MM Science Journal | www.mmscience.eu
ISSN 1803-1269 (Print) | ISSN 1805-0476 (Online)
Special Issue | HSM 2023
17th International Conference on High Speed Machining
October 25-28, 2023, Nanjing, China
DOI: 10.17973/MMSJ.2023_11_2023120

HSM2023-00057

QUALITY MONITORING FOR DRILLING BASED ON INTERNAL DATA OF MACHINE TOOL

F. He[1]*, M. Weigold[1]
[1]TU Darmstadt, PTW, Darmstadt, Germany
*Corresponding author; e-mail: f.he@ptw.tu-darmstadt.de

Abstract

Drilling is a crucial process in industrial production and the quality of the machined hole has a decisive impact on the final part quality. However, there are various disturbances in the manufacturing process, which makes the non-value-adding quality inspection unavoidable. In this paper, high-frequently recorded internal NC-signal data and the vibration sensor data from the machine protection control unit (MPC) are used to predict hole quality for the drilling process. The analysis of the preprocessed data reveals a linear association between the hole quality characteristics and extracted features. For inline quality monitoring, interpretable models for the quality characteristics of straightness and roundness are developed. The proposed approach showcases the potential as an economical alternative to quality inspection by random sampling in mass production.

Keywords:
Drilling, quality monitoring, machine learning, NC-signal

1 INTRODUCTION

The hole is an important functional unit in mechanical and structural applications, so its machined quality is critical for fulfilling the designed function. For example, the hole diameter determines whether the fit of two parts is a clearance fit, a transition fit, or a interference fit. Or in the case of hydraulic valves, a low hole straightness error and roundness error are essential to ensure the shaft sliding and at the same time to avoid liquid leakage. In the drilling process, there are a variety of disturbances that can affect the machined hole quality, such as temperature changes, tool deflection, and inhomogeneity of material [Hauer 2012]. Hence, quality inspection with measuring devices after the machining process is indispensable. To eliminate the no-value-adding quality inspection and reduce the waste in production, some research publications in the field of quality monitoring of drilled workpiece are presented [Teti 2022]. These approaches mostly use black box machine learning models and are therefore difficult to understand. In addition, the stability and transferability of these models are not sufficient. This currently represents a major challenge for the practical application on a broad scale.

The aim of this paper is to develop simple, understandable, and stable models based on the internal data of machine tool for inline quality monitoring. This study is carried out based on the hypothesis, that the machined workpiece quality is influenced by tool deflection and oscillation and their effect can be detected in the internal data of machine tool (NC-signals and vibration data of machine protection control unit). By finding such physical correlations, the simplicity, transparency, and acceptability of the model will be greatly enhanced.

2 STATE OF THE ART

Due to the rapid development of sensor technology and data science in the last decades, inline quality monitoring during the machining process becomes feasible [Teti 2022]. According to the type of sensors or sensor systems, the research in the field of quality prediction during machining can be divided into three categories.

The first category consists of quality monitoring with external metrology sensors, such as force sensor, sound sensor and vibration sensor. In recent years, the process forces are widely and effectively used for quality monitoring. During the drilling process, the radial forces reflect the interaction between the tool and workpiece perpendicularly to the drill axis. Therefore, force data is of great importance in the evaluation of drilling tests regarding the hole quality. Abele et al. [Abele 2006] present an experimental methodology to determine hole quality based on process forces. The results show a strong correlation between hole roundness and the frequency response of the radial cutting force. Wang et al. [Wang 2020] measured the thrust force and moment with a dynamometer during the drilling of 42CrMo4 steel. Based on the collected data and expert knowledge, a Bayesian network was built to predict the hole roundness and roughness, in which both outputs are divided into five classes. The average prediction accuracy of hole roundness and roughness is 83.7% and 94.8%, respectively. Another commonly utilized sensor for quality prediction in research is the acoustic emission (AE) sensor. Acoustic emission is the radiation of local stress waves in the workpiece that is caused by the rapid release of elastic energy during machining. Li et al. [Li 2018] built a surface quality monitoring model with time-frequency features of AE signals in end milling. The classification accuracy of surface roughness and surface defects could be up to 99% and 72%, respectively.

Besides of the usage of external metrology sensors, there are several researches that use sensor-integrated tools for quality monitoring, by which the sensor is integrated in the tool or tool holder. The advantage is that the sensor is near the cutting zone so that the cutting force or temperature can be captured precisely. Bretz et al. [Bretz 2020] developed a sensor-integrated reaming tool, by which the strain gauges are installed on the reamer shank. Based on the voltage level signal of the sensors an Artificial Neural Network is trained to predict the hole straightness by the reaming process. The root-mean-square error (RMSE) of this model is 2.87 µm in the X-direction and 5.16 µm in the Y-direction. In recent years some commercial sensor-integrated tool holders have started to enter the market. Schunk GmbH has introduced a hydraulic chuck with an integrated acceleration sensor [Schunk 2023] and the company pro-micron has assembled force sensors in the hydraulic chuck or machine spindle to measure the thrust force and the bending moment [pro-micron 2023]. The disadvantage of these tool systems is the complicated assembly and difficult data transformation, which is therefore expensive and not suitable for general industrial production.

