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Simulation-based feed rate adaptation considering tool wear condition

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Abstract

The process forces generated in machining are related to a deflection of the milling tool, which results in shape deviations. In addition to process parameters like feed rate, width and depth of cut or cutting speed, the wear condition of the tool has a significant influence on the shape deviation during flank milling. In process planning it is important to take the tool condition and the ideal time for tool change into account when selecting the process parameters. An assistance system is being researched at the Institute of Production Engineering and Machine Tools (IFW) in cooperation with Kennametal Shared Services GmbH to support this task. The assistance system adjusts automatically the feed rate considering a predefined maximum shape deviation. Additionally, it identifies an optimal moment for tool change. The advantages of the system are particularly evident in planning of individual milling processes. The assistance system is based on a combination of a material removal simulation and empirical models of the shape error. For this purpose, spindle currents as well as measured shape errors are stored in a database. These data are extended by the actual local cutting conditions calculated by a process-parallel material removal simulation. Afterwards, the data is transferred into process knowledge via a Support Vector Machine (SVM). Within a technological NC simulation before the start of manufacturing, the generated knowledge is applied to predict the shape error of the workpiece and to automatically adjust the feed rate. By adapting the feed rate, it is possible to control the tool life. The required tool change is defined by specifying a limit for the permitted width of flank wear land. The presented assistance system enables the prediction of the shape error parallel to the manufacturing process and the automatic determination of the feed rate as well as the ideal time for tool change.

Keywords: Simulation; Milling; Machine learning; Wear

1. Introduction

Due to process forces during the milling process, the tool is deflected and shape deviation on the machined workpiece occur. In addition to process parameters like feed rate, width and depth of cut and cutting speed, the wear condition of the tool has a significant influence on the resulting shape deviation in flank milling. The wear of the tools increases continuously during milling operations. Because of the wear, intolerable shape errors occur on the workpiece and scrap parts can be produced.

In manufacturing practice, two ways to identify a suited moment for tool change exist. In large-scale production, tool change intervals are determined empirically. In production of small batches, the decision for tool change is delegated to an experienced machine operator. However, both strategies result often in sub-optimal decisions about the moment of tool change. If the tool is changed too late, the manufacturing tolerances are exceeded and the risk of producing scrap parts increases. In case of an early tool change, the remaining tool life is wasted. Exact methods to determine the ideal time to change tools do not exist for the practical use on shop floor.

To improve the process planning quality, Denkena et al. [1] developed a method for condition-based tool management. The aim of this method is to provide all necessary information for process planning in order to forecast the remaining service life of each tool. By feeding the information back into the process planning, both tool use and tool procurement can be reliable

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planned. Cutting edge coefficients are used to estimate tool wear. For an exemplary process, a linear dependence between width of flank wear land and process forces was proven.

To control the condition of the tool during metal cutting, monitoring systems are used. These systems detect tool breakage, collisions between tool and machine structure as well as defined inadmissible process conditions using force signals or other recorded signals like acoustic emissions [2, 3]. Moreover, systems for adaptive feed control are already commercially available, e.g. [4]. Implemented in the programmable logic control (PLC) of the machine tool, the systems adapts the feed rate to avoid exceeding the maximum spindle power. The feed adaptation can reduce both, the load during processes as well as the tool deviation. If the calculated feed rate falls below a predefined limit, the PLC supposes a tool change. However, these systems do not take into account the resulting shape error of the workpiece.

For the continuous improvement of tool monitoring systems supervised machine learning methods are used. Hsueh and Yang [5] implemented Support Vector Machines (SVM) to predict tool breakage by analysing force signals. Hassan et al. [6, 7] developed a method to detect tool wear using standardized force and current signals. Next, characteristics are extracted, which are sensitive towards tool condition, but robust to tool size and cutting conditions. Finally, different methods of machine learning for the investigation for real-time wear monitoring in terms of accuracy, computing time and false alarm rate were investigated. Recommended methods for tool management systems are linear discriminant analysis (LDA) and SVM. Both methods provide an accuracy of 90% with a small database and a low false alarm rate. Due to the lower computation time, Hassan et al. favour the LDA to the SVM.

Another approach for monitoring tool wear in real time is presented by Nouri et al. [8]. Force model coefficients are identified, which are independent from cutting conditions, and correlate to the tool wear. For further analysis, these coefficients are tracked during milling. The presented method consists of three stages. First, the G-Code part program must be pre-processed to determine the cut geometry. The results are stored in a look-up file. During the following manufacturing of the workpieces, cutting forces are measured and stored in the same file. Finally, the force model coefficients are estimated and the state of tool wear derived. This method uses expensive sensors installed in the machine tool to gain the required information. Thus, it is unlikely to be implemented into the industry. Another approach to detect on-line tool wear based on acoustic emission is presented by Giriraj et al. [9]. If a defined threshold of the tool wear is extended, the work offset is adjusted.

