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Failure sensitivity and similarity of process signals among multiple machine tools

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Abstract

For a monitoring system to provide considerable performance, it usually requires machine- and process-specific information. This includes information about which process signals are sensitive to failures and which signal behavior indicates these failures. However, this information is mostly unavailable when monitoring the manufacturing of individual parts or small series. The transfer of process-specific information among similar machine tools can provide the required information, thereby improving monitoring performance. Nevertheless, no systematic research exists on what process signals are best suited for such an information transfer. This paper investigates a) whether information about the sensitivity of a signal to failures is transferrable among multiple machine tools and b) whether the behavior of these signals, modelled as probability distributions, is similar among multiple machine tools. Initially, a measure is introduced that quantifies the capability of a signal to separate two process conditions, the signal overlap factor SOF. It is then demonstrated how the SOF can be calculated for transient process conditions. The SOF is then empirically determined for a set of process signals for three different machine tools, individually, to assess failure-sensitivity of the signals for slot milling in steel. Additionally, the SOF is calculated for the union of the data of the machine tools to assess the similarity of signals among machine tools. The set of evaluated process signals includes process forces, the torque of the main spindle, and the torque and position control deviation of the feed axes. All machine tools were operated with identical instructions, tools, and materials. Bores were machined in workpieces to simulate material anomalies. Results suggest that low-pass filtered process forces or position control deviations, if sensitive to failure in a machine tool with linear direct drives, are also sensitive to failure in other machine tools. Also, low-pass filtered process forces were the most similar signals among the investigated machines. Possible causes that impair the similarity of signals among machine tools are discussed.

Keywords: machine tools; process monitoring; fleet monitoring; similarity measure

1. Introduction

Machining is an essential part of modern manufacturing. However, anomalies and failures in machining processes, such as material with hard inclusions, tool breakage, incorrect clamping, or collisions impair its productivity. These failures can lead to critical consequences, such as downtimes, machine damages, as well as scrap and rework. While optimal process preparation mitigates the risk of process failures, it cannot fully prevent failures and their consequences [1]. Process monitoring reduces the risk of such critical consequences by detecting abnormal processes and tool conditions. Process monitoring systems that prevent critical consequences reliably enable unsupervised and economical operation of machine tools [2]. Consequently, process monitoring is considered a prerequisite for autonomous machine tools [3].

To achieve peak performance, state-of-the-art monitoring systems require references for the classification of correct (OK) and faulty (NOK) processes. Such references are used to identify process models and sensor signals sensitive to failures,

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along with the corresponding monitoring limits. In series production, process signals of previous processes can be used as references. For the monitoring of small series and manufacturing of individual parts, however, these references are usually unavailable.

One approach to improve monitoring performance for small series and individual parts is to transfer the references, limits, or models from similar machine tools. In [4], for example, an artificial neural network to detect chatter from microphone signals was trained on one machine tool and used to monitor a milling process on another machine tool. In [5], deep learning models were transferred between machine tools to detect failure patterns in power signals. In [6], limits for torque signals of the main spindle were transferred between multiple lathes to detect material anomalies online. However, while these approaches transfer models among multiple machine tools, no approach evaluates what signals are best suited for a transfer.

This paper investigates a) whether information about the sensitivity of a signal to failures is transferrable among multiple machine tools and b) whether the behavior of these signals is similar among machine tools. Section 2 introduces a method to quantify how well a signal distinguishes OK and NOK processes for online monitoring. Section 3 describes the experiments and section 4 compares the capability of different signals to detect NOK processes and their similarity among machine tools. Additionally, disturbance factors are identified.

2. Measure to assess the suitability of signals

Industrial applications require a certain decision quality, usually defined as a compromise of high sensitivity and low false alarm rates. Therefore, the behavior of signals is modeled statistically. Signals are interpreted as a random variable V whose observed values v_i follow different distributions depending on the condition of the process.

