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Elaborated analysis of force model parameters in milling simulations with respect to tool state variations

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Abstract

Geometric physically-based simulation systems for milling processes can provide the possibility to analyze and predict characteristically behaviors of a certain process. The parametrization of the simulation models is a crucial task when optimizing the quality of the simulation prediction. In order to determine tool load, process forces have to be calculated. Thus, the parametrization of the cutting force model that is mainly subject to the processed material and tool characteristics has a versatile impact on the simulation results. However, the tool state is expected to be constant within common milling simulations and therefore tool state variations like several tool wear effects are not represented. The tool state is defined through the geometric constitution of the cutting edges of the tool. This paper aims to analyze tool wear effects by re-calibrating the parameter values of the force model within the simulation system. To validate the simulation system, several milling experiments were conducted. In order to induce a fast change of the tool state within the process and to provoke high tool loads, the powder metallurgic high speed steel 1.3344 was machined. Advanced surrogate modeling techniques from the design and analysis of computer experiments (DACE) were applied to analyze the contribution of the force model parameter values. The fitting of the surrogate model is performed by means of sequential design of experiments. This allows the retrieval of sets of fitting parameter combinations for each tool state with a relatively small amount of simulation runs compared to genetic algorithms or gradients based methods. The surrogate models are exploited to analyze the behavior of the force model parameter values over the varying tool states. Approaches for further research are recommended and potential practical applications are discussed.

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Keywords: Milling; Geometric modelling; Surrogate models

1. Introduction

In industrial applications, the layout and optimization of machining processes is often time consuming and costly. Simulation systems allow to predict important process characteristics, such as forces and dynamic effects, for a given process layout. As a consequence, simulations can reduce the number of real experiments and therefore time and costs. Altintas et al. provide a comprehensive survey of recent capabilities of machining process simulations [1]. In this paper, a geometric physically-based simulation system, developed at the Institute of Machining Technology (ISF), is used. This tool enables the prediction of the material removal process, the resulting cutting forces and resulting effects like chatter vibrations [2]. A description of the system is given in section 2.

A main requirement for the simulation system is an accurate calculation of the process forces. To achieve this, an empirical force model is used [3], whose parameters have to be calibrated by physical experiments. This is usually done a priori to the actual milling process using the same tool and material as in the process. However, tool wear during the milling process causes a change of the process forces. Research of tool wear effects is already known in literature, e.g., for simulation systems based on the finite element method (FEM) [4,5]. Further investigations were made regarding an extension of an analytical cutting force model to represent tool wear and to predict the remaining tool life [6]. The calibration of the force model was done through a genetic algorithm and the idea of an online adaptive control system using a time series analysis was proposed. The modeling of tool wear using regression models or artificial neuronal networks is also possible [7]. Kolar et al. developed a force model, which is highly dependand on tool wear effects and the basic tool geometry [8]. The averaged flank wear value was measured in advance in order to integrate the characteristics of tool wear into the force model. To provoke wear effects, C45 carbon steel was machined using a coated carbide tool.

In geometric physically-based simulation systems, however, a geometric representation of the tool wear within the simula-

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tion system would significantly increase the computation time. In addition, the measurement of tool wear for each regarded tool state is inefficient and only represents the tool wear effects for the discrete measured states. Therefore, this paper discusses the implicit modeling of the tool wear effects by adapting the calibration parameters. For this purpose, simulated forces are fitted to the measured forces of different states of tool wear over the time and the resulting information about the calibration parameters is compared.

Since the evaluation of simulation runs with different calibration parameter values can be time consuming, mathematical or statical methods are generally utilized to determine fitting calibration parameter values from all possible calibration parameter combinations, the so called parameter space. In existing studies, the best solution for these calibration parameter values is found straightforward by optimization algorithms [9–12]. This procedure is appropriate when optimizing isolated single problems. However, regarding the force calibration task, it will be shown that there are several parameter value combinations which lead to equally good results. The existence of entire regions of optimal solutions makes the comparison of single points from the parameter space over different tool wear states therefore inappropriate. Moreover, for a model-based interpolation of the tool wear states, the information from all calibration parameter combinations is required. Since optimizers are not able to provide more than single (best) points from this parameter space, they are not sufficient to tackle this task. Models from the Design and Analysis of Computer Experiments (DACE), however, can be used to gather information about the whole space of force coefficients based on a small set of simulation experiments. Thus, it is possible to analyze and visualize the progression of suitable calibration parameter values with increasing tool wear.

