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A defect-driven diagnostic method for machine tool spindles

Gregory W. Vogl *, M.A. Donmez

Engineering Laboratory, National Institute of Standards and Technology (NIST), 100 Bureau Drive, Gaithersburg, MD 20899-8220, USA
Submitted by J. Peters (1), Leuven, Flanders, Belgium

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A B S T R A C T

Simple vibration-based metrics are, in many cases, insufficient to diagnose machine tool spindle condition. These metrics couple defect-based motion with spindle dynamics; diagnostics should be defect-driven. A new method and spindle condition estimation device (SCED) were developed to acquire data and to separate system dynamics from defect geometry. Based on this method, a spindle condition metric relying only on defect geometry is proposed. Application of the SCED on various milling and turning spindles shows that the new approach is robust for diagnosing the machine tool spindle condition.

1. Introduction

Unexpected failure of machine tool spindle bearings will result in production loss. Hence, condition monitoring for spindles plays an important role in improving productivity [1]. Yet there is currently no universally accepted method for determining the machine tool spindle condition. The vibrations of the spindle housing have been analyzed for machine acceptance purposes. However, resulting diagnostic methods are insufficient since the measured vibrations are often not clearly related to bearing damage. Therefore, a robust method to detect bearing faults early and avoid expensive repairs and machine downtime is needed.

One simple approach for diagnosing the spindle condition is to compare the root-mean-square (RMS) vibration of the spindle housing to threshold values [2]. More intricate approaches use the high-frequency resonance technique [3], envelope spectrum analysis [4], wavelet transforms [5], neural networks [6], synchronous sampling [7], auto-correlation analysis [8], modal decomposition [9], fractals and kurtosis [10].

A significant problem with all methods is that spindle diagnoses can be corrupted by system dynamics. The rotor excitation is transformed by system dynamics to yield the vibration data; vibration is a convolution of spindle dynamics and excitation from bearings. Resonances can adversely affect spindle condition metrics [2], and metrics based on vibration data may depend on spindle speed [11], even though spindle damage is not speed-dependent. For example, Fig. 1 shows that the long term spindle condition (LTSC) metric from ISO/TR 17243-1 [2] rates a new spindle, with only 510 h of operation time and excellent performance, as a 'C' and 'not suitable for long term operation'.

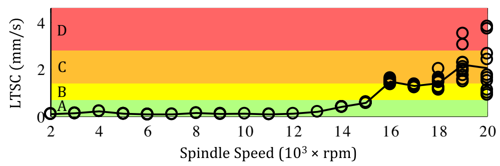

Fig. 1. Example of dubious spindle condition metric.

2. Method for estimating spindle condition

Ideally, only the bearing defect geometry should be used to estimate the spindle condition. Therefore, measured data must be used to separate system dynamics from defect geometry. In that case, a metric could be devised that depends only upon bearing defects and is hence truly representative of the spindle condition.

Fig. 2 shows a methodology for estimating spindle condition based on the separation of spindle dynamics and defects.

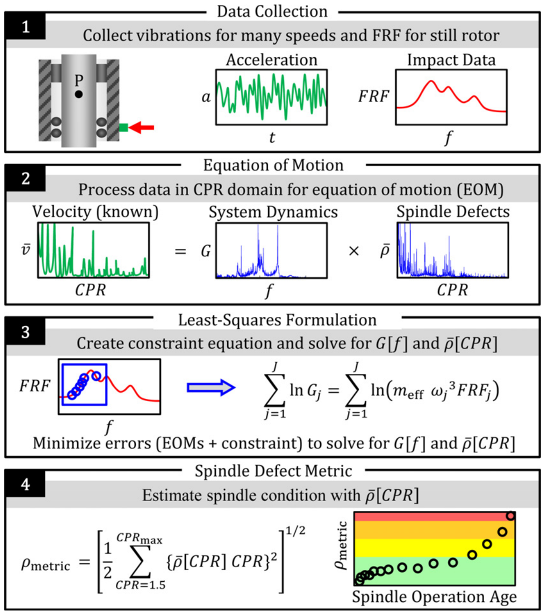

Fig. 2. NIST methodology for estimating spindle condition based on separation of system dynamics and bearing defect geometry.