2.1. Quantifying the suitability of an individual signal

Repetitive processes without wear and anomalies can be modeled with a normal distribution [7]. In Fig. 1, $N(\mu_{OK}, \sigma_{OK}^2)$ is the normal distribution of signal values originating from an OK process with the expected value μ_{OK} and the standard deviation σ_{OK}. The distribution of NOK processes is fault-specific. However, it is also assumed to be normally distributed. Therefore, $N(\mu_{NOK}, \sigma_{NOK}^2)$ is the normal distribution of signal values originating from NOK processes.

When monitoring a process, a value v_i of the signal is observed. The monitoring system decides whether the observed value originated from the distribution of OK processes or not. Often, a limit l is used as a critical value to classify the observed value. In this case, a monitoring system acts as a binary classifier. The decision quality of a binary classifier can be quantified by sensitivity and false alarm rates. The sensitivity or true positive rate (TPR) is the probability with which a NOK process is detected as NOK. The false alarm rate or false positive rate (FPR) is the probability with which an OK process is falsely assessed as NOK.

The false positive rate FPR is determined by the position of the limit l to the expected value of the distribution of OK

Nomenclature

B2, B4	Process condition "bore ⌀2 mm", "bore ⌀2 mm"
e	Position control deviation
F	Process force
FPR	False positive rate or false alarm rate
l	Limit or critical value for monitoring
N	Feed drive force
NOK	Process condition "not correct"
OK	Process condition "correct"
P	Probability
p	Probability density
SOF	Signal overlap factor
T	Feed drive torque
TPR	True positive rate or sensitivity
V	Signal as a random variable with observed values v_i
X, Y, Z	Position coordinates
z	Standard score
μ	Expected value of the population
$\hat{\mu}$	Estimate for the expected value
σ	Standard deviation of the population
$\hat{\sigma}$	Estimate for the standard deviation

processes μ_{OK}. To not exceed a given false alarm rate FPR, the limit l has to be at least placed in a certain distance to the right of the expected value μ_{OK} as defined in Eq. 1:

$$|\mu_{OK} - l| \geq |\sigma_{OK} \cdot \Phi^{-1}(1 - FPR)| \quad (1)$$

With $\Phi^{-1}(P) = z$ being the quantile function of the standard normal distribution, it assigns the standard score $z = (v\text{-}\mu)/\sigma$ to a probability P. The standard score z is the number of standard deviations by which a value is above or below the expected value. As for the observed values v_i from an OK distribution $\Phi^{-1}(0.9773) \approx 2$ indicates that 97.73% of the observed values are less than or equal to $\mu_{OK} + 2\sigma_{OK}$.

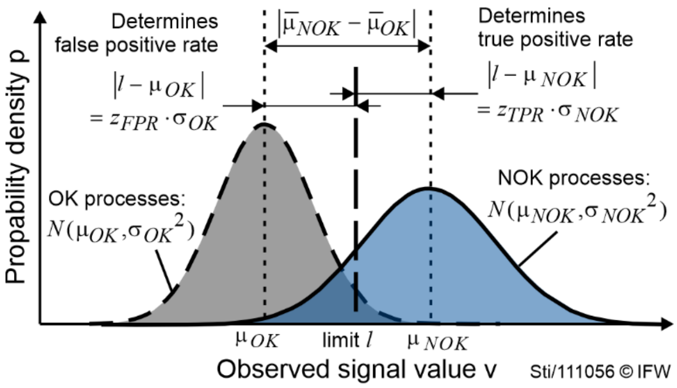

Fig. 1. Relationship between signal distributions, true positive rate, and false positive rate.