The third category is the usage of internal machine tool data captured from the numerical control (NC-Signals), which includes the time series data such as motor drive current, spindle rotational speed, and machine tool axis position. The major advantage of using internal NC-signals is that the data collection does not disturb the machining process. In the hole-making area, Schuh et al. [Schuh 2019] and Schorr [Schorr 2020a]; [Schorr 2020b]; [Schorr 2020c] applied machine learning methods based on the internal NC-signals to predict the hole quality characteristics like diameter, roundness, and concentricity. In their research, several methods like principal component analysis (PCA), correlation, and python tsfresh package are used for feature extraction, and different algorithms like KNN, Support Vector Machine, and Decision Tree are tested and compared. It is shown that the ensemble algorithms provide the best prediction results. Ziegenbein et al. present a similar approach for the OK/NOK classification of drilled holes based on the algorithm random forest [Ziegenbein 2020]; [Ziegenbein 2021]. For the 6 mm diameter hole, the position deviation tolerance is set to ±0.12 mm, which corresponds approximately to tolerance grade IT14 and that does not meet the general industrial requirements. The model prediction accuracy can reach 0.9975, but the model transferability is not ideal and is about 0.78.

When comparing these three categories, each has advantages and disadvantages. But the third has a good potential for a wide range of industrial applications, because the process does not need to be modified, and the investment is relatively low. However, in the field of quality monitoring, the presented studies are focused on building black box machine learning models and there is a lack of research on the NC-signals themselves. Firstly, a large number of features are extracted based on diverse methods like transformation, PCA, and the python tsfresh package. Then, various machining learning models are tried, such as random forest, neural network, and support vector machine. This approach requires a huge data volume, is very time-consuming, and is difficult to understand. In addition, the stability and transferability of these models cannot be guaranteed. As a result, the current research is not yet ready for industrial application. [Schorr 2021]

To improve the model transparency, stability, and transferability, an interpretable machine-learning approach for the inline quality monitoring of drilled holes based on the internal data of machine tool is presented in this work. The term “Interpretable machine learning” is understood to mean that the behavior and predictions of machine learning methods and models are understandable to humans [Molnar 2020]. To this end, a foundational analysis and processing of the acquired signals are first conducted, which are based on the domain knowledge of the manufacturing process and signal processing. Then, few interpretable features from the internal data of machine tool are extracted. In the end, interpretable linear regression models are developed for the monitoring of hole quality characteristics of straightness and roundness.

The data analysis, visualization, and modeling are implemented in the programming language python.

3 EXPERIMENT & DATA GENERATION

3.1 Experimental Design

For the purpose of development of interpretable quality monitoring models, a drilling experiment is carried out to generate the internal data of machine tool and the hole quality data (see Fig. 1). The workpiece material is EN-GJL-250 (5.1301), which has a wide range of applications such as machine bed, pump housing and engine cylinder block [BDG 2010]. The workpiece is first face milled and then drilled with a solid-hardmetall twist drill in accordance with [DIN 6537]. The machined hole has a diameter of 5.6 mm and a depth of 30 mm. The technology parameters v_c = 187 m/min and feed f = 0.2 mm/rev are used, which result in a drilling time per hole t_h = 0.79 sec. A total of 400 holes are machined, which are distributed in a 20 x 20 matrix. The tests are carried out on the vertical machining center DMC 850V from the manufacturer DMG Mori, which is equipped with a SINUMERIK 840D sl control system. An installed Edge-Computing solution provides a process-parallel acquisition of NC-signal-data at a frequency of 500 Hz. In total, more than 40 signals are recorded, which are summarized in Tab. 1 and visualized in Fig. 1. Corresponding to the machine tool axis, the position and drive signals are also recorded in three dimensions, namely the X, Y, and Z direction. The resolution of the machine tool axis position encoders (ENC1_POS and ENC2_POS) is 0.01 µm [DECK 2019]. The signal CYCLE and SYG are used for contextualization and slicing of the data [Fertig

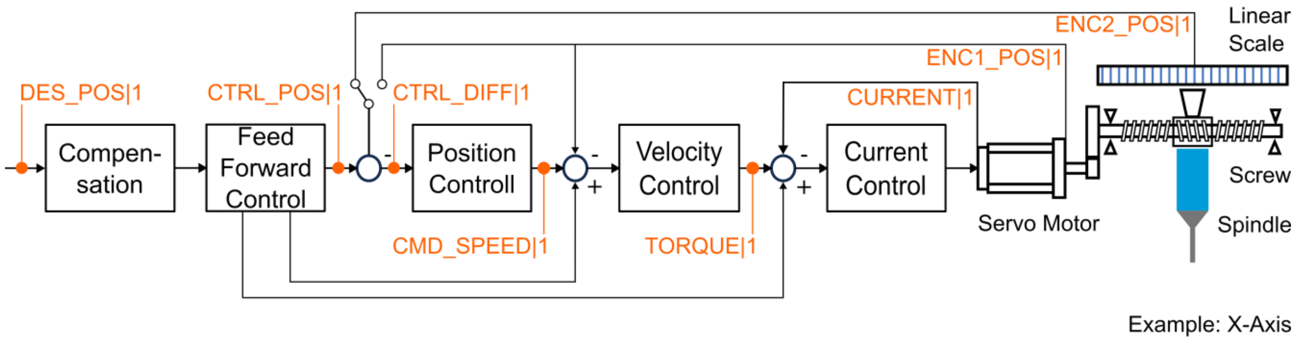

Fig. 2: high-frequency signals from the machine tool position control loop [Fertig 2023].

