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Augmenting milling process data for shape error prediction

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Abstract

New integrated sensors and connected machine tools generate a tremendous amount of in-depth process data. The continuous transformation of the obtained data into deployable machining knowledge allows for faster ramp-ups, more reliable process outcome and higher profitability. A system for recording data from various sources - including a simultaneous material removal simulation - is implemented to aggregate and store process data. In addition to the simulation results, process data from the machine control, cutting forces and shape error samples are collected. A series of slot milling processes are carried out with varying cutting speed, feed per tooth and width of cut in a full factional design.
In order to continuously evaluate process data, automatized methods are required. This is achieved using the simulation results to determine all relevant cutting conditions. Dependencies between cutting parameters, sensor signals and cutting result are identified and quantified. However, a one-dimensional model does not predict the shape error accurately. As an alternative model, a multidimensional model based on a Support Vector Machine is trained, using process forces and simulation data. The obtained prediction accuracy is significantly higher compared to the one-dimensional model and can be used to design highly reliable cutting processes.

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1. Introduction

New integrated sensors and connected machine tools generate detailed processes information. Where conventional experiments need sophisticated measurement equipment like dynamometers and are therefore only conducted for a limited of number of tests, built-in sensors allow data collection for every workpiece. Smart machine components such as a sensory Z-slide [1] and a sensory clamping device [2] enable recording of process forces for every machining process in an industrial scale production. Previous research focused on process monitoring [3, 4], machine health monitoring and maintenance scheduling [5, 6] based on process information. In contrast, the presented methods aim to utilize all obtained process data and transform it into machining knowledge for planning and optimizing machining processes. In this way, reliable quality forecasts allow to reduce ramp-up time and optimal process parameters increase profitability while assuring the manufacturing result.

In order to permanently gain knowledge from the recorded data, the process of knowledge generation needs to be automatized. However, an automatization of the signal processing is not trivial, as cutting forces and conditions vary in the course of the process. To gain detailed information about the process, a simultaneous material removal simulation can be used to determine the relevant cutting conditions throughout the whole process. These information are used to gain further machine knowledge, like correlation between the tool engagement and the cutting forces.

In this paper, the developed system for process data recording and storing with a parallel cutting simulation is presented. To investigate the capabilities of the system and the range of information that can be extracted, a series of cutting experiments is conducted. To transform the obtained data into accessible process knowledge, which can be

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deployed for process planning, the relationship between parameters and target values needs to be identified. For that purpose, a multidimensional model is trained to predict the resulting shape error.

2. System setup

In this section, an overview of the implemented system for data acquisition and types of data sources is given. Process forces are measured with a dynamometer. Tool positions and spindle loads are provided by the machine control. The tool positions are send into the cutting simulation CutS [7]. The simulation deploys a dexel-based workpiece representation that allows an efficient calculation of cutting parameters. The received axis values are directly assigned to the virtual machine model that is shown in Fig. 1. The machine tool model is extended to be directly driven by streamed position values from the machine tool.

