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Integrating Cloud Computing, Bayesian Optimization, and Neural-Additive Modeling for Enhanced CAM Systems in 5-Axis Milling

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Abstract

This publication introduces the development and application of an advanced CAD/CAM/CAE system that leverages the computational capabilities of an edge-cloud infrastructure. The developed system consists of containerized technology models for various complex process planning simulation tasks in 5-axis-milling, such as toolpath calculation, cutter-workpiece-engagement, uncut chip geometry or cutting force simulations. Moreover, a Bayesian optimization (BO) algorithm is coupled with the system enabling multi-objective optimizations of the considered machining operations by varying predefined CAM-parameters. The result of the optimization consists of a set of Pareto-efficient solutions. Each solution realizes a different tradeoff between the technological objectives of the process planner. Since mastering the complexity of the design space is a major challenge in today's CAM programming workflow, a Neural-Additive Model (NAM) is coupled with the system improving guided search through the configuration/result space. This reduces the convergence time to an optimal CAM parameter set. The coupling of the cloud computing, multi-objective optimization and artificial intelligence method with a CAM-kernel is demonstrated based on the process design of 5-axis milling operations for a blade-integrated disk (blisk).

Keywords: "Computer-aided Manufacturing systems (CAM-Systems); Multi-objective optimization; Design methodology, tools and technologies"

1. Introduction

Programming the toolpath is an essential step in the process design of machining processes. Specifically for highly complex 3D geometries in a 5-axis machining processes, such as blisks in the turbomachinery sector, CAM systems are the key technology for efficient process planning. Moreover, CAM systems represent Advanced Systems [1] and are often utilized in conjunction with design tools for experts, such as collision prevention, dexel-based material removal or multi-physic simulations. CAM-integrated simulation tools provide the process designers with a data-driven assessment of their work, while simultaneously increasing the effort for information processing required for handling these expert tools. For a potential improvement of an existing solution, the CAM programmer must engage in multi-objective optimization problems within a highly complex solution space, given through simultaneous presence of numerous interactions among (A) system, (B) control, (C) process and objective variables [2]. Today, the human intuition plays a significant role in guiding the exploration through the complex solution space. This paper addresses the multi-objective optimization of pre-generated

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milling operations by the user through the variation of CAM parameters and subsequent process simulations executed by virtual machines in the cloud.

(A) System variables: For an efficient toolpath calculation / process simulation, the user needs to consider all relevant boundary conditions for the job setup, as depicted in Table 1. Within this work, the system variables of the workpiece, tool, machine, fixture, and machining strategy are kept constant. Possible examples are material properties, geometries, coordinate system offsets, clamping forces, etc.

Table 1. Constant system variables as starting point for optimization

Systems	(A) Constantly held system variables within this work
Workpiece	Blisk Ti-6Al-4V
Tool	Ball end mill, solid carbide, ø16 mm
Machine tool	GF Mikron HPM 800U HD
Fixture	Static axial clamping forces
CAM strategy	Multiblade

(B) Control variables: The complete parameterization of a CAM strategy includes not only cutting parameters but also requirements for NC point distribution, tool orientations, cutting area limitations and (many other input information. The number of required inputs varies depending on the CAM strategy. The complexity of the solution space and computation times scale significantly with the number of parameters to be varied. Table 2 represents the portion of relevant CAM parameters considered in this work as design variables for optimization.

Table 2. Variation of CAM parameters as control variables for optimization

(B) Variation of control variables for the CAM strategy 'Multiblade'	CAM parameter unit	Practical range [min; max]
Feedrate (v_f)	mm/min	[50; 5,000]
Spindle speed (n)	rpm	[500; 20,000]
Distance between layers (a_p)	mm	[0; 10]
Blade offset (a_e)	mm	[0; 5]
Preferred lead tilt angle (α)	deg	[-90; 90]
Maximum side tilt angle (β)	deg	[0; 90]
Maximum point distance	mm	[0.01; 10]
Toolpath smoothing	%	[0; 100]
Check surface clearance	mm	[0.01; 1]
Tool angular clearance	deg	[0; 5]
Toolpath cut tolerance	mm	[0.003; 1]

(C) Process and objective variables: A significant constraint for optimizing an existing NC program based on technological key-performance indicators (KPIs) lies in the accuracy of the simulation models. The highly complex calculations and modeling techniques are not always intuitively comprehensible to humans. Figure 1 provides a partial representation of potential process and objective variables that may be of interest to the process designer. Within a possible optimization context, a score of 0 % denotes substandard performance, while a score of 100 % signifies optimal performance within the specific target dimension, constrained within a limited solution space.

