculated date minus the standard deviation. On the other hand when costs are guidelines it's not always the best to maintain as early as possible. It has to be left to quality management when to take measures. The remaining lifetime has to be extrapolated from the recent measurements. Contrary to reality where it's unknown at which actual cycle the observation has begun here the complete set of data is already sampled. Therefore the characteristics c_1 and c_2 may be extrapolated.

$$c_{1,xpol}(n) = a \cdot n^b \quad with \quad a = 41.95 \qquad b = 0.1536 \tag{2}$$

where n is the number of the cycle. c_2 is extrapolated as a Gaussian model with the following coefficients:

$$c_{2,pol} = a_1 \cdot e^{(-((x-b_1)/c_1)^2)} + ... + a_8 \cdot e^{(-((x-b_8)/c_8)^2)} \tag{3}$$

with

$$\begin{array}{llllll}
a_1 = 53.62 & b_1 = 29.48 & c_1 = 6.89 & a_2 = 26.41 & b_2 = 255.3 & c_2 = 39.57 \\
a_3 = -7.941 & b_3 = 70.23 & c_3 = 18.7 & a_4 = -4.364 & b_4 = 190.3 & c_4 = 10.69 \\
a_5 = 5.65 \cdot 10^{13} & b_5 = 1364 & c_5 = 203.6 & a_6 = 47.58 & b_6 = 55.77 & c_6 = 55.5 \\
a_7 = 41.56 & b_7 = 180 & c_7 = 70.54 & a_8 = 1.754 & b_8 = 196.7 & c_8 = 10.45
\end{array}$$

The behaviours of the characteristics may only be determined by experiment. Therefore significant statements will only be possible if there is a basis of data of a considerable number of independent experiments. Here the behaviours of the characteristics are known for the observed period. Therefore the total lifespan L_{max} may be estimated. At a given moment t_1 the forthcoming data may not bee foreseen. Equation (2) can be solved. If c_{max} is the preset threshold to define end of life the estimation of L_{max} for c_1 is:

$$L_{\max,90} = \left(\frac{c_{\max}}{41.95} \right)^{\frac{1}{0.1536}} \qquad with \quad c_{\max} = 90\% \qquad L_{\max,90} = 144 \tag{4}$$

Fig. 7 shows the extrapolation of c_1 with its 95 % confidence bounds. If the confidence bounds are taken into account the maximum Lifespan $L_{max,90}$ is 144 cycles with a confidence interval [n_{lo}, n_{up}] of [118],[176] cycles. c_2 doesn’t feature a steady grow. Therefore it is difficult to estimate the lifespan on its basis. So its interpretation is left to further investigations. The above considerations show that for the evaluation of the characteristics it is important to take into account their sensitivities and their standard deviations as well as the standard deviation of the sensitivities. A characteristic by itself is not very meaningful.

4. MODEL BASED APPROACH

The following model based approach is based on the dynamic behaviour of the feed drive [6]. The principal hypothesis is that wear causes the concerned component’s stiffness to decrease. This causes the appropriate Eigen frequency to decrease also. For investigation the drive feed is modelled as a multi-mass oscillator (Fig. 8).

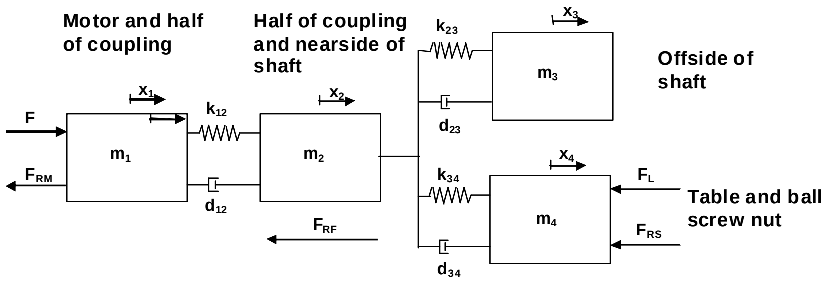

Fig. 8. Feed drive modelled as a multi-mass oscillator

The drive's dynamic behaviour is determined by solving the associated differential equation (5).

