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ScienceDirect

Procedia Technology 26 (2016) 221 – 226

Procedia Technology

3rd International Conference on System-integrated Intelligence: New Challenges for Product and Production Engineering, SysInt 2016

Self-optimizing cutting process using learning process models

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Abstract

The continuous integration of manufacturing systems and sensory components leads to an increasing amount of available process data. In addition, new database systems and the parallelization of data processing enable to record and analyze these large amounts of process data. The continuous transformation of the obtained data into deployable machining knowledge hold out the perspective for faster ramp-ups, more reliable process outcome and higher profitability. By using the manufacturing data for extensive analyses, models can be derived to describe the effects of machining parameters and external conditions on the cutting result. To utilize the available process data for process planning and optimizing, the data has to be handled and interpreted appropriately and finally transferred into machining knowledge. This paper presents a method that uses a support vector machine as a machine learning approach to model the obtained process data. With a numerical optimization of the model, optimal process parameter can be determined, that minimize machining time and satisfy given boundary conditions. By modelling the process variance as well, the determined process parameters guarantee the process outcome within a freely selectable confidence interval. Through the complete automation of data capturing, data storing, modeling, optimizing and machining, a self-optimizing cutting process is achieved.

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Peer-review under responsibility of the organizing committee of SysInt 2016

Keywords: Process Planning; Self-Optimization; Machine Learning

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Peer-review under responsibility of the organizing committee of SysInt 2016
doi:10.1016/j.protcy.2016.08.030

1. Introduction

Through sensory [1, 2] and connected [3, 4] machine components and work pieces, an increasing amount of process data is available. New database systems are optimized for horizontal scaling and allow to store these large amount of process data. In addition, new programming models like MapReduce [5] enable the processing of large data sets. Consequently, all occurring process data can be used to parameterize models that can be deployed for the planning of cutting processes. One of the main task of process planning is the selection and optimization of suitable process parameters, that lead to the desired process outcome in terms of quality requirements while minimizing machining cost and machining time. As the choice of process parameters such as speed of cut, feed rate and width per cut determines the profitability of a cutting process, the optimization of these parameters have a long history in production research [6, 7].

The reviews from Mukherjee [7] and Yusup [8] give an overview on applied optimization techniques in metal cutting. Recent research work focuses on evolutionary optimization algorithms, particularly Genetic Algorithms (GA), Simulated Annealing (SA) and Particle Swarm Optimizing (PSO) [8]. However, these algorithms do not explicitly model the correlations between process parameters and their effects, as they do not require an explicit model for the optimization process. Consequently, the determined process parameters are only valid for one certain process with a particular set of boundary conditions. Therefore, these algorithms do not lead to sustainable machining knowledge, that can be applied to different processes or different quality requirements. Extensive process models however, can be deployed for process planning and enable faster ramp-ups, a more reliable process outcome and a higher profitability. Model based optimization methods, such as Statistical Regression (SR), Respond Surface Method (RSM) or Artificial Neural Network (ANN) allow for building such models [7]. These known modelling approaches are able to map input and output parameters reliable. However, they are used to predict the expectancy value of a process and do not forecast the process variance as well. This paper presents a method that uses a support vector machine as a machine learning approach to model the obtained process data. With a numerical optimization of the model, optimal process parameter can be determined, which minimize machining time and consider given boundary conditions. By modelling the process variance as well, the determined process parameters guarantee the process outcome within a freely selectable confidence interval. Through the complete automation of data capturing, data storing, modeling, optimizing and machining, a self-optimizing cutting process can be achieved.

2. Data Acquisition & Experimental Setup

In this section, an overview of the implemented system for data acquisition, storage and processing is given. The used machine tool is connected to a computer, which runs the Virtual Planner via Ethernet. The Virtual Planner [9] is an application that is responsible for storing the process data and making it available for analyses. The program is also responsible for selecting the cutting parameters for the conducted cutting processes based on the knowledge that can be extract from previous processes. The geometric deviation is used as a target value. The measured 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. The access to machine data is realized through the DDE interface. While continuously changing information like the axis values are streamed via TCP sockets, static variables as the geometric deviation are transferred with HTTP requests. 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.

The side milling processes are conducted on a Sauer 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 $\varepsilon = 38°$. The workpiece material is Al-Mg4.5-Mn. The geometric deviation Δ is quantified as the deviation normal to the tool path and is measured with an integrated machine tool probe DMG PP-400. Table 1 shows the varied process parameters that represent the degrees of freedom of the self-optimizing process and the parameter limits that are predetermined to avoid machine and tool failure.

Table 1. Summary of process parameters and limits.