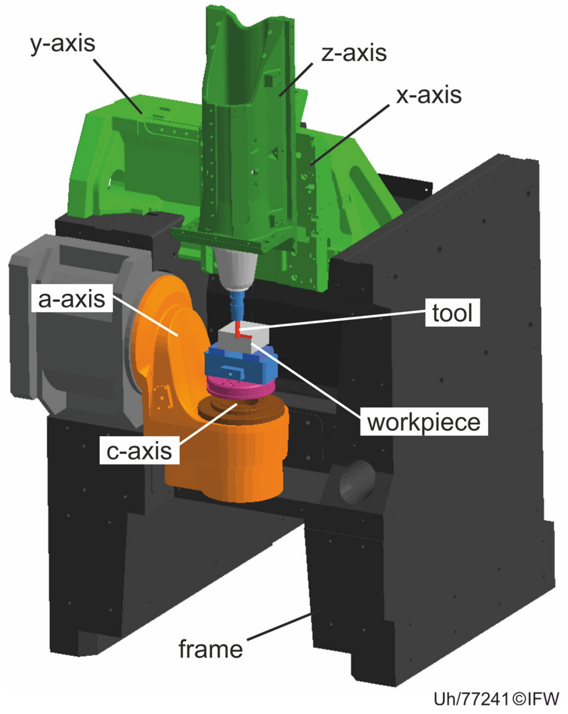

Fig. 1 Virtual machine tool with tool and workpiece model

In this way, the simulation mirrors the real process and considers the original trajectory. One simulation step is performed per axis reading. The cutting simulation determines effective cutting conditions, such as depth of cut, width of cut and material removal rate (Table 1).

Table 1. Summary of calculated values

Data type	Symbol	Unit	Frequency
Width of cut	a_e	mm	25 Hz
Depth of cut	a_p	mm	25 Hz
Material removal rate	Q_w	cm^3/min	25 Hz

The shape error is quantified by sampling the machined surface with an integrated machine tool probe. The shape error is then calculated as the measured deviation normal to the tool path.

As shown in Fig. 2, all data is aggregated centrally by an application called Virtual Planner. The Virtual Planner stores the received process data using the high throughput, write speed optimized database Cassandra [8]. Cassandra is designed to scale horizontally and allows adding database nodes to increase the amount of data that can be handled. Therefore, the setup can be used for a large number of machine tools in a large scale production.

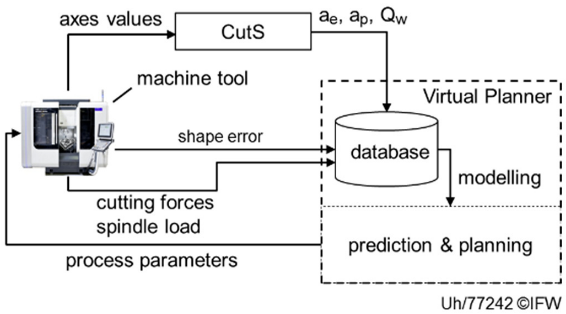

Fig. 2. Data sources and system structure

The shape error values are transferred to the Virtual Planner using an NC-based communication routine. The communication is realized with variables - R-parameters - on the machine control, which can be read and written by the NC-program as well as by applications running on the machine tool. A communication protocol has been developed, that uses status indicators and read/write restrictions for certain variables as well as an error detection to securely transfer data from the machine tool to the Virtual Planner and vice versa. It is used to transfer the shape error results and can also be used to enable the Virtual Planner to adjust cutting parameters. Table 2 shows the measured signals and the corresponding measuring frequencies.

Table 2. Summary of measured signals

Data type	Symbol	Unit	Frequency
Tool position	-	mm	25 Hz
Spindle current	i_s	A	25 Hz
Feed force	F_f	N	100 Hz
Normal feed Force	F_{fN}	N	
Shape error	σ	mm	4 per process

All obtained and generated datasets are equipped with a timestamp which allows to compare the system state in discrete states.

3. Experimental setup

To investigate the presented system, a series of cutting processes is performed. The side milling processes are conducted on an Ultrasonic 10 5-axis machine tool using a solid carbide end mill Kennametal MaxiMet ABDE with a diameter D = 5 mm, tooth count z = 3 and a helix angle ε = 38°. The workpiece material is Al-Mg4.5-Mn. Cutting forces are measured with a multicomponent dynamometer Type 9256C1 by Kistler. The shape error σ is measured with an integrated machine tool probe DMG PP-400. The width of cut a_e, the cutting speed v_c and the feed per tooth f_z are varied in a full factorial designed experiment. Three repetitions for each setting and four surface measuring points each yield 108 iterations and 432 shape error samples. An overview of the experimental design is given in Table 3.

Table 3. Summary of experimental design.