However, before the information of these models can be exploited, their approximation and prediction quality has to be validated to guarantee a sufficient fit over the considered parameter space. Therefore, a cross validation of the models is performed. To finally prove that the regions of good parameter values found by the models are actually optima, they will be compared to the solution found by an established optimization algorithm. The surrogate models and the calibration procedure are presented in section 3. Section 4 gives a brief overview of the experiments. The model validation and the results of the comparison of the calibration parameter values is presented in section 5. The paper ends with a conclusion in section 6, which also discusses potential practical applications and how the models can be used to interpolate the optimum force coefficients between the tool states.

2. Simulation system

Using a geometric physically-based milling simulation system, the material removal process and resulting effects, e.g., tool vibrations and heat input, can be predicted. The geometric model of the used simulation system is based on the Constructive Solid Geometry technique (CSG) [13] to model the geometry of the tool and the workpiece. To achieve a representative tool model, basic shapes like spheres, cylinders and tori can be combined. As initial workpiece model for the stock material typically a cuboid is used [14]. The calculation of the process forces is based on the undeformed chip thickness of the milling process at discrete points in time. To represent the irregular shape of the undeformed chip, the cutting edge of the tool model is approximated by rays, whose origin lie on the center axis of the tool model (Fig. 1). These rays are distributed along the cutting edge. Furthermore, a time-related discretization is used to represent the envelope of the tool and the feed movements. The sum of the lengths of the ray intersections with the workpiece model represents the undeformed chip thickness. The computed thickness and the width of the chip can be fed into an appropriate force model to predict the process forces. This force model [3] is described by the equation

$$F_i = b \cdot k_i \cdot d_0 \cdot \left(\frac{d}{d_0}\right)^{1-m_i}, i \in \{c, n, t\}, \tag{1}$$

where d is the thickness and b is the width of the undeformed chip, which results from the Euclidean distance between the first and the last endpoint of the intersected rays. Furthermore, $d_0 = 1$ mm and F_c, F_n, F_t are the resulting forces in the cutting, normal and tangential direction.

3. Empirical surrogate modeling

3.1. DACE models and correlation functions

The functional relationship between input and output parameters of complex nonlinear systems can be approximated by empirical surrogate models. The most popular choice of a surrogate model is a polynomial regression model [16]. In this modeling approach, a set of N observations with d input variables $X = (x_1, \ldots, x_d)$ is generated by methods of design of experiments. The evaluation of the design on the complex system leads to N observation pairs $(X^{(i)}, y^{(i)})$, $i = 1, \ldots, N$ of input parameters and corresponding response values. Polynomial regression models assume the functional relationship $y(X) = f(X) + \boldsymbol{\varepsilon}$, where the vector of residuals $\boldsymbol{\varepsilon}$ is assumed to be a random noise variable with a mean of zero and an unknown standard deviation σ. The function f represents a predefined functional term of the input parameters. Polynomial regression models are efficient, if the actual underlying problem function is close to linear or quadratic [16]. However, if the investigated system is highly nonlinear, this model tends to a poor fit or local overfitting [17]. DACE models [18], also called Kriging or Gaussian process models, enhance the polynomial regression

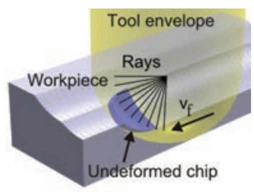

Fig. 1: The undeformed chip results from an intersection operation with the current workpiece and tool model. The undeformed chip thickness is approximated using rays, which originates from the axis of the tool model [15].

