Fraunhofer IPT

Documentation for the enclosed reference data sets

for the detection of anomalies in the manufacturing process of cutting machine tools

The present data sets were created and published within the project "Glassist - Smart-Glass-based Assistance System for Machine Tools". The project is being carried out in collaboration with the project partners Nuromedia GmbH, Oculavis GmbH, Innolite GmbH and Starrag Technology GmbH. The data sets can be assigned to series of experiments. The individual experiments were carried out with a process-integrated measuring system on a machine tool under process parameter variations. In this documentation, the data sets are described in detail and notes on interpretation are presented.

EFRE.NRW
Investitionen in Wachstum und Beschäftigung

EUROPÄISCHE UNION
Investition in unsere Zukunft
Europäischer Fonds für regionale Entwicklung

Content

1 Introduction

The present data sets represent data obtained from experiments, which were recorded with a CNC milling machine with variation of process parameters. The data sets are to serve as a basis for developing algorithms to be able to determine various anomalies online at the cutting time. In relation to the algorithms, analytical and also machine learning methods are to be used here. The aim is to detect anomalies or deviations to the machine data based on the information contained in the data sets. To obtain the data sets, a process-integrated measuring system was integrated into an existing milling machine of the Fraunhofer IPT. Various experiments have been carried out with the machine and the measurement system, which on the one hand represent processes that are running well, and on the other hand experiments in which parameters have been deliberately changed so that anomalies have occurred. These anomalies are divided into the following categories:

1) Tool wear
2) unbalance in tool holder
3) Workpiece side chatter
4) Low productivity detection
5) Collision detection

Categories 3, 4 and 5 can only be implicitly assigned to the datasets, all categories are assigned to use cases in the project "Glassist", these are described in detail in chapter 3, "Use cases". The respective datasets contain clustered sensor information, which is deterministically recorded and stored in a structured way in an hdf5 file. The sensor technology as well as the measurement system for data acquisition are described in chapter 2. The data sets (description see chapter 4) contain a multitude of measured values, which were acquired from sensors integrated in the machine. For an algorithm that runs online to the process it makes sense to detect the respective anomaly with as few sensors as possible. Therefore, the focus should be on solutions that require as little sensor information as possible on the one hand, and on the other hand, care must be taken to ensure that the sensor is easy to integrate. For example, a signal splitter, which detects the actual positions of the axes at high frequency, has the advantage that it can be placed in the control cabinet of the machine with little effort, while a vibration sensor, for example, which must be integrated directly into the clamping system, does not have this advantage. A disadvantage of the signal splitter compared to the vibration sensor, however, is that physical values are measured from a significantly greater distance to the process. In relation to the milling machine and the process, this means a significantly higher damping, which increases the demands on the measurement technology and the necessary algorithms for detecting anomalies.

This document contains the chapters "Experimental Setup", "Use Cases", "Description of Data Sets" and "Hypotheses and Approaches". The chapter "Experimental Setup" describes the milling machine with the process-integrated sensors and the measurement system. The chapter "Use Cases" describes the use cases associated with the experiments. In chapter "Description of data sets" the experiment series as well as the data sets are described in detail. The chapter "Hypotheses and Approaches" describes assumptions and approaches on how the data sets can be processed. This chapter and the previous chapter are necessary for the interpretation of the data.

The data is intended for companies working in the field of data science or in the machine tool industry, but also for scientists, students and those interested in integrating algorithms into production.

In the "Glassist" project, the consortium has integrated the measuring system developed at the Fraunhofer IPT on the software and hardware side, in addition to the solutions for data collection presented here in the document, with the following functions:

- Interface to the machine control for recording machine data
- Data aggregation
- Live data processing
- Data distribution to cloud systems or analytics applications
- Modular change of the setup
    - Sensors
    - Sampling times (up to 100 kHz)
    - Machine information

These functions are needed to process live data, with which the displayed anomalies are detected online using algorithms developed in the project. In order to further develop our system, we would be grateful for feedback or even for a cooperation in the framework. We would be happy to provide you with additional information on request, if this is not included here.

2 Test setup

This chapter describes the test and measurement setup used in the project to generate the data sets, which is located at the Fraunhofer IPT. This essentially comprises the machine tool (or milling machine) (see Figure 1) and an integrated measuring system (see Figure 2, schematic representation) which also includes a process computer for data processing.

The machine tool (see Figure 1) is a milling machine with a 3-axis machining center from the manufacturer DMG Mori with the type designation HSC 55 linear. The machine includes a Heidenhain CNC control of the type iTNC530. This machine was extended by an integrated measuring system. To access the machine data, the DNC (Distributed Numerical Control) component of the machine control must be enabled in the machine. The component can be used to read, write and process data from the machine controller via a manufacturer-specific API. The data is used in the project, but is not included in the data records, since the data records are focused on additional information from the process-integrated sensors of the measuring system.

