INDIRECT DRILL CONDITION MONITORING BASED ON MACHINE TOOL CONTROL SYSTEM DATA

PETR KOLAR[1], DAVID BURIAN[1], PETR FOJTU[2], PETR MASEK[2], STEPAN FIALA[1], STEPAN CHLADEK[1], PETR PETRACEK[1], JIRI SVEDA[1], MICHAL RYTIR[1,2]

[1]Czech Technical University in Prague, Czech Institute of Informatics, Robotics and Cybernetics, Department of Industrial Production and Automation, Prague, Czech Republic

[2]Czech Technical University in Prague, Faculty of Mechanical Engineering, Department of Production Machines and Equipment, Research Centre of Manufacturing Technology, Prague, Czech Republic

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e-mail to corresponding author: p.kolar@rcmt.cvut.cz

Automatic process monitoring, including tool wear monitoring, is a key aspect of improving the energy efficiency and cost of the machining process. The tool flank wear continuously increases during drilling operations. The intensity of tool wear may vary depending on the local properties of the material and the process settings. This paper shows the potential of drill condition monitoring based on machine tool control system data, namely spindle drive current and Z slide current. The workpiece vibration measurement is used as a reference method. Correlations of various features of monitored signals are evaluated. These features are shown to depend, in general, on the instantaneous drilling depth. Among the features investigated, the RMS signal has been shown to exhibit a significant correlation with tool wear. The results were compared for two values of cutting speed. The correlation of selected features is shown to be independent of the total lifetime of the tool, thus demonstrating the attractiveness of these features for tool wear prediction. Specifically, the root mean square of the vibration and spindle torque signals strongly correlate with flank wear near the bottom of the hole while the root mean square of the drive current of the drilling axis strongly correlates with flank wear near the middle of the hole.

KEYWORDS

tool wear monitoring, spiral drill wear, smart machine tools, edge computing, correlation analysis

1 INTRODUCTION

Tool wear is a natural part of the machining operation reflecting the changes of the cutting edge micro-geometry. It influences the size of cutting forces and the final quality of the workpiece. Thus, automatic process monitoring, including tool wear monitoring, is a key aspect of the cost and energy efficiency improvement of the machining process [Tönshoff 1988].

Tool wear monitoring is a subtask of the more general topic of tool condition monitoring. The whole workflow consists of a processing chain that includes sensor selection, signal processing, feature extraction, and setting of the classification method for the final decision [Zhu 2009], see Fig. 1.

The monitoring of the tool condition can be based on direct or indirect measurement [Lauro 2014]. In this context, direct measurement means the measurement of a specific physical parameter that is a direct product of the monitored phenomenon. Indirect measurement means the measurement of a specific physical parameter that is a secondary product of the monitored phenomenon. Since the machining process generates time-varying forces, sensors of acoustic emission and accelerometers are often used for process monitoring due to relatively simple sensor integration. Direct force measurement using dynamometers is often used as a reference signal. [Lim 1995] presented a non-monotonous vibration level change for increased tool wear during turning. [Inasaki 1998] reported the application of an acoustic emission sensor for tool condition monitoring, tool breakage, and chatter detection for milling, turning, and grinding operations. [Lee 1999] presented the monitoring of milling tool wear using a discrete wavelet transformation of the spindle current. [Scheffer 2001] presented wear monitoring in turning operations using vibration and strain measurements.

The recorded signals have to be processed, and the signal features (signal properties) extracted for the subsequent analysis. The features can be extracted from the time-domain, frequency-domain, or time-frequency domain. [Kalvoda 2010] used the Hilbert-Huang transform for cutting tool state monitoring. [Fu 2019] presented an application of deep belief networks for the learning of automatic feature selection from vibration signals for machining state monitoring.

Various machine learning methods have been investigated for both tool wear prediction and feature selection. [Atlas 2000] used hidden Markov models for the detection of tool wear in milling. [Gao 2015] compared the efficiency of the hidden Markov model and the Gaussian mixture model for turning tool wear monitoring. [Krishnakumar 2015] proposed the application of decision tree J48 on the feature parameter selection and artificial neural network (ANN) for drill wear identification. [Corne 2017] studied the usage of spindle power data processed with a neural network to predict real-time tool wear-breakage during Inconel drilling.