To compensate the shape error, Dittrich et al. [10] used engagement conditions provided by a process-parallel material removal simulation and merged them with the measured shape error. With the help of an SVM, the shape error is predicted and the tool path automatically adapted. With this method, the shape error was reduced by 50%. In further investigations, SVM were compared with other machine learning methods and evaluated with regard to the performance. However, the effects of tool wear were excluded from the investigation. For the evaluation and estimation of surface roughness of CNC turning Caydas and Ekici [11] compared the performance of SVM with that of artificial neural networks (ANN). With regard to prediction accuracy and computational time, SVM gave better results than ANN. More recent results also indicate a better performance of SVM compared to ANN in modelling [12]. An SVM to predict the shape error during milling processes with high accuracy was also implemented by Denkena et al. [13]. In this case, the prediction error was below 5% in most cases.

This paper presents a novel approach for feed rate optimization. In contrast to existing methods, the approach detects tool wear in real time and optimizes the manufacturing quality of the workpieces by taking into account the measured shape error. Using sensors that are already integrated in most machine tools, the method can be transferred easily into the industry.

2. Approach

The developed approach consists of three components: (1) the machine tool, (2) a process-parallel simulation (IFW CutS) and (3) a database (see Fig. 1).

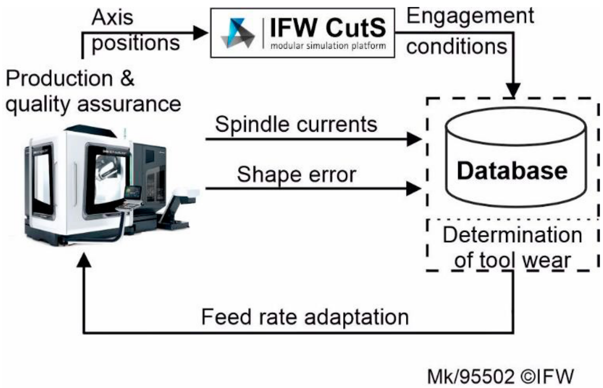

Fig. 1. Approach for simulation-based feed rate adaptation.

The process-parallel simulation is driven by actual axis movements and translates the machine tool movements into technological measures in terms of spatial cutting conditions. For this purpose, the modular simulation platform IFW CutS [14] is used. The axis positions are transmitted to IFW CutS from the PLC of the milling tool. Using these positions, the material removal is simulated during the machining process and the local cutting conditions, such as chip removal volume, width and depth of cut, are determined. These engagement conditions are transmitted to a database and combined with measured spindle currents of the machine tool and shape deviations of the workpiece. The shape deviations are measured with a machine-integrated tactile probe. In order to predict the current tool condition, the current shape error of the workpiece is to be predicted spatially resolved during the process. To avoid a complex analytical parameterization of the prognosis model for each tool-material combination, an SVM is used, which is taught with recorded process data and quality information. A learning behaviour is achieved by regularly updating the model. By using the SVM, models are created that generate workpiece-independent technological knowledge from the data. This knowledge is applied to determine the shape deviations of the workpiece and the wear condition of the tool during machining. This information is also stored in a process data platform for use in work preparation and planning.

With the presented approach, process parameters, e.g. the feed rate, can be adapted for the subsequent process taking into account the wear condition of the previously used tool. If the predicted flank wear land leads to exceedance of the shape tolerance for the following workpiece, the feed rate is adjusted. The minimum feed rate depends on both economic and technological aspects, such as the minimum chip thickness. If the feed rate falls below a predefined minimum, it is necessary to replace the tool and a recommendation for tool change is given to the operator. The system is designed to maximize tool life and reduce the waste of energy-intensive resources. In contrast to earlier approaches, the presented method is based on machine-internal signals only, which enables an easy transfer to the industry.

3. Process-parallel simulation

A central part of the approach is a process-parallel material removal simulation. Local cutting conditions are calculated to obtain the actual feed rate, the material removal rate and the depth of cut from real milling processes. However, the simulation requires a kinematic model of the machine tool including the structure and the exact position of the axes in relation to the rotary axis zero point. To avoid manual design of the kinematic model, a method for an automatic model generation is created. The method reads archive files automatically from the programmable logic control (PLC) and extracts relevant information for the model generation. Currently, the method has been only tested for 3- and 5-axis milling machines with a Siemens 840d sl PLC.

The process-parallel simulation is connected to the PLC of the machine tool [10]. The data exchange between the process simulation and PLC and vice versa achieved through the communication library ACCON-AGLink by Deltalogic. By this, the process simulation is enabled to read continuously the axis positions as well as the information of the used tools from the PLC.