$$\mathbf{M}\cdot\ddot{\mathbf{x}}(t)+\mathbf{P}(t)\cdot\dot{\mathbf{x}}(t)+\mathbf{Q}(t)\cdot\mathbf{x}(t)=\mathbf{h}(t) \tag{5}$$

M : *mass – matrix*
P : *matrix of forces dependent on velocity*
Q : *matrix of forces dependent on displacement*
h : *excitation – vector*

To simulate the effect of wear the ball screw nut's stiffness k_{34} is decreased from initially 100 % to 5 %. The shifting s_{k34} of the ball screw nut's Eigen frequency versus loss of stiffness k_{34} is the figure to be monitored. This sensitivity is calculated as:

$$s_{k_{34}}=\frac{dF_{k_{34}}}{dk_{34}} \qquad with \qquad F_{k_{34}}=eigenfrequency(ball\;screw\,nut) \tag{6}$$

Fig. 9 shows the system's normalized frequency responses versus the decreasing stiffness of the ball screw nut k_{34}.

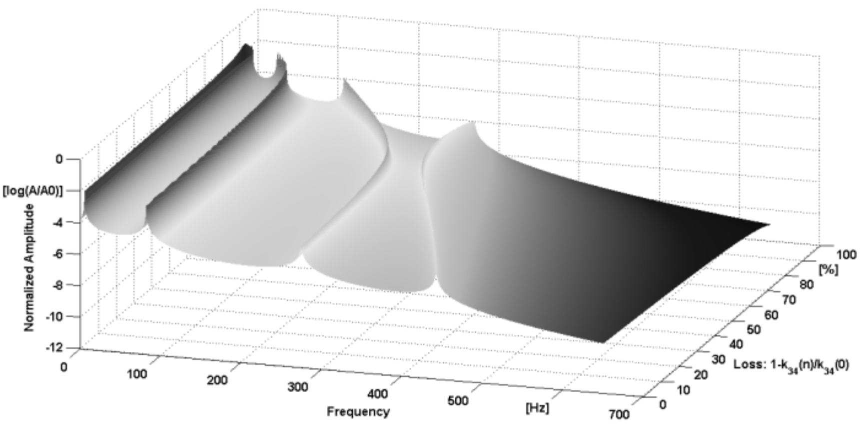

Fig. 9. Frequency responses of the feed drive versus decreasing stiffness k_{34} of the ball screw nut

The system's Eigen frequencies F_i and respective sensitivities s_i are shown in Fig. 10. F_{off} is the Eigen Frequency of the offside shaft i.e. behind the ball screw nut F_{near} of the nearside shaft F_{k34} of the ball screw nut and F_{Mot} of the motor and the coupling.

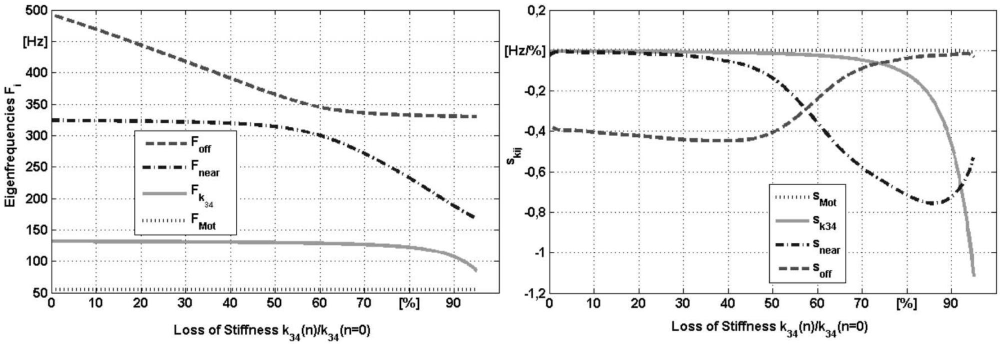

Fig. 10. Frequency shifting and respective sensitivities versus loss of stiffness

Fig. 10 right s_{k34} shows that is insensitive. Until loss of stiffness reaches 50 % it's close to zero. The practical meaning of a loss of stiffness of 50 % is left to be discussed. A model based approach also needs data that has to be fed into the model. In [5] a measurement is presented (Fig. 11).

