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Automated Design of Experiments supporting Feature-based Optimisation of Manufacturing Processes

Lea Tonejca[a], Thomas Trautner[*,a], Emna Slimane[a], Natalia Peso[a], Julian Zulehner[a], Friedrich Bleicher[a]

[a]*TU Wien - Institute of Production Engineering and Photonic Technologies, Getreidemarkt 9, 1060 Vienna, Austria*

* Corresponding author. Tel.: +43-1-58801-311380. *E-mail address:* trautner@ift.at

Abstract

This paper presents a novel process design to enhance time and cost-efficient AI training in manufacturing. As an alternative to time and resource expensive trial-and-error loops, the data basis of the proposed design enables data-driven parameter selection, where the parameter range in which the optimal solution is likely to reside, can be explored in a reproducible and systematical manner. A full-factorial DOE is generated and implemented from within the CAM software. Necessary production artefacts, like NC code, bill-of-material or work plan, are supplied per experiment. The heterogeneous data of different product life cycle phases are collected and related to the according manufacturing feature (i.e., drilling, face-milling, etc.). From within the CAM software, the NC-Code is manipulated to enable the identification of features during production, using feature markers. Instantiated as Siemens NX CAM extension, the novel design was tested on a 5-axis milling and drilling process on aluminium parts. The automated data set generation with feature correlation between different live-cycle phases was verified. As a result, the design supports feature optimization strategies for decision support systems - either as input for CAD/CAM, PLM, ERP and MES.

Keywords: Feature Technology; DOE; AI Training; CAM Plugin

Glossary

CAD	Computer-aided Design
CAM	Computer-aided Manufacturing
ML	Machine Learning
DOE	Design of Experiments
IPW	In Process Workpiece
CNC	Computerized Numerical Control
CAQ	Computer-aided Quality
PMI	Planning and Manufacturing Information
BOM	Bill of Material
API	Application Programming Interface
DSR	Design Science Research

1. Introduction

Trial-and-error-loops, in the search for optimal manufacturing parameters, are resource and time inefficient. For the use case of investigating optimal CAM parameters, ML could be applied. Quality or process data, like surface finish or energy consumption, may be the target parameters to be optimized. Planning data, like CAM settings, may be manipulated by an optimization algorithm to achieve the predefined target value. However, AI training requires a high effort in data collection, data correlation and data cleaning, if parameter ranges of uncertainty are not investigated specifically. The approach of this work is generating data sets in a structured and traceable manner that allow targeted data analysis. To enhance feature optimization algorithm, planning, manufacturing and quality data are correlated between different product live-cycle phases and classified per feature.

2. Related Work

2.1. Knowledge Integration into Production Systems

According to Ansari [1], combining knowledge-based assistance systems with AI in decision support systems can

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lead to improved productivity in the manufacturing industry. Knowledge-based management can be addressed through either organizational and individual knowledge (human-centric) or data-driven strategies (technology-centered) [2]. Glawar et al. [3] introduce a conceptual model for integrating knowledge into production systems, called PriMA. Its primary objective is to generate actionable and reusable information within CPPS. Its architecture has three layers: The data management layer collects planning and operational data from machines, products, and processes.The recommendation layer provides actionable suggestions for improving or optimizing future maintenance plans.

2.2. Feature Technology for Process Optimization

As defined by [4], a manufacturing feature from the production plan can be subdivided into one or more machining features. Each machining feature represents a machining step executed with the same tool. Feature recognition is already established in commercial CAD/CAM software, like Siemens NX, Esprit and TopSolid. From its initial role in production planning, Feature Technology became a universal tool for managing information across different phases of the product life cycle by integrating diverse tools like CAD, computer aided production planning, CAM, and FEM, which is demonstrated by Schorcht et al. [5]. Initiatives like ISO 10303 ”STEP” categorize features by geometric properties but lack support for additional functional or surface quality information and their standardization.

2.3. Manufacturing Parameter Optimization

ML methods have shown to minimize chatter vibrations or surface roughness by optimizing machining parameters:

The ML model developed by Cherukuri et al. [6] is based on an ANN and predicts the stability limit of a turning machine, based on cutting depth and spindle speed data for improvement. The ratio of correct chatter prediction to the number of data points is at least 90% and depends on the number of neurons and hidden layers. Tian et al. [7] applied a combination of RSM with a teaching–learning-based optimization (TLBO) algorithm. The effectiveness is shown by the increase of cutting force and material removal rate by 2.7% and 49.4% respectively and a decrease in the surface roughness of 6.6%.