Comprehensive reviews of the state of the art in sensors, signal processing, feature extraction, and feature classification were presented in [Jantunen 2002], [Teti 2010], [Lauro 2014], [Abellan-Nebot 2020], and [Serin 2020]. These review papers report that the dominant volume of recent work focuses on turning and milling applications using additional sensors for process monitoring. Moreover, the mutual resemblance of specific sensors (e.g., accelerometers) and reference sensors (e.g., dynamometers) is often evaluated. There is a minority of papers focused on the analysis of power signals from the machine tool with respect to the tool wear. As mentioned by [Jantunen 1996], signals from additional sensors of vibration, sound or acoustic emission provides more reliable signals for tool condition monitoring than methods based on the power consumption or drive current measurement. [Kim 2002] presented improved real-time drill wear estimation based on the spindle motor power monitoring with support of the simulative drill wear estimation model. A similar approach using a calculation model of the spindle power and comparison of simulated and measured data was used by [Axinte 2003].

The signal processing and feature extraction is often motivated by the application of machine learning models. [Ziegenbain 2020] studied the quality of the drilled holes with respect to the drill wear using statistical approaches and machine learning approaches. The risk of overfitting of the proposed ML method and the limited training possibility based on the small, imbalanced data sets typical for practical application are mentioned. Concurrently, the quite successful transferability of the method is presented.

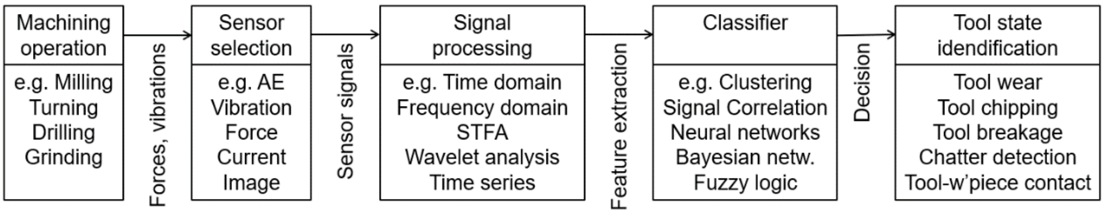


Figure 1: Workflow of the tool condition monitoring (according to [Zhu 2009]).

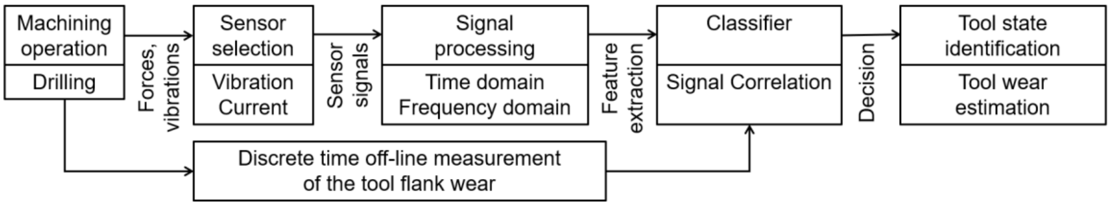


Figure 2: Schematic view of the method presented in this paper.

Recently, a growing interest in the use of deep learning methods can be seen. These methods are generally better at avoiding issues such as overfitting and the complicated process of feature selection on training data which, in a typical machining experiment, are both multidimensional and polluted with noise and outliers making the feature selection a particularly difficult task (see e.g. [Nasir 2021]).

Recent advances in machine tool digital drives provide new opportunities in tool condition monitoring. This paper focuses specifically on the methodology and potential of machine tool control system data usage for the tool wear estimation during the drilling process. The various features computed from the indirect signal measured from the additional acceleration sensor and signals acquired from the machine tool control system are correlated with the current values of drill flank wear measured directly off-line in discrete time periods (see Fig. 2). The method shows a potential for reliable tool wear monitoring during drilling. The paper is organised as follows: Section 2 presents the experimental setup, methods of data segmentation and synchronisation, and the method of tool wear measurement. Section 3 describes general signal properties, tool wear time evolution, and feature selection based on correlation the individual signal features and reference tool wear measurements. The results are discussed in Section 4. The final conclusions are presented in Section 5.

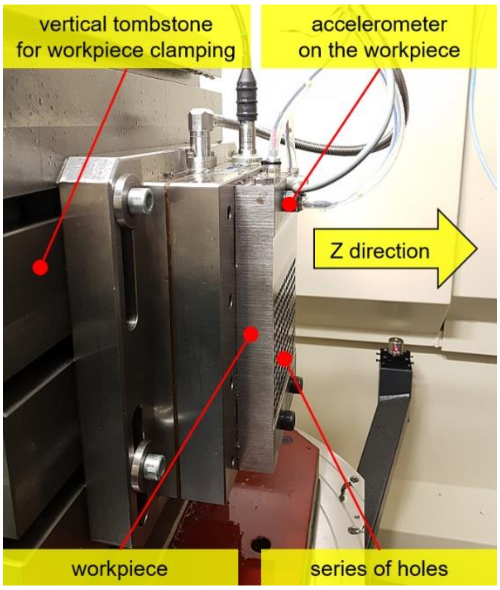


Figure 3: Set-up of the experiment.