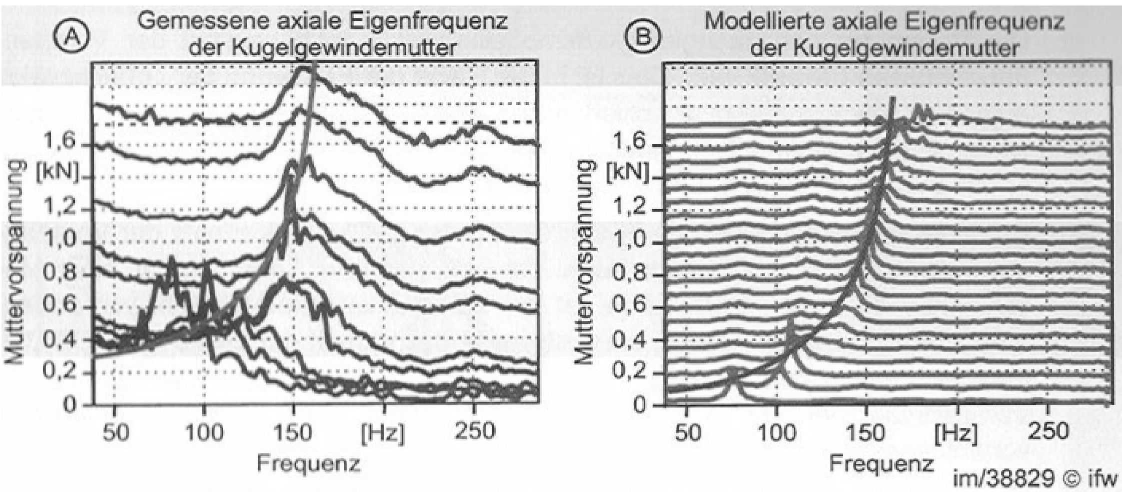

Fig. 11. Measurement of frequency shifting (left) and respective simulation (right) [5]

Fig. 11 left shows that the measurement has a high variance that increases at low stiffness when the measurement becomes sensitive. In [5] the investigations of the sensitivity and the variance for neither the measurement nor the model are conducted. The goodness of a model based approach depends on both the measurement and the model. The model is based on the accurateness of the technical data.

Fig. 12 shows the shifting of F_{k34} versus loss of stiffness k_{34}. The confidence bounds of 95 % accurateness were caused of a variance of ±0.5 % to ±4 % of the technical data. It is obvious that until ca. 65 % loss the confidence interval of a monitored threshold is too wide. If the measurements behaviour (Fig. 11, left) is token into account the narrowness of the later confidence interval will probably also be compensated.