The other essential requirement, the sensitivity of a monitoring system, is determined by the position of the limit l to the expected value of the distribution of the NOK processes. To achieve or exceed a required sensitivity TPR, the limit l has to be placed at least in a certain distance to the left of the expected value μ_{NOK} as defined in Eq. 2:

$$|\mu_{NOK} - l| \geq |\sigma_{NOK} \cdot \Phi^{-1}(1 - TPR)| \quad (2)$$

Instead of the quantile function $\Phi^{-1}(P) = z$ the standard score z can be used in Eq. 1 and 2 for a more compact representation:

$$z_{FPR} = |\Phi^{-1}(1 - FPR)| = |\Phi^{-1}(FPR)|$$
$$\text{and} \quad z_{TPR} = |\Phi^{-1}(1 - TPR)| = |\Phi^{-1}(TPR)| \qquad (3)$$

Integrating Eq. 1, 2 and 3, to represent the combined requirements in terms of sensitivity *TPR* and false alarm rate *FPR* leads to Eq. 4:

$$|\mu_{NOK} - \mu_{OK}| \geq z_{FPR} \cdot \sigma_{OK} + z_{TPR} \cdot \sigma_{NOK} \qquad (4)$$

For a defined decision quality (*FPR, TPR*) to be reached, the distance between the expected values of the distributions (μ_{OK}, μ_{NOK}) must be at least $z_{FPR} \cdot \sigma_{OK} + z_{TPR} \cdot \sigma_{NOK}$ as in Fig. 1.

A special case is when requirements for sensitivity and false alarm rate are equally demanding (1-*TPR* = *FPR*). This causes z_{FPR} to be equal with z_{TPR}. Equation 4 can then be converted into a measure that quantifies the capability of a signal to distinguish between two conditions, the signal overlap factor:

$$SOF = \frac{|\mu_{OK} - \mu_{NOK}|}{\sigma_{OK} + \sigma_{NOK}} \qquad (5)$$

Contrary to other discussions of the SOF (e.g. [8, 9]), Eq. 5 is designed with standard deviations instead of variances to increase interpretability in the context of process monitoring.

2.2. Signal overlap factor for transient process conditions

Existing literature uses the SOF to quantify how well a signal discriminates between different conditions that are rather stationary, such as "wear" and "no wear". In online monitoring, however, conditions are mostly temporary and anomalies are only present for a short period of time, e.g. local material flaws. To account for the transient behavior of signals, the SOF is subsequently calculated at the tool position or time where an anomaly causes the highest signal deflection. Mathematically, this corresponds to the minimum or maximum of the course of a signal. Whether the maximum or minimum applies depends on the failure, as well as the signal, and is determined manually. In the analysis, the search for extrema is limited to an interval where the anomaly is known to occur.

Fig. 2a gives an example of process signals as a function of the tool position for different process conditions. Minima are determined in the interval from 43 mm to 55 mm of the tool position Y. One minimum is determined for every OK process (one for every gray curve $v_{min,1,OK}$ to $v_{min,30,OK}$, a total of $N_{OK} = 30$) and one minimum for every NOK process with a temporary anomaly (one for every blue curve $v_{min,1,NOK}$ to $v_{min,9,NOK}$, a total of $N_{NOK} = 9$). Once the extrema (either minima $v_{min,k}$ or maxima $v_{max,k}$ of the processes k) are determined, the probability distributions are estimated, one specific to each process condition. The expected value μ of the population is estimated by the arithmetic mean:

$$\hat{\mu} = \frac{1}{N} \sum_{k=1}^{N} v_{min/max,k} \qquad (6)$$

The standard deviation σ is estimated by:

$$\hat{\sigma} = \sqrt{\frac{1}{N-1} \sum_{k=1}^{N} \left(v_{min/max,k} - \hat{\mu}\right)^2} \qquad (7)$$

Equations 6 and 7 yield the condition-specific means ($\hat{\mu}_{OK}$, $\hat{\mu}_{NOK}$) and standard deviations ($\hat{\sigma}_{OK}$, $\hat{\sigma}_{NOK}$) that enable the approximation of the SOF using Eq. 5. For the example in Fig. 2b, the SOF is 6.1. While the SOF is calculated from extrema to account for the transient signal behavior, it does make a statement about the suitability of the evaluated signal itself.