2 EXPERIMENT SETUP AND RESULTS

2.1 Machine, tool, and cutting conditions used

Several series of holes were drilled during the experiment. A horizontal machining centre with maximum electrospindle parameters of 31 kW/197 Nm and max. 18,000 rpm was used. The workpiece consisted of a plate of C45 carbon steel. The workpiece was fixed on the dynamometer clamped on the vertical tombstone, see Fig. 3. The hardness of the workpiece material was 268.75 ± 9 HB. The dynamometer data are not used in this presented study.

Table 1: The cutting conditions used in the experiment and the number of holes drilled during every tested tool.

Cutting conditions		Number of holes drilled during the tool lifetime for specific cutting speed			
Cutting speed [m/min]	Feed per revolution [mm]	Test run 1	Test run 2	Test run 3	Test run 4
20	0.138	80	159	60	40
23	0.138	35	52	29	4*

**This tool was not included in the analysis due to the low number of holes.*

The standard Dormer drill type A777.8 made of cobalt high-speed steel with a diameter of 8 mm and bronze oxide coating for the avoidance of adhesion of the material was used for the drilling of holes with a nominal depth of 24 mm (L/D=3). The optimal cutting speed according to the drill producer with respect to the hardness of the workpiece should be 24 m/min (hardness less than 300 HB, carbide class P2.3). In the experiment two slightly lower cutting speed levels were used: 20 and 23 m/min. This choice was made due to a measurement error; see the explanation below. The feed per revolution was fixed at 0.138 mm for both cases of cutting speed (Tab. 1). The process used external emulsion flood cooling. Four drills were tested for each cutting speed. The end of the experiment was connected with massive flank wear. In practice this means that each tool was used for as long as was deemed possible and safe. Thus, each tool was used well beyond the point when it would be changed in standard practice. This was done in order to collect meaningful process data related to high tool wear states, which would be difficult to collect outside the laboratory setting for economical and safety reasons. The overall technology was not optimally set due to an inaccurate measurement of material hardness. This led to a selection of slightly lower than optimal cutting speeds, which in turn led to a significant variation of tool lifetime (expressed as number of holes drilled by the individual tool, see Tab. 1.).

Regardless of this variability in the number of holes drilled by each tool, a higher number of holes was drilled overall for the lower cutting speed, as expected.

2.2 Machine-tool acquired data

Both the spindle torque current and the Z slide drive current were monitored during the experiment. The monitoring was done using the internal scope of the Siemens Sinumerik control system. Current values were acquired at a frequency of 500 Hz. The raw data were continuously recorded for each series of five holes. These raw records were later segmented into intervals corresponding to the drilling of individual holes (data corresponding to out-of-cut operations were removed). The Z slide position signal was used for spindle current record segmentation by detecting time stamps for which the signal value crossed a predetermined threshold.

2.3 External sensor acquired data

The experiment also involved external sensors. The vibrations of the workpiece were monitored with the unidirectional piezoceramic accelerometer KS78 by MMF. The signal acquisition frequency was 25,600 Hz. Analogously to the data acquired from the machine tool, the vibration signal was also recorded continuously for each series of five holes. These raw records were later segmented in time domain into five separate records for drilling of each individual hole. The Z-axis dynamometer was used for segmentation by detecting the time stamps for which the signal value crossed a predetermined threshold (again, analogously to the process of segmentation of machine tool acquired data; see Chapter 2.2). In this way, the signal records for individual holes were synchronised across the machine tool and external sensor acquired data.

2.4 Tool wear measurement

The flank wear on the tool was measured using a Keyence VHX7000 microscope. Each tool was modified with two physical adjustment points made with laser markings on the flank. These adjustment points were used for the optical adjustment of the flank surface figures. This approach ensured a consistent orientation of the tool blades for subsequent batch processing of the flank wear size on the worn drills. The tank wear value defined by the parameters VB and VBmax was then evaluated. These two parameters represent the average flank wear value along the major cutting edge and the maximal wear value on the cutting drill edge corner, respectively (see Fig. 4)

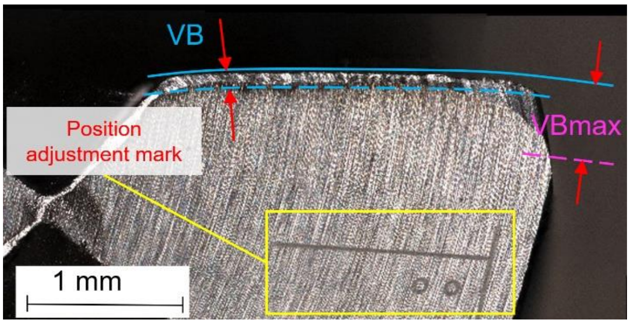


Figure 4: Schematic view of the flank wear measurement. All pictures were adjusted by using marks on the drill flank.