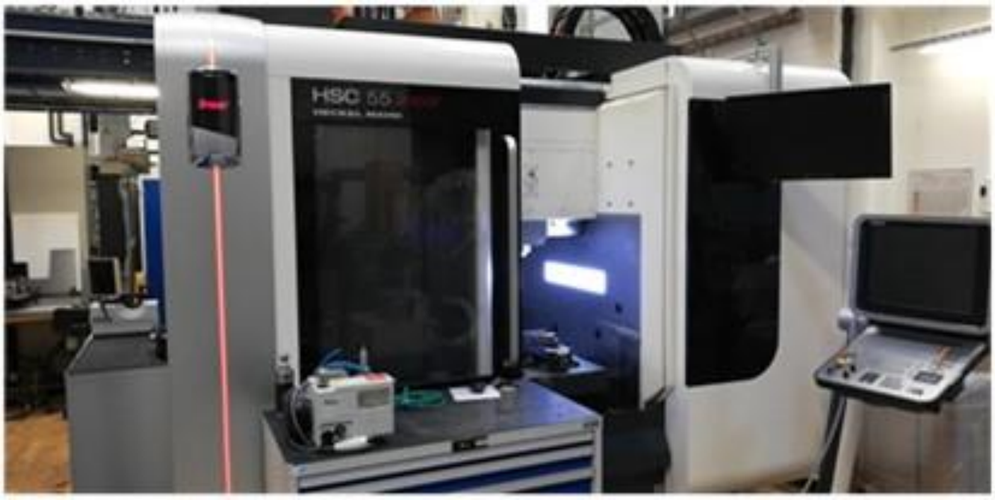

Figure 1: Machine tool (experimental machine) at the Fraunhofer IPT

The entire measurement setup, shown schematically in Figure 2, includes on the one hand the described machine tool and on the other hand the integrated measurement system. With the measuring system, sensor information is acquired at high frequency (up to 100 kHz) with a high resolution (64 bit). Table 1describes all available sensors including further metadata (designation, naming in data set, sampling rate, unit, mounting location, hardware data acquisition etc.).

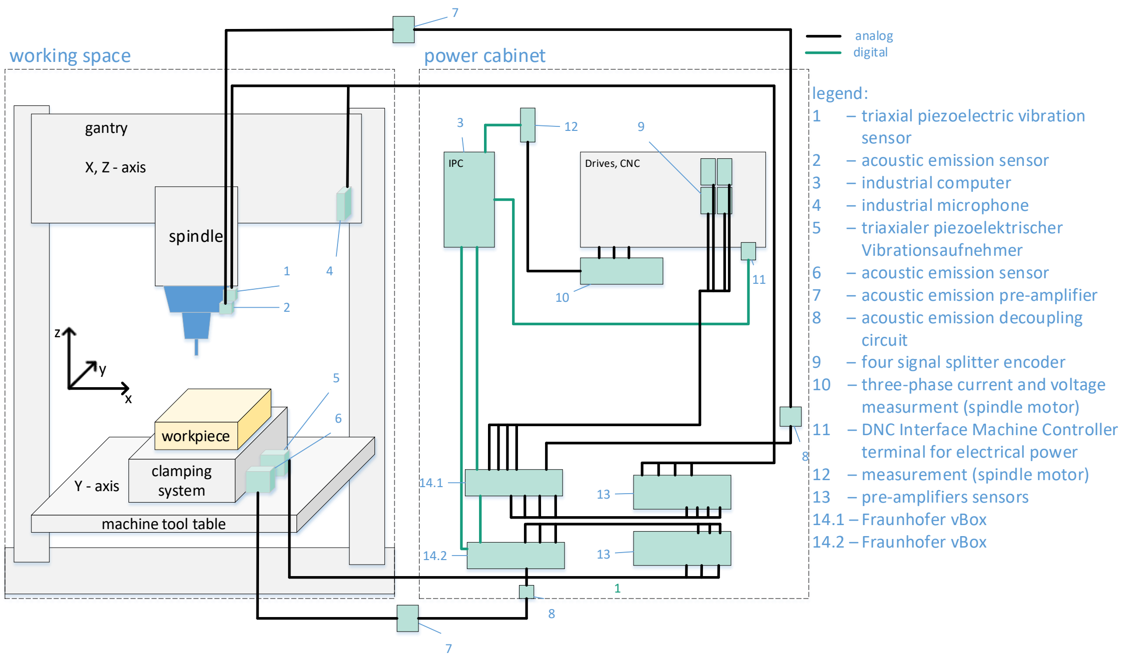

Figure 2: Schematic representation of the experimental setup

Figure 2describes the components used in the measurement system together with the legend. The sensors are connected together with analog signal processing to two vBoxes (see Figure 3), which acquire the data synchronized and deterministically, via BNC connectors. On the input side, the vBoxes require voltage signals (measurement signals) from -10 V to 10 V. The resulting data are forwarded via a real-time bus to the industrial computer, where software acquires and stores the data. The vBoxes (Figure 2, components 14.1 and 14.2) digitize sensor data with configurable sampling times of up to 100 kHz. An integrated hardware FFT also makes it possible to process high-frequency data, here e.g. data from acoustic emission (AE) sensors, at up to 5 MHz. Via a high-speed input (5 MHz), the vBox reads in the data, calculates FFT coefficients in a 1 ms cycle and makes the data available in the frequency domain register, which must be sampled at 100 kHz. The 100 kHz data contains the individual coefficients. The following sensors are located in the machine:

- Location: working area, clamping system of the machine
  - Triaxial (X,Y,Z) piezoelectric vibration sensor (Figure 2, component 5)
  - Acoustic Emission Sensor (Figure 2, Component 6)
- Place: Workroom, spindle
  - Triaxial (X,Y,Z) piezoelectric vibration sensor (Figure 2, component 1)
  - Acoustic Emission Sensor (Figure 2, Component 2)
- Place: Workroom
  - Piezoelectric microphone (Figure 2, component 4)
- Location: control cabinet, between encoder and drive
  - 4x encoder signal splitter (Figure 2, component 9)

In addition, the electrical power of the spindle is recorded using a measuring terminal (Figure 2, component 12). The following sensors are used here.