The conducted investigation on the suitability of signals for the transfer among machine tools evaluates anomalies in the form of bores. The SOF is determined as described in Fig. 2.

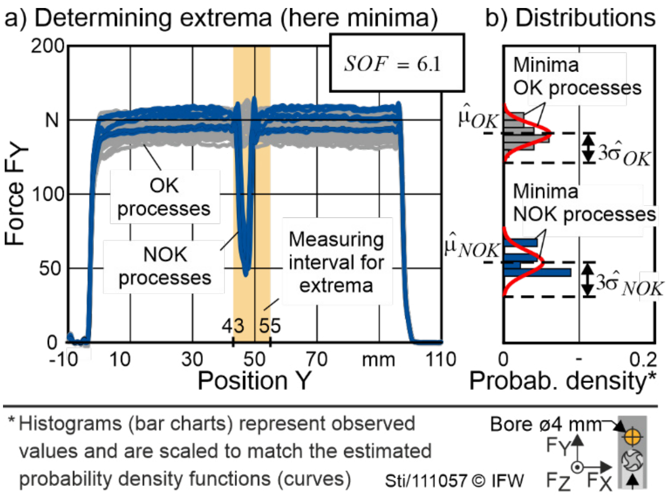

Fig. 2. (a) Determining extrema and (b) estimated probability functions specific to process conditions

2.3. Interpretation of the signal overlapping factor

The SOF requirements depend on the monitoring application. For reference, the following examples are considered: high demands, enabling less than 1 false alarm on average in a 24 h period of continuous monitoring making 100 decisions a second (requires FPR < 1/8,640,000 or $SOF \geq 5.2$). Medium demands are less than 1 false alarm on average in an 8 h period of continuous monitoring making 10 decisions a second (requires FPR < 1/288,000 or $SOF \geq 4.5$). Low demands are less than 1 false alarm on average in an 1 h period of continuous monitoring making 1 decision a second (requires FPR < 1/3,600 or $SOF \geq 3.5$). In practice, however, σ is often underestimated due to a small sample size that does not include all variations. Therefore, all SOF requirements are rounded up to the nearest integer (Tab. 1) More precise requirements can be determined from an economic perspective [10] or a perspective of functional safety [11].

Tab. 1: Examples of SOF requirements for univariate, one-sided monitoring

Demands for monitoring	Requirement incl. safety margin
High: <1 false alarm in 24h at 100 Hz	SOF ≥ 6
Medium: <1 false alarm in 8h at 10 Hz	SOF ≥ 5
Low: <1 false alarm in 1h at 1 Hz	SOF ≥ 4

3. Experimental setup

To evaluate which signals are suited best for a transfer scenario, experiments were conducted on three different milling centers of similar size (Tab. 2). The machine tools differed in terms of controls, feed drive design, and spindle performance. The same NC instructions were used for all machine tools (G-code according to ISO 6983), except for the machine-specific file headers. Workpieces were from normalized heat treatable steel (1.0601). The employed end mill cutters had a diameter of 8 mm and four teeth (no. 19940 by Gühring KG). A single batch of workpieces were used.

Tab. 2: Examined 5-axis milling centers

ID	Model	Control	Feed drive	Main spindle	Machining space
MIL	DMG Mori Milltap 700	Siemens Sinumerik 840D sl	Ball screw	4 kW / 8 Nm	700x420x380 mm
HSC30	DMG Mori HSC 30 linear	Siemens Sinumerik 840D sl	Direct drive	15 kW / 12 Nm	320x300x280 mm
HSC55	DMG Mori HSC 55 linear	Heidenhain iTNC 530	Direct drive	55 kW / 19 Nm	450x650x460 mm

Experiments were comprised of slot milling with consistent process parameters (Fig. 3). The depth of cut a_p was 2 mm, feed per tooth f_z was 0.05 mm, and cutting speed v_c was 150 m/min. The Y-axis is the feed axis, the X-axis is resting, and the Z-axis is the vertical axis. Process conditions varied between OK, B2, and B4 according to Tab. 3. Bores constituted a reproducible material anomaly, thereby allowing a more precise focus on the variances between machine tools. Three tools and three workpieces were used per machine tool.