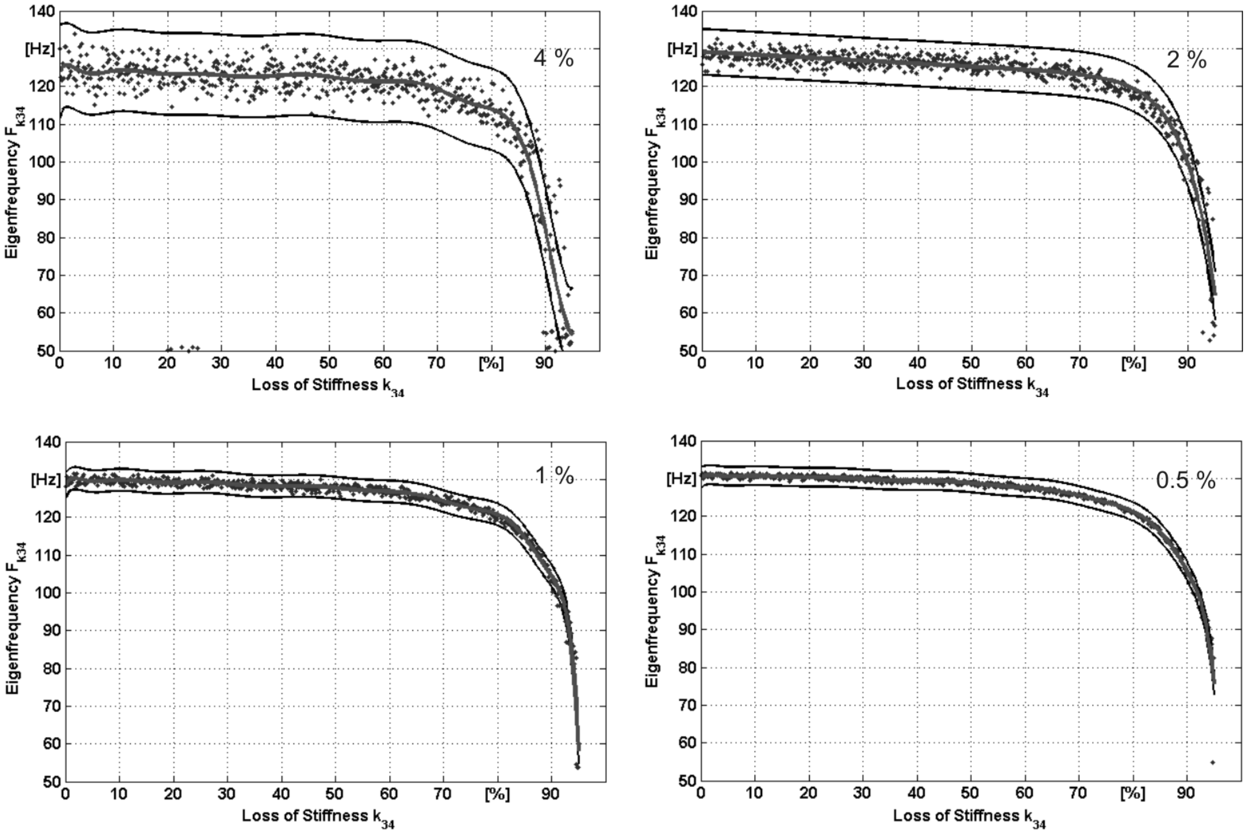

Fig. 12. Shifting of Eigen frequency F_{k34} versus loss of stiffness k_{34} with confidence intervals for 0.5 % 1 % 2 % and 4 % error of technical data

The simulation was done with the assumption that the loss happens with a constant rate. This behaviour is an idealisation that is not likely to be realistic. In [5] the measurement was done by adjusting the ball screw nuts preload to achieve the desired stiffness. Any kind of “natural” wear hasn’t happened. The experiment has been designed in a way that it will prove the model’s basic assumption in any way. Hence there also is no relation to any cycles that have been passed until the current state was reached. The state was preset for every individual measurement. Hence there is no relation to lifespan. It is therefore not possible to predict or estimate the remaining lifespan on this basis left apart the missing discussion of the model’s confidence bounds and the variation of the according measurement.

5. MODE SEPARATION

If condition monitoring is to be enhanced to identifying the concerned part of the monitored system one is faced with the task to separate the relevant modes of the data, signals or characteristics. By analysing the kinematic behaviour of the monitored parts a filter to separate the modes can be parameterized.

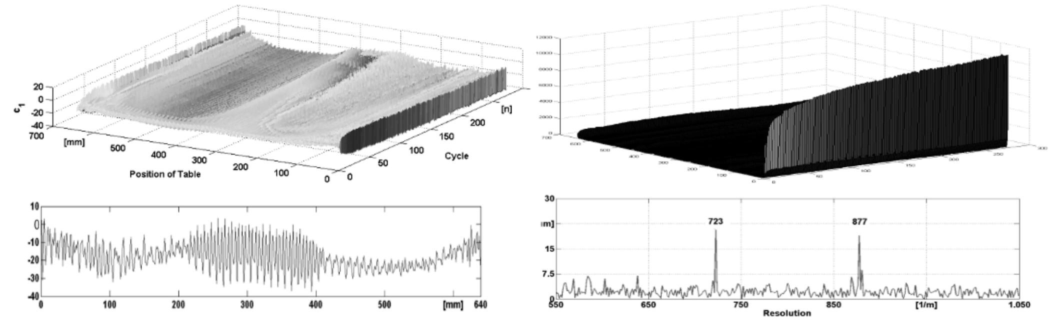

Fig. 13. Characteristic c_1 in time-domain (left) and its Fourier-transformed for all cycles and sliced for a single cycle (below)

The detected peaks can be assigned to the ball screw nut by investigating its kinematics. Fig. 14 shows the velocity plan for calculating the ball screw drive's ball passing frequencies.