2022].

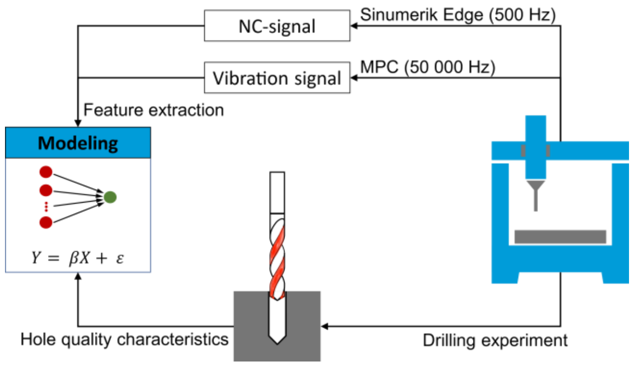

Fig. 1: Framework of experimental design.

Tab. 1: Summary of the recorded NC-signals.

Signal	Description	Axis
DES_POS	Position command after the fine interpolator	X, Y, Z
CTRL_DIFF	Control difference	X, Y, Z
CONT_DEV	Contour deviation (not shown in Fig. 2)	X, Y, Z
ENC1_POS	Indirect machine tool axis position of the rotary encoder on servo motor	X, Y, Z
ENC2_POS	Direct machine tool axis position of the linear encoder	X, Y, Z
CMD_SPEED	Speed command the NC sends to the drive	X, Y, Z
TORQUE	Drive actual torque	X, Y, Z
CURRENT	Drive actual current	X, Y, Z
CYCLE	Position control cycle counter	-
SYG	Predefined variables for the machining process information	-

This machine tool is also equipped with a machine protection control unit (MPC) from the IFM electronic GmbH, by which a micro-mechanical accelerometer is installed in the machine frame to monitor the vibration, so the machine tool will be rapidly shut down in case of a crash [DMG 2023]. The vibration data is received and processed by a diagnostic electronics device and then transferred to a measurement computer with a frequency of 50.000 Hz during the machining process.

3.2 Drilled hole quality analysis

To determine the quality, the holes are measured on a coordinate measuring machine (model: Leitz PMM 864) after machining and subsequent cleaning. The hole quality characteristics are determined in ten depth planes, where is from hole depth z = -0.5 mm to z = -27.5 mm, and the distance between each measurement plane is 3 mm.

In this study, the quality characteristics straightness and roundness are set as target variables for quality monitoring (see Fig. 3). The hole straightness T_S is defined as the amount of linear deviation of the hole center axis [Drake 2001]. The roundness T_R is the radial distance between the two concentric circles, the minimum circumscribed circle, and the maximum inscribed circle. Because of the drill bit lateral oscillation, the multilobe hole could be produced. According to [Tschannerl 2007], the relationship between the drill bit lateral oscillation frequency and machine tool spindle rotational frequency can be expressed as equation (1) :

$$f_{Oscillation} = 2qn \cdot f_{Spindle} \tag{1}$$

Where q stands for a correction factor ($0<<q<1$) and n for an integer running variable (n = 1, 2, 3, etc.). In case of the triangle shape hole as shown in Fig. 3b), the variable n equals 1, and the drill bit oscillation frequency is approximately double the spindle rotational frequency.

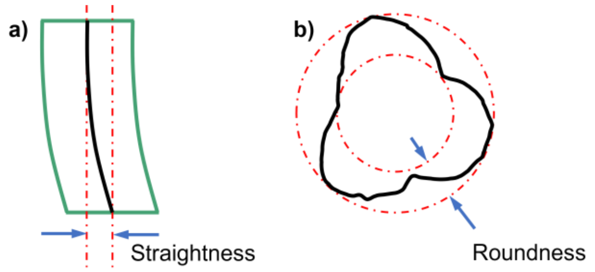

Fig. 3: Hole quality characteristics a) Straightness; b) Roundness.

The statistical overview of the measurement results is shown in Fig. 4 and Fig. 5. The distribution of the straightness of the total 400 holes is represented in Fig. 4, the straightness varies from 0.001 mm to 0.319 mm and its mean value is 0.060 mm. The roundness of the drilled holes is visualized in Fig. 5. The measured circles have a triangle shape. Along the hole depth direction, the roundness T_R per measurement plane increases first and then stabilizes in the lower section of the hole. In total, the max. roundness error per hole varies from 0.007 mm to 0.056 mm and the mean value is 0.039 mm.

Fig. 4: a) An example of hole straightness, b) The histogram of the machined hole straightness.

Fig. 5: a) An example of hole roundness; b) The histogram of the machined hole roundness.