Tab. 3: Conducted slot milling experiments

Condition	Description	Repetitions	Parts &
OK	No anomalies, OK process	30/machine	3/machine
B2	Anomaly: single bore ⌀2 mm	9/machine	3/machine
B4	Anomaly: single bore ⌀4 mm	9/machine	3/machine

Acquired signals comprise the measured process forces (F_X, F_Y, F_Z), the actual position of the tool center point (X, Y, Z), position control deviations (e_X, e_Y), and the torque of the main spindle (T_{SP}). Additionally, torque of the feed drives (T_X, T_Y, T_Z) was recorded for machine tools with ball screw drives (MIL) and forces of the feed drives (N_X, N_Y, N_Z) were recorded for machine tools with linear direct drives (HSC30, HSC55). Process forces were recorded with a dynamometer (type 9257B by Kistler Instrumente AG) with a sampling frequency of 20 kHz. The remaining signals were recorded from the control of the machine tools with a sampling rate of 125 Hz. All signals were lowpass-filtered with a cut-off frequency of 10 Hz.

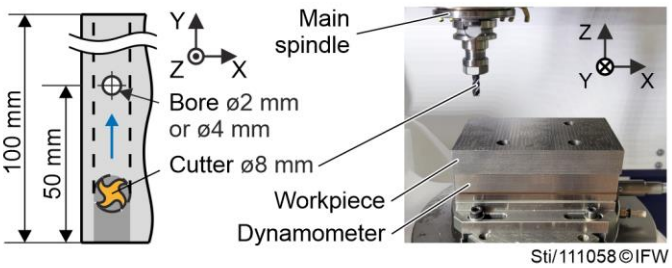

Fig. 3. Experimental setup for slot milling processes

4. Evaluation of process signals

The subsequent analysis uses the signal overlap factor *SOF*, as in Fig. 2, to quantify the capability of process signals to distinguish process conditions. All signal values are assumed to be normally distributed. Signals are assessed for individual machine tools and among multiple machine tools, the latter representing a transfer scenario. Bores 2 mm and 4 mm represent material anomalies (conditions B2 and B4). The analysis focuses on the B4 condition since it demonstrates the same type of failure as the B2 condition, but with more pronounced effects.

Figure 4 gives an overview of the signal overlap factors *SOF* for the three individual machine tools and the union of their data sets (transfer scenario). For individual machine tools, signals that meet at least low demands ($SOF \geq 4$) are the control deviation of the X-axis e_X, the torque of the main spindle T_{SP} and the process forces F_X, F_Y and F_Z. For the transfer scenario, the *SOFs* are generally lower than for individual machine tools.

The differences among machine tools present a disturbance factor when transferring references for signals among machine tools. The only signals in the transfer scenario that meet at least low demands are measured process forces. Due to the varying feed drive concepts of machine tools, controls provide different physical quantities (torque T and force N) that form no meaningful union set. Consequently, no *SOF* is available (marked '-'). The suitability of signals is subsequently analyzed in detail.

