

Available online at www.sciencedirect.com

**ScienceDirect** 

Procedia CIRP 118 (2023) 193-198



### 16th CIRP Conference on Intelligent Computation in Manufacturing Engineering, CIRP ICME '22, Italy

# Identical NC-code on Different Machine Tools – Similarities and Differences in Timing and Positioning

## Berend Denkena<sup>a</sup>, Benjamin Bergmann<sup>a</sup>, Tobias H. Stiehl<sup>a,\*</sup>

<sup>a</sup>Leibniz Universität Hannover, Institute of Production Engineering and Machine Tools, An der Universität 2, 30823 Garbsen, Germany

\* Corresponding author. Tel.: +49-511-762-18003; fax: +49-511-762-5115. E-mail address: stiehl@ifw.uni-hannover.de

#### Abstract

Process and tool condition monitoring systems are a prerequisite for autonomous production. For online monitoring, it is the state of the art to use reference signals of correct processes to improve failure sensitivity and reduce false alarms. Transferring these reference signals from other machines economizes on teach-in processes and complex simulations. However, the varying behaviour of the two machines leads to differences that need to be considered for the transfer. This work aims to identify similarities and differences in the timing and positioning of multiple machines when executing identical machining instructions. A comparison of process signals quantifies similarities and differences among machines. Results describe differences between process sequences, rapid traverse speeds, rapid traverse paths, machining feed speeds, machining feed paths, tool engagement time, and the temporal alignment of signals. Differences primarily originated from different control parameters and strategies as well as physical drive limitations. During machining differences occurred most frequently when axes were accelerated. Differences accumulated over prolong periods of machining and eventually became relevant from the perspective of online monitoring.

© 2023 The Authors. Published by Elsevier B.V. This is an open access article under the CC BY-NC-ND license (https://creativecommons.org/licenses/by-nc-nd/4.0) Peer-review under responsibility of the scientific committee of the 16th CIRP Conference on Intelligent Computation in Manufacturing Engineering

Keywords: Machine tools; Knowledge transfer; Tool condition monitoring

#### 1. Introduction

Process and tool condition monitoring systems are a prerequisite for autonomous production [1, 2]. The systems reduce downtime, machine damage, and scrap and allow for autonomous operation of machine tools [3]. Furthermore, the determined condition of tools, workpiece quality, and processes are input to higher-level functions such as process planning. The industrial application of monitoring systems is, however, mostly limited to series production. Due to the repeating processes, systems have abundant signal references of correct processes available for monitoring. When monitoring individual parts, no such references exist. This is addressed by process as a reference. The generated signal course is usually high in detail, allowing simulation-

based monitoring approaches to achieve high sensitivity and robustness. To model processes more realistically, simulations are becoming increasingly complex. Models include microand macro-mechanics of cutting, such as stress, temperature, white layer characteristics of the finished surface, and thermomechanical behavior of the material [4]. Consequently, simulations require extensive information and validation, resulting in high expenditures that cause monitoring to become uneconomical.

Transferring reference signals and monitoring parameters from similar, real machines has the potential to reduce parameterization requirements and improve detection rates. However, little research was found on the transfer of knowledge among different machines to monitoring processes or tool conditions. [5] detected failure patterns in power signals using deep learning. [6] show the online detection of

2212-8271 $\ensuremath{\mathbb{C}}$  2023 The Authors. Published by Elsevier B.V.

 $Peer-review \ under \ responsibility \ of \ the \ scientific \ committee \ of \ the \ 16th \ CIRP \ Conference \ on \ Intelligent \ Computation \ in \ Manufacturing \ Engineering \ 10.1016/j.procir. 2023.06.034$ 

This is an open access article under the CC BY-NC-ND license (https://creativecommons.org/licenses/by-nc-nd/4.0)

chatter during milling with a model trained at another milling machine. The approach evaluates the signal of a microphone. Results show correct and false process classifications, but quantification is missing. [7] monitor a face turning process online using signal course references sourced from other machines. The approach detects material anomalies in workpieces when the source machine is the same model as the monitored machine.

The existing research demonstrates that the transfer of knowledge for online monitoring is possible in principle. However, the specific challenges and mechanism of the transfer in the domain of online monitoring are yet to be investigated. This knowledge, however, is required to avoid situations where a transfer lowers performance [5, 7]. While [7, 8] report the challenge of timing differences, a systematic investigation is yet to be performed.