3 EXPERIMENT RESULTS EVALUATION

3.1 Tool wear measurement and processing

VB and VBmax values (Fig. 4) were measured on the drill after the machining of five holes. This means that there was a time step of approximately 1 minute for the flank wear measurement. Because tool wear was physically measured every fifth hole, it was necessary to estimate wear for those measurements for which wear was not directly evaluated to consistently assess the correlation of features with tool wear. This was achieved by interpolating the measured values of tool wear with respect to the hole order/time in cut for a particular drill bit (the hole depth and the feed rate were constant during each individual test). This interpolation was performed using a piecewise Hermitian spline interpolation curve (PCHIP) (see e.g., [Fritsch 1984]). The advantage of this type of interpolation is its ability to respect the monotonicity of the interpolated data (this distinguishes it from standard spline interpolation methods) combined with a higher degree of continuity compared to e.g., piecewise linear interpolation. For an example of PCHIP interpolation of the VB and VBmax parameters, see Fig. 13.

3.2 Time series processing and feature selection

All time-domain signals acquired from the machine tool control system, as well as from the additional accelerometer, were synchronised and segmented, as mentioned in the previous section. As a result of this, synchronised time-domain records of all recorded signals were available for every drilled hole. The signals varied with respect to the flank wear ratio and hole depth; see Tab. 2 (Figs. 7-12) for an example. Thus, all time-domain records were split into six regions in order to evaluate the signal within various hole depth ranges.

The selected signal examples in Tab. 2 represents typical records. As can be seen, both the mean value and standard deviation of the signal increased along with the flank wear. There are also differences between various depth segments. Following this preliminary observation, the mean value, the RMS value, and the standard deviation value were defined as features and calculated for every signal type (spindle torque current, Z slide drive current, workpiece Z acceleration) and for every hole depth segment. These features were expected to display a consistent monotonic relationship with tool wear and thus be useful parameters for indirect flank wear monitoring. See Fig. 13 for an example of the growth in the time domain of the flank wear and the simultaneous growth in the time domain of the spindle current RMS.

Apart from the above-mentioned features, a range of other statistical features were computed for the investigated signals including skewness, kurtosis, coefficient of variation, crest factor, shape factor, and peak-to-peak. These features were mentioned in works such as [Kossakowska, 2018] as potentially significant predictors of tool wear. However, the presented study did not find strong correlations of these features with tool wear.

3.3 Correlation analysis of machine data and tool wear data

The correlation of time-series statistical features with tool wear was evaluated using the Spearman rank correlation method [Conover 1999]. Specifically, the correlation of individual features with tool wear expressed by the VB parameter was calculated (see Chapter 3.1) while controlling for the effects of cutting speed. The Spearman correlation method is a classical nonparametric method expressing the degree of monotonic dependence between selected variables. The reason for using the Spearman method instead of the often-used Pearson method is its generally less restrictive assumptions. While the Spearman method requires only the existence of a monotonic dependence between the variables under study, the Pearson method requires the existence of a linear dependence, an approximate normal distribution of the variables, and the absence of outliers. The assumptions of Pearson's correlation method are not met in the presented case (e.g., the VB parameter does not have the properties of a normal distribution due to the nature of its trend; see Figure 13). The advantage of the Spearman correlation method is that the nature of the monotonic dependence does not have to be known in advance and can thus vary for individual variables.

As mentioned above, the parameter of cutting speed was controlled for when computing the correlations. In other words, the effects of cutting speed on the individual signal parameters and tool wear were first removed and the final correlation parameters were then computed with respect to the residual values. The coefficients reported thus describe the correlation between the parts of variability of the investigated signals that do not depend on cutting speed.

Calculation of the correlation parameters was performed in Matlab software. The values of the correlation coefficients of the selected features for the individual segments are presented in Table 3.

The results of the correlation analysis show that the following features are most strongly correlated with wear: the mean value and RMS of the spindle torque current for depth segments 5 and 6, the mean value and RMS of the Z axis drive current on segment 3, and finally the RMS and standard deviation of the workpiece accelerometer in the Z-axis direction for segments 5 and 6.

4 DISCUSSION OF THE RESULTS

The tool flank wear continuously increases during the drilling operation. The wear intensity may vary depending on the local material properties and the optimal process setting (Tab. 1). Avoiding the approach of a fixed time in cut per drill and maximising the use of the drill lifetime can bring both economic and environmental benefits.