- Location: Switch cabinet
  - 3x current measurement spindle currents by means of current transformer (Figure 2, component 10)
  - 3x voltage measurement (Figure 2, component 10)

Figure 2, component 11 is an RJ45 connector of the machine control (Heidenhain iTNC530 control). Via Ethernet and protocol TCP/IP, machine data can be tapped here via a DNC component, which is not included in the data records for the reasons given above.

Figure 3: vBox, Fraunhofer IPT, hardware for deterministic data generation

Software on the industrial computer is used to configure the connected sensors according to the values in Table 1. As soon as the measuring system is switched on and the configuration is completed, the measurement can be started by means of the software at the start of the test. The data sets are stored in the data format hdf5 on the industrial computer. The structuring of the data sets is described in chapter 4

No.	Designation	Designation Data set	Number of channels	Sampling rate	Unit	Mounting location	Hardware data acquisition
1	Triaxial (X,Y,Z) piezoelectric vibration sensor	Vib_T_X_50k Vib_T_Y_50k Vib_T_Z_50k	3	50 kHz	m/s^2	Working area, clamping system	Analog input, vBox
2	Acoustic Emission Sensor	AE_T_FFT_500k	1	100 kHz [1]	-	Working area, clamping system	High-Speed Analog Input, vBox
3	Triaxial (X,Y,Z) piezoelectric vibration sensor	Vib_S_X_50k Vib_S_Y_50k Vib_S_Z_50k	3	50 kHz	m/s^2	Working space, spindle	Analog input, vBox

[1] This data is the frequency spectrum, the sensor signal is read into the vBox at 5 MHz and there transformed into the frequency range with a frequency resolution of 5 kHz by means of FFT, which is executed at 1 kHz. The output data is written to a register which is sampled at 100 kHz by the measurement system. The register is divided into two areas, one containing the information on the respective coefficient and the other the information on the amplitude. With a sampling rate of 100 kHz, a total of 100 coefficients can be acquired per clock cycle for an FFT performed at 1 kHz, resulting in a total value range of 500 kHz at a resolution of 5 kHz. Higher coefficients (> 500 kHz) are written to additional registers, so measurements up to 2.5 MHz are possible with the vBox. **This is for explanation only, the data sets are structured in suitable format for easy interpretation of the data.**

4	Acoustic Emission Sensor	AE_S_FFT_500k	1	100 kHz [1]	-	Working space, spindle	High-Speed Analog Input, vBox
5	Piezoelectric microphone	Micro_50k	1	50 kHz	Pa	Workroom	Analog input, vBox
6	4 x encoder signal splitters for X, Y, Z position and spindle position	Enc_X_50k Enc_Y_50k Enc_Z_50k Enc_S_50k	4	50 kHz	mm	Control cabinet	Analog input, vBox
7	Calculation of the electrical active power by means of 3x current and voltage measurement of the spindle	Power_S_100	1	100 Hz	W	Control cabinet	Power monitoring terminal

Table 1: Sensor data description

3 Use cases

In the following, the above five use cases for anomaly detection are described. Chapter 4 describes the data sets for these use cases. The chapter is intended to describe the goal of the necessary algorithm in order to generate added value compared to the state of the art.

1) Application: Tool wear

The tool shows signs of wear, which can be seen in different ways in the spectrum of the acoustic emission data or in other data during the milling process. Gradual wear will eventually lead to breakage or even before that to inferior component quality, which is associated with very high costs for complex components such as turbine blades. On the other hand, the service life of the individual tool differs from the manufacturer's specification due to the different manufacturing condition or usage condition. With the help of machine learning, each tool can be used up to the relevant wear condition.

2) Application: Unbalance in the tool holder

The tool holder is not set up correctly or the spindle is defective, so the machine vibrates at the frequency of the excitation. The algorithm should detect this oscillation based on the process information.

3) Application: Workpiece side chatter

The machine excites the workpiece, which vibrates at an exceptionally high amplitude during machining. This leads to poor process conditions that can cause component failures or related machine overload. The unusual frequencies can be detected in the sensor data. If such oscillations are detected, the manufacturing process can be optimized by adjusting the process parameters. A visual representation of the machining point at which these vibrations occurred can be used on the one hand as an indication of where reworking of the workpiece may be necessary and at which point in the machining program process parameters need to be adjusted.

4) Use case: Low productivity detection

The performance of the machine is not fully utilized, this manifests itself in relatively low forces and cutting performance. However, this condition is also set during finishing (work step for producing the highest accuracy). Based on the sensor data, the current productivity and utilization should be calculated to maximize productivity (indicators: air cuts during machining, finishing or roughing processes, spindle power, etc.).

5) Use case: Collision detection

The tool has been moved at too high a speed or too far into the workpiece so that the forces/vibrations increase too much. This causes damage to the tool and/or the machine. Damage that has occurred is to be shown here.

