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Method for Data-Driven NC-Code Optimization based on Dexel Material Removal Simulation and Tool Holder Vibration Measurements

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Abstract

This paper presents a novel approach for data-driven NC-Code optimization, based on the integration of dexel-based material removal simulation and an instrumented tool holder, capable to measure vibrations during milling close to the cutting zone. Considering measured cutting vibrations, machine tool axis and NC-line data, a model has been developed optimizing cutting parameters to generate a NC-Code right after a first machining trial with mitigated vibration effects. Different modules for human-assisting vibration visualization and automated optimization of cutting parameters are presented, using milling use-cases implemented on a CNC machining center.

Keywords: Milling, CAD/CAM, Vibration, Multidexel Model, NC-Code Optimization

1. Introduction

Vibrations occur in all metal cutting processes and have been studied extensively by various researchers in the last decades. Depending on different factors (e.g. dynamic stiffness of the machine tool / tool holder, clamping situation or cutting parameters), such vibrations may be self-excited by the interaction between the tool and the workpiece, leading to instable and uncontrollable cutting conditions. Chatter is unwanted vibration in the process and impacts the quality of the workpiece surface, the geometrical accuracy and tool wear negatively [1].

Current trends linked to initiatives like Industry 4.0 and Cyber-Physical-Systems such as the *Digital Twin* concept, provide new opportunities to optimize process planning and process control to avoid unwanted vibration behavior. The *Digital Twin* concept has been presented at the University of Michigan and was further defined by NASA in recent years. Fundamentally, the model describes the relations between a real and a mirroring virtual system, consistently exchanging data and information [2,3,4]. Based on the basic idea, various models for *Digital Twins* around machine tools and machining process have been developed [5]. The *Digital Twin* connects machine tool and process modelling approaches with the real representation of the machine. Combining real data with simulation models provide further advantages such as [6]:

- Virtual commissioning / virtual process planning for faster setup of real machine
- Simulation model tuning utilizing real data fed back from the real machine
- Condition Monitoring to detect anomalous performance
- Advanced Process Analysis utilizing finite element models

In order to predict and control cutting vibrations in milling application using end mills, all aspects of the *Digital Twin* concept, combining system modelling techniques with real

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feedback on the system behavior, need to be implemented accordingly.

2. Related Work

Research has been done to understand, measure and optimize vibrations in machining. In the context of this paper, a selected number of publications focusing on vibration measurement, process simulation and NC-Code optimization are listed.

One of the first analytical approaches for stability lobe prediction in milling has been presented by [7]. The authors model the cutter-workpiece contacts to predict cutting forces and derive stability lobes to analyze stable and unstable cutting processes. The work focused on the modelling aspects, thus, no measured vibration data from the machine tool is used.

In [8] authors present a simulation system to model cutter engagement conditions along arbitrary NC-programs. The model results are used to predict tool deflections and regenerative tool vibrations. However, the work focused on modelling and predicting vibrations and did not take measured cutting vibrations into account.

[9] highlights an analytical approach to predict milling forces and tool tip displacements for stable and instable cutting processes. However, no in-process vibration measurements have been used in this work.

In [10] the authors use measured cutting forces to predict and compensate workpiece deformations utilizing a dynamic feature model associated with CAD / CAM planning features. While the approach highlights opportunities given by matching process models and actual measured machining data, the authors did not use vibrations measurements for optimization.

In [11], an NC-code optimization strategy is presented, utilizing analytically predicted stability lobes. Instable cutting areas are used in CAD / CAM system, to automatically adapt axial depths and radial width of cuts to create a chatter vibration-free NC tool path. No sensor data feedback has been used / integrated for the optimization.

[12] presents an approach for human-driven NC-code optimization by integrating data from the machine control (e.g., axis acceleration) in a selected CAD / CAM system. The data provided by the CNC is pre-processed, supporting manual process analysis and optimization. However, no sensor system providing vibration data has been integrated in this work.

An adaptive feed rate control system has been presented in [13]. Based on measured power consumption during machining, feed rates in the NC-code are adapted to ensure constant cutting loads. While results also indicate improvements in regard to chattering, there is no actual vibration sensor integrated in this system and thus, the sensitivity is limited.