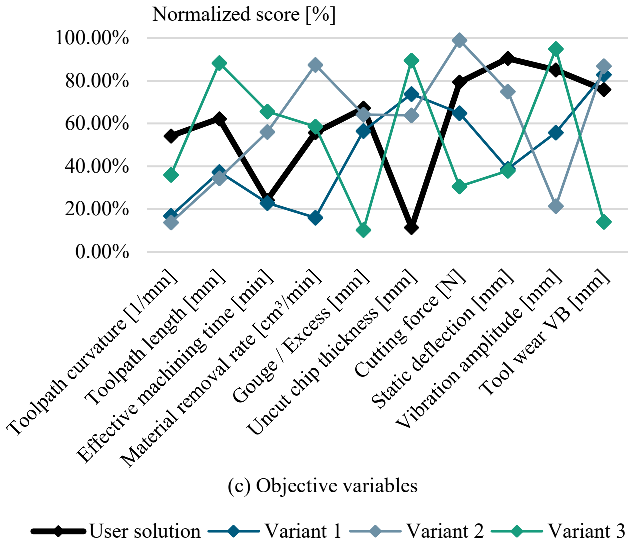


Figure 1: Possible variables for a multi-objective optimization in milling

2. Related work

2.1. Virtual manufacturing systems and digital twins

Altintas et al. presented an overview [3] in simulating machining processes along the toolpath using virtual environments. Further, they optimize NC programs considering the physical constraints of the machine tool and the cutting process. The main objective is to predict: (i) cutting forces, torque, power; (ii) macro-mechanics: dimensional surface errors; (iii) micro-mechanics: temperature, stresses or strain distributions with high accuracy and within short computation time windows. Cutter workpiece engagement simulations represent the baseline for process simulations. This requires the geometric modeling of the engagement of the cutter at discrete intervals along the toolpath with high-resolution settings for tool (within this work CSG-based [4]), toolpath and workpiece (within this work dexel-based [5]).

In the context of machining, virtual manufacturing systems support technical employees to design a digital representation of the physical system often tailored for a specific purpose. The range and limitations of digital twins [6] and shadows [7] depend on three primary factors [8]: (i) application: e.g., real-time or offline; (ii) viewpoint: e.g., product, process or systems; (iii) context: e.g., information model and visualization. During the toolpath planning stage, technology models rely on various methods, including analytical, numerical, empirical, or AI-based modeling, to predict the physical process conditions [9]. Moreover, there is a growing tendency to integrate these technology models as microservices within a cloud-based framework, with the aim of enhancing the computational capacity of the utilized algorithms [10]. Within a digital twin framework interconnected in the cloud environment [11], these models can interact in a modular and scalable manner. This approach ensures easy accessibility for all stakeholders and facilitates the implementation of data processing services for data-driven process simulations.

2.2. Bayesian Optimization (BO)

Bayesian optimization is a powerful technique for the simultaneous optimization of design parameters since it generally can find efficient solutions with few evaluations of costly objective functions. BO is an iterative method using a surrogate model [12] trained on the available data to suggest the next function points to be evaluated. After evaluation, the model is retrained with the new data included. This process is repeated until a stopping criterion, in the context of a minimization or maximization problem, is met. To obtain function points to be evaluated, the output of the surrogate model is passed through an acquisition function balancing a tradeoff between exploration, favoring regions of the parameter space with high uncertainty on the predicted objectives, and exploitation, favoring regions with optimal values for the predicted objectives [13].

2.3. Neural-Additive Modeling

NAMs are instances of Generalized Additive Models [14]. These neural network-based algorithms are suitable for regression and classification of tabular data [15]. This modeling technique expresses objective variables as the sum of individual feature-dependent functions in an interpretable manner. In the context of CAM-integrated simulations and optimizations, NAM is intended to validate and potentially enhance expert knowledge, providing a valuable tool in the design of machining processes including sensitivity and uncertainty assessments, intuitive checks and gaining insights into the simulation's behavior [16].

3. Developed CAM system demonstrator

3.1. Cloud Architecture

All simulation models were developed as containerized microservices and function as interconnected components of a cloud-based architecture, depicted in Figure 2. Due to parallelized cloud computing of the simulation workers, 100 or more process variants can be considered simultaneously for any optimization scenario of a cutting process. Significant patterns within large datasets can be identified and extracted purposefully, so time-consuming optimization tasks including calculations such as dexel-based engagement simulation or FEA, typically taking hours to days on a local PC, can now be accomplished in minutes or hours within the cloud architecture.