2.4. DOE and AI

DOE allows simultaneous variation of multiple factors. In situations where data is limited or expensive to obtain, DOE can be employed to generate informative datasets for ML analysis.Concerning Arboretti et al. [8], the predominant type of DOE + ML application involves applying ML algorithms to analyse DOE data, referred to as the ”ML on DOE data” strategy. In their literature survey, the distribution of publications over the years indicates a growing interest in the research area.Engineering, particularly in mechanical, materials, and chemical fields, constitutes the most influential application area.

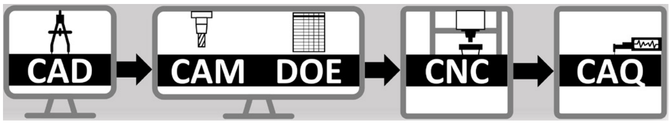

Fig. 1. In the data management layer, the generic design is included as CAM extension between production planning and manufacturing. Together with the analytical and recommendation layer, the design enhances feature-based parameter optimization.

In the study by Outeiro et al. [9], orthogonal cutting experiments were conducted on Ti-6Al-4V titanium in a $2\hat{k}$ full factorial DOE to explore the impact of cutting conditions, like speed and edge radius, on forces, chip compression ratio, and residual stresses.

3. Research Question and Contribution

- How to automate DOE in the manufacturing domain for the generation of training data?
- Specifically, how to enhance the development of feature optimization algorithms?

This work aims at realizing a CAD/CAM plugin for the automatic DOE generation and parameter variation according to user defined levels per feature. It is fully integrated into the process chain, as illustrated in Figure 1, thus extending the data management layer of the PriMa model [2]. As an extension of the CAD/CAM software, the application has access to the most significant amount of process knowledge and is able to manipulate manufacturing artefacts for later data correlation. Its target is a structured data basis for feature-based AI training using automatic planning data ingestion and accurate cutting depth calculation in all axis. Through feature correlation from the planning to the quality evaluation phase, the aim of this research is to enable actionable AI feedback, e.g., to the CAD/CAM software.

As a research method, DSR is applied, which aims at innovative designs for actions, processes, and systems to solve problems [10]. Its core product is a generic design, guided by a design proposition for practical application. To assure the effectiveness of the CAM-DOE extension, which is the main element, it is necessary to first create a prerequisite data extraction tool that ensures a data basis suitable for AI training. Once the data extraction tool is accomplished, the design of the DOE tool takes place. The design of both, the prerequisite and the main element, follow the six-step process for conducting design science research by Peffers et al. [11]: (a) problem identification and motivation; (b) objectives of a solution; (c) design and development; (d) demonstration simulation; (e) evaluation; and (f) communication.

This work is structured as follows: In Section 4, the generic design of the prerequisite CAM data extraction tool and of the proposed CAM-DOE extension is explained in detail. A generally applicable manual for implementing the design in manufacturing infrastructures is given in Section 5. Section 6 covers the instantiation of the designed tools in commercial CAM software and their validation in a DOE for milled and drilled aluminium parts, with subsequent relation between surface roughness and CAM parameters. In Section 8, the outcome of the design validation and its implications for the manufacturing industry are discussed.

4. Integration of DOE into Feature-based Data Management for AI Training

4.1. CAD/CAM Data Extraction

As a scope of this design element, the planning and metadata are automatically exported out of the CAM software and their correlation to process and quality data is enabled in the same step. The data schema in which the CAD/CAM data is structured supports Feature Technology, as the operation settings are stored in operation objects that are connected to the manufacturing features.

To realize this structure, relevant entities of a CAM setup and associated attributes are collected. The objects in Figure 2 define the classes of the object oriented software. Each entity holds a collection of data points that specify the production step. Additionally, the system handles the generation and upload of 3D-PDFs containing the work plan and gathers data for the BOM. The BOM itemizes components in the clamping system, aiding production planning for estimating setup times and fixture availability. Essential information, including identifiers and the CAM setup's revision number, is stored. All other functionalities, like logging management which is utilized by multiple classes, are located in the base class. In CAM setups, where operations, PMIs, machining parts, features, and tools may occur multiple times, collection classes are utilized for effective management.