Authors in [14] demonstrate capabilities to integrate machine sensor information in a dexel material removal simulation using a green-red-colour scheme. In the presented use-case, sensor information regarding spindle torque is used, however, no data about cutting vibration is utilized.

In [15], a collision avoidance system is described, utilizing measured CNC axis information in a dexel based material removal simulation. The system uses the look-ahead information from the CNC control to predict future machine moves, thus, enabling a machine stop in case of potential collisions. However, no vibration data is used for optimization.

[16] presents a model for in-process surface roughness prediction, based on measured vibration signals and given cutting parameters. The integration of the process data in CAD / CAM or material removal simulation systems has not been targeted in this work.

Authors in [17,18] utilize a virtual CNC to analytically predict cutting forces and optimize feed rates in NC-code accordingly. NC-lines are split up in individual G-code commands, giving the opportunity to apply various optimized feed rates. However, no measured vibration signals have been used for the optimization.

Past research work mostly focuses on analytical and numerical prediction (pre-machining) of cutting forces and stability lobes to optimize dynamic process behaviour and respective cutting parameters. However, the integration and utilization of in-process measured vibration data for post-machining NC-code optimization has not been investigated sufficiently. Alternatively, researchers used measured spindle torque and axis-drives power consumption to infer information about cutting forces and vibration, to optimize programmed feed rates in the NC-Code. Especially in the context of industrial applicability, a vibration measurement system, providing direct feedback about the dynamic process behaviour during machining and being easy to integrate in material removal simulation for process analysis and NC-code optimization would provide several benefits (e.g., utilization of more precise vibration data directly measured near the cutting zone, modular extensibility etc.), compared to current state of the art.

3. Concept for Data-Driven NC-Code Optimization using an Instrumented Tool Holder

This paper presents a novel method for data-driven NC-code optimization utilizing an innovative instrumented tool holder system and a material removal simulation.

The method proposes a “second time right” strategy, indicating the utilization of real vibration data gathered during first-piece machining in order to optimize the process for all following parts in a closed-loop system. During machining of a first-piece, complex interactions of machine stiffness, part geometry, tooling and clamping setup, as well as the selected cutting strategy and parameters are monitored using innovative sensor technology integrated in the machine tool. The sensor data is being put in context to NC-code lines and machine axis positions to provide individual data sets for further manual and (semi)automated process analysis and optimization, such as adaption of spindle speed / feedrate or cutting depths / widths.

Compared to state-of-the-art literature, the proposed method focuses on utilizing sensor data and the definition of generic optimization rules, rather than modelling complex dynamic machining behavior. Hence, the method supports an easier introduction in industrial setups and a flexible utilization for a variety of processes and setups. Especially small-lot-size manufacturers benefit from such a system, becoming capable to reduce costly “trial and error” process planning loops and faster time-to-market for new production orders. Additionally, experienced operator feedback is enriched with systematic machine data, enabling higher level of automation and reduced risk of know-how loss.

The measured vibration data is provided by an instrumented tool holder system, developed by the *Institute of Production Engineering and Photonic Technologies* at *TU Wien*. The system uses a capacitive acceleration sensor integrated in a standard HSK63 tool holder; hence, the sensor is positioned close to the cutting zone allowing very accurate data acquisition for a defined excitation with a frequency of 100 Hz-3 kHz [19]. A signal processing unit is receiving the raw acceleration data via a stationary transceiver unit, using signal algorithms to identify stable or unstable process conditions in real time utilizing figures of merit. Furthermore, the processing unit manages a set of optimization strategies, allowing to react on unwanted vibration effects during machining. The gathered data can be accessed via OPC UA (non-real time) and Profibus (real time) communication interfaces [20-24].

For contextualization of the vibration data with respect to the actual machining process, real machine data from the machine control is additionally required (axis values, NC-lines, zero-point, feeds, spindle speeds). Using a process-oriented orchestration platform, a flexible data collection system was developed. Thereby, the entire system remains adaptable in case of transfer to different machine tools and / or controls as well as for integration of different / additional sensor systems. The gathered information can then be used in material removal simulation for further process analysis. Matching the machine and vibration data, a feedback loop is created, enabling manual as well as automated NC-code optimization.

