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INVERSE MATERIAL MODEL PARAMETER IDENTIFICATION FOR METAL CUTTING SIMULATIONS BY OPTIMIZATION STRATEGIES

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Abstract
Numerical modeling of machining processes exhibits a high potential for shortening process development times. When modeling the machining process, an accurate material model is essential for the success and reliability of the simulated results. Especially, the simulation results depend largely on the material model and on the material parameters. To identify the parameters for machining conditions, inverse methods are used, where results from simulations are matched iteratively with those obtained experimentally. This procedure is, however, time-consuming and a large number of iterations is needed. This paper presents a new methodology for the inverse identification of material parameters by an optimization algorithm.

Keywords:
Johnson-Cook model; Simulation; Optimization; Inverse identification; Machining

1 INTRODUCTION

Machining processes are one of the major manufacturing processes in the production industry. Therefore, they play a significant role in today's industry. Typically, machining processes are designed empirically by trial-and-error approaches [Shi 2004]. This conventional machining process design, however, is limited in its capabilities, since it is just of descriptive nature and not predictive. Furthermore, the experimental evaluation is expensive and very time-consuming [Arrazola 2014].

Another approach for the process design of machining processes with the capability of reducing the time to market is the usage of modeling approaches [Filice 2008]. Modeling of manufacturing processes shows a high potential for shortening product and process development times. The approaches for metal cutting modeling can be divided into five types: analytical, numerical, experimental, artificial Intelligence (AI), and hybrid modeling [Arrazola 2013]. An example for a numerical method, and focus of this study, is the finite element analysis (FEM).

One major advantage of the FEM analysis, compared to experimental machining experiments, is the capability to predict process quantities accurately, such as stress, strain, strain rate, and temperature. These process quantities are difficult to measure during machining experiments, however, they play a pivotal role when enhancing the process comprehension [Lei 1999]. The use of FEM techniques to the field of engineering and specifically in the field of machining was first introduced by Zienkiewicz, respective by Klamecki in the 1970s [Zienkiewicz 1971, Klamecki 1973]. Ever since, modeling of machining processes became more and more popular in the scientific community. In 1995, the CIRP STC "Cutting" started the "Cutting Working Group" with the aim to improve the quality of predictability and performance of machining process simulations with a defined cutting edge, as well as to promote the use of these models in the industry [van Luttervelt 1998].

To set up numerical models of the machining process several input information are necessary. Thereby, an accurate material and friction model is essential for the success and for the reliability of the simulated results [Childs 1998]. Nevertheless, accurate modeling of the material behavior depends largely on the selected material model as well as on the chosen material parameters. In the state of the art, there is a large number of different material models that are used for metal cutting simulations. The material models can be classified into empirical/ phenomenological, semi-empirical, and physically based constitutive models. Empirical constitutive material models often describe the material flow stress as a function of strain ϵ, strain rate $\dot{\epsilon}$ and temperature T. One example for an empirical constitutive material model is the Johnson-Cook model, which found wide application in metal cutting simulations [Johnson 1983].

Commonly, the parameters of the material models are determined by quasi-static or by dynamic tests, such as the Split-Hopkinson-Pressure-Bar (SHPB) test [Abouridouane 2012]. Using the SHPB test, conditions with strains up to 0.5, strain rates up to $5 \cdot 10^3$ s^{-1}, and temperatures up to 1,000 °C are achievable [Poulachon 2001]. However, these conditions are far away from those conditions encountered in machining, where strains up to 2 or even 6, strain rates up to 10^6 s^{-1}, and temperatures between 500 °C and 1,400 °C can occur [Shi 2004, Bäker 2015, Arrazola 2013]. This deviation results in the need of extrapolation when using flow stress data from SHPB tests to simulate the material behavior under metal cutting conditions. This might

lead to deviations between the predicted and the actual material behavior [Shatla 2001].