4.1.1. Optaining valid cutting depth for AI training

To obtain the cutting depths of milling operations, the volumes of the IPW and toolpath are represented as triangular facets usig the toolpath, IPW, face, edge and point class. Finding the intersection points between the IPW and the toolpath volume is achieved by cycling through the edges of the IPW and checking for intersections with the triangular faces of the toolpath volume. The resulting intersection points are evaluated in terms of their distance from the toolpath volume's surface, providing insights into the axial and radial cutting depths of planar milling operations. Overall, this detailed methodology ensures accurate assessments of these core values, contributing to the optimization of milling processes.

4.2. DOE Generation Extension with Feature-markers

Our proposed design for generating DOE artefacts aims to automate data correlation, involving the extraction and linkage of data from diverse sources. To design the DOE extension for commercial CAD/CAM software tools, the design element in Section 4.1 is used, resulting in the architecture in Figure 3.

The feature technology used in CAx systems cannot be seamlessly transferred to CNC machining, due to the intermediate translation into G-code, which follows a structure preset by the machine tool. To nevertheless enable Feature-based Data Management [12], the introduction of feature-markers in the G-Code is the proposed solution. During post-processing, macro variables (e.g., Fanuc) or message commands (e.g., Sinumerik), depending on the CNC's options for reading user defined CAM information, are included as feature-markers into the G-Code before and after an operation. If live data is collected during machining, the feature-markers can be collected with other time series data, enabling feature identification and, thus, an initial basis for feature optimization.

5. Manual for Instantiation

5.1. CAD/CAM Data Extraction

- Access, gather and extract the required data, defined in Section 4.1.
- Create a uniquely identified JSON document, including revisions and the creation date of the document.
- Create relations between the entities of the extracted data according to Figure 2 in Section 4.1 and add them to the JSON document. Apart from the JSON document, also extract the following data: 3D PDFs of the machining parts, including the views containing PMIs; 3D PDF of the CAM setup showing the clamping situation and work instructions for tool placement in the machine; Geometries of the contained parts as STL files; G-code of the conducted machining steps.

5.2. DOE Generation Extension with Feature-markers

- Establish operation parameter manipulation and verify its reliability.
- Add operation identifiers to the post-processed NC-Code, either as macro variables, messages or other CNC specific functions. They need to influence the CNC's state in such a way, that its value can be collected during manufacturing with position and other data. Add the identifiers as start or stop event to each operation, or manipulate the processed G-Code afterwards by searching the document for comments that indicate a new operation.
- Implement the function flow as described in Figure 3.
- For creating a full-factorial DOE, construct a set of all possible level combinations.
- During runtime, all dialogue windows should be neat and consistent with the present GUI.
- Upload and store the data per experiment to an HTTP-Endpoint or database.
- Show warnings and issues while gathering and exporting the data within the user interface, and create and store appropriate logging files.
- Provide a button for the user to trigger a callback function within the CAM software's GUI, initiating the runtime.