Parameter	Symbol	Levels	Unit
Cutting speed	v_c	400, 500, 600	m/min
Feed per tooth	f_z	0.01, 0.02, 0.03, 0.04	mm
Depth of cut	a_p	2	mm
Width of cut	a_e	0.5, 1.0, 2.0	mm

4. Data Analysis & Machining Knowledge

All sensor signals and simulation results are equipped with a consistent timestamp. Thus, an integrated process view can be composed. An exemplary data set for a machining process is shown in Fig. 3. It contains axes positions, spindle current, forces as well as the cutting volume obtained from the material removal simulation.

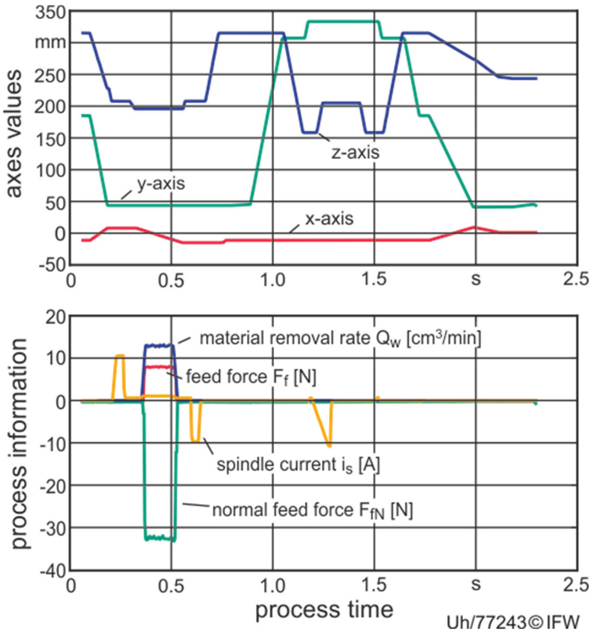

Fig. 3. Process view with aggregated process information

Next, it is shown, how an automatized evaluation of the data can be accomplished. Afterward, it is presented, how correlations can be identified and modeled. Exemplary, the influencing factors on the shape error will be identified and the shape error will be predicted by a trained and verified model.

4.1. Data Analysis

The recorded process data is located in a database and sorted by the process number and data type. In order to model the machining processes, the measured signals need to be aggregated into data points that represent one process configuration each. However, it has to be considered that some process signals, like forces and spindle load, vary in the course of a machining operation without influencing the machining process itself. For example, the spindle load varies when accelerating and decelerating and intervals with no load are not relevant to the cutting process. Also, the process start and end time vary process specifically and cannot be used as a criteria to isolate the cutting stage of a process.

Aiming to include measurements from phases of steady tool engagement and cutting conditions, the measurements are combined with the material removal simulation. First a section with constant material removal, depth of cut and width of cut is identified which indicate a steady-state milling phase. Both start and end time of that interval are stored. An average value of the force of that section is calculated, resulting in one averaged force value per process.

The corresponding shape error values σ are loaded from the database and an average of the four values from each process is calculated. The resulting data points can be seen in Fig. 4, each data point represents one cutting process.

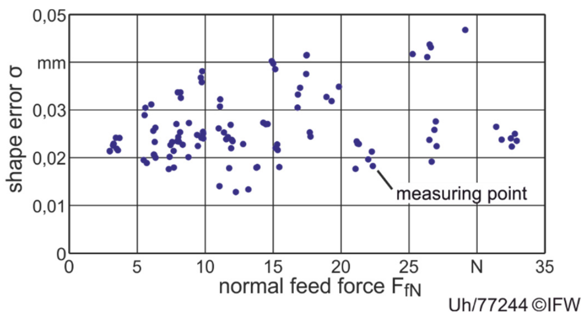

Fig. 4. Effect of normal feed force on the shape error

4.2. Machining Knowledge

To transfer the process data into deployable machining knowledge, dependencies between cutting parameters, sensor signals and cutting result have to be identified and quantified. This allows the prediction of the results and consequently appropriate parameters can be chosen for specific shape tolerance requirement. In Fig. 4 is shown, that there is no distinct relation between the normal feed force F_{fN} and the shape error σ, which is substantiated by a low correlation coefficient of R = 0.2321. Consequently, the shape error σ can only be predicted within a wide corridor, considering the normal feed force exclusively.