To circumvent the problem of extrapolation, several researchers used inverse techniques in the last 10 years, where machining simulations are matched with cutting experiments by varying the parameters of the implemented material model [Bäker 2015, Klocke 2013a, Klocke 2013b]. By matching integral simulation results (e.g. cutting force, chip shape or cutting temperature) with those obtained from (e.g. orthogonal) cutting experiments until a predefined objective or error-function is undercut, the expression of the material model itself and the parameters of the material model are validated [Warnecke 2002].

However, the inverse iterative identification processes are time-consuming and might need a large number of iterations and, therefore, high computational efforts [Bäker 2015]. To determine the material models faster and more robust, different optimization strategies and algorithms have been used in the field of modeling manufacturing processes, such as in stamping [Chaparro 2008] or in sheet metal forming [Chaparro 2008]. In the field of machining modeling, there are just a few publications on using optimization algorithms to determine material parameters. Özel and Karpat used the evolutionary computational algorithm of Particle Swarm Optimization for optimizing the Johnson-Cook parameters from SHPB tests for metal cutting simulations [Özel 2007]. Later Shrot and Bäker used the Levenberg-Marquardt algorithm for an iterative re-identification of Johnson-Cook parameters from cutting simulations [Shrot 2011]. Denkena et al. used the Particle Swarm Optimization to determine the parameters of the Johnson-Cook material model in combination with Oxley's machining theory [Denkena 2015]. Another approach using the Levenberg-Marquart algorithm was presented by Hor et al., who used the algorithm to optimize the material parameters from a modified TANH-model, presented in its original form by Calamaz et al. [Calamaz 2008], by using experimental data from compression tests [Hor 2013]. These approaches show the capabilities and the improvements, especially compared to the classic inverse iterative procedure, to determine material parameters for metal cutting simulations.

In this paper, a new methodology for the inverse identification of Johnson-Cook material parameters from FE-simulations by means of an optimization algorithm is presented. As optimization algorithm, the Downhill-Simplex algorithm (also called Nelder-Mead algorithm) is utilized. To assess the approach, the simulation results from an initial parameter set from the literature for the steel AISI 1045 were used as target values. The goal of the optimization strategy is to re-identify the initial material parameters. Finally, the computational effort when using the proposed algorithm was evaluated as well.

The paper is organized as follows: The material model, that is used for the optimization approach is presented in the following Chapter 2. Thereafter, the orthogonal cutting model that is implemented into the software ABAQUS is outlined, followed by the presentation of the used algorithm to optimize the material model parameters. The optimization approach is presented in Chapter 5 and 6. In the last chapter the conclusions will be given and an outline will be drawn.

2 MATERIAL AND FRICTION MODEL

The chapter is divided into two subchapters to present the two models used for the FE-cutting simulations, namely the material and friction model. Both models have a major influence on the simulation results.

2.1 Material Model

One of the most widely used material models to describe the constitutive workpiece material behavior in metal cutting simulations was developed by Johnson and Cook, see Equation (1) [Johnson 1983]. In this equation, the effects of strain ϵ, strain rate $\dot{\epsilon}$ and temperature T on the flow stress σ are expressed separately (uncoupled) [Voyiadjis 2005]. The considered effects are presented by the three terms in the brackets.

$$\sigma = (A + B\epsilon^n)\left(1 + C \cdot ln\frac{\dot{\epsilon}}{\dot{\epsilon}_0}\right)\left(1 - \left(\frac{T-T_0}{T_m-T_0}\right)^m\right) \quad (1)$$

The first bracket represents the strain hardening effect of the strain on the flow stress and is expressed by the Ludwik equation. The second term represents the strain rate hardening effect, expressed in a logarithmic form. The last bracket expresses the thermal softening effect based on a power function [Klocke 2018]. In the Equation (1), A, B, n, C, and m are material constants, $\dot{\epsilon}_0$ the reference plastic strain rate with $\dot{\epsilon}_0 = 1\ s^{-1}$, T_0 the reference temperature (usually room temperature) and T_m the melting temperature [Johnson 1983].

