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AUTONOMOUS MACHINING – RECENT ADVANCES IN PROCESS PLANNING AND CONTROL

While autonomous driving has come close to reality over the recent years, machining is still characterised by many manual tasks and prone to costly errors. In this article, an overview is given about the potential of autonomous machining and uprising technologies that support this vision. For that purpose, a definition of autonomous machine tools and the required elements is presented. Next, selected elements of an autonomous machine tool, e.g. sensory machine components and control loops, are discussed. Finally, some insights into ongoing research projects regarding the use of machine learning for process planning and control are given.

1. INTRODUCTION

Globalisation and a trend toward higher product individualisation have led to an increasing competitive pressure, higher product variability and highly dynamic product lifecycles. Consequently, production systems must be more flexible, versatile and robust than ever before. However, conventional production systems display stiff procedures and processes. Thus, they are often not able to cope with the dynamic environment. In contrast to this, autonomous systems enable a more flexible automation and versatile production [1].

The vision of an autonomous production system includes the ability of a system to plan and control the production by itself. Moreover, the system should be able to adapt to unforeseen changes of the environment. Key to such production systems are machine tools that can act autonomously as well. While the concept of autonomous driving draws currently much attention and first prototypes of autonomous cars are already tested, the idea of an autonomous machine tool seems to be far away. However, this article aims to propose a first definition of autonomous machine tools and the required machine components. Next, different levels of control loops within autonomous machine tools are presented. Based on

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the theoretical framework, ongoing activities of the authors in the field of adaptive control and self-optimizing process planning are highlighted. The article closes with an assessment of the currently available technologies and an outlook on potential research questions.

2. DEFINITION AND ELEMENTS OF AUTONOMOUS MACHINE TOOLS

While much research regarding automation and intelligent or autonomous decision-making has been carried out over the last decades, e.g. [2, 3], there is no distinct definition of an autonomous machine tool. From the author's point of view, an autonomous machine tool should be able to plan and conduct a machining operation based on a digital workpiece model and information on the current machine state. Potential deviations should be identified and controlled automatically during the process. Moreover, an autonomous machine tool should be able to learn from prior machining operations and self-optimise its behaviour continuously. In order to communicate with workers, other machine tools or higher levels within the production system, the machine tool should contain communication devices. In accordance to prior definitions by Kienzle and Tönshoff [4], the authors propose the following definition for an autonomous machine tool:

An autonomous machine tool is a machine that brings a tool and a workpiece in contact under mutual guidance (Kienzle). It takes over the monitoring, processing, modelling and storage of information for a self-optimising planning, execution and control of the manufacturing process. It is integrated in higher-level systems via standardised communication structures and protocols (extension).

From this definition, it can be derived that an autonomous machine tool contains all elements of a conventional machine tool. However, sensing abilities and data processing become crucial in order to fulfil the tasks mentioned in the second part of the definition. Thus, autonomous machine tools are equipped with sensors, besides already existing sensors, e.g. in drives. Moreover, the use of soft-sensors allows to quantify measures that would otherwise not or very hard to measure, e.g. temperature distributions within the workpiece [5]. In order to process the obtained data and to derive correlations, existing control systems of machine tools must be enhanced drastically. An intelligent signal processing enables a context-specific analysis of sensor data and a comparison to expected states. A centralized or decentralised knowledge base stores context-based information and models, which are updated continuously by sophisticated modelling techniques. Due to recent progress in the field of machine learning, these techniques offer novel possibilities for modelling and representing knowledge. The obtained knowledge is used for adaptive process planning and adaptive control of machining processes. The ability to self-optimise corresponds to the highest level in the maturity system of cyber-physical systems (compare [6]). Communication systems and human-machine-interfaces enable the machine tool to communicate with the environment and workers. In accordance with a reference architecture for autonomous systems by the German National Academy of Science and Engineering [1], the mentioned functionalities and elements of an autonomous machine tool are summarised in Fig. 1.