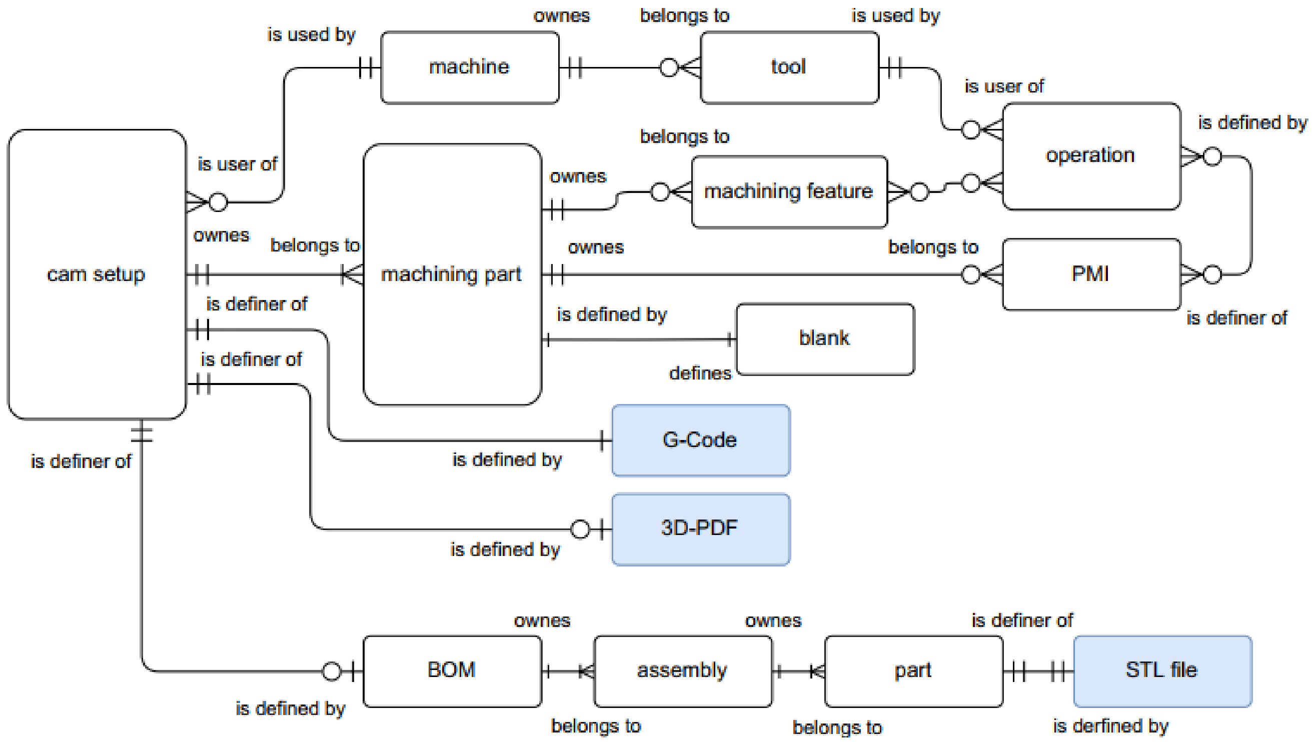

Fig. 2. Illustration of the data entities including relations and relation types in an Entity-Relationship diagram. The blue fields are entities that are stored in their specific document types. This includes STL files, the G-code, and the 3D-PDF. the storage directory must be used to point at these documents.

6. Instantiation in Siemens NX CAM

6.1. CAD/CAM Data Extraction

The instantiation of the proposed design was realized as extension of Siemens NX CAM, version 1953 using its application programmable interface NX Open in Python version 3.8. Siemens NX employs builder classes in NX Open to configure complex objects like operations, which contain material stocks, feeds and speeds, geometric limits and many more. The drilling operations are defined using feature-based technology, specifically selecting the STEP1HOLE machining feature. However, the milling operations are configured differently, with the relationships between milling operations and machining features requiring identification through mapping surfaces to obtain the schema in Figure 2. The GUI ribbon in Siemens NX is consumable, enabling the addition of a button for executing the Python script. By clicking the button, the serialized data in JSON format and the non-serializable data, like G-code and STL files, are stored on an HTTP endpoint. MongoDB, a document-based NoSQL database, was chosen to store the serialized JSON data described in Section 4.1.

6.2. DOE Generation Extension with Feature-markers

The following scope has been set for implemented DOE functionality: The response variable is the surface roughness; operations to be analysed are face milling, end milling and drilling, while the cutting parameters to be studied are spindle speed (vc [m/min]), feed per tooth (fz [mm]), and cutting depth [mm]. Cutting speed and feed per tooth can be related to spindle speed [rpm] and feedrate [mmpm]. Two levels per parameter were selected, resulting in 8 experiments in total (Table 1).

Table 1. DOE Parameters

Feature	Ø(mm)	vc(m/min) +	vc(m/min) -	fz(mm) +	fz(mm) -	depth(mm) +	depth(mm) -
Drilling	16	45	30	0.25	0.10	40	10
Drilling	12	30	15	0.32	0.20	40	10
Face mill.	16	200	60	0.25	0.025	2.0	0.5
Cont. mill.	16	200	60	0.15	0.035	1.5	0.5

Each experiment's data basis includes CAM planning data, process data from an external sensor and the machine's CNC, and quality measurement data. Upon completion of the software execution, Siemens NX data is stored in the MongoDB server and the experiment artefacts on a network drive, using the implementation of the requirement design element in Section 6.1, with respective IDs. Two sets of valid experiments were conducted, with eight experiments each, carried out randomly. After completing the manufacturing of all experiments, the surface roughness per part and manufacturing feature are measured with a Waveline W912RC from Jenoptik. Macro variables play a key role in segregating the numerical control data and acceleration values for the different manufacturing features. In this instantiation, macro variables are used to segregate the