model by

$$y(X) = f(X) + Z(X), \quad (2)$$

where $f(X)$ is usually a constant term β_0 or a first order polynomial with a (known) linear trend. The term $Z(X)$ is a Gaussian process with mean $E(Z(X)) = 0$ and a covariance function $\mathrm{cov}(Z(X^{(i)}), Z(X^{(j)})) = \sigma R(Z(X^{(i)}), Z(X^{(j)}))$, where $R(Z(X^{(i)}), Z(X^{(j)}))$ is a correlation function, or kernel, which has to be chosen in advance. In this paper, three popular approaches of correlation functions will be applied and compared to find the best possible fit of the surrogate model. The considered correlation functions are the Gaussian correlation function [19]

$$R\left(X^{(i)}, X^{(j)}, \Theta_j\right) = \exp\left(-\frac{1}{2}\sum_{j=1}^{d}\left(\frac{\left|x_j^{(i)} - x_j^{(i)}\right|}{\Theta_j}\right)^2\right), \quad (3)$$

the Matérn correlation function [19]

$$\begin{aligned} R\left(X^{(i)}, X^{(j)}, \Theta_j\right) = & \left(1 + \sqrt{5}\frac{\left|x_j^{(i)} - x_j^{(i)}\right|}{\Theta_j} + \frac{5}{3}\left(\frac{\left|x_j^{(i)} - x_j^{(i)}\right|}{\Theta_j}\right)^2\right) \\ & \cdot \exp\left(-\sqrt{5}\sum_{j=1}^{d}\frac{\left|x_j^{(i)} - x_j^{(i)}\right|}{\Theta_j}\right) \end{aligned} \quad (4)$$

and the power-exponential correlation function [19]

$$R\left(X^{(i)}, X^{(j)}, \Theta_j, p_j\right) = \exp\left(-\sum_{j=1}^{d}\left(\frac{\left|x_j^{(i)} - x_j^{(i)}\right|}{\Theta_j}\right)^{p_j}\right). \quad (5)$$

DACE models have proven to show a very good fit for the approximation of computer experiments and have therefore been used in several applications considering simulations of mechanical engineering problems [20–22].

3.2. Formalization

To make use of surrogate models, the problem has to be formalized by defining the input parameters and responses. The actual force calculation within the simulation system is conducted using the force model, which is defined by equation 1. The set of coefficients

$$P = (k_c, m_c, k_n, m_n, k_t, m_t) \quad (6)$$

will represent the input parameters. For given values of these coefficients, the process forces can be simulated. For a comparison with measured forces, a coordinate transformation from the rotating tool system (c, n, t) to the fixed machine system (x, y, z) of the simulated forces can be done. Using equation 1 and the transformation based on the position of the tool at discrete time step t_i, the corresponding simulated force components can be described by

$$F_{\mathrm{j}}^{\mathrm{sim}}(P; t_i),\ j = x, y, z. \quad (7)$$

The measured forces were acquired using a triaxial force dynamometer. The discretization of the time $t_i, i = 1, \ldots, m$ of the measured forces $F_{\mathrm{j}}^{\mathrm{meas}}$ can be set according to the discretization of the simulated forces and, thus, the difference of both values can be calculated. Fig. 2 exemplarily shows a comparison of measured and simulated data. To calibrate the force parameters of the simulation system to a certain set of measured forces, a fitness value has to be defined. In this paper, this value is given

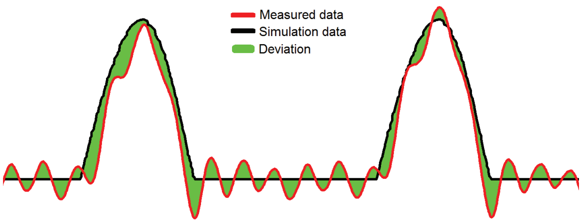

Fig. 2: Exemplary comparsion of measured and simulated data. The diversion can be calculated directly or can be transformed to a individual fitness value. The noise in the measured data results from slight vibrations of the force dynamometer.

by

$$r(P) = \sum_{i=1}^{m}\sum_{j=x,y,z}\left|T_j\left(F_{\mathrm{j}}^{\mathrm{meas}}(t_i)\right) - T_j\left(F_{\mathrm{j}}^{\mathrm{sim}}(P; t_i)\right)\right|, \quad (8)$$

where T_i is a normalization function to map the forces to [0,1] in order to ensure that all three directions are represented equally in the fitness value. The value $r(P)$ therefore represents the response value and the relationship of r(P) and the input vector P will be approximated by the DACE model. This enables to analyse and to discuss this relationship for the different tool states in section 5.