This paper aims to identify and describe similarities and differences that arise between machines from the perspective of online monitoring. Considering that statistical, referencebased approaches are the state of the art in online monitoring in series production, the requirements of these approaches are subsequently used as evaluation criteria.

Figure 1 shows an example where limits are calculated statistically from references of good processes, as in [7]. The limits closely follow the reference signals (grey color), resulting in a high sensitivity to failures and a short reaction time. However, these characteristics also make the approach prone to false alarms resulting from variations in the course of the process. For example, transferring the limits to another machine executing the same NC-instructions results in false alarms. While the amplitude of the monitored process force  $F_y$  varies within expectations, different machining speeds lead to a temporal misalignment, eventually causing a false alarm.

An alternative to aligning signals over time is to align signals over positions. However, variations also occur in positioning of processes. Consequently, signal course references given over time or position are a fundamental source of differences from the perspective reference-based online monitoring. This holds independently of what signals are monitored (e.g., process force, drive torque).

This paper investigates similarities and differences in the timing and positioning of multiple machines when executing identical machining instructions (NC-code). The results identify effects that are to be considered when transferring knowledge across different machines for online monitoring. Section 2 describes the turning and milling processes analyzed for similarities and differences as well as methods used to support the analysis. Section 3 presents the similarities and different machines when executing and positioning across different machines when executing identical NC-instructions.

#### 2. Experiments, Data Acquisition and Measures

#### 2.1. Setup and Experimental Machining

Two types of experiments were conducted: three-axis milling on three different machines and face turning on three different lathes. G-code based NC-instructions (ISO 6983) defined the corresponding processes. Machine-specific

adoptions to the program were limited to the program headers, e. g. due to varying tool names, and control-specific instructions, such as variable calls. The subsequently analyzed signal segments result from a G-code section that is identical across different machines. Tables 1 and 2 list the machines used and their properties. Each machine processed three workpieces. In the case of milling, a workpiece comprised 15 slots and six pockets, one of which is subsequently analyzed and depicted in Fig. 2. In the case of turning, each workpiece yielded 16 face turning operations, one of which is subsequently analyzed and described in Fig. 3.

Milling of the square pockets employed end mill cutters (effective cutting diameter 8 mm) and workpieces from structural steel (S235JR as defined in DIN EN10025-2, equivalent to ASTM A 36 M). The milling cutter entered the material in a helical motion. The milling cutter then followed the G-code defined tool path from the inside of the pocket outwards in a counter-clockwise motion (Fig. 2). The pocket was milled in four consecutive layers with an axial depth of cut of  $a_p = 2$  mm each, reaching a total depth of 8 mm. The radial depth of cut was  $a_c = 4$  mm, the feed per tooth  $f_z = 0.05$  mm and the cutting velocity  $v_c = 90$  m/min. The workpiece coordinate axes were set up to be parallel with the

Table 1. Examined machine tools - group A - lathes.

ID	lathe	control
CTX	DMG Mori CTX 1250 TC	Siemens Sinumerik 840D sl
NTX	DMG Mori NTX1000	Siemens Sinumerik 840D sl
NEF	DMG Mori NEF400	Siemens Sinumerik 840D sl

Table 2. Examined machine tools - group B - mills

ID	mill	control
MIL	DMG Mori Milltap 700	Siemens Sinumerik 840D sl
HSC	DMG Mori HSC 30 linear	Siemens Sinumerik 840D sl
ROB	FANUC ROBODRILL α-	FANUC Series 31i-B5
	D21LiB5	



Fig. 1. False alarms in statistical, reference-based monitoring due to timing differences between the machine providing the limits and the machine monitored.

machine coordinate axes.

Face turning experiments were performed with coated cemented carbide indexable inserts of the ISO type CNMG 120408. The workpieces had a length of 110 mm, and a diameter of 60 mm, and were from structural steel type S355JR (DIN EN10025-2, equivalent to ASTM A 573 M Grade 70). After the clamping of a workpiece, its face and the radial surface were machined to match the initial experimental geometry. The subsequent experimental face turning operation was defined with a constant cutting speed of  $v_c = 150$  m/min, a feed of f = 0.2 mm, and a depth of cut  $a_p = 1.5$  mm (Fig. 3). Unless stated otherwise, the speed of the workpiece spindle was limited to 3,000 rpm with the G-code.