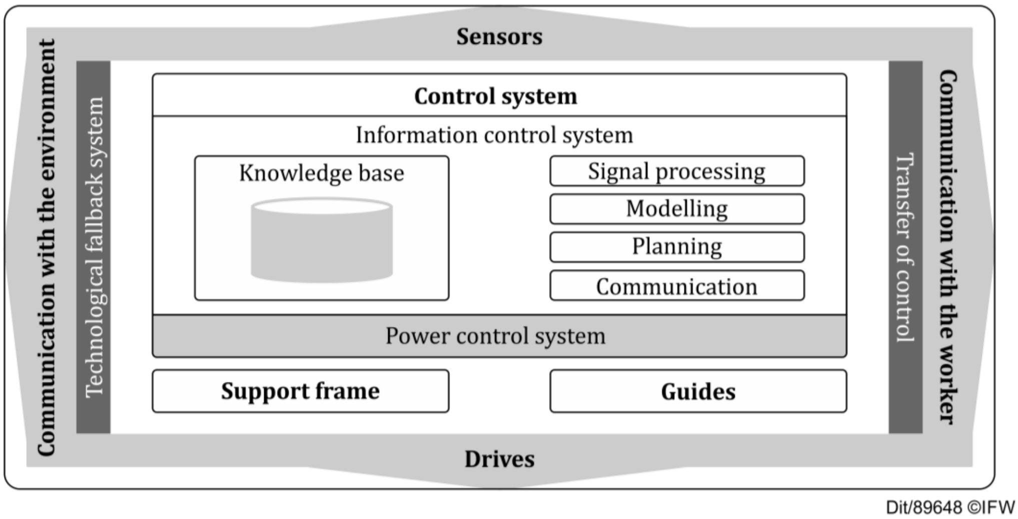

Fig. 1. Reference architecture of an autonomous machine tool

The actions of autonomous machine tools are planned and controlled by several – partially overlapping – control loops. The different control loops can be characterised by their decision range and time span. Fig. 2 gives a simplified overview about the different control layers in autonomous machine tools.

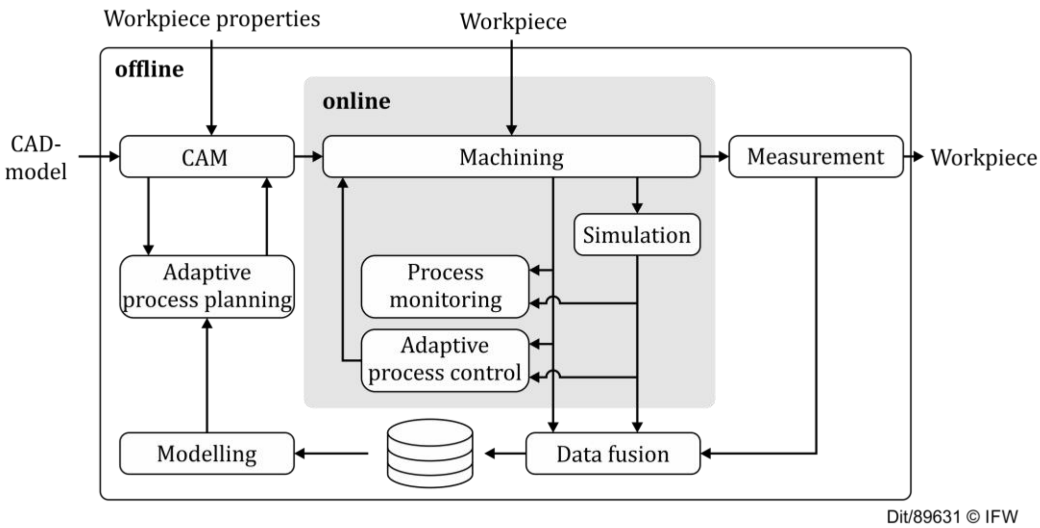

Fig. 2. Simplified overview about control loops in autonomous machine tools

While adaptive control focusses on short-term adaption and must react in real-time (online), adaptive process planning concentrates on a longer time span and requires no real-time changes (offline). However, adaptive process planning must cope with more variables and a higher degree of freedom. These different layers of planning and control can be compared to human reflexes, adjustments and intentional behaviour. Still, there are certain actions that could be carried out by multiple decision layers, e.g. feed rate adaption.

Consequently, it is necessary to design the control layer accordingly to avoid potential conflicts between them. In the following two examples for adaptive process control and planning and their implementation into a machine tool are presented.