* Corresponding author.
E-mail address: gvogl@nist.gov (G.W. Vogl).

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This section outlines the method, while later sections describe its use.

2.1. Data collection

As seen in Fig. 2, the first step of the new spindle condition estimation method is to collect data on the spindle housing. Fig. 3(a) shows a spindle condition estimation device (SCED) created for this purpose. The device attaches to spindle housings via a magnetic base. A solenoid with a force sensor is used for impacts, yielding a frequency response function (FRF) through use of force and acceleration data. Two accelerometers of varying sensitivity and range allow for robust collection of vibration data. As seen in Fig. 3(b)–(d), the device can be used on milling and turning spindles in various configurations.

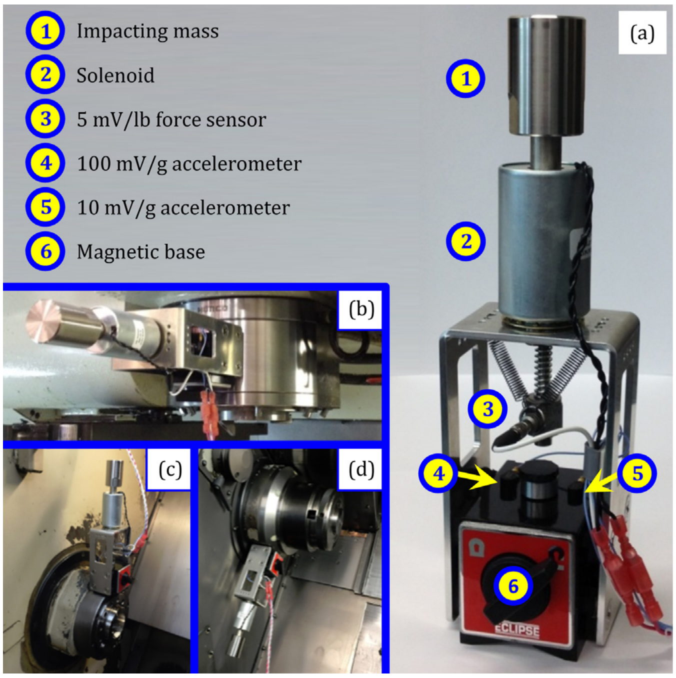

Fig. 3. (a) Spindle condition estimation device, being (b) horizontal on a vertical milling center, (c) upright on a turning center, and (d) upside-down on a turning center.

The SCED with instrumentation and custom software are used for data acquisition at a sampling rate of f_s = 51 200 Hz. First, ten impacts are performed with no rotor motion and repeatable maximum force (≈200 N). Then, accelerometer data are collected for various spindle speeds, from 1200 rpm (20 Hz) up to the spindle's maximum speed, e.g., spindle speeds from 1200 rpm to 3000 rpm with a 100 rpm interval. For statistical purposes, ten trials (N_r = 10) are conducted for each spindle speed.

2.2. Equation of motion

Defects in the spindle bearings affect the rigid-body component of the rotor motion. For any spindle speed, the motion of the point P on the rotor (see Fig. 2) can be described in the cycles per revolution (*CPR*) domain as $\rho(CPR)$, where *CPR* is defined as

$$CPR = \frac{f}{f_{sp}} \tag{1}$$

f_{sp} is the spindle speed in hertz, and f is the frequency (Hz) of interest. Hence, $\rho(CPR)$ is a measure of displacement associated with bearing defects.