The message broker is the central (internal) communication component, which uses Advanced Message Queuing Protocol (AMQP) to facilitate the exchange of messages between different microservices in an asynchronous manner. It uses a publish-subscribe communication pattern, where an entity subscribes to a message queue and receives messages only relevant to its area of operation. This approach allows the use of scalable, loosely coupled architecture and enables support of features like message persistence, message routing and message acknowledgment.

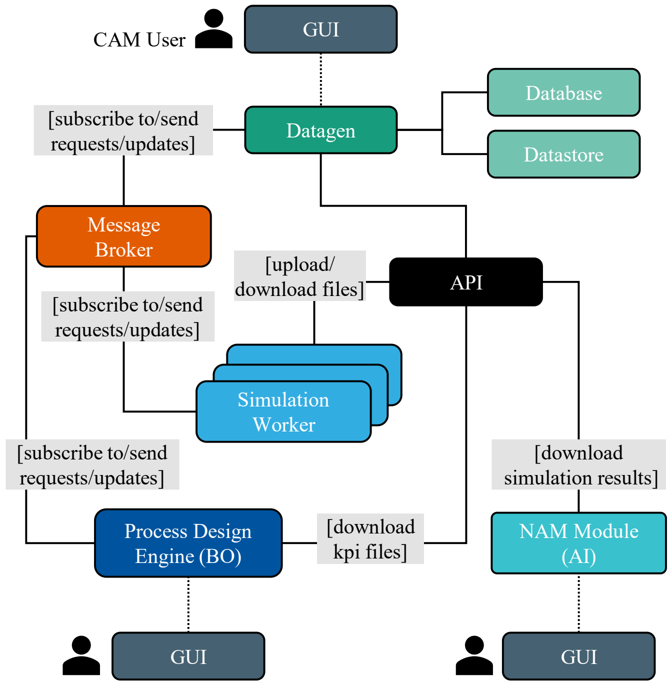


Figure 2: Cloud architecture

The core module of the introduced cloud architecture is the data generation component (Datagen), which is responsible for processing and coordination of simulation and optimization requests sent by the CAM user either via the dedicated REST API endpoint or by using an AMQP request message. Datagen then validates the request against a defined message format schema and in case of success transforms the data into a database model. The request is then divided into tasks, which are requested by the Datagen and can be processed by the responsible microservices. Furthermore, Datagen is connected to a Datastore module and is responsible for serving and storing all simulation-related data.

The Simulation Worker is a collection of containerized microservices responsible for execution of different simulation tasks ranging from toolpath calculation and cutter workpiece engagement to cutting forces or static tool deflection simulations. In the idle state, each microservice waits for messages pertinent to its specific tasks by subscribing to one of the message queues of the message broker component. The connection to the message broker is also used to send task status updates or receive specific control command messages. Additionally, all simulation workers employ REST API endpoints, which are primarily used for simulation data exchange.

The Process Design Engine (PDE) is the optimization component of the developed cloud system and consists of the following containerized microservices: (1) a state machine for each optimization performing the Bayesian optimization itself and holding the state of the optimization, including the values of the CAM parameters and objectives for the simulated operations; (2) the communicator managing the state machines and serving as an interface between them and the central message broker.

The NAM module is a component, which uses neural network-based models described in chapter 2.3 to model regression and classification of the simulation data to reveal correlations between various simulation parameters in the provided datasets.

To facilitate user interaction with cloud components, some of them provide a dedicated Graphical User Interface (GUI) module, which can be accessed using a webbrowser and provides visual feedback in form of data representation or requests management to the user.

3.2. Multi-objective process design optimization method

The general workflow of the multi-objective process optimization is presented is illustrated in Figure 3. The milling process to be optimized may consist of one or multiple consecutive machining operations. In both cases, the simulation stages are considered as a single black box functions $f(\boldsymbol{x}) = \boldsymbol{y}$ with continuous CAM parameter values $\boldsymbol{x}$ and multiple optimization objectives $\mathbf{y}$. An individual Gaussian Process surrogate is used for each objective.

In the very first step, the CAM user specifies the optimization request by entering essential input information via a seven-step-guided GUI (A), e.g., raw part geometry, tool parameters, initially designed operations by the user, varying CAM parameters and their limits, objectives, stopping criteria etc. In the second step, the CAM parameters for the initial BO sample are calculated. They correspond to a quasi-random Sobol sequence [17] for better coverage of the sample space. Based on the known points to be sampled, the optimization request is subsequently transformed to an initial simulation request with a specific task description for the Datagen module.