4. Proof of Concept

To demonstrate the feasibility of the proposed approach, a proof-of-concept prototype has been implemented at *TU Wien Pilotfabrik Industrie 4.0* in Vienna. Establishing and utilizing the required laboratory infrastructure, first successful applications of the proposed approach could be determined.

4.1. Experimental Test Setup / Data Collection

The proposed approach has been implemented as a prototype on a 5-axis CNC machining center *EMCO MaxMill500* with a *Siemens Sinumerik 840d sl* CNC control and an instrumented sensory tool holder developed by the *Institute for Production Engineering and Photonic Technologies* in previous work [19].

Input data required for the material removal simulation is created during the machining process and provided using modern OPC UA communication technology. First, machine axis data (X / Y / Z) as well as executed NC-Code lines are obtained using the OPC UA interface provided by *Siemens*, running on the CNC Control platform. Second, the required cutting vibration information is provided through an internally developed OPC UA server. Flexible access to the data has been achieved by unification of different data sources within a single message broker, providing a pub/sub mechanism using MQTT messaging protocol.

To ensure a flexible and contextualized data collection, an orchestration platform called *centurio.work* has been used [25]. The module framework of *centurio.work* provides functions for process-oriented data collection [26], data storage, data analysis following a service-oriented architecture utilizing BPMN modelling language [27], and flexible execution [28]. For data collection in the presented scenario, two data collection processes have been modelled within the *centurio.work* framework, each representing one data stream source. During the machining process, machine axis data, NC-Code lines, as well as vibration data is accessed through the described broker, collected via the *centurio.work* processes, and finally provided as standardized YAML output file for further usage. Using the presented infrastructure allows a very flexible customization of the data collection process in future use-cases such as the integration of another sensor system, adding / removing of data nodes (e.g., feeds, spindle speeds, overrides) or the transfer to different machining centers and CNC controls.

The created YAML file can be used for various applications. However, in respect of the presented work, the YAML file runs through a Phyton script, which matches and connects the data points from the machine (axis data) and the vibration sensor (vibration data) based on their individual server timestamps. Finally, a customized text file in the standard interface format of the material removal simulation is created.

For demonstration purposes, a conventional milling process has been setup using the *EMCO Maxmill500* machining center. The workpiece material used was a rectangle block of Aluminium (EN AW 6060, L x W x H: 133 x 50 x 65 mm) which has been pre-machined to create a geometry allowing to highlight the functionality of the presented prototype system. These pre-machined step elements have a max. height of 5 mm and occur in rectangle, circular and triangular shape on the top of the raw material block (Fig. 1). The used milling tool (HC end mill, d = 12 mm, 3-fluted) is clamped using the instrumented tool holder (HSK63) and provides vibration data during machining with a data rate of 9.5 kHz. Cutting the pre-machined raw material in a linear cutting in X-direction by down milling, vibrations will peak at the location of the step-elements (1 mm ≤ ap ≤ 6 mm, ae = 1.5 mm), while being significantly lower in-between (ap = 1 mm, ae = 1.5 mm). Workpiece zero offset has been set at the front right corner.

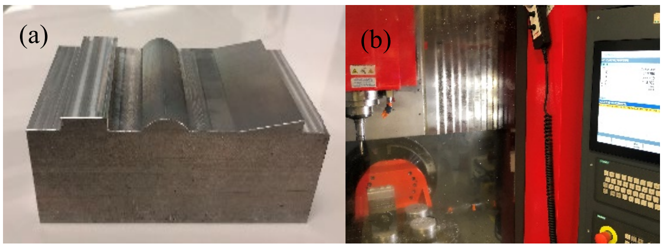

Fig. 1. (a) Pre-machined stock material; (b) EMCO machine setup

4.2. Material Removal Simulation

For integration and visualization of collected machine and sensor data feedback, a (tri) dexel material removal simulation from *ModuleWorks GmbH* has been used. *ModuleWorks* API provides access to a 3D volumetric simulation ensuring reliable performance and precision. The simulation engine computes material removal at discrete intervals, taking into account the swept volume of the tool within a given material model. Via the API, one can access detailed cutter / workpiece engagement data and utilize a variety of visualization functionalities to enable advanced process analysis [14].