3. ADAPTIVE PROCESS CONTROL USING SENSING MACHINE TOOL COMPONENTS

In order to fulfil tasks autonomously, machine tools and their components must be capable of sensing the current condition and provide information about the machining process. Based on this information, the machine tool should be able to control and optimise the machining process on its own. While humans have a natural ability to sense the environment, machine tools need additional sensors for data acquisition. For that purpose, some of the authors have developed several so-called "feeling" components [5, 7, 8]. In the following, the technology of a feeling spindle head as well as adaptive control strategies aiming to compensate the tool deflection in milling are presented. An excellent overview about other sensor technologies is given in [9]. The described control strategies are executed during machining (online). Therefore, they are represented by the inner control loop in Fig. 2.

In milling, the spindle head, which carries the working spindle, is well suited for the integration of sensory machine components, since it is closely located to the cutting process and directly guides the flux of force. Because the spindle is used for all processes in a machine tool, sensor positioning at the spindle head offers a high flexibility with respect to different cutting operations. The load detection is realised by strain measurements on the structure of the component. However, structural components, like the spindle slide or head, are crucial parts with respect to machining accuracy and process stability. Thus, they generally possess a high stiffness. Consequently, strains in the structure are very low and can hardly be used for process monitoring. Finite element analyses with an applied force of 1 kN at the TCP support this statement. As shown in Fig. 3, the strains vary in the range below 10 μm/m. Therefore, modifications of the component's design, which increase the sensitivity without lowering the stiffness, need to be considered. Aiming for a higher sensitivity, the component is locally altered by notches [10, 11]. Due to the irregular strain distribution in the spindle head, suited positions for the notches must be identified by an FE-analysis. A symmetrical notch design (chamfer angle 90–120 degree, depth 2–4 mm) is chosen in order to simplify the manufacturing of the notches and the subsequent integration of the sensors. Because of the dimensions of the notch in comparison to the size of the component, the stiffness is only reduced by about 1% (Fig 3, right).

The signal amplitude can be further amplified by a higher k-factor of the strain gauge, which describes the resistance change of measuring grid with respect to the occuring strain. A possibility to increase the *k*-factor is to reduce the thickness of the interlayer between the measuring grid and the surface to be measured. Therefore, thin foil strain gauges with a polyimide carrier foil as developed by Griesbach et al. [12] are applied to the spindle head of a DMG NTX1000 2nd Gen. (Fig. 4). An alternative are laser patterned thin film sensors [13].

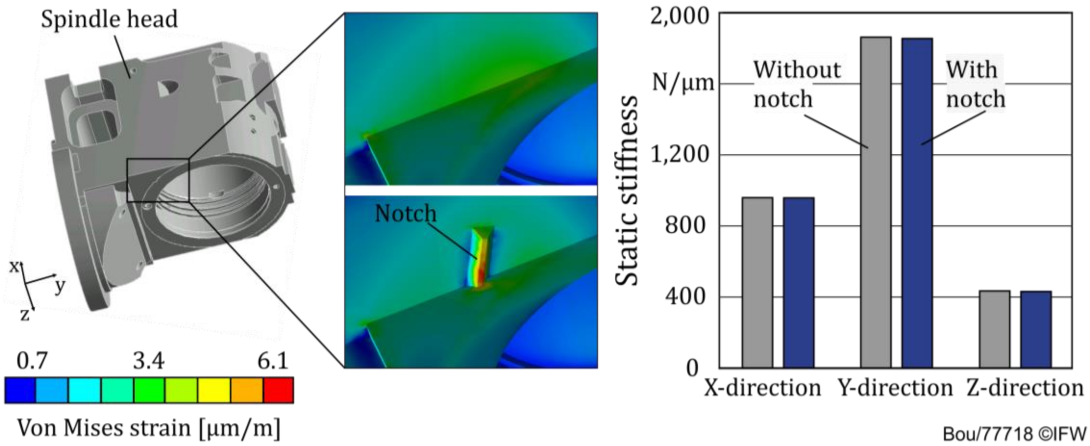

Fig. 3. Strain state in spindle head structure (left) and effects on the structural stiffness (right) [8]

The strain gauges are set up as Wheatstone-bridge and connected to a small processing unit. The sensor and processing unit are enclosed by an aluminium lid to protect the system from humidity, chips and electromagnetic disturbances. The signals are transferred to an external industrial PC via CAN-BUS at a frequency of up to 1.5 kHz.