To allow a more accurate prediction, a multidimensional model based on a Support Vector Machine (SVM) [9] is used as an alternative modelling approach. The applied features are width of cut, cutting speed, feed per tooth as well as the normal feed force. According to [10] one fraction of the generated data set is used to train the model and the other fraction is used to evaluate the model. The data sets are shuffled in advanced and split in a ratio of 75:25. All features are normalized to the range of -1 and 1. The behavior of an SVM is determined by its kernel type and the parameters *gamma*, *epsilon* and *C*. Appropriate values are identified with a grid search algorithm, which combines a large number of

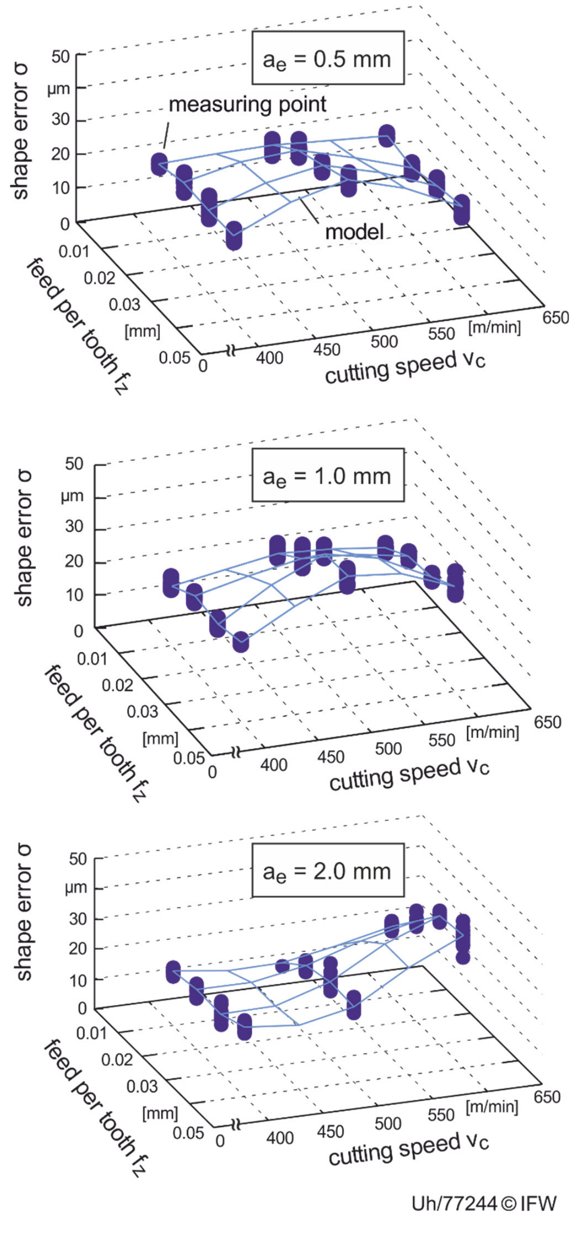

Fig. 5. Measuring points and visualized model

parameters and selects the ones yielding the best predictive model. All data points, broken down per width of cut a_e are shown in Fig. 5. The predictive model is visualized as surfaces. All surfaces originate from the same model, which is trained with the complete data set.

The validation data set is then used to assess the model. Each entry is used to generate a predicted result. By comparing the prediction to the measured value, the relative difference is calculated. The mean square error of all differences serves as an indicator of the prediction accuracy. For the prediction of the shape error, a mean square error (MSE) of 2 µm was obtained. Considering the measured shape deviation range of 15-50 µm and shape error measurements of the same process vary up to 4 µm, the prediction can be rated as highly accurate.