4 MODELING FOR THE HOLE STRAIGHTNESS

4.1 Data Selection and Preparation

The hole straightness error is caused by the tool deflection during the drilling process, and it is a value that changes cumulatively with hole depth and time. Analysis of the raw vibration data of MPC and its double-integrated displacement hasn't revealed any relevant information for that target variable. Therefore, only the internal NC-signals are used to predict the hole straightness.

As mentioned before, there are more than 40 NC-signals recorded during the machining process. The first step is to compute the Pearson correlation coefficient between individual signals in the same direction using the Python pandas package [Pandas 2023], which allows for a reduction in data volume. The result of the correlation analysis is summarized in Tab. 2. It is to be noticed, that the CRTL_DIFF has a correlation of 0.999 with the difference between ENC1_POS (machine tool axis encoder 1 position) and DES_POS (machine tool axis set position). Since the hole straightness is a value of center axis relative deviation, the NC position signals will be analyzed in its relative changes to the set position as well (This data centering step will be described later). On account of this, the signal CRTL_DIFF and ENC1_POS contain the same information for the prognosis of hole straightness. According to the correlation analysis, only the signals ENC1_POS and TORQUE are chosen for the prediction of hole straightness. The typical signal curves during the drilling process are plotted in Fig. 6.

Tab. 2: Pearson correlation coefficient of NC-signals in X and Y-axis.

Signal 1	Signal 2	X	Y
TORQUE	CURRENT	0.998	0.995
CONT_DEV	CTRL_DIFF	1	1
CTRL_DIFF	ENC1_POS – DES_POS	0.999	1
ENC2_POS	DES_POS	0.999	0.999
TORQUE	ENC1_POS	0.380	0.135

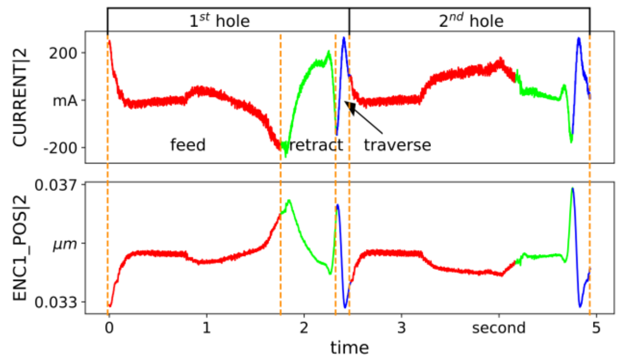

Fig. 6: Typical signals of two consecutive drilling processes.

In the second step, the data slicing and labeling are conducted. Because the NC-signals are recorded in the machine coordinate system (MCS), they are first transformed into the workpiece coordinate system (WCS). The data are then labeled and trimmed into individual holes and machining phases according to the coordinate of the tool center point (TCP). The machining phases are divided into the feed phase, the retracting phase, and the traverse phase. A detailed description of the coordinate transformation and data slicing method is given in [Fertig 2022b].

By analysis of the signals, signal drift before the actual drilling process is observed, which may affect the prediction accuracy. For visualization of this signal drift, the signal ENC1_POS in machine tool Y-axis of two selected holes is plotted in Fig. 7. This phenomenon is probably caused by the rapid tool traverse movement between the holes. It was discovered, the drift can be described with an exponential function for the signals. This allows signal compensation according to the following equation:

$$f_{original} = f_{\exp\_compensated} + a \cdot e^{b} \quad (2)$$

Where *a* and *b* are coefficients obtained by curve fitting of the signals in the idle feed phase when the drilling tool does not yet contact the workpiece. The signal drift in the rapid traverse and idle feed phase also affects the signal trajectory in the drilling process, therefore compensation is carried out on the signal throughout the entire drilling process.

After that, signal filtering is undertaken to eliminate the effects of oscillations and unexpected abrupt changes. Commonly used methods are low-pass filtering and moving average methods, etc. [Puthusserypady 2021]. In this work, the moving average method is chosen because this method focuses narrowly round the 0 Hz component and the hole straightness is a kind of this component (see Fig. 8). The sample window is set as 1 mm in the Z-direction and the following algorithm is implemented:

$$p_j' = \frac{1}{n} \sum_{z-0.5}^{z+0.5} p_z \quad (3)$$

p'_j	the calculated mean value
p_z	raw signal value at z position
z	z position in hole depth
n	count of the sampled data points in the window.

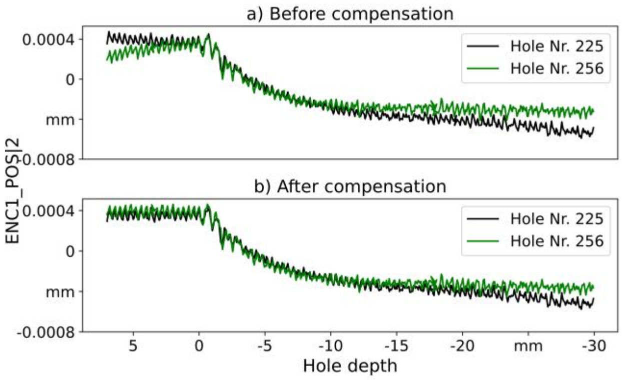

Fig. 7: Visualisation of the signal compensation with an exponential function.