4 Description of the records

In this chapter, the use cases already described in the previous chapters are underpinned with data. The associated series of experiments with the corresponding data sets are described in detail. The focus here is on the "tool wear" use case, so the experiments and data for this are described first in the specific notes. The descriptions of the other use cases follow. Use case "Workpiece side chatter", "Low productivity detection" and "Collision detection" are based on the same data sets where a demo part is manufactured. In the chapter "General notes", general notes on the data sets are first presented

4.1 General information

4.1.1 Description

All the series of experiments described here are carried out using the experimental set-up described in Chapter 2 Depending on the experiment, material is chipped or only an air cut is performed. The experiments are divided into the following three categories:

- Tool_wear
- Imbalance
- Demo_Component

The corresponding folders or subfolders contain files of the file type .hdf5. This data type is a hierarchical data type that is suitable for efficiently storing large amounts of data. The data sets of the experiment series "Tool_Wear" and "Imbalance" belong to the use case "Tool Wear", whereas the data sets of the series "Demo_Component" can be assigned to the use cases "Workpiece Side Chatter", "Low Productivity Detection" and "Collision Detection".

The data structure of the .hdf5 files is largely the same, with additional label data being added only for the "Tool_wear" data sets; this is described in the specific notes. The data structure is described below.

4.1.2 Data sets and data structure

Figure 4shows an overview of the individual data sets in the "Explorer" view. The experiment series are always displayed above and folders with the individual data sets for the sub-experiments are displayed below. These folders contain several .hdf5 files. For each sensor shown in Table 1one .hdf5 file is stored here. An .hdf5 is divided into several data sets, which are to be interpreted according to the naming and contain, for example, repeat measurements, which are specified in more detail in chapter specific notes. Among the individual .hdf5 files, the subordinate structure is always the same, so that the sensors can be compared with each other. The data sets contain the measured values of the sensors, they are on the one hand time series and on the other hand FFT spectra. The values here are already converted to the unit given in Table 1. In addition to the data given in Table 1the data sets also contain a time stamp and, for the FFT data, the frequency axis in addition to the time stamp. The time series are to be assigned to the time stamp according to the following example:

- Vib_S_Y_50k.h5
    - o timestamp_50k.h5

The decisive factor for this is always the last digits of the data set name, "50k" means that the data was recorded with a frequency of 50 kHz. The FFT data are assigned as follows:

- AE_T_FFT_500k.h5
    - frequencies_AE_T_FFT_500k.h5
    - timestamp_AE_T_FFT_1k

Note that "500k" now represents the frequency axis and 1k the time axis (cf. chapter 2, FFT are performed with a frequency of 1 kHz). All sensor data have been acquired synchronously and can therefore be compared/correlated with each other on the time axis.

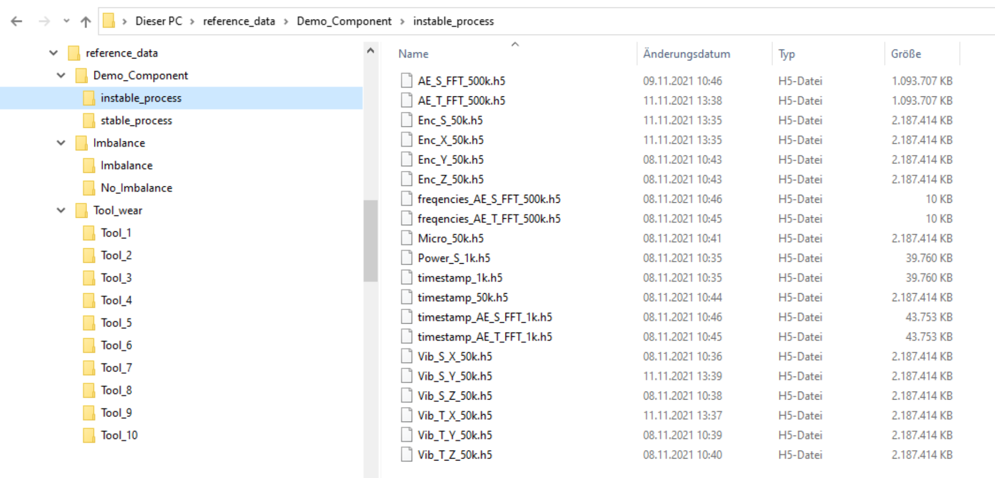

Figure 4: Overview of the individual data sets

The datasets can be processed by machine by including an hdf5 API.

4.1.3 Demo component

The demo component selected in the project is a thin-walled blade which is manufactured in two processes. The two processes differ in the milling strategy and in the machining parameters. One process is a stable process and the other is an unstable process in which the thin-walled component is excited by the milling process. The result of the unstable process is chatter marks on the surface of the part. All components are milled from a solid aluminum block. Figure 5shows this component both as a milled part and in CAD view. In this case the unstable process was present during the milling process, therefore surface inhomogeneities - chatter marks - can be seen here in the upper region of the blade, which are not present in a stable process. The component is produced several times for the experiments, which is described more specifically in the following chapter.