Besides the Johnson-Cook material model, many more material models have been developed in the past. Thereby, some of the material models are modifications of the Johnson-Cook model itself, e.g. by Shatla et al. [Shatla 2001], Bäker [Bäker 2006], Abouridouane [Abouridouane 2015] or Ee et al. [Ee 2005]. Examples of physically-based models are the Zerilli-Armstrong model [Zerilli 1987, Zerilli 2004], the Bammann-Chiesa-Johnson model [Guo 2005] or the Mechanical Threshold Stress Model [Follansbee 1988]. Since the Johnson-Cook material model is implemented within the simulation software ABAQUS, the optimization of the Johnson-Cook parameters is aimed within this paper. The scope of this paper is not to identify the most appropriate material model for simulations of metal cutting, but rather to present a new method for the inverse parameter identification. The presented technique is expected to be applicable to other material models as well.

Tab. 1: Johnson-Cook material model parameters for AISI 1045 underlying the simulations of this study.

Johnson-Cook material parameter AISI 1045	
Material	AISI 1045 normalized
Material model	Johnson-Cook model
A / MPa	546
B / MPa	487
n / -	0.25
m / -	0.631
C / -	0.027
ϵ_0 / s^{-1}	0.002
T_0 / °C	20
T_m / °C	1500

The parameters used for the description of the initial parameter set were taken from the literature [Klocke 2013]. In Tab. 1, the parameters to describe the Johnson-Cook material model are summarized. In this study, the initial parameter set was varied in order to re-identify this set by using the Downhill-Simplex algorithm, see Chapter 5.

2.2 Friction Model

Besides the material model, the friction model has a major impact on the simulation results [Abouridouane 2015]. It has been widely shown, that the usage of a simple Coulomb

friction model is not sufficient to describe the frictional behavior between the tool and the workpiece or between the tool and the chip, respectively [Puls 2014]. To overcome the limitations when using the Coulomb friction model, a large number of different friction models have been investigated in the scientific community, e.g. by Özel [Özel 2006], Filice et al. [Filice 2006] or Puls et al. [Puls 2014].

Puls et al. used in their study a high-speed deformation test, where an indexable insert in an orthogonal cutting experiment was rotated to have a highly negative rake angle. This ensures that the chip formation is suppressed. Based on their findings, a temperature dependent friction model was derived. In this study, this friction model has been utilized, since it was calibrated for the workpiece material AISI 1045 underlying this study, and since it takes the temperature effect on the friction in the interfaces of tool/chip and tool/workpiece into account. The friction law is shown in Equation (2). In this equation, the softening term is formulated analogously to the JC material model [Puls 2014]. The parameters that were used for the underlying simulations of this study when modeling the frictional behavior are summarized in Tab. 2.

$$\mu = \mu_0 \left(1 - \left(\frac{T - T_0}{T_m - T_0}\right)^{m_r}\right) \quad \text{for } T \geq T_0 \tag{2}$$

Tab. 2: Model parameters for the friction model acc. to [Puls 2014].

Friction model parameters AISI 1045	
Material	AISI 1045 normalized
μ_0 / -	0.7
m_r / -	0.35
T_0 / °C	600
T_m / °C	1500

The material model was implemented within the simulation program ABAQUS in a tabular form to describe the contact properties between tool and workpiece material. The friction coefficient was implemented for a temperature step of 10 °C until it reaches zero.

3 ORTHOGONAL CUTTING MODEL

Different formulations of discretization have been used in the literature to model the metal cutting process by means of FEM simulations. Among the formulations, the Lagrangian and Eulerian formulation can be considered as the classical approaches. In the Eulerian discretization, which found wide application in fluid-flow simulations [Movahhedy 2000], the continuum moves through elements that are fixed in space. For machining simulations, the Eulerian formulation can only be used for the steady state, which requires the knowledge of the final chip geometry [Arrazola 2013]. In comparison, the Lagrangian discretization assumes, that the nodes of the mesh are attached to the material and follow its deformation [Vaz 2007].