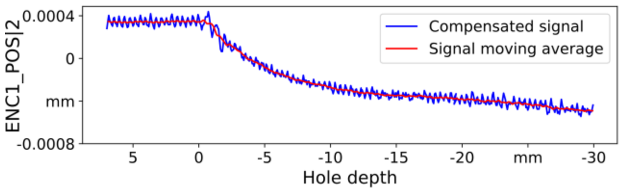

Fig. 8: Visualisation of the signal filtering with the moving average method.

After these preprocessing steps, it can be found that the signal starting values of different bores, at which the drilling tool is about to contact the workpiece, varies slightly to the set position. The initial deviation of each hole may affect the accuracy of the statistical model. To solve this problem, the data centering method is conducted, by which relative signals defined as accumulated signal changes from a reference window are generated (see Fig. 9). For each drilling process, the idle phase at a height of 0.5 mm to 1.5 mm above the hole is set as the reference window.

The signal compensation, signal filtering, and data centering are implemented on both signal ENC1_POS and TURQUE, and in both X-axis and Y-axis.

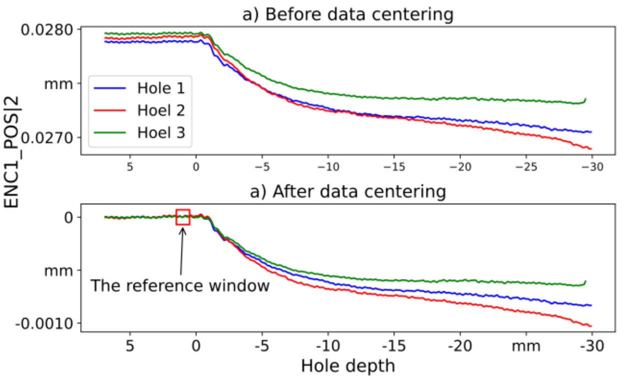

Fig. 9: Visualisation of the data centering method.

4.2 Feature Engineering and Selection

In this section, the data analysis and feature extraction are conducted based on the preprocessed relative signals. When the selected signals are examined, it is noticed that the ENC1_POS signals and the TORQUE signals are significantly affected by the tool deflection in both the X-direction and Y-direction. Thus, these signals may also correlate with the hole center axis deviation. Fig. 10 shows the signal ENC1_POS|1 and the center axis in X-direction of nine randomly selected holes. They seem to have a negative correlation, as the hole deviates in the positive X-direction, the signal ENC1_POS|1 runs into a negative area and the magnitude of these two deviations appears to be proportional. Similar phenomena are also observed by the TORQUE signals and in Y-direction.

In this study, the signal in the feed phase as well as in the retracting phase are analyzed. By the feed phase, the resulting force on the drilling tool consists of feed force, effective cutting, and passive force. Thus, there are more disturbances in the signals by the feed phase. In addition, by the contact moment of the tool and workpiece during machining, the resulting force changes abruptly. The NC-signals react delayed to the step input and this leads to non-linear signal curves by the tool entering moment. In contrast, in the retracting phase exists only the contact and friction force between the tool and hole inner wall. This means that the resulting force on the tool by the retracting phase is almost proportional to the hole deviation. Therefore, the signal curves are more stable and can represent the hole straightness more precisely. For the above reasons, it can be deduced that the selected signals at retracting phase are preferable for predicting the tool deflection.

As mentioned in chapter 3 the hole straightness is defined as the amount of hole center axis deviation. As released in Fig 10, the biggest deviation of center axis is the difference between the first and the last measurement plane. Correspondingly, the value of each signal at the first measurement plane (hole depth z = -0.5 mm) and the last measurement plane (z = -27.5 mm) are chosen as features for the hole straightness prediction. To determine the contribution of each independent variable, the features are scaled to lie between a given minimum and maximum value, and the scale range is set as [-1, 1].

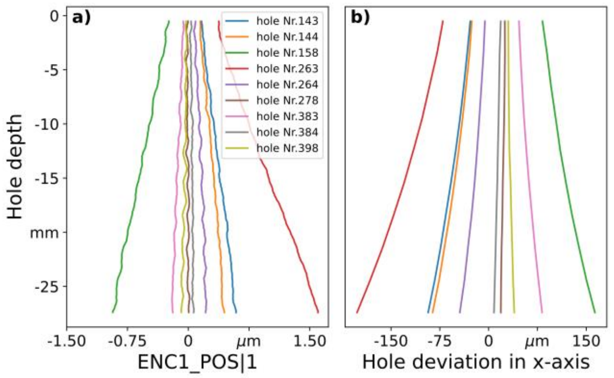

Fig. 10: Signal curve of randomly selected holes: a) Encoder 1 position of machine X-axis in drilling tool retracting phase; b) hole center axis deviation in the X-direction.