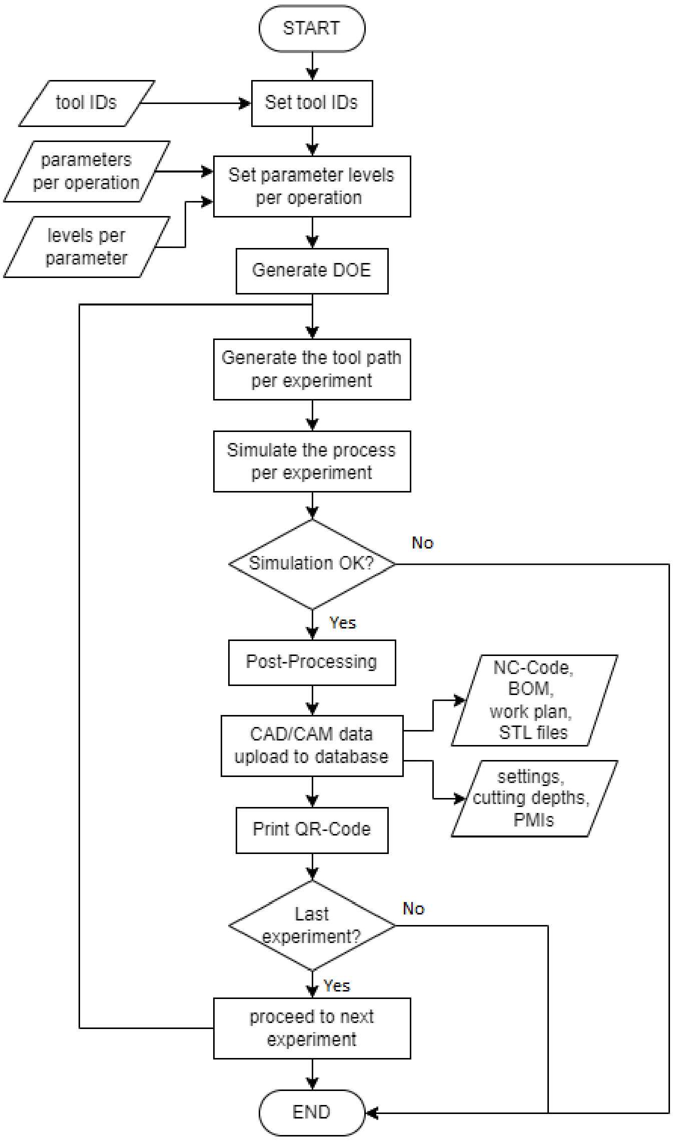

Fig. 3. The flow within the DOE extension for commercial CAM software includes user input for the DOE's factor level specification. For later tool wear estimations, the function "set tool IDs" waits for the user to state if any tool was changed to allow tool wear estimations. "Print QR-Code" calculates a unique ID before printing a label to put on the blank.

data of the numerical control and accelerometer of the different manufacturing features.

From within the CAM setup, start events per operation are used to set a macro variable to the operation's position number. The variable is set back to zero via end events. Acceleration and roughness data are collected solely within the time and position domain respectively. They are correlated using the CNC's live data, which contains both, position and timestamp. Their relation is used to align acceleration data (which is collected with a timestamp in the same time source as the NC data) and surface roughness data (which is collected per position, known as offset w.r.t. the position in the CNC).

Drilling operations are conducted through multiple passes. The data gathered in this procedure encompasses exit and entry movements designed for chip breakage. In this case, the acceleration data has been selectively filtered by phases of material removal. Hence, the outcome of the hereby generated manufacturing experiments is a consistent set of planning, production and quality data, each classified by manufacturing feature.