3.3. Sequential design

Sequential designs of experiments can be used to enhance classic designs of experiments. It ensures that the approximation of the surrogate model is sufficiently precise in interesting regions of the input parameter space by adding additional experiments in these regions. To accomplish this, new design points, e.g. vectors of input parameter values, are found by optimizing a certain criterion. This so-called infill criterion [23] is calculated by the model. It defines a tradeoff, between searching for new design points in the parameter space in regions of model uncertainty (exploration) or in regions where local optima are presumed (exploitation). The new point is evaluated and the observation pair is added to the data. Finally, the model is adapted. This procedure continues until a termination criterion, such as the target accuracy or the maximum number of simulation runs, has been reached.

4. Experiments

4.1. Experimental setup

In order to provoke high tool loads and therefore a high variety of different tool states in a short time, the powder metallurgic high speed steel 1.3344 (hardened to 62 HRC) was chosen as workpiece material. The experimental investigations of a slot milling process were conducted on a 5-axis machining centre (DMU50 eVolution) using a spherical cutter with two teeth and a diameter of 12 mm. In the experiments, a spindle speed of $n = 5300\,\mathrm{min}^{-1}$ and a tooth feed of 0.2 mm were used. The workpiece was machined with a depth of cut of $a_p = 0.5$ mm and a width of cut of $a_e = 0.5$ mm. To measure the process forces, the force dynamometer *Kistler 9257B* [24] was used.

4.2. Model-based calibration procedure

The choice of the design of experiments strongly depends on the chosen model class. DACE models require a space filling distribution of the input parameters. Therefore, a Latin Hypercube Sampling (LHS) [25] was chosen. The input parameter values were distributed in the 6-dimensional space depending on their specified range of values. An advantage of LHS designs is that the number of experiments can be chosen freely. Furthermore, the experimental design can be expanded by further experiments. The initial sample size was set to $N = 600$ simulation experiments. After the evaluation of the experiments, the DACE models with the three different correlation functions (Eqn. (3)-(5)) were fitted to the data and compared. To guarantee a sufficient goodness of fit, the comparison was based on a 20-fold cross validation, i.e. the cross validated (also called predicted) coefficient of determination R^2_{CV} [26]. In this procedure, the data was split into 20 parts. One part was separated from the data and the model was build on the remaining data. Subsequently, the removed data is predicted by the model and compared to the true values. This was performed for each of the 20 data parts. The optimum value is $R^2_{CV} = 1$ (excellent prediction quality). Lower values indicate decreasing prediction quality. The constant prediction of the mean value over all response values would result in a value of $R^2_{CV} = 0$. In case of systematically wrong predictions, even negative values are possible. The correlation function with a maximum value for R^2_{CV} was used in the models for the sequential design of experiments. The maximization of the expected improvement (EI) [25] was chosen as infill criterion.

5. Results

The experiments were conducted according to the experimental setup. A total number of 90 slots were milled until the end of tool life was reached. First, significant differences in different process characteristics caused by the increased tool wear were investigated. Subsequently, the quantity of these effect was analyzed. For this purpose, three tool states at different points of the tool life were considered (Fig. 3). The tool and the resulting wear of the cutting edge is shown. The first tool state represents an almost new tool. Tool state 2 corresponds to an intermediate tool wear while tool state 3 shows deep wear marks, since it is almost at the end of the tool life. The plots

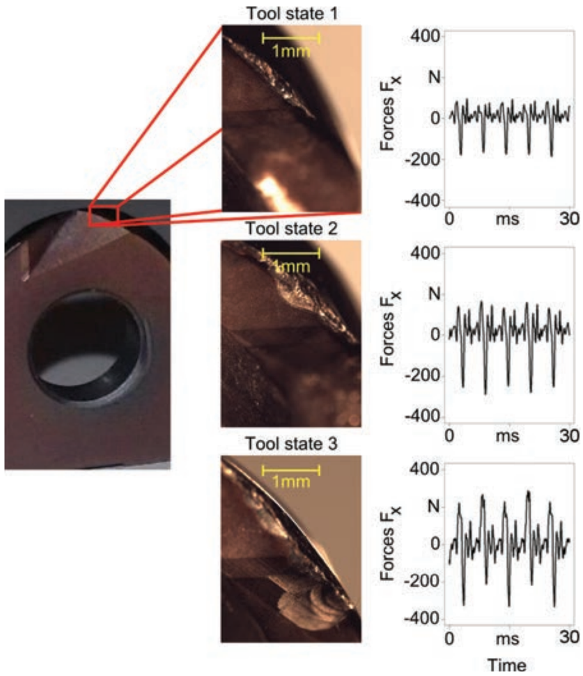

Fig. 3: Visualization of the different tool states and the resulting forces in x-direction.