Signals recorded comprise the actual position, command torque, and actual current of the x-, y-, and z-axis and the actual speed, command torque, and actual current of the main and tool spindle, if available. In the case of machines featuring a Siemens Sinumerik 840D, sl control data was recorded with the built-in "Trace" function of the control at a sample rate of 8 ms. In the case of the FANUC ROBODRILL  $\alpha$ -D21LiB5, the sample rate is 2 ms.

#### 2.2. Preprocessing and Segmentation

Segmentation allows focusing on certain parts of a process (Fig. 4). In the following, segments are formed to represent single machining operations, such as a single pocket layer in milling (Fig. 2) or a single face turning operation (Fig. 3). The employed segmentation method evaluates the feed calculated from the positions signals of the x-, y-, and z-axes:

$$feed_{xyz} = \sqrt{\dot{x}^2 + \dot{y}^2 + \dot{z}^2}$$
 (1)

Machining operations within a process were then identified by their typical feed. This approach is quite robust and versatile. A segment is determined as an interval of the process with:

$$50 \frac{mm}{min} < feed_{xyz} < 1000 \frac{mm}{min} \tag{2}$$

To reduce the impact of noise on segmentation, the feed was low-pass filtered. Employed was a minimum-order finite impulse response filter with a stopband attenuation of 60 dB and a passband frequency of 10 Hz.

#### 2.3. Quantifying Similarity of Processes

The analysis of similarities and differences in section 3 focuses on timing and positioning during the machining process from the perspective of monitoring. Four measures are employed to support the analysis:

- Time to machine a full workpiece t<sub>w</sub>:
- Denotes the period from the start of the first segment to the end of the last segment of a workpiece. A workpiece consists of multiple face turning or milling operations.
- Start of machining t<sub>start</sub>: Denotes the point in time, concerning the segment, when the tool first enters the material as marked by t<sub>start</sub>.
- Tool engagement time t<sub>eng</sub>: Denotes the period of time between the tool first entering

the material at the beginning of a segment  $(t_{start})$  and the tool exiting the material at the end of a segment  $(t_{end})$ .

• Traveled feed path length l<sub>f</sub>: Denotes the length of the feed path traveled throughout a segment as calculated from the x-, y- and z-positions.



Fig. 2. NC code and resulting cutting feed path for the pocket milling process.



Fig. 3. NC code and resulting cutting feed path for the face turning operation.



Fig. 4. Segment with face turning operation, start ts and end te of machining.

The start of machining  $t_{start}$  and end of machining  $t_{end}$  was detected by analyzing the tool spindle torque for milling and the z-axis torque for turning. Process components were isolated by removing the offset of the segment (friction component). The start of machining  $t_{start}$  was determined by the time the process component exceeded the threshold (2/10 of the segment median). The end of machining  $t_{end}$  is the point in time when the process component falls below the threshold. Fig. 4 depicts the procedure for a face turning operation.

The mean spread of each measure is then calculated within individual machines and across different machines (Fig. 5). The mean deviation of individual machines  $s_{ind}$  represents the deviation across three repetitive processes on a single machine averaged across three machines. This corresponds to comparing machines to their data. The mean deviation across machines  $s_{acr}$  represents the deviation of a process across three different machines averaged across three process repetitions. This corresponds to comparing machines to other machines. Milling and turning experiments are evaluated separately.

#### 3. Similarities and Differences in Timing and Positioning

The complexity of a machine tool as a mechatronic system causes processes and process signals to differ among machines despite identical NC-instructions. Differences result, for instance, from different mechanical and electrical properties of the drive system, different designs and parameterization of the control, and different maintenance conditions (Fig. 6).

The subsequent discussion covers differences between machines from a perspective of timing and positioning. An example is the time for machining a full workpiece  $t_w$  which ranged from 88 s to 114 s in face turning an average deviation of 9 s between machines. Time  $t_w$  for milling a full workpiece ranged from 1796 s to 1846 s with an average deviation of 25 s between machines (Fig. 7). Possible causes for the differences and other differences are addressed individually in the analysis. Uncertainties in the analysis originate, for example, from the non-parallelism of the workpiece and machine coordinate axes, environmental factors such as excitation, variations in raw material and tool properties, tool and workpiece deflection, or transient thermal effects.