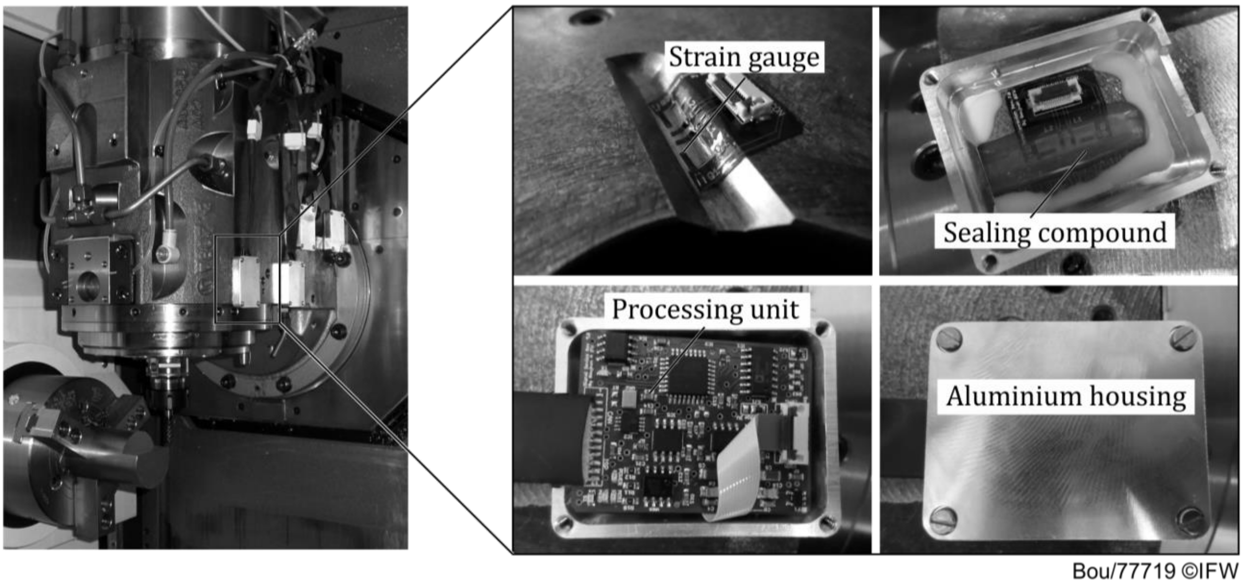

Fig. 4. Implementation of strain gauges onto spindle head [8]

In order to obtain force signals, the strain signals must be converted using a calibration matrix. Fig. 5 shows exemplary results of force measurements with a dynamometer and the integrated strain gauges. Due to the high sensitivity of the strain gauges in radial direction (or feed direction) of about 0.022 µV/N, a measuring accuracy of 25 N is achieved. However, the sensitivity in axial direction is only 0.003 µV/N, because of the higher stiffness of the structural component in axial direction. Thus, the measuring accuracy is lower in feed normal direction. Moreover, the effect of the own weight of the spindle must be considered, when the spindle is rotated, e.g. in 5-axis milling. For that purpose, a signal correction based on a regression model is proposed in [8].

