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A defect-driven diagnostic method for machine tool spindles

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Abstract

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.

Keywords

Spindle; Condition monitoring; Vibration; Machine tools

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 analysed 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, Figure 1 shows that the long term spindle condition (LTSC) metric from ISO/TR 17243-1 [2] rates a new spindle, with only 510 hours of operation time and excellent performance, as a ‘C’ and ‘not suitable for long term operation’.

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.

Figure 2 shows a methodology for estimating spindle condition based on the separation of spindle dynamics and defects. This section outlines the method, while later sections describe its use.

2.1. Data Collection

As seen in Figure 2, the first step of the new spindle condition estimation method is to collect data on the spindle housing. Figure 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 Figure 3(b–d), the device can be used on milling and turning spindles in various configurations.

The SCED with instrumentation and custom software are used for data acquisition at a sampling rate of $f_s = 51200$ 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 Figure 2) can be described in the cycles per revolution (CPR) domain as $\rho(CPR)$, where CPR is defined as

$$CPR = \frac{f}{f_{sp}} \quad (1)$$

f_{sp} the spindle speed in hertz, and f is the frequency (in hertz) 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

$$|\bar{v}[CPR]| = |G[f]| |\bar{\rho}[CPR]| \quad (2)$$

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

$$G[f] = m_{\text{eff}} \omega^3 FRF[f] \quad (3)$$

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 $\bar{\rho}[CPR]$:

$$\ln|\bar{v}| = \ln|G| + \ln|\bar{\rho}| \quad (4)$$

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

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

for the i^{th} spindle speed and the n^{th} CPR value. This process requires the same CPR values, regardless of spindle speed, achieved when the record length N_i is approximately

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

where $\text{round}(x)$ rounds x to its nearest integer, $f_{\text{sp},i}$ is the i^{th} 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., $\Delta CPR = 0.05$.

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, $\bar{v}_i[i, CPR_n]$, for the i^{th} spindle speed and i^{th} trial is averaged in a root-mean-square fashion over the N_i trials as

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

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

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

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

Equation (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 $\frac{1}{\alpha} G[f] \times \alpha \bar{\rho}[CPR]$ still yields $G[f] \times \bar{\rho}[CPR]$. FRF data is used to create the constraint equation,

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

in which only the J number of points with an acceptable coefficient of variation ($COV < 0.03$) and frequency ($100 \text{ Hz} < f < 200 \text{ Hz}$) 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 frequency f that is well below the fundamental frequencies of the spindle assembly from 1.2 kHz to 2.5 kHz [12].

Finally, the set of equations from Eq. (8) with the constraint Eq. (9), are solved in a weighted least-squares fashion using weights that depend on signal to noise, COV, and velocity spectrum magnitudes. The result is the unique solution of $G[f]$ and $\bar{\rho}[CPR]$.

2.4. Spindle defect metric

The defect function, $\bar{\rho}[CPR]$, is used to create a spindle condition metric, independent of spindle speed and dynamics $G[f]$. A spindle defect metric function, ρ_{rms} , is defined as

$$\rho_{\text{rms}}(CPR_{\text{cr}}) = \left[\frac{1}{2} \sum_{CPR_{\text{cr}}}^{CPR_{\text{max}}} \{\bar{\rho}[CPR]\}^2 \right]^{1/2} \quad (10)$$

where CPR_{max} is the maximum CPR value and CPR_{cr} is a chosen minimum threshold. Equation (10) is equivalent to the RMS of $\rho(t)$ that is high-pass filtered to keep terms with sufficiently high frequencies ($CPR_{\text{cr}} = 1.5$) indicative of spindle defects. Figure 4 shows the spindle metric function from Eq. (10) for 11 machine tool spindles, grouped as ‘new’, ‘used’, or ‘worn’ based on the total operation time. As operation time increases, spindle wear increases and ‘defect energy’ moves into higher CPR values.

This trend of defect energy with operation time can be revealed using a single defect metric,

$$\rho_{\text{metric}} = \left[\frac{1}{2} \sum_{CPR=1.5}^{CPR_{\text{max}}} \{\bar{\rho}[CPR] CPR\}^2 \right]^{1/2} \quad (11)$$

Equation (11) is related to the RMS velocity, v_{rms} , of point P (see Figure 2) associated with the rigid-body component of the rotor motion with an angular speed of Ω ; that is, $v_{\text{rms}} = \rho_{\text{metric}} \Omega$. Consequently, Eq. (11) is a measure of the spindle condition that is related to velocity while being independent of spindle speed. Figure 5 shows that the spindle defect metric ranges from 0.3 μm (new spindle) to 18 μm (spindle with about 16 000 hours of operation time) for the machine tools utilized in Figure 4.

3. Example of two turning spindles

The advantage of the metric in Eq. (11) over existing metrics can be illustrated for two turning spindles (‘T1’ and ‘T2’), which are on machines of the same model and configuration but with different operation histories. Spindle T1 is relatively new with only 120 hours of total operation time, and Spindle T2 was used in production for 2210 hours. Table 1 shows that, according to ISO/TR 17243-1, Spindle T2 has a condition that is about 3 times better than Spindle T1, even though Spindle T1 has far fewer operation hours. However, according to the spindle defect metric in Eq. (11), the two spindles have basically the same condition.