To calculate the cutting conditions, the workpiece is discretized in the simulation with a dexel field. The dexels are spaced 0.156 mm apart for each perpendicular direction. The tool is represented as a cylinder.

4. Experimental study

In experimental investigations, the data required to generate the initial prediction models for the shape error were determined. For this purpose, flank milling processes were carried out at a constant cutting speed $v_c = 75$ m/min in down milling. The tests were carried out on a CNC machine type DMG HSC 55 using solid carbide milling tools type WIDIA HANITA VariMill with a diameter D = 6.0 mm and a number of teeth z = 4. Tempered steel C45 was used as workpiece material. The length of one milling path was 80 mm. The engagement width and engagement depth were set constant at $a_e = 2$ mm and $a_p = 7.5$ mm.

A machine-integrated tactile probe type Heidenhain TS649 was used to determine the shape error at defined points. The width of flank wear land VB of the tool was measured optically with a digital microscope type VHX600 from Keyence. The resulting shape error as well as the wear condition of the tool were measured after five milling paths and a corresponding cooling time of the workpiece. The machine-integrated tactile probe measures 3D points at five defined positions of the manufactured workpiece. These points are merged with the ideal points generated by the material removal simulation IFW CutS. The distance between the equalization plane of the corresponding points presents the resulting shape error. To detect the feed influence on the wear progress the feed speed v_f was varied between 55 and 1000 mm/min. The end of tool life was defined by a width of flank wear land VB $\geqslant$ 75 µm.

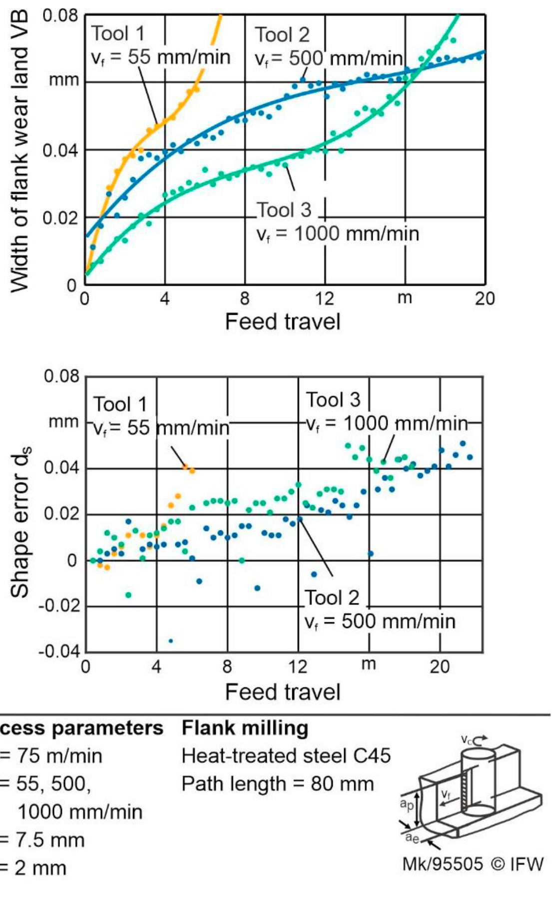

Fig. 2. Experimental results of flank wear land and shape error.

Fig. 2 shows the results for the influence of v_f on the wear development and the shape error. Higher feed rates lead to slow increase of flank wear and greater shape errors.

High feed rates lead to larger shape errors due to the increasing tool deflection caused by increased process forces. Therefore, the shape error of tool 3 is bigger than of tool 2. At the same time, the width of flank wear land of tool 2 increased stronger than for tool 3, which was milled with the double feed rate. During milling different effects like friction because of slow feed rates or tool deflection caused by higher feed rates occur. Depending on the process parameters, the effects outweigh each other. When milling with the unworn tool 2 the friction caused higher tool wear while at the same time the shape error is small because of a slow feed rate.

5. Feed rate adaptation

In a further series of experiments, the feed rate adaptation was investigated. For this purpose, the initial feed rate $v_f = 1000$ mm/min was reduced by 100 mm/min each time a shape error of d_s = 0.035 mm was exceeded. The limit considered for the width of flank wear land VB was 75 µm and the lower limit for v_f was 500 mm/min.