Besides the two classical formulations, two other formulations have been used for the simulation of machining processes: the Arbitrary Lagrangian Eulerian (ALE) approach and the Coupled Eulerian Lagrangian (CEL) approach. These approaches have been developed to combine the advantages and to avoid the drawbacks of both other methods [Movahhedy 2000]. In the ALE formulation, the material flows through the mesh, analogous to the Eulerian formulation. Additionally, the element nodes are able to move free within the area. In the CEL-formulation, which has been used for machining simulations in the past years [Klocke 2014, Ducobu 2016], the workpiece material is modeled as Eulerian so that the material can flow freely through the fixed mesh. The tool on the other side is modeled by using the Lagrangian formulation. Therefore, the tool can move through the Euler domain without influencing its mesh. The set-up of the CEL-formulation that has been used in the simulations here is shown in Fig. 1. As simulation software ABAQUS/Explicit 6.14 has been utilized. For information on the advantages and disadvantages of ABAQUS/Explicit the author refers to further literature [Outeiro 2015, Bäker 2004, Ivester 2000].

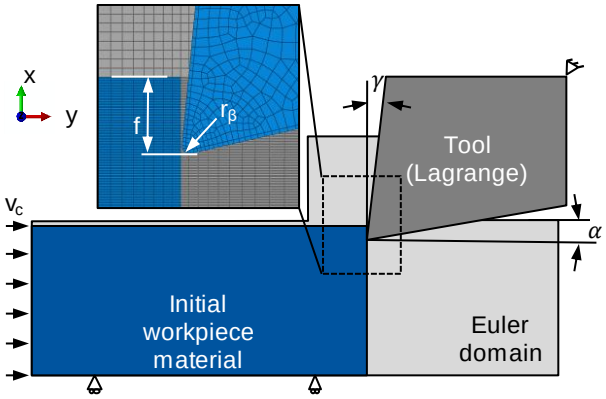


Fig. 1: Set-up of the Coupled Eulerian Lagrangian model of orthogonal cutting.

As boundary conditions, which are shown in Fig. 1, an initial inflow of the material is used to realize the cutting speed. The material flows through the Euler domain and exits in form of chip or machined workpiece material. The Lagrangian tool is set as fixed. Within the Euler domain, an initial area is assigned with the workpiece material, whereby the workpiece material can flow through the whole domain.

The calculation time of a simulation is a critical factor influencing the total computational effort. Especially for the iterative identification of material model parameters, the calculation time of a single simulation should be reduced as far as possible without influencing the simulation results. To ensure this, a quasi-two-dimensional orthogonal cutting simulation was used. Since the EC3D8RT elements used to mesh the Euler domain are three dimensional (3D), a 3D simulation was used to model the orthogonal cutting process. The number of elements in the z-direction was one Therefore, the simulation can be considered as quasi-two dimensional.

For a further decrease of the computational time, the simulation has been optimized by using different strategies. One approach, which has been widely used in the literature [Arrazola 2007, Ducobu 2015] is the mass scaling. For mass scaling the material density is increased to increase the speed of sound [Klocke 2014]. Here, a mass scaling factor of 1,000 was used to increase the density ρ and to decrease the specific heat c, see Equation (3).

$$\Delta Q = m \cdot c \cdot \Delta T \tag{3}$$

Besides the mass scaling, the time increment has a major influence on the calculation time. The time increment has to be smaller than the critical time increment, otherwise the solution becomes numerically unstable [Ng 2002]. The critical time increment can be calculated according to Equation (4). In the simulation underlying this work, a time increment of 1.6e-8 s was used. Therefore, the time increment was smaller than the critical time increment of 1.629e-8 s.

$$\Delta t \cong \frac{L_{min}}{c_d} \cong \frac{L_{min}}{\sqrt{\frac{E\nu}{(1+\nu)(1-2\nu)}+\frac{E}{(1+\nu)}}{\rho}}} \quad (4)$$

Critical in terms of the computational time, but also in terms of the simulation results, is the mesh size [Barge 2005]. The larger the minimal mesh length L_{min}, the higher the computational time, see Equation (4). However, with decreasing mesh size and with less integration points, the gradients of the plastic strain become low [Ambati 2011]. Thus, the minimal element size around the tool tip was set to 0.005 mm, with an increasing trend to the outer range of the domain (see Fig. 1).