Parameter	Symbol	Limits	Unit
Cutting speed	v_c	400 – 600	m/min
Feed per tooth	f_z	0.01 - 0.04	mm
Depth of cut	a_p	2	mm
Width of cut	a_e	0.5 - 2.0	mm

The simultaneous material removal simulation CutS [10] is deployed to determine effective cutting conditions, such as depth of cut, width of cut and material removal rate. By directly assigning the streamed axis values to the virtual machine tool, the simulation mirrors the real process and the original tool trajectory. In this way, the simulation adds further information to the data stream and dynamic processes with changing process conditions can be applied to the learning algorithms.

As shown in Fig. 1, all data is aggregated centrally by the Virtual Planner. The Virtual Planner stores the received process data using the high throughput, write speed optimized database Cassandra [11]. 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.

Through this setup and the connection between the machine tool and the Virtual Planner, a complete automation of data capturing, data storing, modeling, optimizing and machining, a self-optimizing cutting process was achieved.

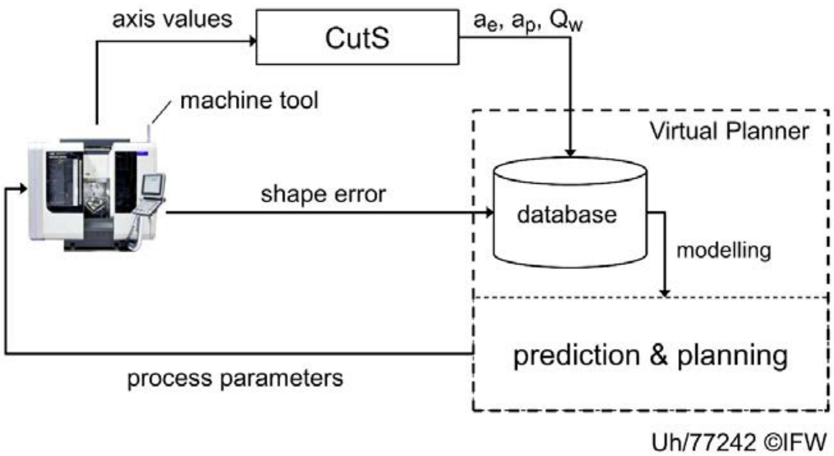

Fig. 1 System structure including the Virtual Planner

3. Machining Knowledge

To transfer the process data into deployable machining knowledge, dependencies between cutting parameters and cutting result have to be identified and quantified. In order to select a suitable modelling approach, a full factorial designed experiment was conducted in advance. A multidimensional model based on a Support Vector Machine (SVM) [12] predicted the shape error highly accurate. All data points resulting from this series of side milling processes are broken down per width of cut a_e and are shown in Fig. 2. Due to process and measurement variance, the shape error varies when the trials are repeated, which leads to different heights of the measuring points. The predictive model is visualized as surfaces. All surfaces originate from the same model, which is trained with the complete data set.

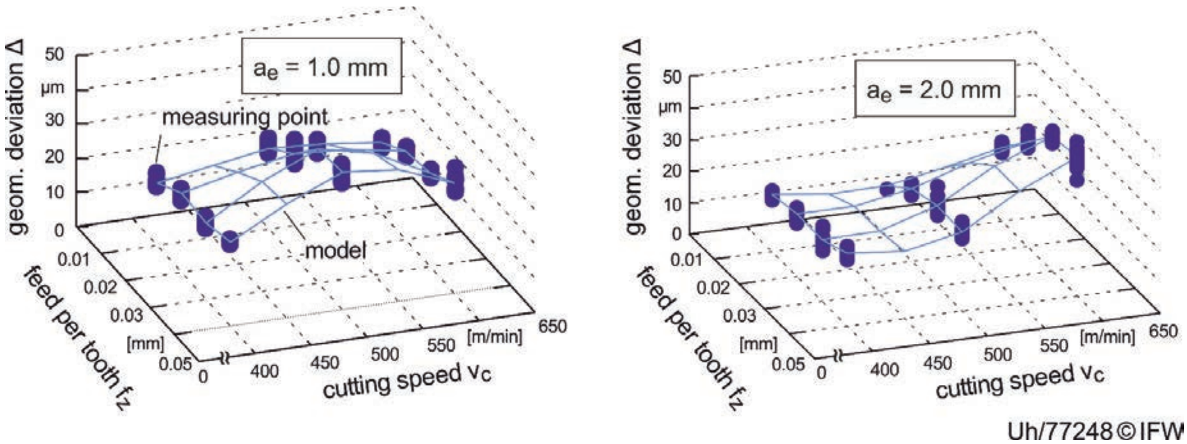

Fig. 2. Results of cutting processes and the resulting predictive model

However, the shown model does not consider the variance of the process yet. The predicted shape error values correspond to the expectancy value. To incorporate the variance as well, the unbiased sample variance s^2 is calculated for every parameter

By modelling the values $\bar{x} \pm 3s$ instead of the measured values and assuming the geometric deviation to be normally distributed, the 3-sigma process limits are modelled, see Fig. 3. They can be used to determine process parameters, that secure the shape error to be located between the modelled process limits. It has to be mentioned, that the variance limits in between of known configurations can only be used as an estimate. The behavior of the interpolated variance models has not been investigated within the scope of this paper.