To connect the material removal simulation with real data inputs from machines and sensors, *ModuleWorks* has developed specialized software called *CNCSim*, which functionalities are used in the presented prototype. *CNCSim* requires two different kind of inputs: (a) the 3D models of the machining setup and its kinematics and (b) the machine and sensor data to simulate machine movements accordingly. For (a), exact 3D Models of the *EMCO* machine tool, the *SCHUNK* zero-point clamping (incl. chuck / jaws), the tool holder and cutting tool have been used. Kinematics of machine axes, the spindle / cutting tool interface, the stock definition incl. zero offset etc. have been integrated using *ModuleWorks MachineBuilder* software (Fig. 2). Based on the 3D models and user inputs, *MachineBuilder* creates XML machine definition files, consisting of data nodes, accessible via the *Moduleworks* API. The XML machine definition file can be imported in *CNCSim* as basis for material removal simulation.

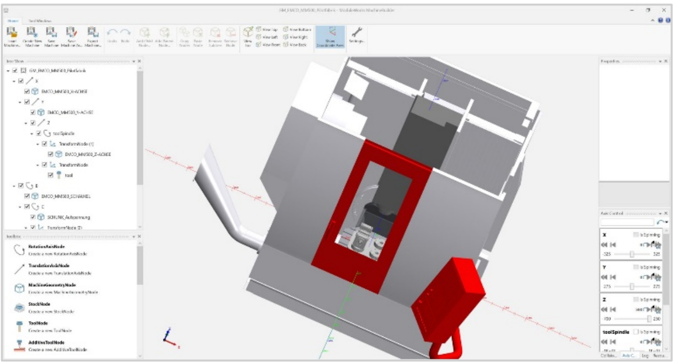

Fig. 2. Virtual machining setup in *ModuleWorks MachineBuilder*

4.3. Vibration Data Visualization for Human-Driven NC-Code Optimization

Based on the experimental setup described, a series of test cuts has been executed. A simple G-code performs a conventional down milling process, starting at workpiece zero offset, and cutting the entire length of the material in X-direction. The pre-machined geometry of the workpiece results in a varying cutting depth, depending on the actual cutting position in X-axis (ae = 1.5 mm, ap = 1 mm in-between step-elements, 1 mm ≤ ap ≤ 6 mm for step-elements). After every cut, the tool moves back to the original X-axis position, adapts Y-axis position accordingly, and executes the next cut under same cutting parameters. The information about the vibration in combination with the respective machine axes is provided through the described data collection system and is imported via the standard interface of the material removal simulation of *ModuleWorks CNCSim*.

The simulation model developed in the context of this work, fulfils the following steps:

- Load virtual machine setup (3D models of EMCO machine tool, tool holder and cutting tool, zero-point clamping system etc.) from machine definition XML
- Load stock mesh and position stock in alignment with defined zero offset from CNC control
- Import series of milling cuts from data collection (X / Y / Z axis, vibration value)
- Set dynamic color-code-scheme (min / max values from current vibration measurements, pre-set modal parameters)
- For each milling cut: (a) set respective material removal color-code and (b) position machine axes accordingly

Executing this algorithm as described, Fig. 3. Highlights the simulation result after executing one selected milling cut.