Within the orthogonal cutting model, the tool was meshed with the element type C3D4T. The Euler domain on the other side was meshed, as stated before, with EC3D8RT elements. The details of discretization, as well as the used thermal and mechanical properties, are summarized in Tab. 3.

Tab. 3: Model input parameters [Klocke 2014].

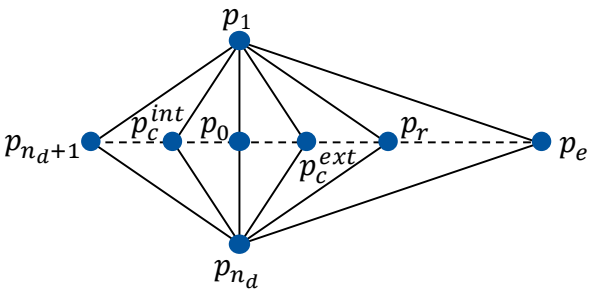
Software	ABAQUS/Explicit 6.14
Model type:	Dynamic explicit CEL model with full thermal-mechanical coupling
Workpiece: thermal and mechanical properties	
Young's modulus E / GPa	
Thermal conduct. λ / W/mK	[Spittel 2009] f(T)
Heat capacity c / J/kgK	
Tool: thermal and mechanical properties	
Material model	Rigid
Thermal conduct. λ / W/mK	[Beiss 2002, Brookes 1992]
Heat capacity c / J/kgK	
Density ρ / kg/m³	
Mesh properties: Euler domain	
Element type	EC3D8RT
Min. element size / mm	0.005
Max. element size / mm	0.1
Mesh properties: Tool (Lagrangian)	
Element type	C3D4T
Min. element size / mm	0.005
Max. element size / mm	0.05

4 DOWNHILL-SIMPLEX ALGORITHM

In this study, the Downhill-Simplex algorithm, also called Nelder-Mead algorithm [Nelder 1965], was used to re-identify material parameters of the Johnson-Cook material model. In general, the downhill-simplex algorithm is a method for a multidimensional problem, that can be employed to minimize the error between predictions and measurements [Sartkulvanich 2004]. In terms of the optimization of material model parameters, this capability can be used to minimize the error between the experimental results from e.g. machining experiments and the output of machining simulations. Thereby, the material model parameters are iterated until a predefined error is reached. In comparison to other optimization algorithms, the Downhill-Simplex algorithm is derivate-free.

To use the Downhill-Simplex algorithm, a simplex is needed. A simplex is a regular polytope, that is defined by n + 1 vertices in a n-dimensional space [Mulyadi 2006, Nelder 1965]. In case of a 3D-space, the simplex is a tetrahedron, generated by three points p_1 to p_{nd+1}. By replacing the worst vertex (p_{nd+1}) by its reflection around the centroid of the hyperplane that is formed by the remaining vertices, the polytope moves towards the optimum [Nelder 1965]. The conceptual procedure for a 2D-space is shown in Fig. 3.

Besides the described operator called reflection, the other operators in the downhill-simplex algorithm are expansion, internal and external contraction. In this work, the parameters to describe the four operators were chosen to be $\rho = 1$ (reflection), $\gamma = 1/2$ (expansion), $\sigma = 1/2$ (internal contraction) and $\beta = 1/2$ (external contraction). The four operators of the downhill-simplex algorithm are shown in Fig. 3.



c: Contraction int: Internal p_1 - p_{nd+1}: Initial simplex
e: Expansion ext: External p_0: Centroid
r: Reflection

Fig. 3: Conceptual operators of the Downhill-Simplex algorithm for a 2D-space [Vaz 2015].

5 OPTIMIZATION OF JC PARAMETERS

In order to reduce the computational effort when using the Downhill-Simplex algorithm for the parameter optimization in metal cutting simulations, selected parameters were chosen for the optimization. In this case, the Johnson-Cook parameters n, C, and m where chosen to be optimized using the proposed algorithm.