Depending on the defined optimization objectives, all necessary microservices are executed. After completing the process simulations, the results are stored in the Datastore. In the PDE module, the q-Expected Hypervolume Improvement implemented in the BoTorch package [18] is used as the acquisition function. To calculate the hypervolume for the acquisition function, a reference point is established in the objective space. In each iteration of the BO, the worst currently observed objective value is used for each dimension of the reference point. The optimization workflow is stopped when the hypervolume fails to increase by more than a user-defined factor or reaches a maximum number of iterations.

For supporting the decision-making process regarding which operations enable an improved operational point in the complex solution space and should be reimported into the local CAM system, additionally developed GUIs provide detailed insights into the processed simulation results. GUI (B) provides the CAM user with an overview of all optimization iterations, including the CAM parameters and objective values (KPIs) for the Pareto-efficient operations. A solution is Pareto-efficient if no other solution is more optimal in all objectives. GUI (C) enables a comprehensive sensitivity analysis, including the extraction of feature importance and shape functions from the simulated datasets during the optimization runs.

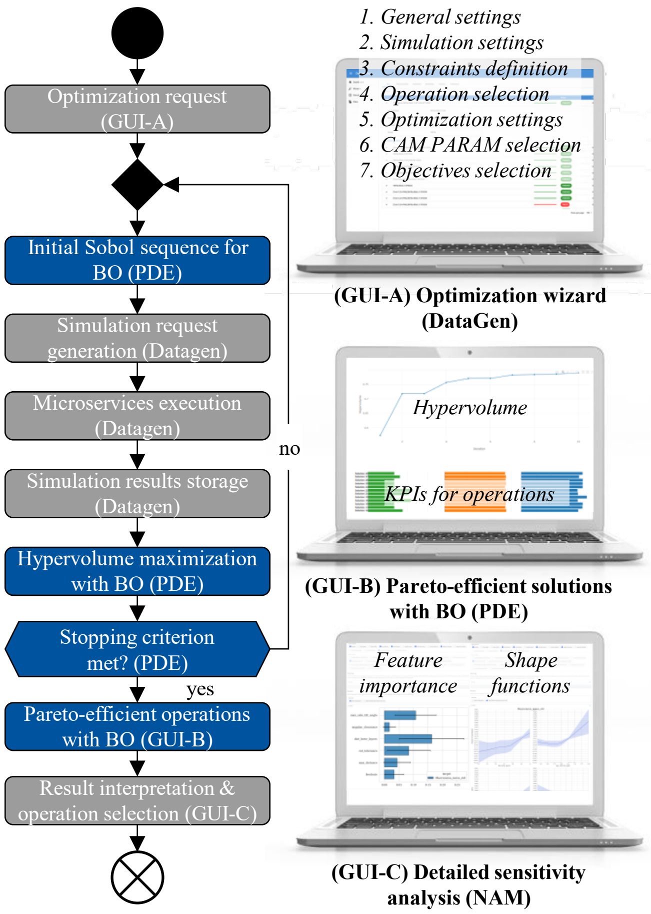
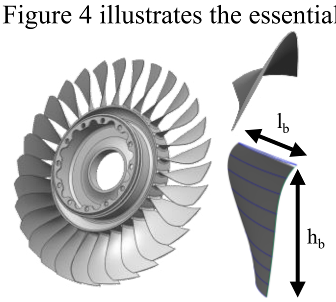


Figure 3: Multi-stage optimization method for process design (CAM)

4. Application of cloud-based architecture

To demonstrate the application of the implemented cloud architecture, this chapter introduces a multi-objective process optimization task in 5-axis milling of a blisk demonstrator. Figure 4 illustrates the essential demonstrator characteristics.



Material	Ti6Al4V
Diameter d	440 mm
Blade number n_b	30
Blade height h_b	100 mm
Chord length l_b	45 mm
Max. thickness th_b	2,5 mm

Figure 4: Blisk demonstrator

A single operation was chosen as the subject of optimization. The reference process is a blade finishing process using a ø16 mm ball end mill. The raw part represents the In-Process Workpiece after the material removal of the blade pockets through a roughing process with a ø16 mm bullnose mill. In Figure 5, the process design solution of the user is illustrated showing the calculated toolpath in the local CAM system. The six depicted parameters were subsequently varied within the specified limits.