The next step of the method is to process the velocity, $v(t)$, which is derived from the measured acceleration, for use within an equation of motion (EOM). Note that either velocity or acceleration can be used to yield the same result. Accordingly, application of classical mechanics yields the approximate EOM as

$$|\bar{v}[CPR]| = |G[f]||\bar{\rho}[CPR]| \tag{2}$$

where an overbar denotes the discrete Fourier transform (DFT) and $G[f]$ is the dynamics transfer function relating force excitation to resulting velocity. For sufficiently small frequencies, $G[f]$ is approximated as

$$G[f] = m_{eff}\,\omega^3\,FRF[f] \tag{3}$$

where m_{eff} is an effective mass based on spindle configuration, $\omega = 2\pi f$, and $FRF[f]$ is the measured FRF that relates vibration displacement (derived from measured acceleration) to applied force. The method uses Eq. (2) to solve for both the spindle defect function, $\bar{\rho}[CPR]$, in the *CPR* domain and the dynamics transfer function, $G[f]$, in the frequency domain. The natural logarithm of each side of Eq. (2) separates the unknowns $G[f]$ and $\bar{\rho}[CPR]$:

$$\ln|\bar{v}| = \ln|G| + \ln|\bar{\rho}| \tag{4}$$

A linear system of equations can be created by utilizing data for all spindle speeds. To this end, the velocity data should be used in

$$\ln|\bar{v}_{i,n}| = \ln|G[f_{i,n}]| + \ln|\bar{\rho}_n| \tag{5}$$

for the ith spindle speed and the nth *CPR* value. This process requires the same *CPR* values, regardless of spindle speed, achieved when the record length N_i is approximately

$$N_i = 2\,round\left(\frac{1}{2}\frac{f_s}{f_{sp,i}\,\Delta CPR}\right) \tag{6}$$

where $round(x)$ rounds x to its nearest integer, $f_{sp,i}$ is the ith spindle speed, and ΔCPR is the desired *CPR* resolution. The resolution ΔCPR should be small enough to successfully separate the spindle defect frequency components, e.g., ΔCPR = 0.05.

For an M number of spindle speeds and an N number of *CPR* values, there are an $M \times N$ number of equations according to Eq. (5). For each *CPR* value, the velocity, $v(t)$, can now be processed for use within Eq. (5). To this end, the velocity DFT, $\bar{v}_r[i, CPR_n]$, for the ith spindle speed and rth trial is averaged in a root-mean-square fashion over the N_r trials as

$$|\bar{v}_{i,n}| = \left[\frac{1}{N_r}\sum_{r=1}^{N_r}|\bar{v}_r[i, CPR_n]|^2\right]^{1/2} \tag{7}$$

Finally, a P number of unique frequencies, $(f_1, f_2, \ldots, f_p)$, are used to approximate Eq. (5) as

$$\ln|\bar{v}_{i,n}| = \ln|G[\tilde{f}_{i,n}]| + \ln|\bar{\rho}_n| \tag{8}$$

where $\tilde{f}_{i,n}$ is the closest value to $f_{i,n}$ within the set of frequencies.

Eq. (8) yields an $M \times N$ number of equations that are linear in the unknowns, $\ln|G_p|$ and $\ln|\bar{\rho}_n|$. Because the linear system is overdetermined, a least-squares solution exists. The variables related to system dynamics and bearing defect geometry are highly coupled for robustness. For data collected at twenty spindle speeds (M = 20), up to 60 values of $\bar{\rho}$ relate to one G variable, and one $\bar{\rho}$ value is related to up to 20 values of G.

2.3. Least-squares formulation

The next step of the method is to create a constraint equation and solve for $G[f]$ and $\bar{\rho}[CPR]$. A unique least-squares solution requires at least one constraint. As Eq. (2) reveals, the product of two unknown functions is the same to within a scaling factor, α, because $(1/\alpha)G[f] \times \alpha\bar{\rho}[CPR]$ still yields $G[f] \times \bar{\rho}[CPR]$. FRF data is used to create the constraint equation,

$$\sum_{j=1}^{J}\ln G_j = \sum_{j=1}^{J}\ln(m_{eff}\omega_j^3 FRF_j) \tag{9}$$

in which only the J number of points with an acceptable coefficient of variation ($COV \leq 0.03$) and frequency (100 Hz $< f <$ 200 Hz) are used. The COV requirement ensures that only robust data is used, while the frequency requirement ensures that Eq. (3) may be used; the spindle rotor can be regarded as being fairly rigid for a