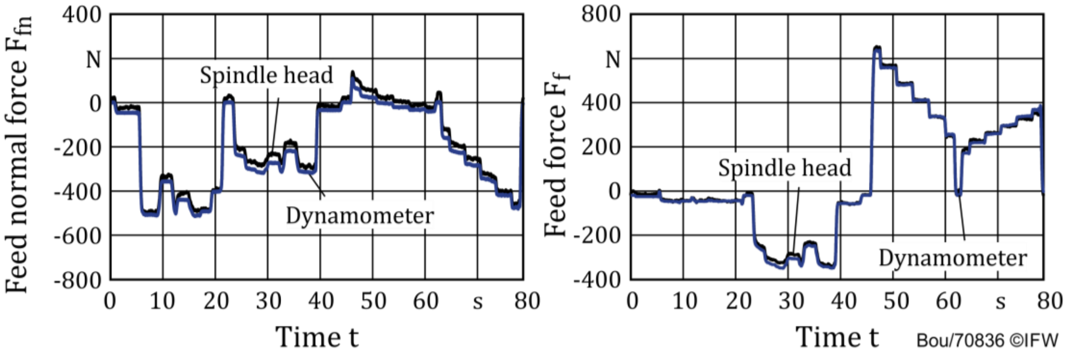

Fig. 5. Comparison of force measurements by dynamometer and strain gauges

In order to realise the desired geometrical accuracy of the workpiece, the tool deflection has to be controlled while machining. This can be done either by adapting the feed rate or by adjusting the tool path. In both cases, it is necessary to estimate the bending of the tool resulting from the process force. In the presented study, a bending beam model is used. However, the model requires information about the bending stiffness of the mounted tool. Denkena et al. presented an automated measurement cycle to accesses the bending stiffness of the mounted tool directly in the machine tool [8].

The general control loop for the two implemented compensation strategies is depicted in Fig. 6. The current deflection d_M is calculated using force data from the feeling spindle head. A comparison of the current tool deflection d_M to a reference tool deflection d_{Ref} results in the residual error e that is handed over to the controller. The controller changes the feed rate via the feed override or adapts the tool path by shifting the position of the TCP. The entire control loop is implemented on an industrial PC and programmed with the programming environment TwinCAT3 from Beckhoff. The compensation signals are transferred to the machine control (Sinumerik 840d) via PROFIBUS communication at the interpolation cycle rate.

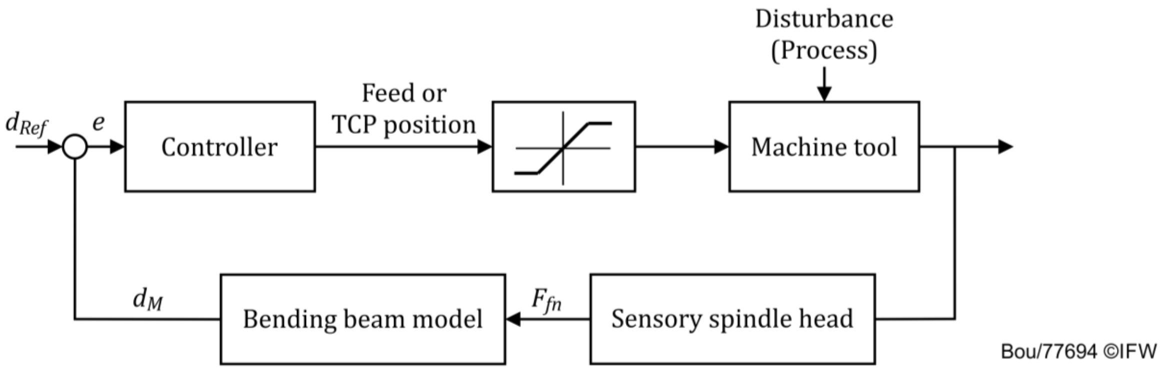

Fig. 6. Control loop for adaptive process control

To evaluate the performance of the compensation approaches, milling experiments are conducted. During the process, the cutting depth varies between 0 and 30 mm causing changes of the tool load and, consequently, the tool deflection. The geometrical accuracy is measured with a touch probe after machining at the position P1 and P2. The difference between the two measuring points is used as evaluation criteria (shape deviation). The process is repeated 10 times with and without the different compensation strategies. Without any compensation, an average shape deviation of 30 μm is observed. The adaptive feed control reduces the shape error by approximately 70%. However, due to a reduced feed, the machining time increases significantly (Fig. 7). The position-based compensation results in a reduction of the shape error by 80%, while the process time is kept constant.