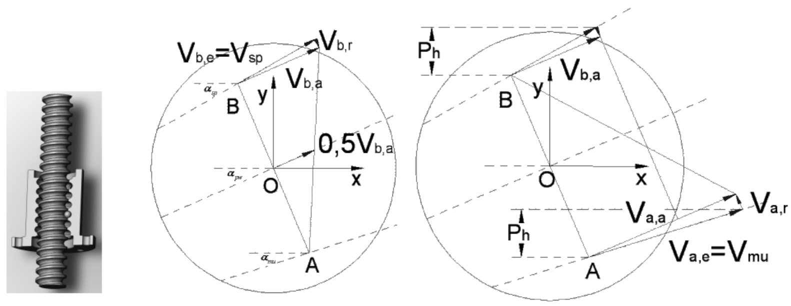

Fig. 14. Velocity plan for calculating a ball screw nut's ball passing frequencies

For D_{Ball} being the ball's diameter and $D_{Nominal}$ being the nominal diameter and α is the contact angle the frequencies are:

$$f_{shaft,nut} = \frac{1}{2} \cdot n \cdot z \cdot \left(1 \pm \frac{D_{Ball}}{D_{Nominal}} \cdot \cos\alpha \right) \tag{7}$$

At constant speeds the characteristic frequencies can be converted to dependency of the position i.e. frequency becomes spatial resolution. The peaks are dominant in the spectrum. Therefore it can be concluded that the dominant mode is caused by the balls being fed back.

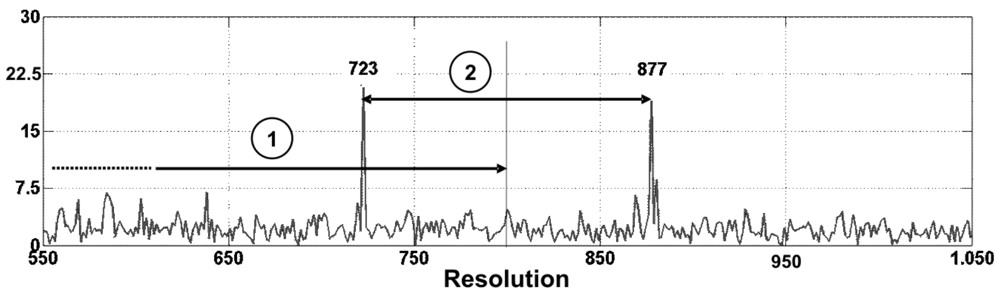

Fig. 15. Experimental proof of ball passing frequencies

Fig. 16 shows the section of the ball screw nut. α dominates the spread and the relation of D_{Ball} / $D_{Nominal}$ determines the frequencies' centres. Wear is visible on the recirculation units.

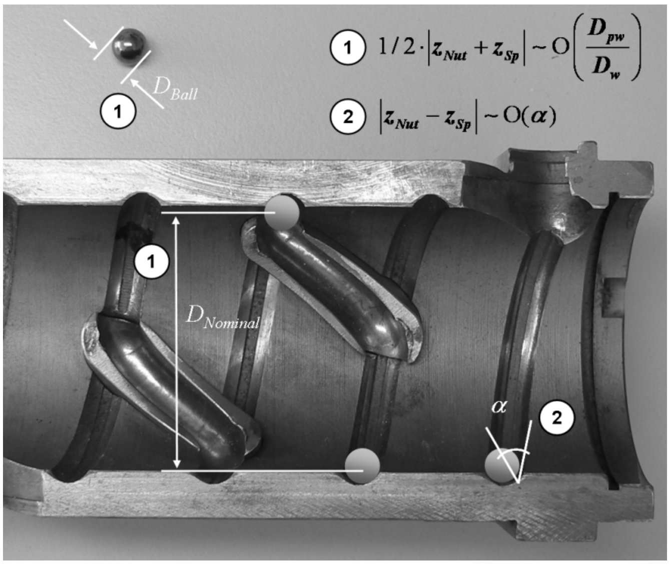

Fig. 16. Section of ball screw nut with figures determining the characteristic frequencies

Another experiment was conducted to determine the recirculation unit's influence. For a series of eight identical worn ball screw drives the idle torque was measured. The measurements were done for both directions feed forward and feed rearward (Fig. 17).