Signal \ Machine	a) Bore ø2 mm MIL	HSC 30	HSC 55	Union	b) Bore ø4 mm MIL	HSC 30	HSC 55	Union
T_X or N_X	2.2	1.0	0.6	-	4.8	1.5	1.4	-
e_X	8.7	7.8	6.7	1.7	8.3	13.2	12.9	1.6
T_Y or N_Y	0.7	0.2	0.3	-	2.7	0.6	0.3	-
e_Y	3.4	0.4	0.9	0.7	3.9	1.3	1.6	0.8
T_Z or N_Z	1.2	0.5	0.5	-	1.1	1.2	1.0	-
T_{SP}	0.9	3.3	6.4	0.8	4.4	9.8	15.9	2.1
F_X	7.6	6.6	11.5	6.9	12.0	12.8	19.1	12.4
F_Y	1.6	4.4	2.5	1.8	4.8	7.8	6.1	5.1
F_Z	2.4	3.0	2.7	2.1	7.0	7.1	6.6	5.0

Z X Y bore

$$SOF = \frac{|\mu_{OK} - \mu_{NOK}|}{\sigma_{OK} + \sigma_{NOK}}$$

0 ≥6

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Fig. 4. Signal overlapping factor for different signals and machines

4.1. Process forces

The probability distributions used to calculate the *SOF* for the process force F_x are shown in Fig. 5. The histograms visualize the distribution of observed signal values (bar charts, scaled to match PDFs). The orange curves represent the probability density functions (PDFs) of the normal distributions estimated by formula 6 and 7 from the observed signal values.

For all machine tools, the locations of the distributions differ between the OK processes (gray, $\hat{\mu}_{OK}$) and the material anomalies (light and dark blue, $\hat{\mu}_{B2}$, $\hat{\mu}_{B4}$). The displacement in the force F_X that is caused by the bore 2 mm is less pronounced than for the bore 4 mm. As a result, the distance between the mean values of the OK and B2 condition ($\hat{\mu}_{OK}$ - $\hat{\mu}_{B2}$) decreases when compared to the condition B4. The deviation ($\hat{\sigma}_{B2}$, $\hat{\sigma}_{B4}$), however, remains similar. Following Eq. 5, the SOF decreases from 12.4 (for B4 vs. OK) to 6.9 (for B2 vs. OK) as a result.

For individual machine tools, the process force F_X of the resting axis, normal to the feed direction, is generally the best suited signal. It is meets high demands for all machine tools. The process forces F_Y and F_Z, in comparison, are generally less sensitive to failures. This is predominantly due to higher variations resulting from the cutting process itself. Consequently, the process forces F_Y and F_Z meet low demands only for the detection of bores 4 mm (*SOF* > 4.8).

In the transfer scenario (union), the process force F_X of the resting axis meet high demands for monitoring (*SOF* ≥ 6.9 for bore 2 mm and 4 mm). The process forces F_Y and F_Z meet medium demands for the bore 4 mm (*SOF* of 5.1 and 5.0). The rather small difference between the *SOF* of individual machine tools and the transfer scenario indicates that low-pass filtered process forces are generally well suited for a transfer.

Differences between machine tools are mostly caused by different standard deviations in the B2 and B4 conditions, e. g. between the HSC30 and the HSC55. Low-pass filtering of process forces suppressed the highly machine-specific part of the frequency response functions at about 100 Hz and above.