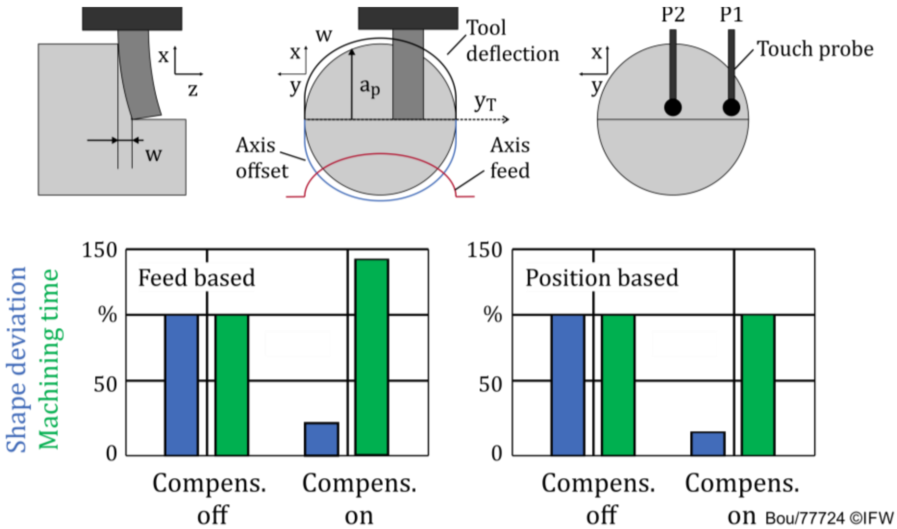

Fig. 7. Results of adaptive process control [8]

4. ADAPTIVE PROCESS PLANNING USING MACHINE LEARNING

In the previous chapter, it has been shown that varying cutting conditions result in different tool loads and, thus, different geometrical deviations due to tool deflection. Besides the nominal depth and width of cut, the tool deflection is also affect by the tool's approaching and receding, the part's contour [14] and the characteristics of the machine tool's drives and axes [15]. In contrast to the aforementioned adaptive process control, adaptive process planning is carried out prior to machining during the process planning stage. While adaptive process control tries to minimise the effect of unforeseen events during machining, adaptive process planning attempts to avoid as many effects as possible based on process data from prior machining operations (offline). Consequently, adaptive process planning represents the outer control loop. As shown in Fig. 2, the outer control loop combines machine data with simulation data and quality measurements. Based on the data, correlations are derived by modelling techniques, e.g. machine learning. The obtained process knowledge is subsequently used to support process planning.

Dittrich et al. [16] presented a self-optimizing tool path generation for 5-axis machining processes. A central part of the approach is a process-parallel material removal simulation. The simulation allows calculating spatial cutting conditions like the actual feed rate, the material removal rate and the cutting depth. By doing this, the cutting process and, also, the process knowledge is broken down into elementary, recurring and workpiece-independent segments. In order to access the actual axis position at a high bandwidth (approx. 250 Hz), the dexel-based simulation is connected to the machine tool via TCP using the software library ACCON-AGLink by Delta Logic. Figure 8 visualises some spatial cutting conditions calculated online by the material removal simulation.

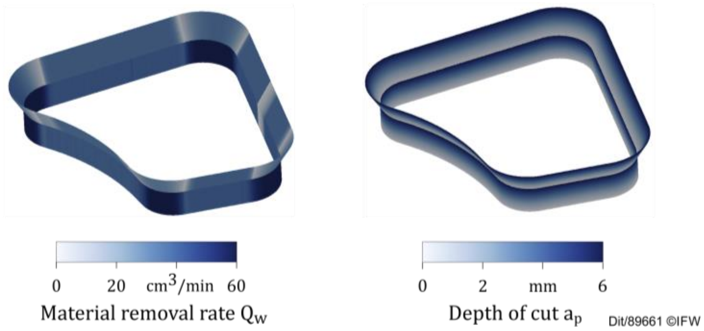

Fig. 8. Calculated material removal rate and depth of cut [16]

After machining, the obtained geometry is measured on-machine with a touch probe. Subsequently, the measurement data is correlated to the spatial cutting conditions using a Support Vector Machine (SVM) [17], which has been successfully applied to regressions problems and a wide range of engineering tasks [18, 19]. An experimental study revealed that the approach is capable of predicting the surface deviation with high accuracy (correlation coefficient of r = 0.94) [16]. In adaptive process planning, the obtained process knowledge is used to optimize an initial tool path. For that purpose, the cutter location file is handed over from the CAM module to a simulation and adaption module, which shifts every interpolation point perpendicular to the feed and the tool vector in accordance to the predicted deviation. The shifted TCP and the unmodified tool vector are written into an NC-file, which can be directly executed by the machine tool. Figure 9 shows an exemplary prediction of the surface deviation and an adapted tool path. It should be noted that the adaption of the tool path is 100 times amplified.