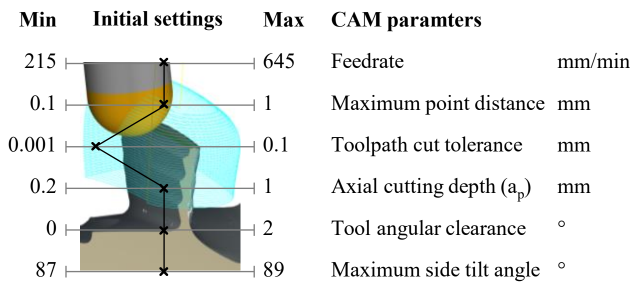


Figure 5: Reference process and six varying CAM parameters

The following three KPIs were defined for the multi-objective optimization: (a) productivity increase: minimization of the cumulated toolpath length; (b) toolpath smoothness: minimization of the 90th percentile of the toolpath curvature; (c) safe process conditions: minimization of the 90th percentile of the cutting forces. During this optimization, three simulation workers were operated in parallel to generate the simulation results including the following microservices:

- Toolpath calculation (containerized CAM kernel)
- Interpolation of the toolpath (per feed per tooth fz)
- Macroscopic engagement simulation (multi-dexel)
- Microscopic engagement simulation (analytical)
- Dual-mechanistic cutting force simulation (Altinas): Ktc: 2746 N/mm², Krc: 981 N/mm², Kac: 14 N/mm² Kte: 14 N/mm, Kre: 55 N/mm, Kae: 55 N/mm

The stopping criteria were defined such that the BO would break either after a maximum of 100 allowed iterations or if, within three iterations, the hypervolume does not increase by at least 1 %. In this case, the iterative BO workflow as described in chapter 3.2, needed 10 iterations and stopped with an output hypervolume of 79 %. Overall, 20 out of 30 simulated results were classified as Pareto-efficient. In Figure 6, the relative increase for each respective KPI resulting from the logic of the BO algorithm is depicted. After 10 iterations, there was an increase in force by 19 %, a decrease of the 90th percentile of the toolpath curvature by 2 %, and a reduction in the toolpath length by 50 %. The use case effectively reflects the technological trade-off that process design engineers must make on a daily basis: either a longer toolpath (e.g., reducing a_p) and lower cutting force level, or vice versa. The results for variants V1 to V3 are examined in detail later in this section.

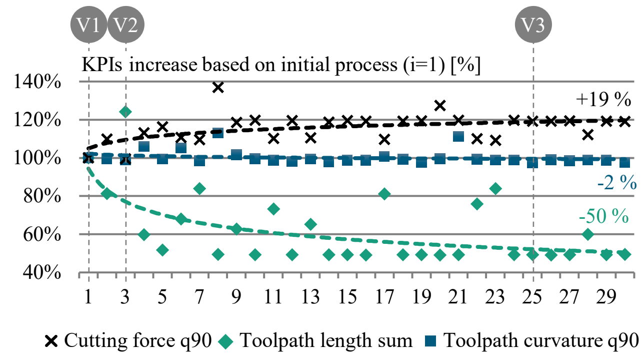


Figure 6: KPI evaluation

In the example of the curvature KPI, it can be derived that the creation of suitable KPIs using statistical metrics is significant for the optimization performance. The initial idea for choosing the 90th percentile was to enhance the stability of the toolpath calculation microservice by utilizing a more resilient depiction of the data distribution, mitigating the impact of outliers. As shown in Figure 7, previous studies demonstrated that an unfavourable choice of CAM parameter combinations can lead to toolpath anomalies. The spikes in the trajectory can be read from the local curvature extreme values. However, in the introduced optimization case the extreme values were 'overlooked' by the 90th percentile.