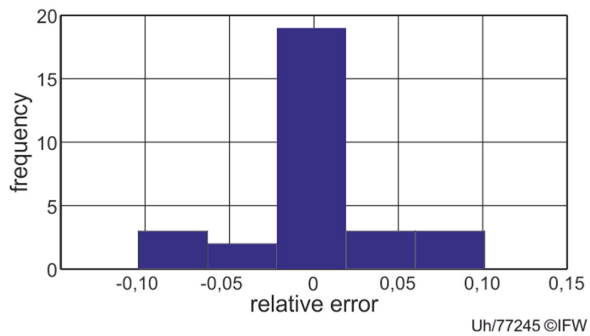

Fig. 6. Distribution of relative error

A histogram of the relative prediction error is show in Fig. 6. The prediction difference is in all cases lower than 12 percent with most predictions even better than 5 percent accuracy. The model can be used to select cutting parameters, which ensure a specified shape error.

5. Conclusions and outlook

Machine sensors and connected machine tools permanently generate various process data. Analyzing the data continuously offers the opportunity to extract knowledge to design better machining processes. Additional data can be generated by enhancing the measurements with simulation results. However, the automatization of the data acquisition and evaluation is key for a permanent knowledge generation. A method for an automatized interpretation of process data is presented in this article. An exemplary analysis of the effect of the normal feed force on the measured shape error is realized. A one-dimensional model could not be used to predict the shape error accurately. Though, the results of this article reveal that more sophisticated multidimensional modelling approaches, like models based on a Support Vector Machine, show high potential transferring datasets into machining knowledge. It has been shown that the trained multidimensional model offers an accurate prediction of the shape with an error lower than 12 %.

By implementing optimization algorithms that use the process database and the modeled relationships, the machining knowledge can be used for self-optimizing processes. Thereby, appropriate parameters can be achieved, that reduce machining time and guarantee the machining result with high process reliability.

As tool wear is relevant to the machining process and its profitability, it should be integrated as a further data source. It could be used to predict the influence of tool wear on the cutting forces, spindle load and on the machining result and take appropriate action when measured results diverge. Also, the tool wear of a specific process and cutting parameters could be predicted in advance of a process to determine the tool costs.

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References

[1] B. Denkena, K. Litwinski, D. Brouwer, H. Boujnah. Design and analysis of a prototypical sensory Z-slide for machine tools. Production Engineering, Springer-Verlag, 2013, 7, p. 9-14

[2] B.Denkena, D. Dahlmann, J. Kiesner. Sensor Integration for a Hydraulic Clamping System. Procedia Technology, Volume 15, 2014, p. 465-473

[3] R. Teti, K. Jemielniak, G. O`Donnell, D. Dornfeld. Advanced monitoring of machining operations. CIRP Annals – Manufacaturing Tecehnology, Volume 2, 2010, p. 717-739

[4] B. Denkena, D.Dahlmann, J. Damm. Self-Adjusting Process Monitoring System in Series Production. Procedia CIRP Volume 33, 2015, p. 233-238

[5] J. Lee, H.-A. Kao, S. Yang. Service innovation and smart analytics for Industry 4.0 and big data environment. Procedia CIRP 16, 2014, p. 3–8

[6] R. Kothamasu, S. Hang, W. VerDuin, System health monitoring and prognostics-a review of current paradigms and practice. International Journal of Advanced Manufacturing Technology, Volume 28, 2006, p. 1012-1024

[7] B. Denkena, V. Böß. Technological NC simulation for grinding and cutting processes using cutS. Proceedings of the 12th CIRP conference on modelling of machining operations, 2009, Volume 2. p 563–566

[8] S. Edlich, A. Friedland, J. Hampe, and B. Brauer, NoSQL. Hanser München, 2010.

[9] C. Cortes, V. Vapnik. Support-vector networks. Machine Learning. Volume 20, Issue 3, 1995, p 273-297

[10] M. Kuhn, K. Johnson, Applied Predictive Modeling. Springer 2013