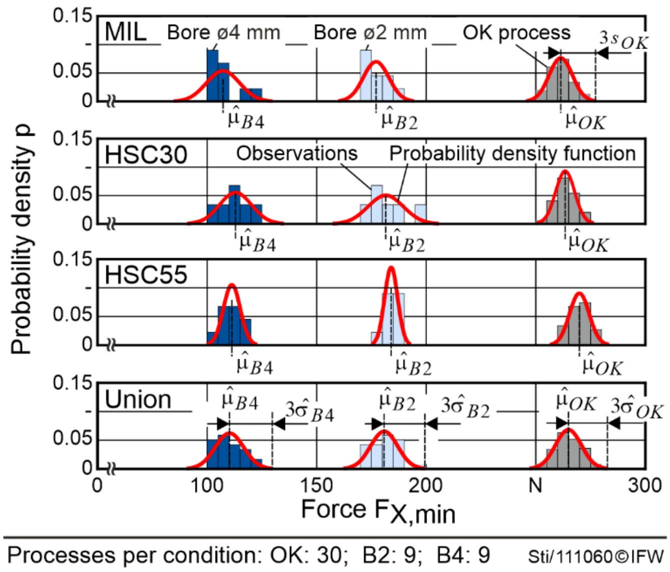

Fig. 5. Condition-dependent distributions of the process force F_X

4.2. Main spindle torque

For individual machine tools, the suitability varies greatly (0.9 ≤ *SOF* ≤15.9). While the main spindle torque T_{SP} meets high demands for monitor the bore 2 mm on the machine tool HSC55, it is unsuited on the machine tool MIL. However, for the bore 4 mm, the main spindle torque meets at least low demands for all machine tools (Fig. 6).

In the transfer scenario (union), the main spindle torque is unsuited for monitoring (*SOF* = 2.1, bore 4 mm). However, the torque of the main spindle T_{SP} has the best suitability among the signals sourced from the machine control.

Differences between machine tools result from varying spindle drive properties and signal processing. For instance, the no-load torque of spindles differs causing different locations of distributions ($\hat{\mu}_{OK}$, $\hat{\mu}_{B2}$, $\hat{\mu}_{B4}$). For the machine tool MIL, the signal processing within the machine control caused an increased standard deviation. Internal filters were deactivated, thereby increasing noise and possibly causing aliasing. Similarity of torque signals could be improved among machine tools by employing observers that isolate the process-related signal components.

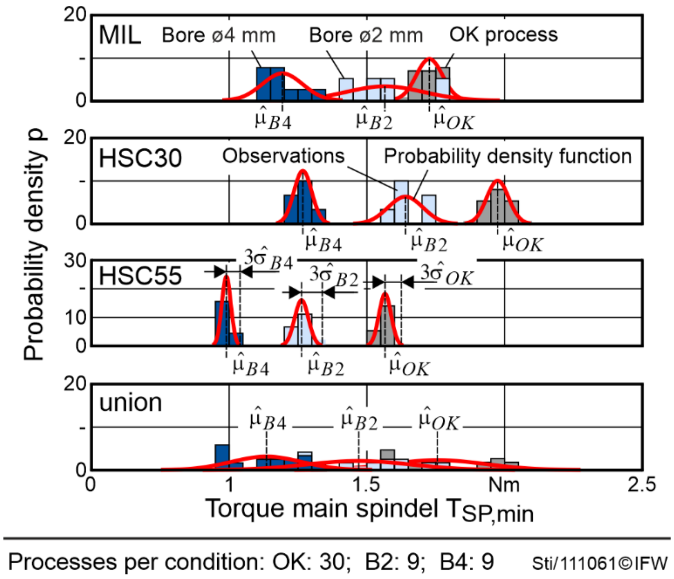

Fig. 6. Condition-dependent distributions of the torque of the main spindle T_{sp}

4.3. Position deviation

For individual machine tools, the control deviation in feed direction e_Y is unsuited for machine tools with linear direct drives (HSC30, HSC55). While the bores affect the control deviation, the effect is superimposed and dominated by a periodic, low frequency disturbance, probably resulting from groove and cogging effects. Future work might eliminate this disturbance by employing a high-pass filter. The control deviation of the resting axis e_x, normal to the feed direction, meets high demands for monitoring (Fig. 7). This is true for both the 2 mm and the 4 mm bore (*SOF* ≥ 6.7).

In the transfer scenario (union), all control deviations are unsuited for monitoring (*SOF* ≤ 1.7). The distributions for the B2 and B4 conditions of the machine tool MIL are located apart from those of the machine tools HSC30 and HSC55 (Fig. 6). Consequently, in the union set, the standard deviation increases and the *SOF* decreases. However, the meaning of the SOF is limited in this situation, as the distribution of the bores in the union set is insufficiently represented by a normal distribution. The distributions of OK conditions are meaningful. OK distributions are sufficiently similar for an anomaly detection that requires no information about failures. With this limitation, the control deviations are considered to meet at least low demands in the transfer scenario. Differences in the control deviation of machine tools arise from dynamic properties of the feed drives and control parameters, such as contour tolerances.