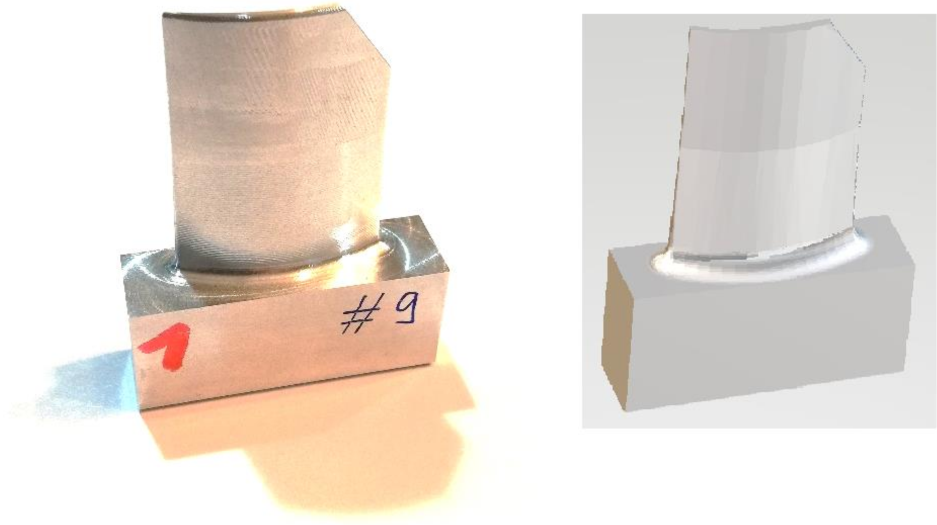

Figure 5 : Demo part (left: milled part, right: CAD)

4.2 Specific notes for the individual use cases

4.2.1 Tool wear - "Tool_Wear"

The data sets of the experiment series "Tool_Wear" are divided into ten subfolders. Each of these subfolders contains data about the lifetime of a tool. The folder "Tool_5", for example, contains the label information "label_VB" and "label_tool_radius" in addition to the sensor data described in chapter 4.1. This information can be used to merge the sensor data with the current wear condition of the tool. "label_VB" was determined by microscopy of the tool and contains the average wear mark friction width of all cutting edges of the tool. "label_tool_radius" contains the measured tool radius over time. Both label information were measured at discrete points in time. They contain information about the respective current wear condition due to the direct measurement procedure. "label_tool_radius" is determined directly on the machine by measurement using a laser measurement system, but since the machine and the workpiece deform thermally, a thermal drift can be seen in this error. For the measurement of "label_VB" the tool has been taken out of the machine and measured on an external microscope. No thermal drift is present here.

During the experiment, one plane was always machined from a solid steel block with varied process parameters and milling operations. The data of a plane are stored in each .hdf5 file and are to be interpreted according to the scheme shown in Figure 6

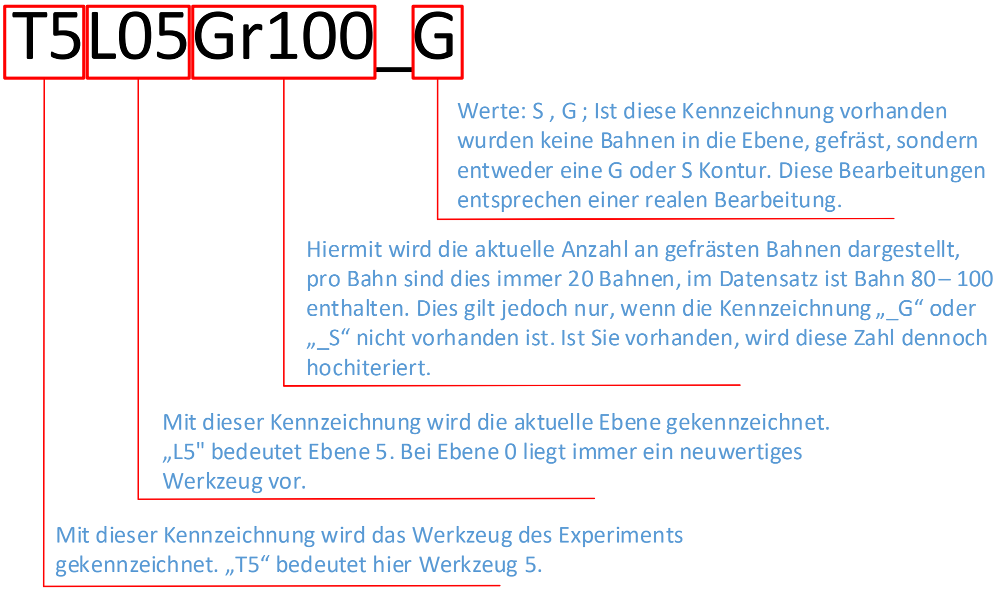

Figure 6: Marking .hdf5 records "Tool_Wear".

4.2.1.1 Description of the series of experiments for data generation

The present data sets represent experiments on tool wear of different end mills. In each experiment, a new tool is used to mill specific contours until the respective tool is worn out. In total, the experiments were carried out for ten tools. The experiments carried out (process parameters, cutting process, tools) are described below. Process parameters and tool types have been varied for the machining operations of the tools. With the previous information on the application and the data sets, the focus here is on being able to assign the data to experiments and thus interpret them as a whole.

Figure 7schematically shows the process of path milling. This is the reference process here to provoke tool wear. The workpiece is a steel block consisting of the material shown in the figure and the following dimensions:

- H/W/L: 100 x 200 x 150 mm

The individual levels and the individual parameters that characterize the process and the tool are shown (e.g. ae := intervention width). This is graphically illustrated and also used for data structuring in the .hdf5 data (cf. Figure 6).