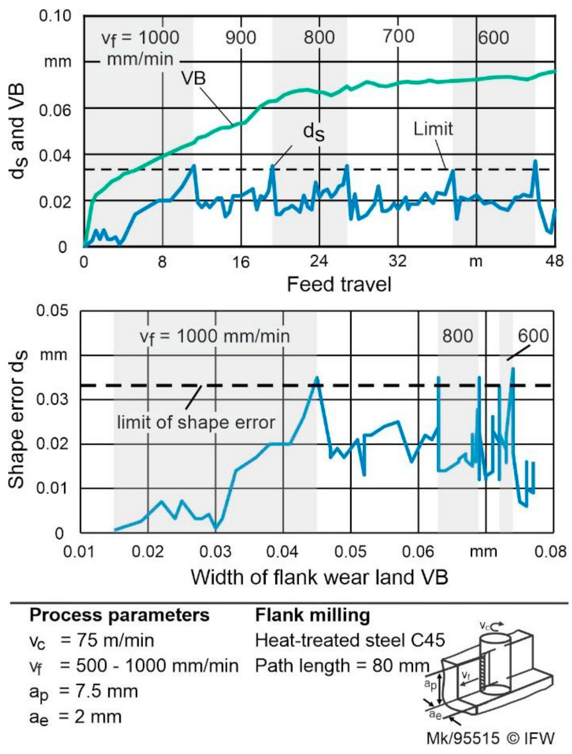

Fig. 3. Progress of tool wear and shape error during feed rate adaptation.

As a result, Fig. 3 clearly shows how shape error and service life can be positively influenced by an adjustment of v_f as the flank wear mark width increases. As shown, reducing the feed rate results in both, reduction of shape error as well as slower increase in width of flank wear land. There is a correlation between the flank wear and the shape error. Higher values of width of flank wear land lead to larger shape errors. As the feed rate as well influences the shape error, reducing the feed rate for worn tools leads to a longer service life. The end of service life of the tool is defined by a maximum shape error and a minimum feed rate. The result clearly shows how shape errors and tool life can be positively influenced by adjusting the feed rate as the width of flank wear land increases. After the adjustment of v_f, a significant reduction of the previously increasing shape error could be observed. In consideration of the maximum shape error, the service life can be extended by 70% by reducing the feed rate by 10%. If a reduction of the feed rate by 50% is tolerated, the service life extension is even 440%.

In order to be able to transfer the automatic feed rate adaptation onto the shop floor, an easy to use software application was developed. The application contains an automatic calculation method to determine the current cutter condition based on the quotient described in equation (1).

$$\frac{I_{initial}}{I_{actual}} = Tool\ status \tag{1}$$

The spindle current I is transferred directly from the machine to the application. The user enters the maximum shape error as well as the minimum feed rate as input values. Based on the process model generated and the current tool status, a recommendation for v_f is given as output of the SVM model. In case of varying local cutting conditions during complicated milling processes, these parameters are considered for the feed rate adaptation. This adaptation takes into account the permissible shape error and the requirements for an economical process. The goal is to provide a high productivity while at the same time maintaining the quality specifications based on the current tool condition. Fig. 4 shows the user interface of the application.

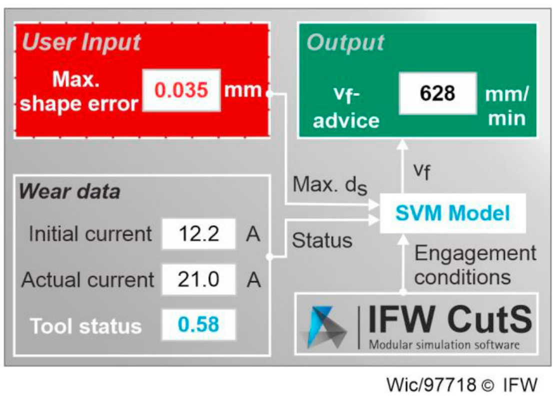

Fig. 4. Application for automatic feed rate adaptation.

In conjunction with the developed application, the assistance system can be used for condition-based optimization of the feed rate. By adapting the feed rate, it is possible to control the operating time of the respective tool. This results in an improved tool planning in the production of batch sizes. The required tool change is defined by specifying a limit for the permissible width of flank wear land. Furthermore, a tool change is necessary in case of a required uneconomical feed adjustment or if the value for the permissible shape error is exceeded.

6. Conclusion and outlook

By using the assistance system presented, it is possible to predict the shape error parallel to the production process as well as the end of tool life in real time. The approach allows an automatic adaptation of the feed rate to extend the service life of the tool. This results in the benefit of an application that enables optimized tool use planning. The possibility of influencing shape error and tool life by adjusting the feed rate with increasing width of flank wear land was demonstrated in an additional test series. The feed rate adaptation showed great potential. For example, reducing the feed rate by 10% lead to an extension of the tool service life by 70%. As the system only uses machine-internal signals, it can be easily transferred to shop floor. To implement the presented assistance system on shop floor, a simulation server for the process-parallel simulation is necessary as well as an experimental investigation as a training set for the SVM to build up suitable models for the setup.

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