The paper shows the potential for monitoring drill wear using indirect parameters: vibration of the workpiece and drive currents monitored through the control system of the machine tool. The research approach was based on a series of experiments. The drill flank wear was measured after every fifth hole drilled. The time-domain spindle torque current, Z slide drive current, and workpiece acceleration signals were recorded for every hole. The signal features selected were the signal mean value, signal RMS, and signal standard deviation for six depth segments of every hole. The correlation of these features with the measured flank wear was first investigated for two levels of the cutting speed to evaluate whether the flank wear could be estimated using other indirect signals (Fig. 14). The correlation coefficients were then computed after controlling for the effect of spindle speed.

The calculated correlation coefficients for various features are presented in Tab. 3. The spindle torque current signal has a similar correlation with the flank wear ratio as the traditional vibration-based approach using the accelerometer attached to the workpiece. In both cases, the signal RMS correlates very well with flank wear. The correlation is higher in the deeper segments of the hole (in this case, segments 5 and 6). This behaviour might be caused by worse chip segmentation and evacuation at these depth levels. The mean value of the spindle torque has quite a high correlation, but the signal standard deviation exhibits a lower degree of correlation with flank wear. The mean value of the acceleration signal seems to be insensitive to the change in flank wear. The reason is that the signal does not have a significant DC component and the mean value is constantly almost zero. The standard deviation of the vibration signal has a high correlation, especially near the bottom of the hole.

The Z slide drive current signal has similar correlation values of the mean and RMS feature. The highest correlation value was in the middle of the hole depth. The increase in chip packing combined with more complicated chip removal is suspected to be the cause behind this result. That is, the more worn the tool, the larger the chip packing and the more complicated chip removal is at larger depths. Therefore, a greater force needs to be applied in the direction of drilling in order to move the tool at the prescribed speed level. The effect is most prominent in the middle of the hole because at its top chip removal is not problematic regardless of the level of tool wear. Similarly, chip removal at the bottom of the hole is complicated even for new tools. Thus, the forces applied near the top and bottom of the hole do not increase significantly with increasing tool wear. The standard deviation of the signal has low correlation for all hole depth segments.

The mentioned features have good correlation with the flank wear ratio that is independent of the total tool lifetime. Therefore, it is possible to display timeless plots of the drill flank wear VB depending on various measured indirect parameters (Fig. 14). The plots are presented for two levels of the cutting speed. The RMS value of the acceleration signal is relatively low up to the flank wear size of 0.3 mm. Then, the RMS of the signal grows rapidly. This behaviour can be used for emergency monitoring of the process: if the vibration RMS absolute value increases and also if the slope over the last few samples changes significantly, then the massive wear area can be detected.

In contrast, the spindle torque current displays a continuous increase in the signal RMS based on the flank wear. The linear dependence could be identified for the direct flank wear calculation using the spindle current RMS. After the tool wear ratio exceeds approximately ~ 0.3 mm, the spindle torque RMS increases nonlinearly with tool wear. This signal trend change could be used to detect the period of sudden tool wear increase.

The Z slide drive current signal RMS increases continuously with the flank wear value up to approximately VB = 0.3 mm. After this limit, the signal values vary significantly, and it is not possible to estimate the flank wear ratio reliably.

For practical implementation, it would be recommended to combine all three machine tool signals. The spindle torque and Z-slide drive current RMS signals can be applied to predict tool wear at lower wear ranges, while the accelerometer RMS can serve as an additional means of detection of the sudden tool wear increase phase.

Two levels of cutting speed were used. Higher cutting speeds shorten the drill life time (less holes were drilled). However, even after removing the effects of cutting speed on the investigated parameters, significant correlations are present. These correlations can be observed in timeless diagrams, see Fig. 14.

Analysing the timeless data, it seems the only significant difference can be observed for the spindle torque current rms on the 6th segment. This does not mean, however, that the cutting speed does not influence the other signals, rather that its influence is probably not as strong as to be readily observable.

The results discussed are valid for the presented experiment. Further work should focus on the validation of the observations presented for different drill size and cutting conditions. The generalised parameters should be used for knowledge transfer to different machining systems. The drive current information should be transformed to forces and torque, and the specific cutting force should be computed based on the specific feed per tooth. In this case, it is necessary to identify and subtract the passive drive current as presented in [Dunwoody 2010], [Aggarwal 2013], and [Janota 2019]. Additionally, future work should also investigate the possibility of using frequency and time-frequency features for tool wear monitoring and prediction.

Table 2: Selected examples of the acquired data. Tool No. 26 was able to drill 52 holes with a cutting speed of 23 m/min. The data are presented for two situations: a slightly worn tool after drilling of 5 holes (left column) and a worn tool after drilling of 40 holes (right column). The individual hole segments are denoted by Roman numerals.

Drill wear state after drilling 5 holes and acquired time-domain signals during drilling of the 6th hole.	Drill wear state after drilling 40 holes and acquired time-domain signals during drilling of the 39th hole.