4.3 Modeling and Model Evaluation

Since the signals ENC1_POS and TORQUE seem to be well correlated to the hole center deviation, a linear regression model can be built to predict the hole straightness. In this section, a multivariate linear regression model is developed for the target variables, namely the hole straightness in the X and Y-direction (T_{SX} and T_{SY}). The machine learning models are trained with 80% of the data and tested with the rest 20% of the data. The linear regression model is shown in equation (4), by which the subscript "up" or "down" indicates the value of the first or last measurement.

$$\begin{bmatrix} T_{SX} \\ T_{SY} \end{bmatrix} = \begin{bmatrix} \beta_{x1} & \beta_{y1} \\ \beta_{x2} & \beta_{y2} \\ \beta_{x3} & \beta_{y3} \\ \beta_{x4} & \beta_{y4} \\ \beta_{x5} & \beta_{y5} \\ \beta_{x6} & \beta_{y6} \\ \beta_{x7} & \beta_{y7} \\ \beta_{x8} & \beta_{y8} \end{bmatrix}^T \begin{bmatrix} ENC1\_POS|1_{up} \\ ENC1\_POS|1_{down} \\ ENC1\_POS|2_{up} \\ ENC1\_POS|2_{down} \\ TORQUE|1_{up} \\ TORQUE|1_{down} \\ TORQUE|2_{up} \\ TORQUE|2_{down} \end{bmatrix} + \begin{bmatrix} \varepsilon_x \\ \varepsilon_y \end{bmatrix} \quad (4)$$

The result of model validation with the test dataset is shown in Fig. 11. Because of the randomly generated train and test dataset, the result varies slightly, but generally the model performance is very stable. The maximal prediction error is about 0.025 mm and the RMSE is about 0.008 mm. In summary, it can be concluded that the hole straightness can be predicted with sufficient accuracy on the basis of the recorded NC-signals. In the next chapter, the procedure for developing the model for hole roundness is presented.

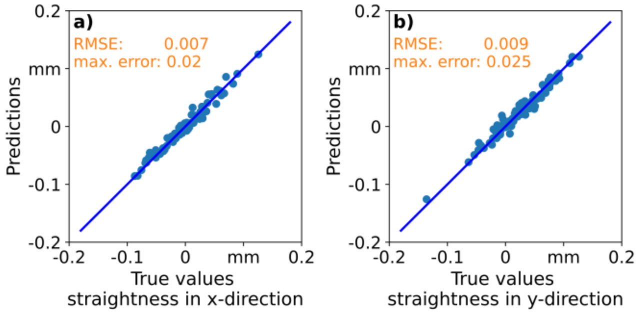

Fig. 11: Predictions vs True values of straightness by model validation.

5 MODELING FOR THE HOLE ROUNDNESS

5.1 Data selection and preparation

As described in chapter 2, the roundness error is caused mainly by the tool oscillation. For multilobe holes, the drill bit oscillation frequency is multiple of the spindle rotational frequency. Abele et al. [Abele 2006] recorded and analyzed the cutting force during drilling with a dynamometer and found, that the hole roundness error correlates with the amplitude of the force signal in the frequency domain, where the frequencies are multiples of the spindle rotation frequency. Since the cutting force also transfers to the machine tool frame, which could possibly be detected by the internal data of machine tool. Derived from the experience of Abele et al., the recorded data is analyzed in the frequency domain.

In our test, the spindle rotation frequency is about 177 Hz. The NC-signals are acquired at a frequency of 500 Hz and according to the Nyquist–Shannon sampling theorem [Shannon 1949], only the information below 250 Hz is meaningful. Moreover, the drilling process lasts only about 0.8 seconds. In contrast, the vibration sensor data of the MPC system is recorded at a frequency of 50.000 Hz. For these reasons, the vibration data by feed phase is applied for the roundness prognosis.

For modeling, the data must be segmented and labeled for each hole. Because the raw vibration data only consists of the timestamp and the acceleration value in the X-axis, this labeling task is accomplished with the help of the NC-signal data, which contains relevant context data about the machining process. Firstly, the start and end timestamps of each hole are found in the NC-signal, then the vibration data is cut and labeled into each hole based on these timestamps. It is important to note that there is a time difference between the measurement computer for vibration signal and the edge computing solution for NC-signals. After testing, it is found the uncertainty is less than 0.1 second, so its effect on the prediction accuracy can be ignored.

5.2 Feature Engineering, Selection

After the data preparation, the fast Fourier transform (FFT) is conducted on the vibration data using the python package scipy [Virtanen 2020]. The data of a hole in the frequency domain is shown in Fig. 12. The peaks in frequency are selected automatically by the scipy function scipy.signal.find_peaks() and it can be found that the peaks appear closely to the multiples of the rotational frequencies. Based on the results of [Abele 2006], the amplitudes of the first five peaks are selected as model features, namely from A_{fft1} (0 Hz) to A_{fft5} (708 Hz).

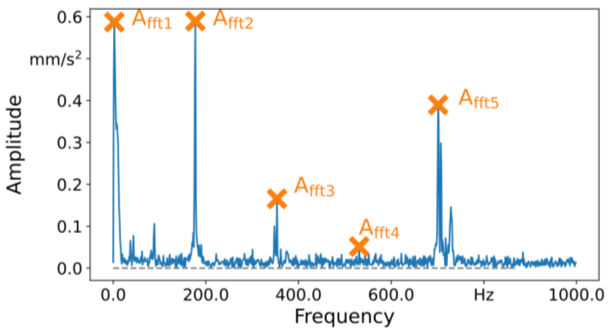

Fig. 12: Vibration data in the frequency domain and the extracted features.