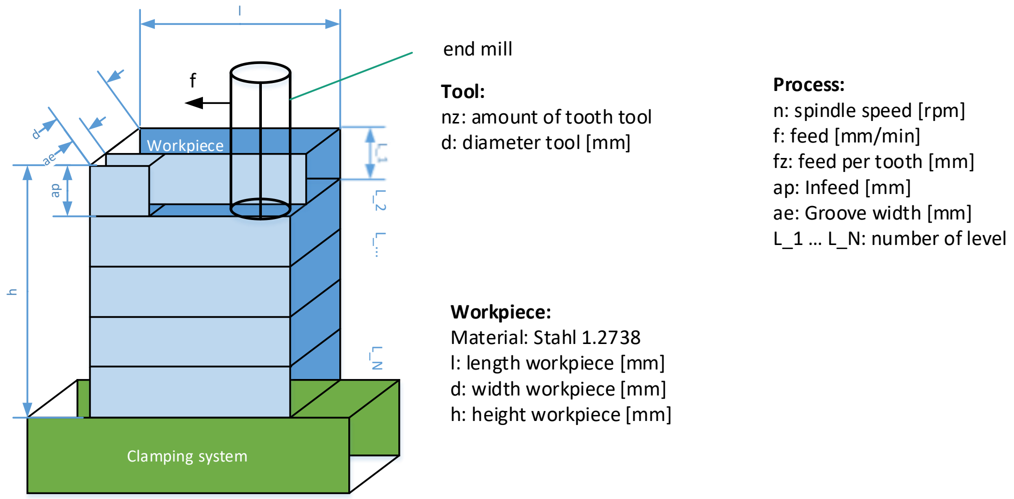

Figure 7: Schematic representation of the "path milling" process

Two different types of tools are used in the ten tools, these are specified in Table 2and Table 3

Parameter	**Value**
Tool type	1
Type	ProSteel carbide roughing end mill (VHM)
Diameter (d)	8 mm
Cutting length (ls)	19 mm
Length (l)	63 mm
Number of teeth (nz)	3
Max. contact with	1 x d at full grooves 0.5 x d at trimming

Table 2: Specification tool 1 (Tool type 1)

Parameter	**Value**
Tool type	2
Type	ProSteel carbide roughing end mill (VHM)
Diameter (d)	8 mm
Cutting length (ls)	12 mm
Length (l)	63 mm
Number of teeth (nz)	4
Max. contact with	1 x d at full grooves 0.5 x d at trimming

Table 3: Specification tool 2 (Tool type 2)

Table 4shows the individual experiment series for each tool. The first column contains the tool number, which can be used to assign the tool to the .hdf5 data sets. The following columns contain information about the tool type, the process parameters for milling the grooves (cfFigure 7) and in the last column information about whether special contours were milled, e.g. G or S contour. The G-contour is shown as an example in Figure 8where the blue line shows the path of the milling cutter. From this it can be deduced that the machining is considerably more complex than simply milling paths. However, this milling path of the e.g. G-contour corresponds more to a "real manufacturing" and can therefore be used as a validation of the wear prediction.

Nbr. tool	Tool type	Spindle Speed n $[rpm]$	Feed rate f $[\frac{mm}{min}]$	Cutting width ae $[mm]$	Cutting depth ap $[mm]$	Additional Information
1	1	6760	1160	5	8	Milling of grooves only with specified parameters
2	1	6760	1160	5	8	Milling of grooves only with specified parameters
3	1	7440	1160	5	8	Milling of grooves only with specified parameters
4	1	7440	1160	5	8	Milling of grooves only with specified parameters
5	1	6760	980	5	8	Milling of grooves with specified parameters as well as milling of G-shape contours (representation of a realistic production process) on selected planes (they are marked in the .hdf5 datasets)
6	1	7400	980	5	8	Milling of grooves with specified parameters as well as milling of G-shape contours (representation of a realistic production process) on selected planes (they are marked in the .hdf5 datasets)
7	2	6800	1290	4	8	Milling of grooves with specified parameters as well as milling of S-shape contours (representation of a realistic production process) on selected planes (they are marked in the .hdf5 datasets)
8	2	7900	1290	4	8	Milling of grooves with specified parameters as well as milling of G-shape contours (representation of a realistic production process), on selected planes (they are marked in the .hdf5 datasets)
9	2	6800	1290	4	8	Milling of grooves with specified parameters as well as milling of G-shape contours (representation of a realistic production process), on selected planes (they are marked in the .hdf5 datasets)
10	2	7900	1290	4	8	Milling of grooves with specified parameters as well as milling of G-shape

						contours (representation of a realistic production process) on selected planes (they are marked in the .hdf5 datasets)

Table 4: Series of experiments

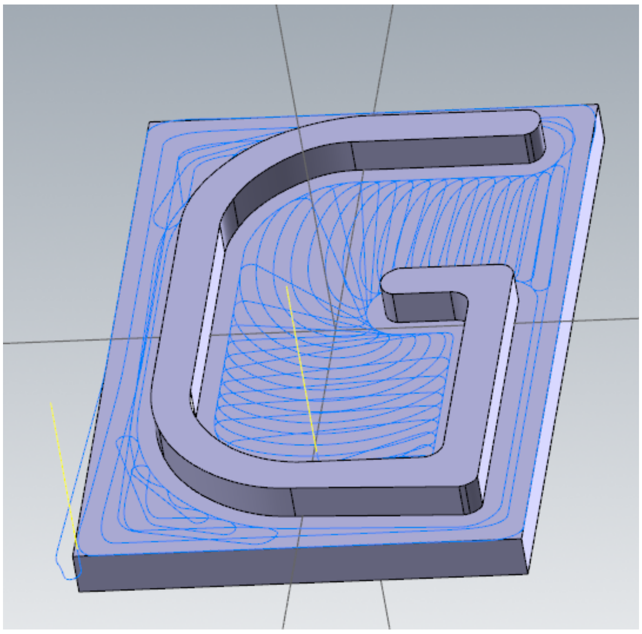

Figure 8: Representation of the G-contour

4.2.2 Unbalance in the tool holder - "Imbalance

The data sets of the experiment series on "Imbalance" are divided into the two subfolders "imbalance" and "no_imbalance". The data stored in the subfolders represent experiments in which imbalance is present or not.