Listing 1. Planning data export as JSON


```
"_id": "2023_1_31_11_1_50",
"setupId": "2022_6_14_11_40_john",
"revision": 1,
"creator": "John Doe",
"editor": "Jane Doe",
"3DPDF": "\\...\3D_PDF\cam_setup_name.pdf",
"NCCode": "\\...\G_CODE.ptp",
"machine": {
    "machineId": "DMG_DMU75_MONOBLOCK_TEC_LAB_BYPS",
    "camSetupId": "2022_6_14_11_40_pless",
    "name": "DMG_DMU75_MONOBLOCK_TEC_LAB_BYPS",
"tools": [
    {
    "toolId": "MILL_PLANAR",
    "machineId": "DMG_DMU75_MONOBLOCK_TEC_LAB_BYPS"
    ...
```


Table 2. Example of process data from the PLC of the CNC machine.

Timestamp	Feature	X	Y	Z	F	S
1.68146E+15	5	50965	-7500	-3200	1194	1193
1.68146E+15	5	48418	-7500	-3200	1194	1193

Num	Timestamp	xAcc
191	1.68146E+15	-3.1967652
192	1.68146E+15	-3.2272832

Table 3. Vibration data.

X	Z
45.509	-7.345199
45.519	-7.487306

Table 4. Roughness profile.

7. Validation

The implementation generates feature-based datasets, combining planning-, process and quality data, which includes data of the following artefacts:

- CAD/CAM software: The planning data including the calculated axial and radial cutting depth (a JSON file snippet is presented in Listing 1).
- Numerical control of the machining centre: These files provide data about the machining processes (Table 2).
- myToolIT Sensory tool holder: This tool holder obtains the vibration data in the radial direction of the tool through an acceleration sensor at the tip of the inserted milling or drilling tool. The data (Table 3) is stored in hdf5 file format at around 10Hz.
- Surface roughness measurement device: The raw profile data (Table 4) were used to calculate Ra and Rz w.r.t. the ISO Norm 25178.

Table 5. ANOVA Results; Contrast: a linear combination of the parameters based on the geometric code; Sums of Square: a measure of variation from the mean; Mean Square: an estimator of the variance; F0 value: determines whether there is a significant difference in means between the group and the individual variability.

Factor	Contrast	Effect Estimate	Sum of Squ.	Contribution	Mean Squ.	F0
Vc (A)	1.63600	0.2045	0.167281	0.3071%	0.167281	0.06944162
fz (B)	23.19200	2.899	33.616804	61.7086%	33.6168	13.9549932
depth (C)	0.77000	0.09625	0.03705625	0.0680%	0.037056	0.01538277
AB	-1.10000	-0.1375	0.075625	0.1388%	0.075625	0.03139342
AC	-4.37400	-0.54675	1.19574225	2.1950%	1.195742	0.49637601
BC	0.03800	0.00475	9.025E-05	0.0002%	9.03E-05	3.7465E-05
ABC	-1.34200	-0.16775	0.11256025	0.2066%	0.11256	0.04672596

The ANOVA analysis based on the DOE methodology reveals crucial insights for each machining operation. In face milling, the feed per tooth has the most significant impact on surface roughness (96.7%). For end milling, feed per tooth dominates the impact (95.41%), followed by cutting speed and their interaction. Ø16 mm drilling shows substantial effects from feed per tooth and cutting speed, with a lower R2 value, suggesting a less accurate fit for drilling. As shown in Table 5, in Ø12 mm drilling, feed per tooth remains highly influential (61.7%), especially when interacting with the depth of cut.

8. Conclusion and Outlook

In this paper, an approach to enhance experiment design and execution in manufacturing processes is presented, which includes a DOE generation tool between CAM planning and post-processing. The present design encourages the systematic investigation of optimal manufacturing parameters by introducing a fully integrated DOE generation tool between CAM and manufacturing. Due to its automatic planning data extraction presented in our design, extensive/inherent expert knowledge is added to the data. Additionally, by automatically setting markers in the NC code for feature beginning and end, feature-based data correlation from the planning phase to the production is enhanced, facilitating feature optimization tasks. In terms of CAQ inspection, the features could be identified similarly but are not discussed in this work.

In addition to the initial predictive maintenance tools, the adapted data management layer allows process optimization. The decision support system might be distributed over various software tools within the recommendation layer. By implementing the herein proposed design, they might have the form of CAD or CAM planning software plugins, that help to achieve specified PMI values automatically. Alternatively, simulations in digital twin instances could enhance live simulations or supporting decisions in evaluating critical surface areas for quality inspection. Hence, in future advancements, we aim at knowledge exploitation in response to the herein proposed knowledge exploration tool.

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