In order to reduce the feature numbers and to find the relevant features, the Pearson correlation analysis between the features and the target variable T_R, the max. roundness error per hole, is carried out. The correlation coefficients r are shown in Tab. 3. It can be seen, the correlation coefficient between the features themselves is very low and smaller than 0.35. But the hole roundness and the feature A_{fft5} have a correlation of 0.68. A possible explanation is that, in this experiment the measured circles have a triangle shape. According to Tschannerl [Tschannerl 2007] the tool oscillation is about double of the spindle rotation frequency. Since the used twist drill has two main cutting edges, the hole roundness reacts at four times of spindle rotation frequency (A_{fft5}).

Tab. 3：Pearson correlation coefficients between the features and hole roundness.

r	A_{fft1}	A_{fft2}	A_{fft3}	A_{fft4}	A_{fft5}	T_R
A_{fft1}	1	-0.23	-0.02	-0.35	0.01	0.10
A_{fft2}	-0.23	1	-0.06	0.23	-0.10	0.11
A_{fft3}	-0.02	-0.06	1	-0.05	0.25	0.06
A_{fft4}	-0.35	0.23	-0.05	1	0.02	0.03
A_{fft5}	0.01	-0.10	0.25	0.02	1	0.68
T_R	0.10	0.11	0.06	0.03	0.68	1

5.3 Modeling and Discussion

To predict the hole roundness a simple linear regression model based on the feature A_{ff5}, the amplitude at four times of spindle rotational frequency, is developed, see equation (4). Following the modeling for the hole straightness the dataset is divided into 80% train data and 20% test data. The prediction result of this model in Validation is shown in Fig. 13. The RMSE is 0.005 mm, which is around 10% of the experimental maximum hole roundness. The maximum prediction error reaches 0.013 mm.

Considering the actual industrial application, the result may be still less-than-ideal. One possible explanation is that the vibration sensor is located far away from the cutting zone. Throughout the force transmission from the tool to the sensor, there are significant damping and many disturbances.

$$T_R = \beta \cdot A_{fft5} + \varepsilon_R \qquad (5)$$

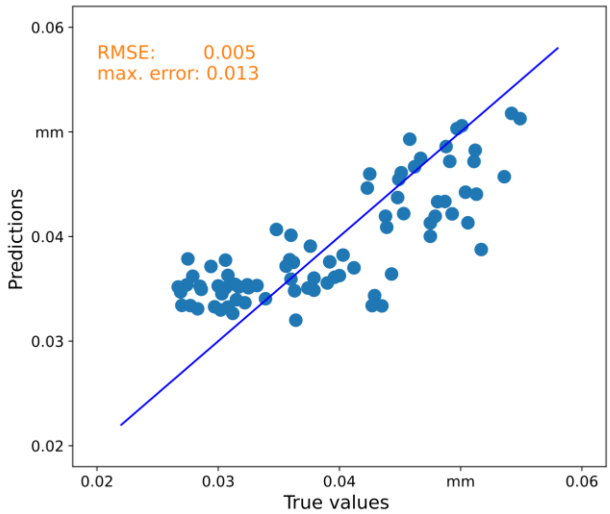

Fig. 13: Predictions vs True values of roundness by model validation.

6 CONCLUSION

In this study, a new approach for quality monitoring by the drilling process based on the internal data of machine tool is presented. Deriving from the domain knowledge of the machining process and signal processing, a fundamental survey of the signals in the time and frequency domain is carried out. It is found that the signals are correlated to the two key quality characteristics: straightness and roundness. This has confirmed the hypothesis that the tool deflection and oscillation can be detected by the internal data of machine tool and therefore inline quality monitoring is feasible. The presence of such physical correlations allows only a few key features to be required and the quality monitoring model to be human-understandable. In addition, the model computing time is very short because of its simplicity. In summary, the presented approach shows the potential to replace the no-value-adding quality inspection by random sampling in mass production.

Still, some measures need to be taken to improve the prediction performance and for implementation in industrial applications. Firstly, more internal data of machine tool, like the sensors in the motor spindle, could be considered. Secondly, foundation investigations in the signals need to be further conducted, for example, the reaction of signals under certain conditions like static force, dynamic force, and machine axis movement. Although the conducted research is based on physical understanding, the model's transferability needs to be validated.

7 ACKNOWLEDGMENTS

This work was carried out as part of the research project DiNaPro, which is funded by the German Federal Ministry of Education and Research (BMBF) and implemented by the Project Management Agency Karlsruhe (PTKA).

8 PUBLICATION BIBLIOGRAPHY

[Abele 2006] Abele, E., et al. Methodology for bore quality prediction through the analysis of frequency response from the radial force signal. *Prod. Eng. Res. Devel.* 2006, Vol.1, pp 5–8.

[BDG 2010] Bundesverband der Deutschen Gießerei-Industrie (BDG). Gusseisen mit Lamellengraphit. Herstellung - Eigenschaften - Anwendungen. Düsseldorf. 2010.

[Bretz 2020] Bretz, A., et al. Measuring the bore straightness during reaming with sensoric tools. *Prod. Eng. Res. Devel.* 2020, Vol.4, pp 535–544.