Figure 5: Drill cutting edge state after drilling 5 holes.

Figure 6: Drill cutting edge state after drilling 40 holes.

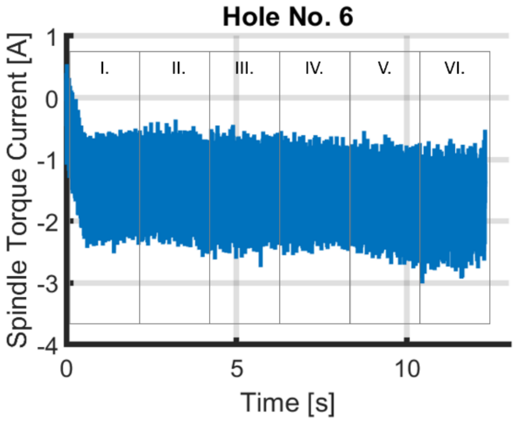


Figure 7: Spindle current torque during drilling of the 6th hole.

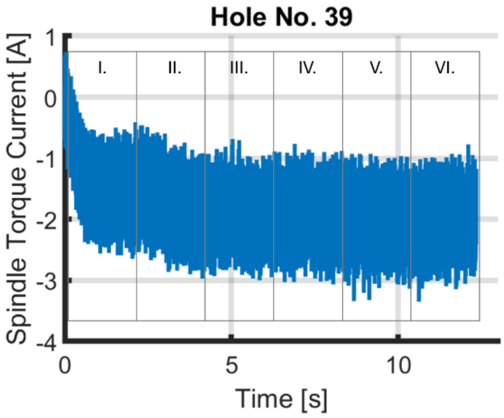


Figure 8: Spindle current torque during drilling of the 39th hole.

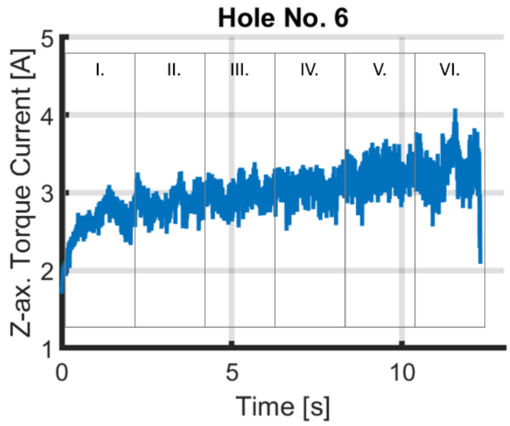


Figure 9: Z slide drive current torque during drilling of the 6th hole.

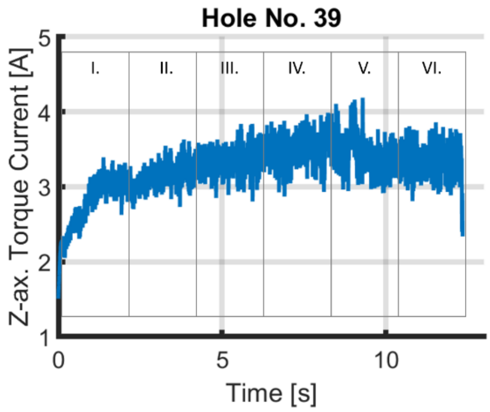


Figure 10: Z slide drive current torque during drilling of the 39th hole.

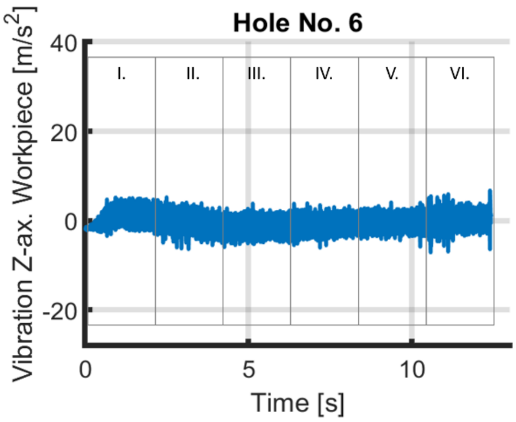


Figure 11: Vibration on the workpiece in the Z direction during drilling of the 6th hole.

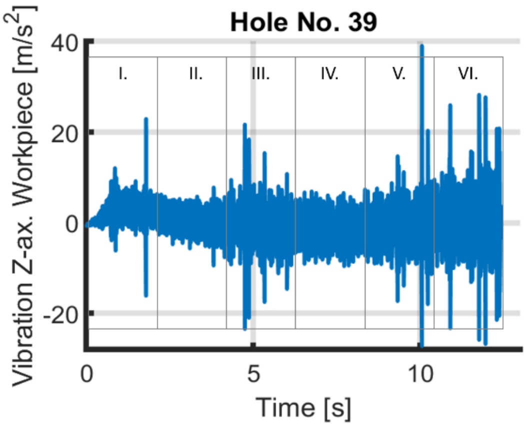


Figure 12: Vibration on the workpiece in the Z direction during drilling of the 39th hole.