on the right show the resulting forces in x-direction of the used force dynamometer. It can clearly be seen that the peak force values increase with tool wear during the process. The forces in x-direction almost triple from tool state 1 to tool state 3.

5.1. Model validation

The measured forces were used to calibrate the force coefficients of the simulation system independently for each tool state. A low fitness value $r(P)$ indicates a good simulation approximation for a given set of coefficients P (cf. Eqn. (6)). To prove the application of the DACE models, they should be able to approximate and predict the functional relationship of P and the resulting fitness value accurately based on the considered 600 simulation experiments. Table 1 shows the R^2_{CV} of each model. It can be seen that all correlation functions show an almost perfect prediction quality with a R^2_{CV} close to 1. For further analysis, the Matérn correlation function was selected as it results in the best R^2_{CV} for all tool states. In the sequential procedure, $N_{seq} = 300$ further simulation experiments were conducted to improve the model quality in regions with a low value for $r(P)$.

5.2. Model-based comparsion of the tool states

Fig. 4 shows the response surface of the resulting DACE models for tool state 1 after the sequential procedure. The plot only shows areas for a fitness value $r(P) < 100$ to get a better view of the regions of satisfactory results. The three force parameter pairs are depicted separately to compare their behavior. In each plot, a ”valley” of solutions can be observed. These results proof the multimodality of the fitting function. Fig. 5

Table 1: Comparsion of the R^2_{CV} value for the three considered correlation function for each tool state.

Tool state	Gaussian	Matérn	Power-exp.
Tool state 1	0.9775	0.9864	0.9848
Tool state 2	0.9821	0.9896	0.9873
Tool state 3	0.9771	0.9853	0.9757

shows the results for all three tool states as contour plots. Regarding k_c and m_c, the response surface for tool states 2 clearly tends to higher values for k_c compared to tool state 1 (Fig. 5a). Comparing the plots of tool state 2 and 3 for these two parameters, however, no clear difference can be observed. Therefore, the influence of k_c and m_c might have a progressive form over the different tool states. For k_n and m_n the progression is continuous over the three tool states (Fig. 5b). The observed valley clearly tends to higher values for k_n as well as for lower values for m_n. Also for the parameters k_t and m_t a continuous progression can be observed whereby k_t is decreasing with increasing tool wear (Fig. 5c). These results therefore indicate a trend of the force parameter values over the three tool states, which proves that the tool wear can implicitly be represented by the force model parameters.

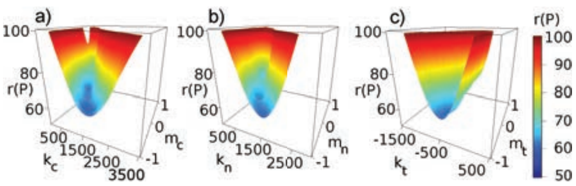

Fig. 4: Response surface of the DACE model for tool state 1 for a) k_c and m_c, b) k_n and m_n, c) k_t and m_t.

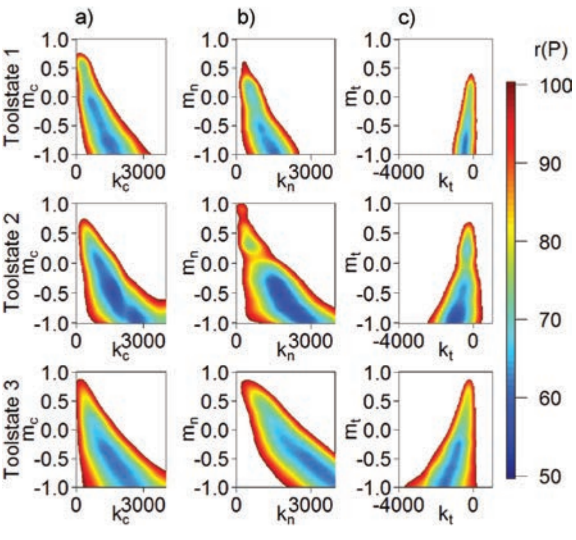

Fig. 5: Contour plots for the fitting value modeled by the DACE model for the three considered tool states for a) k_c and m_c, b) k_n and m_n, c) k_t and m_t.