#### 3.1. Different process sequences

The number of movements differs among machines. A cause is the varying designs of machine tools in combination with the machines executing auxiliary process instructions. An example is changing tools. When the tool magazine is integrated into the spindle slide of a mill, a single linear movement from the cutting point upward is required to reach the tool change point. If the tool magazine is located in a more protected location at the side of the working area, however, multiple movements are necessary to reach the tool change point. These additional movements influence the time required to machine a full workpiece tw. Consequently, the course of process signals differs among the machines. As these different process sequences result from an inherent property of the machine tool design, they cannot be eliminated by adopting control or NC-code parameters. While affecting the time for

machining a full workpiece, the employed segmentation excludes these critical movements from monitoring.



Sti/92168 ©IFW

Fig. 6. Possible causes for differences in signals of multiple machines tools while executing the same NC-instructions.





#### 3.2. Different rapid traverse paths and feed

Different paths for rapid traverse and speed of rapid traverse dominated the process time differences in milling. Variations occur in the path length and shape for the rapid traverse. Causes are different tool changing positions, physical limitations of the feed drives, as well as different control parameters and strategies. It is established practice, for example, that rapid traverse speeds are set separately for every axis by the manufacturer of the machine tool. If axes are controlled individually to reach their destination as fast as possible, the resulting path between two points is not categorically a straight line. Other control strategies might aim to reduce auxiliary process time, drive load, or increase precision.

#### 3.3. Different temporal alignment of machining

Differences in process sequence, execution speed, and feed paths introduce misalignment between signals. Accumulating over the course of a full workpiece, misalignment reached several seconds in the experiments (Fig. 7). Employing the described segmentation process greatly reduces misalignment. Within segments across the machines, the start of machining  $t_{start}$  only deviates by 23 ms on average in the face turning operation and by 25 ms in the milling process (Fig. 8a).

However, the segmentation procedure is limited in how precise it can split up processes. In addition, data acquisition and the cycle time of the control (8 ms) introduce uncertainty. Consequently, variations arise within individual machines as well. Within segments of individual machines, the start of machining  $t_{start}$  only deviates by 11 ms on average in turning and by 17 ms milling. Further, machine properties influence the results of segmentation. Misalignment is higher between different machines as it is between repetitions of the same machine.

#### 3.4. Different duration of tool engagement

For a single face turning operation lasting about 6 s, the mean deviation between machines amounted to 168 ms on average (Fig. 8b). This is due to machines varying in execution speed during cutting because of control parameters or physical limitations. For instance, when performing a face turning operation defined with a constant cutting speed and feed per revolution. In that case, the tool moves towards the center of the workpiece. To maintain the cutting speed, the spindle then accelerates towards its speed limit. If the reached spindle speeds differ, e. g. due to physical or set limitations, then the tool engagement time differs as well. A separate experiment was conducted to illustrate these effects (Fig. 9). The machine Gildemeister CTX420 linear operates within power and speed limits. The machine DMG MORI NTX 1000 also operates within its power limits. However, it does reach a set speed limit of 2500 rpm (Fig. 9b). Consequentially, revolutions are lower towards the end of the machining phase than for the CTX 420 linear, thereby prolonging the machining phase. The machine DMG MORI NEF400 reaches its power limit at a workpiece spindle drive current of about 25 A. This is demonstrated in Fig. 9a, which shows the uncompensated, raw current signal of the workpiece spindle drives. As a result, the machining is prolonged by 336 ms compared to the CTX 420 linear.

Considering that online monitoring usually requires a reaction time << 100 ms [9], the example above demonstrates that significant differences can occur within a single machining operation.

Further, control features aiming to boost productivity, such as adaptive feed control by Heidenhain, modify the



programmed feed speed to reduce machining time. Also, controls might reduce feed speed to ensure the tool path is interpolated in time when computing capacities are insufficient. If only a subset of machines uses these productivity features, machining time might varies. While machining time differences might be introduced by any axis or spindle, they do affect all process signals.