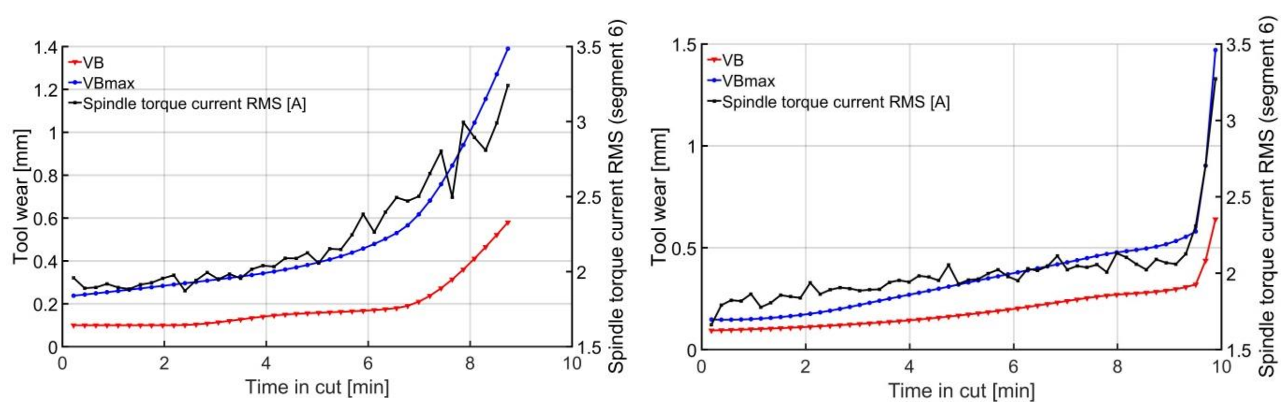


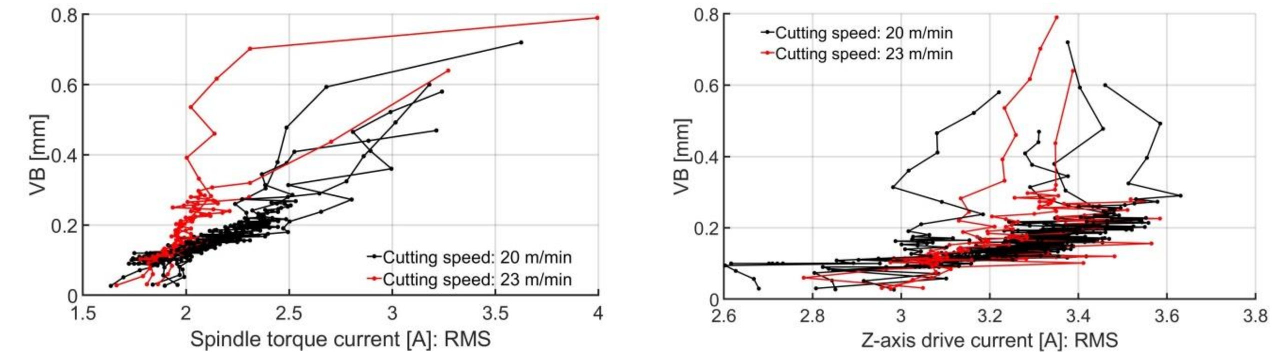
Figure 13: Dependence of wear parameters VB and VBmax on time in cut compared to RMS of spindle torque (6th segment) for cutting speeds of 20 m/min (left) and 23 m/min (right).

Table 3: Correlation of the selected signal features with the measured tool flank wear depending on the depth of the hole. The colour scale highlights the absolute value of the Spearman coefficients (Mean: mean value of the time-domain signal; RMS: RMS value of the time-domain signal; Std: Standard deviation of the time domain signal): The results represent correlation between signals after controlling for the effects of cutting speed.

absolute value ≤ 0.5	absolute value > 0.5	absolute value > 0.6	absolute value > 0.7

Measured parameter:	Signal feature:	Hole depth segment:					
		I. (surface)	II.	III.	IV.	V.	VI. (bottom)
Spindle torque current [A]	Mean	-0.061*	-0.464	-0.592	-0.689	-0.712	-0.710
	RMS	0.135*	0.457	0.589	0.686	0.709	0.707
	Std	0.317	0.049	0.147	0.368	0.508	0.560
Z slide current [A]	Mean	0.553	0.668	0.721	0.620	0.510	0.412
	RMS	0.552	0.667	0.720	0.619	0.510	0.412
	Std	0.335	0.185	0.270	0.234	0.150	0.141
Workpiece Z acceleration [m/sec²]	Mean	0.180	-0.109	0.172	-0.212	-0.209	-0.184
	RMS	0.247	0.311	0.302	0.581	0.702	0.731
	Std	0.400	0.340	0.434	0.559	0.687	0.732

*Correlation values for this signal were not found to be significant at the 5% significance level.