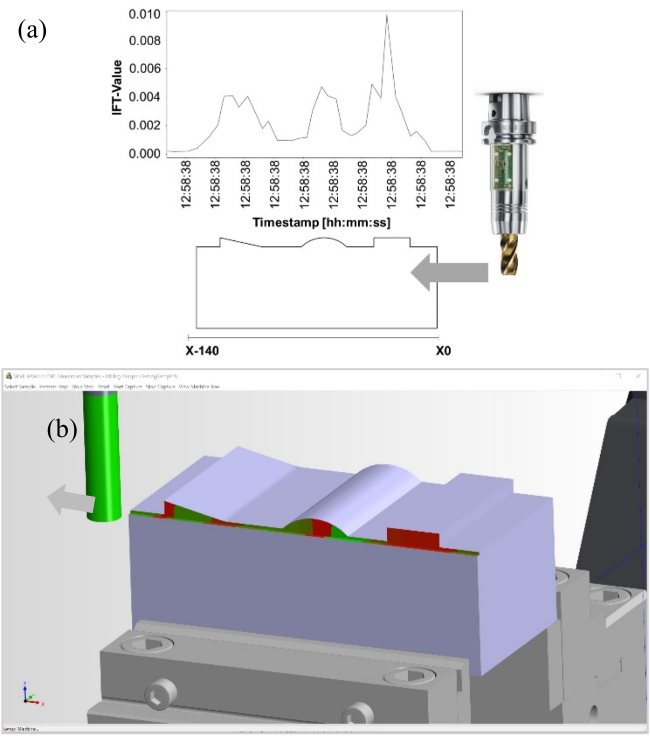

Fig. 3. (a) Correlation of geometry and measured vibration signals; (b) real sensor data imported in simulation environment using original NC-code

Based on the green-red-color scheme defined in this simulation example, one can see a mix of red and green colored cutting areas along the simulated toolpath. Starting with a green-colored area at the beginning of the cut, the tool passes the different step-elements, increasing the cutting depth instantaneously, leading to higher vibrations in the process, thus, to a red-colored cutting area. The situation changes again after the first step-element, leading to a greener area and so on. The used color-code-scheme is created dynamically for each import file containing real measurement data and is taking into account the minimum and maximum vibration values of a single cut as well as a reference threshold. This parameter is used to calibrate the green-red-color scheme, puts the vibration values in perspective to actual process instabilities and therefore illustrates stable and unstable areas along the toolpath respectively. For demonstration purposes in this work, the parameter has been set to an IFT-value of 0.002.

The presented visualization functionality combines advantages of process simulation capabilities and real process feedback from the machine and its sensors, hence, provides expanded opportunities for human machine operators / NC programmers for improved process analysis and more efficient optimization of cutting parameters.

4.4. Algorithm for Automated NC-Code Optimization

In addition to manual adaption of NC-Code based on visualized process information, gathered machine and sensor data also provide new opportunities for (semi)automated optimization of cutting processes.

As described in previous sections, the implemented data collection framework matches data points from the instrumented tool holder (vibration value; acceleration sensor) and machine axis positions (X / Y / Z) for visualization and manual NC-code optimization purposes. However, on top of the actual vibration value and the machine axes positions, several other data points are provided by the respective OPC UA servers. In the context of this work, selected data points have been added to the prototype system to develop a simple algorithm for an automated update of cutting parameters (programmed feed and speed) to create a vibration-optimized NC-Code. Therefore, the described data collection file (machine axes, vibration value), has been extended to additionally gather the following important parameters during machining:

- Actual NC-line executed (CNC control)
- Actual feed rate (CNC control)
- Actual spindle speed (CNC control)
- Vibration optimization strategy (instrumented tool holder)

Utilizing the extended data collection file, an algorithm has been developed, analyzing the cutting process along the toolpath, and separating areas that are categorized as unstable due to sensed vibration data. Every separate toolpath fragment is documented with a start and end position (X / Y / Z machine axis position), the associated line of the NC-code (e.g. N180…), the actual feed rate and spindle speed, as well as a proposed optimization strategy as defined in the configuration of the instrumented tool holder setup. For the presented work, a simple demonstration strategy has been selected, suggesting reducing actual feed rate / spindle speed by 20% in case of unstable process conditions.

After identifying and documenting unstable toolpath fragments, the algorithm loads the original NC-text file and searches for the associated G-code program lines defining the unstable cutting parameters (F, S parameters). Having identified the correct lines, cutting parameters are adapted based on the optimization strategy accordingly. For optimization of different unstable fragments along a programmed toolpath, the original moving command eventually needs to be replaced with several optimized ones. *Table 1* presents an exemplary result.