During the experiments, the spindle was always rotated at one position and measured values were recorded. The .hdf5 data sets are divided into the position at which the measured values are recorded, resulting in the following three categories:

- Z_axis_extended
- Z_axis_not_extended
- Z_axis_on_tool_change_position

The individual data in the .hdf5 records are as described in the General Notes.

4.2.2.1 Description of the data generation experiment

In the following, the experiments on "unbalance" are presented. In the experiments on unbalance - stored in the subfolder "imbalance" - an unbalance of 21.8 gmm was artificially created with balancing rings mounted on the tool holder. This unbalance has been determined by means of a balancing machine. This tool holder was rotated at different positions (see Figure 9) with different speeds in the machine. The data for this are included in the data sets. No machining was present during the experiments.

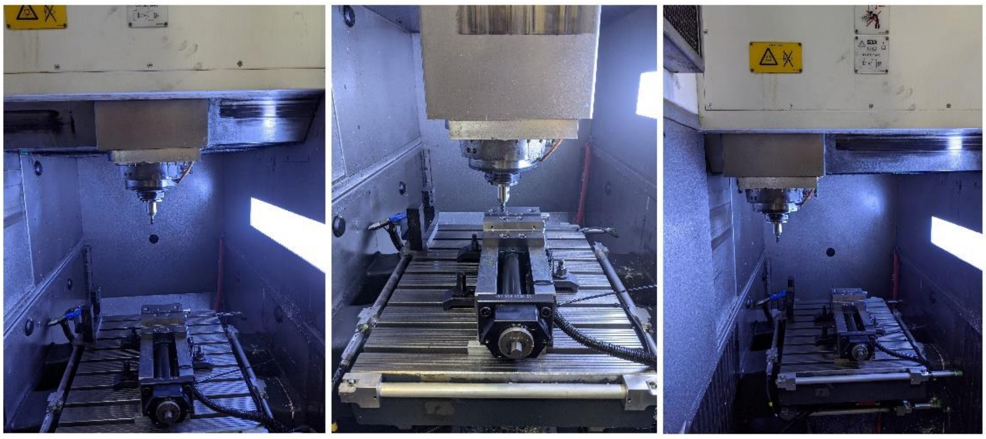

Figure 9 : Unbalance measurement positions (left: Z-axis not extended (Z-Axis not extended), middle: Z-axis extended, right: Z-axis on tool change position).

In order to identify a difference in the data sets, the same experiments were additionally performed with a tool holder without imbalance (< 1 gmm). These data are located in the subfolder "imbalance". Especially the data from the spindle side sensors are very interesting for the analysis here, but the unbalance is also recognizable in the other data.

4.2.3 Workpiece side chatter, low productivity detection, collision detection - "Demo_Component".

The data sets of the experiment series for "Demo_Component" describe the production of a reference component. The following use cases are to be interpreted from the data:

- Workpiece side chatter
- Low productivity detection
- Collision detection

The data is divided into two subfolders "instable_process" and "stable_process". In one, the machining was performed according to a stable milling strategy and in the other with an unstable milling strategy.

In the case of the .hdf5 data, there is always an air cut (without cutting (Air_Cut)) for each subfolder and then several data sets for individual workpieces in order to have repeatability in the measurements and to be able to identify changes when comparing the same manufacturing processes. For the data on the unstable milling strategy, the position of the workpiece was also varied.

The individual data in the .hdf5 records are as described in the general notes.

4.2.3.1 Description of the series of experiments for data generation

The data for the experiments represent the repeated production of a thin-walled component (see Figure 5) with two milling strategies. In the following, both milling strategies are briefly described. The exact machining path can be taken from the sensor data. The component represents a "blade".

In the unstable process (unstable milling strategy), the process for manufacturing the aluminium component can be divided into three stages - "roughing", "pre-finishing" and "finishing". After the cuboid workpiece blank has been set up in the machine, the roughing process begins. First, rough machining is performed to bring the entire blank into a rough shape similar to the target geometry. In a further, finer machining step, further material is removed along the entire surface of the workpiece. At the end, the fine machining begins, material is again removed along the entire surface in a final step to achieve a surface with high quality.

In the stable process (stable milling strategies), the workpiece is divided into several machining planes. On each plane, the three steps described above are performed - "roughing", "pre-finishing" and "finishing". In each plane, material is first roughly removed, then finer material is removed, and in a final step a high surface quality is produced. This segments the machining process so that large, thin-walled, vibration-prone structures are avoided during the fine machining process (“finishing”).