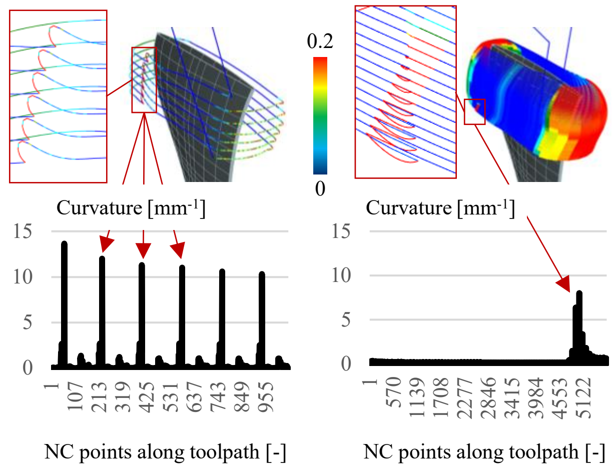


Figure 7: Toolpath curvature as indicator for toolpath anomalies

Figure 8 depicts a detailed 3D visualization of each individual objective variable (a) to (c) along the fz-interpolated toolpath for process variants V1 to V3. It demonstrates the complexity and variety of the data which can vary significantly in space. If the process constraints allow it (e.g., max. permissible static or dynamic deflections through force increase, etc.), the CAM user would tend towards process variant V3. While the cutting force increases from 137 to up to 185 N, it simultaneously covers a significantly shorter distance (50 %) with a slightly improved toolpath smoothness (2 %).

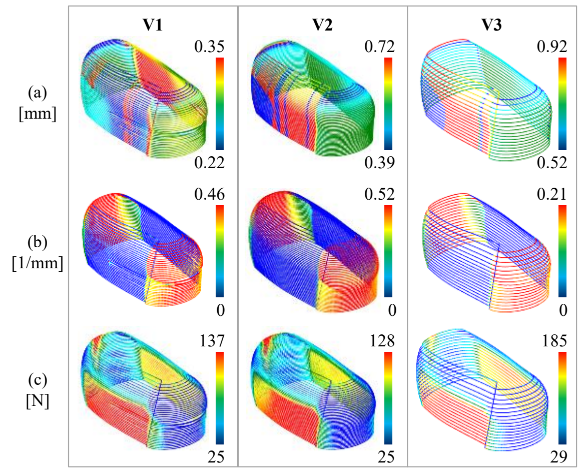


Figure 8: 3D visualization of tooltip positions for process variants V1-V3: (a) distance of 2 consecutive points; (b) toolpath curvature; (c) cutting force

Figure 9 illustrates the shape function of the cutting force for the conducted optimization study calculated by 20 ensemble members and 400 training epochs of the NAM model. In this case, the shape function describes the correlation between the target quantity 'cutting force' and the input variable 'feedrate' within a finite parameter range. It can be observed that the force increases significantly in the 250 to 400 mm/min range before a small plateau is reached. Although the planning engineer would roughly expect this correlation, he is nevertheless unaware of the exact quantitative relationships, particularly in the case of considering all combinations of objective and control variables at the same time. Additionally, it is feasible to conduct an uncertainty evaluation for the shape functions, so design engineers can estimate the reliability of the outcomes and determine whether further simulation results are required. This enables the selection of an improved design/operational point in the complex solution space.

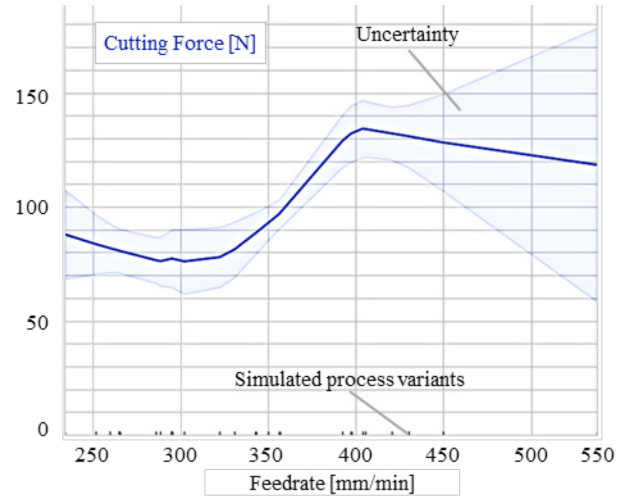


Figure 9: Shape function for cutting force calculated by NAM

5. Conclusion

In this research paper, an interdisciplinary developer team has introduced a cloud-based architecture that incorporates essential process simulation capabilities in 5-axis milling, a multi-objective algorithm (BO), and NAM-driven results interpretation. The presented case study illustrates, that this architecture and optimization workflow is a key enabler for mastering the complexity of the process design space of a CAM engineer. Furthermore, the case study highlights the necessity for tailoring statistical tools to individual technological optimization challenges when aggregating optimization-related data from the point level to KPIs at the operation level. An initial integration of the cloud architecture in the commercially available CAM software EXAPTsolid (EXAPT Systemtechnik GmbH) was tested. As an outlook, the cloud-optimize feature can be fully integrated into new generations of CAM systems to make process planning efficient, assessable and scalable.

Acknowledgements

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