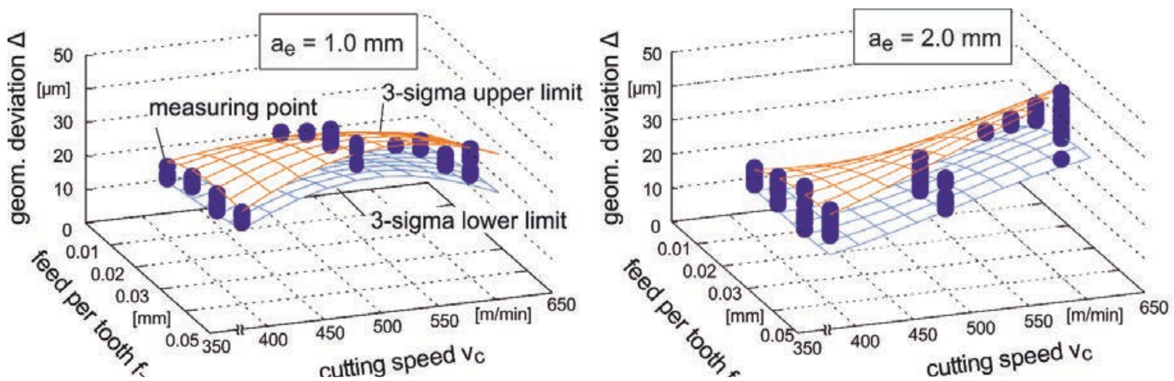

Fig. 3. Process model with process variance

4. Self-Optimization

In this section, it is shown how the described models can be used to implement a self-optimizing cutting process. To gain process data for the initial model, the predetermined process limits are used to derive a number of initial process parameters. By this means, the general shape of the model is obtained. The process models can consequently be used to obtain suitable process parameters with a numerical optimization. As the prediction of the shape error with a built up model can be calculated with fairly low computational time using a grid search algorithm. Therefore, the complete model is sampled with a high resolution. A filter is applied to reject all parameters that do not satisfy the boundary condition. Process parameters that do not fulfill the given quality requirements are excluded in this way. Following,

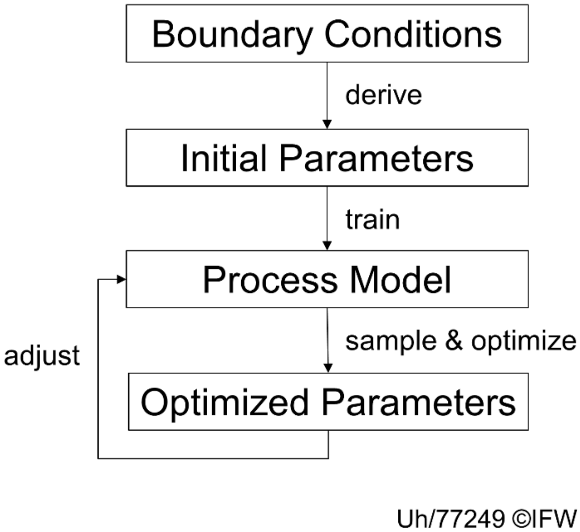

Fig. 4. Self-optimization procedure

all parameters are sorted according to the optimization criteria, for instance the material removal rate. The process parameters that lead to the highest material removal rate is used for the subsequent process. The procedure is shown in Fig. 4.

The data basis grows with every conducted process and the process model becomes more detailed and accurate. By connecting the machine tool directly with the Virtual Planner, an autonomous loop is established.

5. Conclusion & Outlook

Machine sensors and connected machine tools permanently generate various process data. Analysing the data continuously offers the opportunity to extract knowledge to design better machining processes. A method for an autonomous, self-optimizing process with learning process models is presented in this paper. It was achieved by consistently automatizing the data storing, modelling and optimizing together with connecting the machine tool with the planning device.

As tool wear is relevant to the machining process and its profitability, it should be integrated as a further data source. In this way, the conflict between machining time and tool wear could be considered within the optimization algorithm. In the presented scenario, a number of processes has to be performed to gain the initial process model. To avoid these trials, the generalization of the models could be a promising approach. Different machine tools, tools and materials could be considered by such a model. With a cloud based approach, several machines could learn simultaneously while being located at different sites. The machining knowledge could be composed collaboratively and could be deployed by each machine.

Acknowledgements

The approach described above is part of the Collaborative Research Centre 653 (SFB 653) “Gentelligent Components in their Lifecycle” founded by the German Research Society (DFG).

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