The optimization in this study did not consider experimental results, but rather the simulation results using the initial parameter set, called S_0, from Klocke et al. [Klocke 2013]. The aim was to re-identify these parameters by applying the described algorithm. To evaluate the deviation between the simulated results from the initial parameter set (respective of experimental results) and the results from the simulations using the material model parameters that have to be optimized, an error function has been defined. The error function has to consider different simulated outputs. In this study, an error function was defined that evaluates the deviation of the cutting force F_c, chip thickness h', and cutting temperature T. The error function r is shown in Equation 5. Thereby, the influence of the validation sizes can be weighted by the weighting factor ω. The weighting factors were set to $\omega_{F_c} = 0.5$, $\omega_T = 0.3$, and $\omega_h = 0.2$.

$$r = \omega_{F_c} \cdot \left|\frac{F_{c,S_0} - F_{c,S_i}}{F_{c,S_0}}\right| + \omega_T \cdot \left|\frac{T_{S_0} - T_{S_i}}{T_{S_0}}\right| + \omega_h \cdot \left|\frac{h'_{S_0} - h'_{S_i}}{h'_{S_0}}\right| \quad (5)$$

The algorithm was implemented into a MATLAB code. The simulation results were extracted from ABAQUS/Explicit and entered into MATLAB. Based on the algorithm and the previous simulation results, a new parameter set was calculated. Tab. 4 shows the specifications of the computer that has been used for the cutting simulations. Based on the approaches presented in Chapter 3, the computational time

of a single cutting simulation with a cutting time of $t_c = 0.02\ s$ was reduced from approximately 6 h to an average computational time of 1:41 h.

Tab. 4: Specification of the computer for the cutting simulations.

Memory	64 GB
CPU	Intel® Xeon® E5-2637 v2 @3.5 GHz
Parallelization method	Domain parallelization
No. of parallel domains	16

6 OPTIMIZATON OF MATERIAL PARAMETERS BY MEANS OF THE DOWNHILL-SIMPLEX ALGORITHM

In this study, the Down-Hill-Simplex algorithm was used to optimize the three Johnson-Cook parameters m, n, and C. Since the Downhill-Simplex algorithm requires n+1 vertices, an 4D-simplex has been defined. To evaluate the Downhill-Simplex algorithm for the material parameter optimization, two different approaches were conducted: In the first approach, the initial simplex was defined by parameters that were relatively close to the target parameter set S_0. Additionally, the value ranges of the three parameters to be re-identified were set in a small range to $m_{T1} \in [0.25, 0.75]$, $n_{T1} \in [0.1, 0.5]$, and $C_{T1} \in [0.01, 0.2]$. In contrast, for the second approach, the initial simplex was defined by parameter sets that deviated more from the target parameter set S_0 as it was the case for the first approach. The value ranges were larger than in the first approach, too: $m_{T2} \in [0.1, 1]$, $n_{T2} \in [0.1, 1]$, and $C_{T2} \in [0.01, 0.5]$. For both approaches, the target value of Equation (4) was set to $r \leq 1$ %.

When using the Downhill-Simplex algorithm the operators reflection and expansion could calculate a parameter, which's value is not within the predefined value range. In this case, the value was manually set to the interval boundary that was overstepped.

Approach 1:

For the re-identification of the target parameter set S_0 using the first approach, the error value decreased rapidly with increasing number of iterations. The development of the error value over the number of iterations is shown in Fig. 4 by the dark blue dots. Individual outlier of the error values, as it is the case for iteration 6 and 9, can be attributed to the algorithm's operator reflection and expansion.

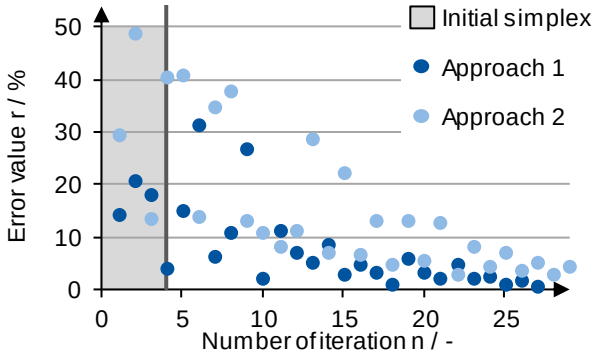
For the first approach, the algorithm was successfully completed after 27 iterations, since the error value undercut the predefined value with $r_1 = 0.7$ %. In comparison to the results of the target parameter set, the determined parameter set deviated by 0.95 % for the cutting force, -0.54 % for the chip thickness, and 0.39 % in terms of the temperature. When comparing the target parameter set $S_0 = \{0.631, 0.25, 0.027\}$ with the determined parameter set from the first approach $S_{1,27} = \{0.359, 0.3782, 0.0618\}$ the deviations are obvious. This shows, that there is no uniqueness of Johnson-Cook parameters when evaluating the cutting force, chip thickness and cutting temperature for just one cutting condition.