5.3. Optimization ability of the model

The existence of the "valleys" shows that single optima found by optimization algorithms would not be sufficient to compare the progression of the calibration parameters with increasing tool wear. However, they can be used to validate the optimization ability of the surrogate models for each tool state separately by comparing the best results found by both methods. Therefore, a solution from the best region found by the surrogate models is compared with the best solution found by the BroydenFletcherGoldfarbShanno (BFGS) algorithm [27] as an established optimization algorithm. The results are shown in Table 2, where the best values found and the required simulation runs are compared. It shows that the DACE models were even able to find significant better results for tool state 1 and 3 than the BFGS algorithm. Regarding tool state 2, both methods found equally good fitness values. To show that these fitness values indicate a sufficient fit, the measured and simulated forces are compared for each tool state in Fig. 6.

Table 2: Comparsion of the best found fitness values by BFGS and the DACE models and the required number of simulation evaluations.

Tool state	BFGS		DACE	
	Best r(P)	Sim. runs	Best r(P)	Sim. runs
Tool state 1	90.46	897	61.35	900
Tool state 2	57.21	2015	57.17	900
Tool state 3	84.13	832	61.69	900

The results have therefore shown that the DACE model are able to sufficiently approximate the global relationship and are furthermore accurate in the regions of good solutions. The analysis of the response surface indicated that it can be possible to express the obtained trend in a functional relationship in future research work. With this information, the prediction of the forces of the simulation can be adapted and, thus, the effects of the tool wear can be taken into account within the simulation system.

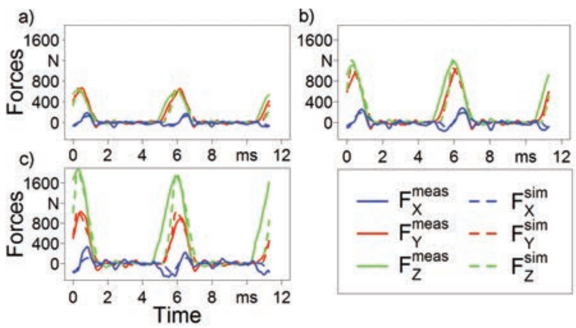

Fig. 6: Comparsion of the measured and simulated forces in x-, y- and z-direction for a) tool state 1, b) tool state 2 and c) tool state 3.

6. Summary and Outlook

In this paper, the force model coefficients of a milling simulation system were analyzed with respect to variations induced by tool wear. To accomplish this, milling experiments were conducted in the powder metallurgic high speed steel 1.3344. The resulting forces were measured and the differences in the forces with increasing tool wear were shown. In addition, the force model coefficients of the geometric physically-based simulation system were adjusted to the forces measured for each tool state. To obtain information about the response surface of the defined fitness value, empirical surrogate models were fitted based on the simulation results. It could be shown that more than one optimum coefficient value vector exist for each tool state. For a deeper investigation of this observation, the response surfaces in the vicinity of optimum solutions were shown and the differences over the considered tool states were analyzed. The results showed that the use of the established optimization algorithm BFGS can only be recommended when the simulation system has to be adapted to one specific data set. However, if the results of several tool states have to be compared and the variation in the parameter values has to be considered, the entire force parameter space has to be analyzed due to the valley of possible solutions. It could be shown that the surrogate models, which are based on sequential designs of experiments, are an excellent choice for this analysis. The investigations within this paper can serve as basis for further applications. The models can be used to interpolate the optimum force coefficients between the tool states by setting up characteristic values for the parameter regions with good solutions. This allows to integrate tool wear into the simulation system.

Acknowledgements

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