[DECK 2019] DECKEL MAHO Seebach GmbH Betriebsanleitung - DMG MORI DMC850V, 2019.

[DIN 6537] DIN 6537:2020-10, Solid-hardmetall twist drills with stepped parallel shank - Dimensions, 2020.

[DMG 2023] DMG Mori AG. MPC 2.0 – Machine Protection Control. MPC 2.0 Machine Protection Control - DMG MORI Exclusive Technology Cycles. Available online at https://en.dmgmori.com/products/digitization/integrated-digitization/production/technology-cycles/mpc-2-0-machine-protection-control, checked on 1/4/2023.

[Drake 2001] Drake, P. J. Dimensioning and tolerancing handbook. Norwich, NY: Knovel, 2001.

[Fertig 2022] Fertig, A., et al. Consistent Contextualisation of Process Consistent Contextualisation of Process and Quality Information for Machining Processes Processes. In: Behrens, B.-A. et al. (Eds.): Production at the Leading Edge of Technology. Proceedings of the 11th Congress of the German Academic Association for Production Technology

(WGP), Dresden, September 2021: Springer International Publishing, pp 195–202.

[Fertig 2022] Fertig, A., et al. Machine Learning based quality prediction for milling processes using internal machine tool data. *Advances in Industrial and Manufacturing Engineering* 2022, p. 100074.

[Fertig 2023] Fertig, A. J. Datenbasierte, prozessparallele Qualitätsprognose für spanend hergestellte Werkstücke mittels maschinellen Lernens. Dissertation. Darmstadt, 2023.

[Hauer 2012]. Hauer et al. Uncertainties in process chains with focus on the drilling and reaming process. 1st International Symposium on Uncertainty Quantification and Stochastic Modeling. Maresias, São Sebastião, SP, Brasilien, 2012.

[Li 2018] Li, Z., et al. Surface quality monitoring based on time-frequency features of acoustic emission signals in end milling Inconel-718. *Int J Adv Manuf Technol* 2018, Vol.5-8, pp 2725–2733.

[Molnar 2020] Molnar, C. Interpretable machine learning. A guide for making black box models explainable. [Victoria, British Columbia]: Leanpub, 2020.

[Pandas 2023] The pandas development team. pandas-dev/pandas: Pandas.

[pro-micron 2023] pro-micron GmbH. spike -overview. https://www.pro-micron.de/spike-en/?lang=en, checked on 1/5/2023.

[Puthusserypady 2021] Puthusserypady, S. Applied Signal Processing. [S.l.]: Now Publishers, 2021.

[Schorr 2020] Schorr, S., et al. In-process Quality Control of Drilled and Reamed Bores using NC-Internal Signals and Machine Learning Method. *Procedia CIRP* 2020, pp 1328–1333.

[Schorr 2020] Schorr, S., et al. Quality Prediction of Drilled and Reamed Bores Based on Torque Measurements and the Machine Learning Method of Random Forest. *Procedia Manufacturing* 2020, pp 894–901.

[Schorr 2020] Schorr, S., et al. Quality Prediction of Reamed Bores Based on Process Data and Machine Learning Algorithm: A Contribution to a More Sustainable Manufacturing. *Procedia Manufacturing* 2020, pp 519–526.

[Schorr 2021] Schorr, S. Prozessparallele Prognose der Werkstückqualität mithilfe von NC-internen Daten und maschinellem Lernen. With assistance of Universität des Saarlandes: Universität des Saarlandes, 2021.

[Schuh 2019] Schuh, G., et al. Prediction of Workpiece Quality: An Application of Machine Learning in Manufacturing Industry. In: 6th International Conference on Computer 2019, pp 189–202.

[Schunk 2023] Schunk GmbH & Co. KG. iTENDO². https://schunk.com/us/en/tools/toolholder-quickfinder/itendo2/c/PGR_6468, checked on 1/5/2023.

[Shannon 1949] Shannon, C. E. Communication in the Presence of Noise. *Proc. IRE* 1949, Vol.1, pp 10–21.

[Teti 2022] Teti, R., et al. Process monitoring of machining. *CIRP Annals* 2022, Vol.2, pp 529–552.

[Tschannerl 2007] Tschannerl, M. Beitrag zur Qualitätssteigerung beim Bohren mit VHM-Spiralbohrern unter Berücksichtigung radialer Schwingungen und Kräfte. Aachen: Shaker, 2007.

[Virtanen 2020] Virtanen, P., et al. SciPy 1.0: fundamental algorithms for scientific computing in Python. *Nature methods* 2020, Vol.3, pp 261–272.

[Wang 2020] Wang, X., et al. Prediction and optimization of machining results and parameters in drilling by using Bayesian networks. *Prod. Eng. Res. Devel.* 2020, Vol.3, pp 373–383.

[Ziegenbein 2020] Ziegenbein, A., et al. Data-based process analysis in machining production: Case study for quality determination in a drilling process. *Procedia CIRP* 2020, pp 1472–1477.

[Ziegenbein 2021] Ziegenbein, A.; Metternich, J. Data-Based Quality Analysis in Machining Production: Influence of Data Pre-Processing on the Results of Machine Learning Models. *Procedia CIRP* 2021, pp 869–874.