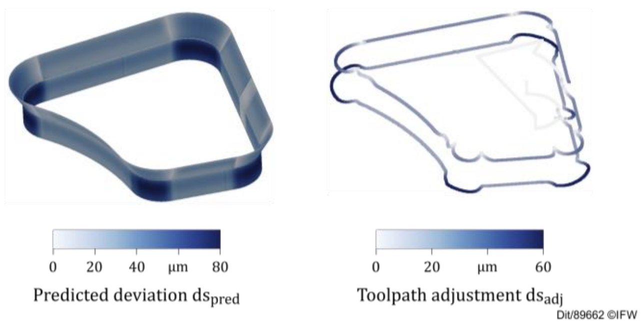

Fig. 9. Example of tool path compensation [16]

To evaluate the developed approach, machining experiments on high strength aluminium (EN AW 7075) are conducted. The experiments are carried out on a DMG HSC 30 linear with a carbide solid end mill (D = 6 mm, z = 4). The depth of cut is set to a_p = 6 mm, the cutting speed to v_c = 400 m/min and the feed per tooth to f_z = 0.04 mm.

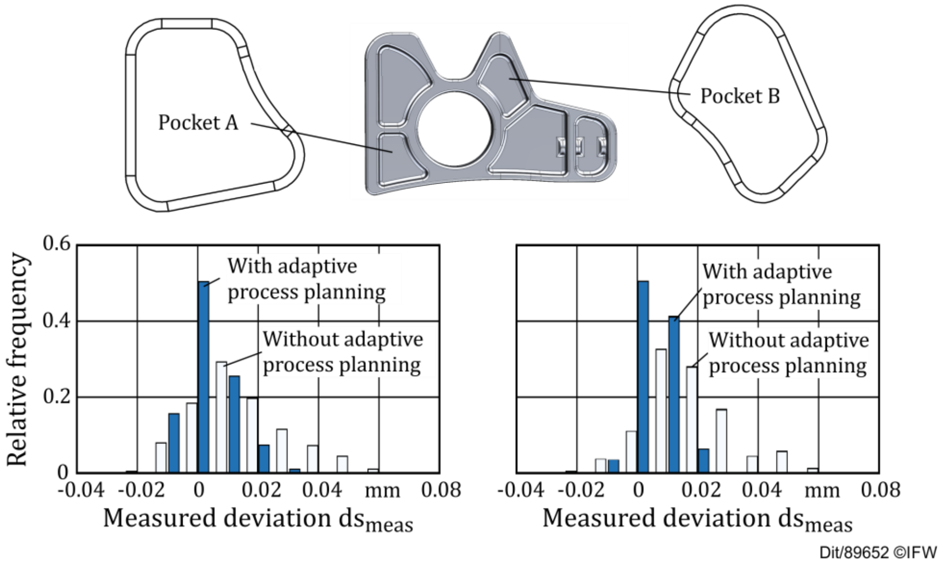

Fig. 10. Results of adaptive process planning, adapted from [16]

The machined feature is measured at 200 points after machining. In a first step, the tool path of pocket A is adapted using process knowledge from prior parts with the same geometry. The results reveal that the maximum surface deviation is reduced by 50% (Fig. 10, left). Moreover, the number of points having a deviation of smaller 10 µm is significantly increased. In a second step, the tool path of a different pocket geometry (pocket B) is modified using only process knowledge from pocket A. It becomes clear that the approach also reduces the maximum surface deviation in this case drastically (Fig. 10, right). Consequently, the obtained process knowledge can be transferred from one geometry to another as long as similar process segments occur during machining.

5. CONCLUSION

It has been shown that autonomous machine tools may offer a solution to cope with the ever increasing demands regarding competitive pressure and product variability. Despite the omnipresent use of the word “autonomous”, no distinct definition of an autonomous machine tool and the required technologies has been given so far. The article has tried to close this gap by offering a first definition and a framework. It has become clear that sensor systems and a sophisticated information control system are key to a successful implementation of autonomous machine tools. Based on this background, the attempt has been made to describe the different – partially interconnected – control loops of autonomous machine tools. In the second part of this article, sensory machine components and an approach for adaptive process control has been presented. Additionally, a methodology for adaptive process planning using machine learning has been discussed. Even though both approaches show promising results, it can be stated that research of autonomous machine tools is still in its infants. Thus, larger research initiatives and a close collaboration between academia and industry are indispensable to bring autonomous machining into reality.

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