Table 1. NC-code snippet before / after optimization algorithm

	Original NC-Code			**Optimized NC-Code**		
N	**G/M**	**S [U/min]**	**F [mm/min]**	**G/M**	**S [U/min]**	**F [mm/min]**
N160	M03	S14600	-	M03	S14600	
N170	G1 Z-6	-	F1000	G1 Z-6	-	F1000
N180	X-140	-	-	X-16	-	-
N190	G40 Y-6	-	-	X-21	S11680	FB=800
N200	-	-	-	X-52	S14600	-
N210	-	-	-	X-60	S11680	FB=800
N220	-	-	-	X-95	S14600	-
N230	-	-	-	X-107	S11680	FB=800
N240	-	-	-	X-140	S14600	-

Importing the machine and vibration data from the optimized NC-Code into the presented simulation model, an improved process result is visible. The reduced feed rates and spindle speeds lead to reduced cutting vibration, indicated by the green-colored cutting surface, as in Fig 5.

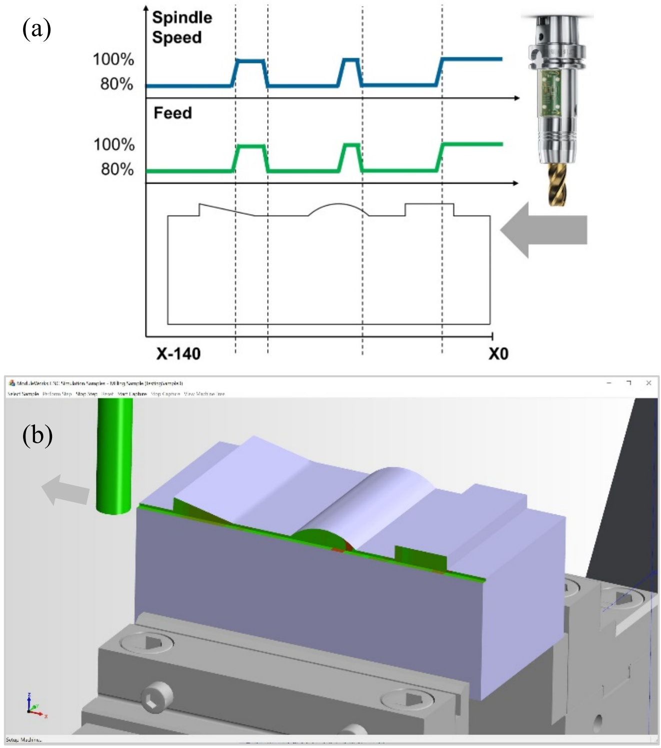

Fig. 4. (a) Correlation of geometry and speed/feed override adaptions; (b) real sensor data imported in simulation environment using optimized NC-code

5. Conclusion and Future Work

Modern sensor and communication technology enable the collection of machining data in real time. The data generated by sensors integrated in the machine tool / CNC control combined with additional 3rd party sensor systems provide detailed feedback on the machining process and can be utilized for human driven as well as (semi)automated process optimization.

This paper presents a novel and industrial-relevant approach to optimize a given NC-code using an instrumented tool holder for in-situ process measurements and a dexel material removal simulation engine. Results have been implemented in a demonstration scenario. Firstly, the implemented system architecture, utilizing OPC UA and MQTT communication protocols and a process execution engine *centurio.work*, provides an efficient approach for process data collection, supporting flexible extension towards various machine tools, CNC controls and 3rd party sensor systems. Secondly, importing such process data into material removal simulation, provides advanced visualization functionalities enabling the machine operator / NC-programmer with new opportunities for efficient NC-Code optimization. Thirdly, process data is used for (semi)automated adaption of cutting parameters and NC-code files, creating a closed loop system.

While the provided visualization functionalities provide immediate benefits for industrial applications, intensive future research and work is necessary to analyze interdependencies between gathered vibration data, process meta information and quality results (e.g. surface quality) to develop more sophisticated adaption and optimization rules. Current research in the field of machine learning could be adopted and integrated. In addition, more detailed process meta information from CAM systems would be beneficial and provide new opportunities towards feature-based data gathering techniques.

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