The unstable milling strategy is the established one, a component is always fine-machined - "finished" - in a final step. However, if you compare the two milling strategies with each other, you will see that with the unstable strategy, a particularly thin-walled component is machined, especially in the final finishing step - this is pliable and particularly susceptible to vibrations, which lead to chatter marks on the surface and to the rejection of the workpiece. Due to the segmented machining in the stable milling strategy, one has stable machining in each fine machining step, due to the fact that more residual material is available. These differences can also be seen in the data sets.

The data records for the "Demo_Component" represent a real manufacturing process. From the information contained in the data sets, information can be extracted on the named use cases "detection of low productivity", "detection of collisions" and "workpiece-side chatter". Hypotheses and approaches for this are described in chapter 5. The datasets should focus on the workpiece side chatter, as this correlates strongly with the quality of the part and poor quality leads to rejection of the part. These chatter marks occur more frequently with the unstable milling strategy, but not with the stable strategy.

5 Hypotheses and approaches

1) Application: Tool wear

The data sets and their description contain information on the varied process parameters (cutting material, feed rate, spindle speed, etc.), tools (tool type, number of cutting edges, diameter, etc.) and raw sensor data. The raw sensor data are divided into two groups, those that are recorded continuously at process runtime and those where the condition of the tool is measured directly at discrete points in time. The direct measurement of the condition allows to state concretely how the tool wear is at the respective time, but has the disadvantage that the cutting process has to be interrupted for the measurement of the tool. The continuously recorded sensor data are recorded in the process and contain information about the process (e.g. acoustics in the working area, vibrations, performance data, etc.). Due to the process information in the continuously recorded data, it is difficult to extract conclusions about actual tool wear from the continuously recorded data. Together with the discretely recorded data (true value of the tool wear) and with appropriate data processing, these conclusions can be made so that the condition of the tool in the process can be modeled or approximated at any time. If this succeeds during the runtime of the machining process, it has the particular advantage that tools are only replaced in production when they are really worn.

The information about the correct value of the tool wear from the direct discrete measurement of the tool can be used as a label for the sensor data. Among the sensor data, the AE data, the vibration data (force differences in the process) and the current data (correlate with cutting force) are of particular interest. Literature shows that these data sources contain information about wear. During model development, various features are to be extracted from the raw data, which contain information about the condition of the tool. A feature selection method can be used to select meaningful features. Regression models can be used to determine the relationship between the selected feature data and the label information. After modeling and validation, however, the question remains whether the model can be used with different processes and/or tools and whether it approximates the target value correctly. For this purpose, the data sets can be used, since they contain experiments with different tool types and different machining contours (e.g. G-shape, S-shape, milling path), especially the G-shape and S-shape represent real manufacturing conditions. However, it remains open whether the model can also be generalized; in order to validate this, deployment and inference under real manufacturing conditions is necessary in a further step.

2) Application: Unbalance in the tool holder

Relevant data sources here are the sensors installed on the spindle side, as well as the performance data of the spindle, the spindle position in the workspace and the encoder data of the spindle. Machine learning or analytics can be used to make a prediction about the spectra of the input data. An increased vibration amplitude at resonance frequency can be detected.

3) Application: Workpiece side chatter

The detection of the vibrations of the component, which lead to chattering, in the data of the vibration signal at the clamping system is simple. However, this sensor is difficult to accommodate in production because it is located in the working area of the machine, close to the workpiece. One question here is whether this information is also available in other sensors. One approach would be to use the vibration sensor on the clamping system to generate a label for the chatter and to extract this information from another ("cheaper") sensor.

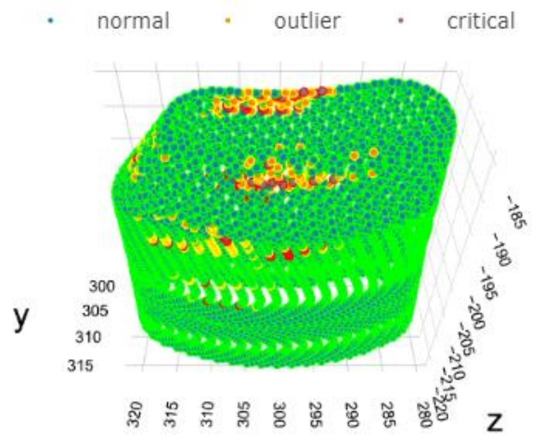

Figure 10: Visualization of inhomogeneities on the workpiece surface

In the case of chatter on the workpiece side, the data sets from the unstable milling strategy can be compared with the data sets from the stable milling strategy. In the stable strategy, there is hardly any chatter in the fine machining process, and in the unstable strategy, the chatter is predominant, especially in the upper areas of the workpiece. Figure 10shows the encoder data of the machine in X,Y and Z, correlated with other sensor data. The sensor data is used to calculate machining inhomogeneities in the process (shown in red), and these are shown in context to the machining position. Poor surface quality is to be expected at these positions.

4) Use case: Low productivity detection

There are many criteria for low productivity. The data from the component production shown can be used to make a statement about when there is material contact between the tool and the workpiece and when there is not. Furthermore, during a machining operation, the output can be monitored; if it is sufficiently high and there is no fine machining, the productivity is also high.

5) Use case: Collision detection

Data on a collision are not available in the data sets, as a collision would lead to damage. However, due to the large number of repeat measurements, a large database is available. With this, an algorithm can be trained using unsupervised learning, which recognizes a collision as an anomaly.