4.4. Feed axes torque and force

For individual machine tools, the force or torque of feed axes are mostly unsuited for monitoring. An exception is the machine tool MIL, where the torque of the X-axis meets low demands for detecting the bore 4 mm. On the machine tools HSC30 and HSC55, the force signal is dominated by a periodic disturbance. While the bore affects the force signals, the failure pattern is superimposed and dominated by groove and cogging effects. Both machine tools have linear direct drives. As for the transfer scenario, no comparison was possible as the machine controls output different physical quantities (forces vs. torque).

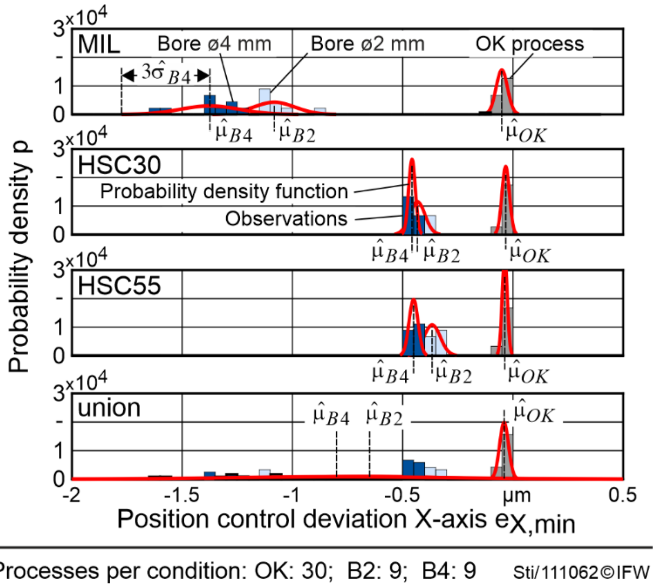

Fig. 7. Condition-dependent distribution of the position control deviation e_X

5. Conclusion

Effective monitoring requires signals that are sensitive to failures, such as material anomalies, tool breakage, and collisions. Signals that are sensitive to failures on one machine tool might not be sensitive to failures on another machine tool. However, the conducted investigation suggests, for the selection of signals sensitive to material anomalies in slot milling on individual machine tools, that

- measured and low-pass filtered process forces are among the most sensitive signals on all machine tools,
- the resting axis, normal to the feed direction, provides the most suitable signals of all feed axes,
- low-pass filtered process forces or position control deviations, if suited for monitoring on a machine with linear direct drives, are also suited for monitoring on other machine tools.

Sharing references for signals among multiple machine tools requires signals that are sensitive to failure on all machine tools and, additionally, are similar among all machine tools. As for the similarity of signals among multiple machine tools, the conducted investigation suggests, that

- measured and low-pass filtered process forces are among the most similar signals among machine tools,
- the distribution of correct processes of the position control deviation of the resting axis, normal to the feed direction, is similar among machine tools,
- the more pronounced a failure pattern is, the less similarity is required for a transfer of references to still be successful,
- process forces and the main spindle torque are independent of machine-specific kinematics.

The examined machine tools were of similar size, had similar spindle drive power and similar kinematics (Tab. 2). In addition, only a selection of low-pass filtered signals were examined. Future research should assess a broader variety of machine tools, processes, failures, signals, and signal processing. Furthermore, future research should investigate the typical probability distributions of failures. The signal overlap factor *SOF* could then be generalized to evaluate arbitrary probability distributions. For the concept of the *SOF* to yield robust results, probability distributions have to model all occurring variations in an application. This modelling can be challenging in industry. Consequently, future work should investigate how probability distributions change when boundary conditions vary, e.g. machining aluminum instead of steel. Future research might also determine how precise process force observers or force sensors need to be to enable a successful transfer of signal references.

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