The deviations of the parameter sets are attributed firstly to the way the algorithm works. If the simplex underlying the algorithm approaches a local minimum, it may happen that the simplex no longer breaks out of the local minimum and thus no longer approaches the global minimum. This problem could be avoided, or at least be improved, by selecting other parameters describing the operators of the Downhill-Simplex algorithm. Secondly, the remaining deviations can be attributed to numerical deviations and uncertainties when measuring the chip thickness.

Approach 2:

For the second approach, the criteria to undercut the error value of r = 1 % was not reached within 30 iterations. The smallest deviation between the results from the initial parameter set and the set calculated by the algorithm was r = 2.73 %. Nevertheless, with the algorithm it was possible to reduce the deviation from the initial parameter sets, defining the initial simplex, significantly within an acceptable number of iterations. The error value is expected to decrease further for additional iterations.

During the iteration of the second approach, the algorithm calculated a parameter set after 12 iterations close to the target set. For small deviations of the material parameters, however, there were large deviations for the set $S_{2,12} = \{0.625, 0.35, 0.02\}$ with regard to the validation variables. Thus, the algorithm neglected the calculated parameter set since the other parameter sets of the simplex resulted in a smaller deviation. The challenge of using the Downhill-Simplex algorithm for material parameter identification is obviously: the identification of the global minimum cannot be guaranteed.



Initial sets test 1:	Initial sets test 2:
$S_{1,1} = \{0.3, 0.4, 0.05\}$	$S_{2,1} = \{0.15, 0.8, 0.12\}$
$S_{1,2} = \{0.4, 0.45, 0.1\}$	$S_{2,2} = \{0.9, 0.4, 0.08\}$
$S_{1,3} = \{0.5, 0.35, 0.075\}$	$S_{2,3} = \{0.5, 0.2, 0.04\}$
$S_{1,4} = \{0.4, 0.3, 0.065\}$	$S_{2,4} = \{0.75, 0.5, 0.04\}$

Fig. 4: Deviation of the error value for the two presented approaches over the number of iterations.

Since the computational time is not just a crucial factor for simulations, but also for iterative methods like the inverse determination of material model parameters, the computational time has to be evaluated. In this study the total computational effort for the first approach totals up to 45 h. Since the evaluation of the simulation results is not yet fully automatized, additional time was needed for the analysis of the simulation results and for the data transfer between MATLAB and ABAQUS.

7 SUMMARY AND OUTLOOK

The algorithm-based procedure to determine material parameters from metal cutting simulations showed to be a capable way to improve the procedure for the inverse parameter identification. Compared to the conventional iterative procedure, the use of the Downhill-Simplex algorithm can reduce the computational time and enhance the reliability of the determination of the model parameters. However, the computational effort to improve the model

parameters until the predefined criteria was reached is still high. Due to the computational effort, the optimization process for the second approach was terminated after reaching a number of 30 iterations. It is expected, that the choice of the initial parameter sets, as well as the range of values of the parameters, has a major influence on the results, and therefore on the computational effort. This influence as well as the influence of the parameters of the Downhill-Simplex algorithm will be investigated in the future.

The results of the first approach using the Downhill-Simplex algorithm showed that there is no uniqueness of parameter sets when just one cutting condition is considered. The uniqueness of model parameters will be further investigated in the future by taking multiple cutting conditions and additional validation results (e.g. passive force) into account.

8 AKNOWLEDGEMENTS

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