Figure 6 helps explain the differences among the ISO metric and the proposed metric. The ISO metric is generally the largest RMS of filtered vibration, and as seen in Figure 6(a–b), Spindle T1 has a greater vibration (and hence ISO metric) than Spindle T2. However, Figure 6(c–d) shows that only Spindle T2 shows noticeable wear, especially due to defects on the outer race of the front bearing. Therefore, Spindle T2 has greater wear due to its use in production, despite the ISO metric suggesting otherwise. The reason for the greater vibrations and ISO metric for Spindle T1 is seen in Figure 6(e): the dynamics function, $G[f]$, for Spindle T1 is significantly greater than that for Spindle T2 for frequencies below 2.5 kHz, which leads to greater vibrations for Spindle T1 compared to Spindle T2.

The NIST method, however, accounts for vibration differences due to system dynamics. The spindle defect metric is almost the same for both spindles, as seen in Table 1. In order to verify this result, a round brass test piece was turned on the two turning spindles at 1200 rpm, the same speed used for Figure 6(a–b). Finally, the roundness profiles were measured. Figure 7 shows that, in support of the NIST method, the spindles have similar peak-to-peak magnitudes in roundness variations.

4. Example of two milling spindles

Another example using two milling spindles ('M1' and 'M2') illustrates the advantages of the new method for spindle diagnostics. Similar to the turning spindle example, the two milling spindles are on machines of the same model and configuration but with different operation histories. As seen in Table 2, ISO/TR 17243-1 [2] indicates that the condition of Spindle M2 is about 16 times worse than the condition of Spindle M1. Figure 8(a) shows that the ISO metric estimates that Spindle M2 is in the red 'D' zone, while Spindle M1 is in the green 'A' zone.

However, the ISO metric values in Table 2 are not consistent with other operational information. Both spindles have been used for more than 14 000 hours of production, so Spindle M1 is not 'newly commissioned', per Zone A [2]. On the other hand, both spindles still produce acceptable parts, without any indication of a 'critical condition' for Spindle M2, per Zone D [2].

Contrary to the ISO metric and yet more consistent with other information, the spindle defect metric indicates that the two milling spindles are in 'used' conditions with more similar levels of degradation and Spindle M1 having a condition that is worse than Spindle M2.

Thus, the significant difference between the two ISO metric values in Table 2 appears to be a result of the influence of system dynamics. Due to this possibility, the ISO method allows for the exclusion of 10 percent of data near resonances. For the two milling spindles, Figure 8(b–c) shows typical acceleration signals for spindle speeds remaining after data exclusion. For this case, the apparent discrepancy in the accelerations within Figure 8(b–c) is attributed to the differences in dynamic behaviors of the two spindles.

5. Conclusions

A new method and device were developed for estimation of machine tool spindle condition. The method separates system dynamics from defect geometry, and based on this method, a spindle defect metric relying only on defect geometry was proposed. The metric includes effects due to rolling elements, inner races, and outer races. Therefore, the metric is not corrupted by resonances and other unwanted system dynamics.

Application for various milling and turning spindles shows that the new approach is robust for diagnosing the machine tool spindle condition. Hence, a spindle condition estimation device could be used within a time-based maintenance schedule for monitoring spindle degradation. The metric could be tracked and outputted to the user as a diagnostic based on

thresholds (e.g., ‘new’ to ‘unacceptable’), and the trend of the metric could be used to predict remaining useful life (RUL) for maintenance planning.

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Figure 1.
Example of dubious spindle condition metric.

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

Figure 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.

Figure 4.
 $\rho_{rms}(CPR_{cr})$ for numerous machine tool spindles.

Figure 5.
Spindle defect metric for numerous spindles.

Figure 6.

(a–b) Typical vibration data and (c–d) defect function for two turning spindles with different total operation times of 120 hours or 2210 hours; (e) dynamics function for spindles.

Figure 7.
Roundness data for part turned at 1200 rpm on (a) Spindle T1 and (b) Spindle T2.

Figure 8.

(a) Long term spindle condition metric from ISO/TR 17243-1 [2] and vibration data for two milling spindles with similar total operation times of (b) 14 200 hours for M1 and (c) 14 700 hours for M2.

Table 1

Metrics for conditions of two turning spindles

Spindle	T1	T2
Total Operation Time (hours)	120	2210
ISO Metric (mm/s RMS) ^a	0.155	0.050
Spindle Defect Metric (μm)	2.51	2.46

^a long term spindle condition metric from ISO/TR 17243-1 [2]

Table 2

Metrics for conditions of two milling spindles

Spindle	M1	M2
Total Operation Time (hours)	14 200	14 700
ISO Metric (mm/s RMS) ^a	0.522	8.71
Spindle Defect Metric (μm)	16.7	7.02

^a long term spindle condition metric from ISO/TR 17243-1 [2]