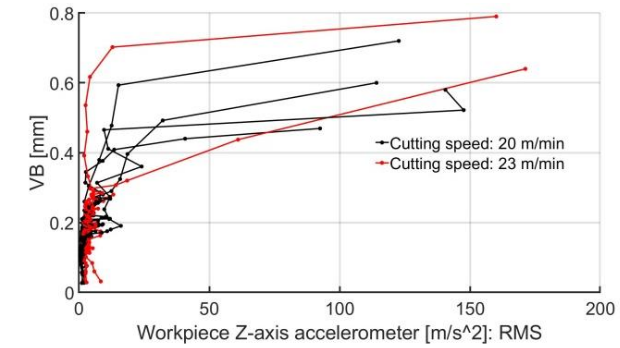


Figure 14: Timeless plot of the VB drill flank wear depending on various measured indirect parameters for two levels of cutting speed: spindle torque current rms in segment 6 (top left), Z axis drive current rms in segment 3 (top right), workpiece acceleration in Z direction in the segment 3 (bottom left).

Note that a lower maximal tool wear is reported for one of the tools with v_C = 23 m/min compared to the other tools. This was due to a failure of the internal sensors at the very end of its lifetime (3 last holes). In this case, the maximum measured VB = 0.3 mm was reached.

5 CONCLUSIONS

The monitoring of flank wear in drilling is an important function that enables the automated detection of the need for a tool change. Such an approach can increase the overall effectivity of the drilling process while lowering production costs. This paper presents a comparison of the directly measured flank wear ratio with other indirect signals: drive currents and workpiece vibration.

The results showing higher system vibration for increased drill wear follows the findings of other publications, e.g., [Jantunen 1996]. The correlation analysis results show that vibration and spindle torque signals have a very similar correlation with the flank wear ratio. Thus, it is possible to use the spindle torque current signal instead of the accelerometer signal for tool wear monitoring in practical applications. However, the properties of the signals vary depending on the instantaneous depth level. Thus, the analysis of signals in the bottom sections of the hole is recommended. The method is reliable and independent of the tool life time: The signals present a monotonic relationship with tool wear that holds for both low and high degrees of tool wear.

The spindle torque current RMS increases linearly with the flank wear ratio up to the tool wear value of ~ 0.3 mm, after which the spindle torque RMS increases nonlinearly with respect to tool wear. Therefore, it is possible to use the value of this signal for the estimation of drill wear after system calibration, while the rate of change of the spindle torque RMS can be used to detect the phase of the sudden tool wear increase near the end of the tool lifetime. Similarly, the vibration signal RMS and the Z slide drive current have a piecewise linear character that can indicate the switching point of a rapid increase in tool wear and thus the need for tool change. It is recommended to combine both approaches for the monitoring system on real machines.

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CONTACTS:

Czech Technical University in Prague,
Czech Institute of Informatics, Robotics and Cybernetics (CIIRC),
Department of Industrial Production and Automation
Jugoslavskych partyzanu 1580/3, 160 00 Prague, Czech Republic
Website: https://www.ciirc.cvut.cz/teams-labs/ipa/

Doc. Ing. Petr Kolar, Ph.D.
E: p.kolar@rcmt.cvut.cz

Ing. David Burian, Ph.D.
E: d.burian@rcmt.cvut.cz

Ing. Stepan Fiala, Ph.D.
E: s.fiala@rcmt.cvut.cz

Ing. Stepan Chladek, Ph.D.
E: s.chladek@rcmt.cvut.cz

Ing. Petr Petracek, Ph.D.
E: p.petracek@rcmt.cvut.cz

Ing. Jiri Sveda, Ph.D.
E: j.sveda@rcmt.cvut.cz

Ing. Michal Rytir
E: m.rytir@rcmt.cvut.cz

Czech Technical University in Prague,
Faculty of Mechanical Engineering,
Department of Production Machines and Equipment (FME),
Research Centre of Manufacturing Technology
Horska 3, 128 00 Prague, Czech Republic
Website: https://rcmt.cvut.cz/

Ing. Petr Masek, Ph.D.
E: p.masek@rcmt.cvut.cz

Ing. Petr Fojtu, Ph.D.
E: p.fojtu@rcmt.cvut.cz

Ing. Michal Rytir
E: m.rytir@rcmt.cvut.cz