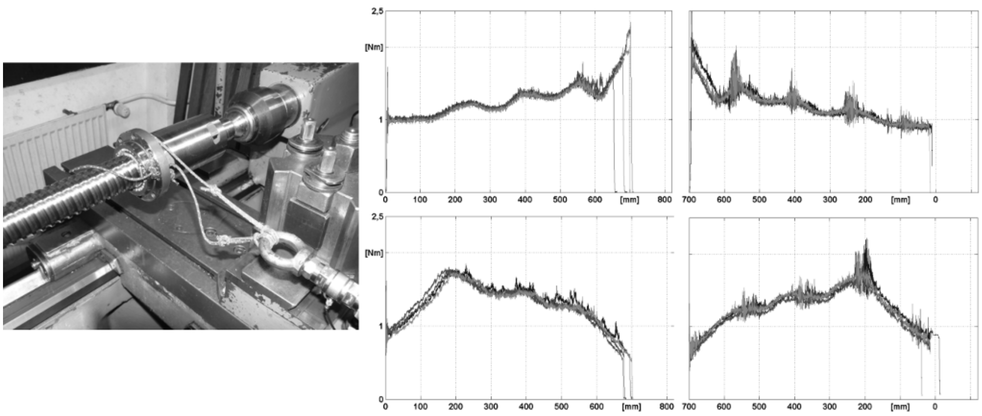

Fig. 17. Measuring the idle torque of a ball screw drive with a piezoelectric load cell

The depicted exemplary two measurements show different behaviours for forward and rearward feed respectively. Because the torque's trend should be symmetrical for both directions the peaks have to be assigned to the recirculation units. These measurements lead to the conclusion that the recirculation units are key factor of a ball screw drive's behaviour. The stochastic behaviour (Fig. 17) can not be foreseen. Therefore it also can not be simulated. To underlay a steady grow of a characteristic will surely lead to the wrong results.

6. CONCLUSION AND PROSPECT

To construction the lifespan of a ball screw is determined by the key figure L_{10}. The formula is similar to a bearing's:

$$L_{10} = \left(\frac{C}{F_m}\right)^3 \cdot 10^6 \quad [Revolutions] \tag{8}$$

The intention of the model-based approach is to determine the current dynamic stiffness C of a ball screw drive during its lifespan. Knowledge of current C shall enable to predict the remaining lifespan according equation (8) [5]. For determining the current stiffness a model is necessary. This observer principle is triple fold prone to inaccuracies. The measurement's and the model's inputs are varying. Additionally the growth of a measured characteristic is different from the simulation's constant iteration steps. The experiments show if any that progression of wear is not constantly steady. It even may be stochastic. That makes model based prediction difficult.

Axial movement differentiates a ball screw drive from a bearing. Therefore the method based on position as reference is suggested. Prerequisite for the axial movement is recirculation of the balls. That is the dominant operation mode when the feed drive is moving. For determining the operation mode a position based measurement is applicable. Basis for prediction is an appropriate sensitivity combined with narrow confidence bounds. The sensitivity has to be dependent on time or even better machining cycles i.e. the machine's actual load.

A single characteristic by itself is not meaningful. The problem only can be described when different characteristics are captured during one and the same experiment. Here two position based characteristics were compared this way.

Lifetime often is connected to the term "total failure". But there is no definition of "total failure". That's why the practical meaning of a wear depicting characteristic is often questionable. For the operator it is important to quantify the sate of wear by his own criterion. Such a criterion can only be an established figure as it is e.g. suggested in DIN ISO 230-2. At the Institut fuer Werkzeugmaschinen of the Universitaet Stuttgart currently experiments are conducted during which several characteristics are recorded simultaneously. Concurrently measurements according DIN ISO 230 are undertaken as well examples of workpieces are fabricated. During the early state of wear that was investigated in the experiment stiffness proved not to be relevant. The experiment was calibrated by comparing the results to positioning accuracy according DIN ISO 230-2. The positional accuracy decreased from 4 µm to 20 µm, averaged over a range of 640 mm.

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