#### 3.5. Different machining paths

While the feed path is defined in the machining program, the actual machining path is determined by the properties of the machine tool and the process. Control features, for instance, the "smart overlap function" on FANUC controls, vary the feed path to increase productivity. The feature reduces cycle times by overlapping the transition between the rapid traverse (G00) and machining feed phases (G01) of the process. If the utilization of the function varies among machines, the consequences are differences in the course and overall length of the feed path. While the overall length of the segment is shorter, the process phases of actual machining usually remain unaffected.

The actual feed path during tool engagement is influenced by control parameters and the physical limitations of the machine. Fig. 10 shows different feed paths for milling of a pocket corner, as machines handle the defined rectangular feed path differently. These differences occur in every corner of the milled pocket and accumulate. For milling a layer of a pocket, the cumulated feed path deviated across machines by 679  $\mu$ m on average (Fig. 8c). The depicted differences result from employing the continuous-path mode of machines, which smooths edges. Machine manufacturers often activate the mode by default as it reduces machining time and improves surface quality. However, the parameters of the smoothing process are often machine specific. Additional control parameters and functions exist that influence the feed path, such as NC-code compression or general contour tolerances.

#### 4. Conclusion

This paper describes similarities and differences in the timing and positioning of multiple machines when executing identical machining instructions (NC-code). Examined are different process sequences, rapid traverse speeds, rapid traverse paths, machining feed speeds, machining feed paths, tool engagement times, and temporal alignments of signals. The following conclusions are drawn: During machining, the differences in timing and positioning primarily arise in process phases where axes are accelerated, such as edges. Differences that are relevant from the perspective of online monitoring can occur within a single machining operation. Smaller differences can accumulate over prolonged periods of machining and become relevant from the perspective of online monitoring. Differences in positioning mainly result from path optimization strategies and control parameters, such as contour tolerances. Differences in timing mainly result from different acceleration behavior and different feed paths, both of which are determined by control parameters and drive properties.



Fig. 10. Tool path for milling of a pocket corner on different machines.

Further research might investigate how the described differences affect different types of monitoring approaches, e. g. online monitoring of tool breakage or offline monitoring of tool wear. In addition, differences between the signals monitored, e. g. process forces, might be considered. New monitoring approaches could be developed that are robust against the differences described. Future work might also address to what extent G-code can be designed to improve the similarity of processes among machines. This might involve G-code based feed speed limitations and machining feed path contour tolerances.

#### Acknowledgment

The authors acknowledge the financial support from the Federal Ministry for Economic Affairs and Climate Action of Germany (BMWK) in the project IIP-Ecosphere (project number 01MK20006A).

#### References

- Salgado DR, Cambero I, Herrera Olivenza JM, García Sanz-Calcedo J, Núnez López PJ, García Plaza E. Tool wear estimation for different workpiece materials using the same monitoring system. Procedia Engineering 2013, 63:608-615.
- [2] Lee KJ, Lee TM, Yang MY (2006) Tool wear monitoring system for CNC end milling using a hybrid approach to cutting force regulation, Int. J. Adv. Manuf. Technol. 32:8–17.[3]
- [3] Byrne G, Dornfeld D, Inasaki I, Ketteler G, König W, Teti R (1995) Tool Condition Monitoring (TCM) — The Status of Research and Industrial Application. CIRP Annals 44(2):541–567.
- [4] Altintas Y, Kersting P, Biermann D, Budak E, Denkena B, Lazoglu I (2014) Virtual process systems for part machining operations. CIRP Annals – Manufacturing Technology 63:585-605.
- [5] Li WD, Liang YC (2020) Deep transfer learnig based diagnosis for machining process lifecycle. Procedia CIRP 90:642-647.
- [6] Rahimi MH, Nam H, Altintas Y (2021) On-line chatter detection in milling with hybrid machine learning and physics-based model.
- [7] Denkena B, Bergmann B, Stiehl TH (2021) Transfer of Process References Between Machines for Online Tool Condition Monitoring. Machines 9:282.
- [8] Kan C, Yang H, Kumara S (2018) Parallel computing and network analytics for fast Industrial Internet-of-Things (IIoT) machine information processing and condition monitoring. Journal of Manufacturing Systems 46:282-293.
- [9] Rudlf T, Brecher C, Possel-Dolken F (2007) Contact-based collision detection – A new approach to avoid hard collision in machine tools. In: Proceedings of the International Conference on Smart Machining Systems, Gaithersburg, March 13-15, 2007