A new method to determine material parameters from machining simulations using inverse identification

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Abstract

Realistic simulations of machining processes require a correct description of the material behaviour. Due to the large strains and strain rates in the shear zone, the conditions during machining are difficult to reproduce in material testing so that extrapolation from testing data is often necessary. One way to circumvent this problem is to use inverse identification methods and to match machining simulations with experiments by varying the material parameters.

The inverse identification process, however, is time-consuming because standard optimisation methods like evolutionary algorithms or Newton methods usually need a large number of finite element simulations. In this contribution, we use a new parameter identification method to identify Johnson-Cook material parameters from machining simulations. Target simulations with known parameters are used instead of experimental results since material parameters can be varied. The method is able to correctly reproduce the target simulations for different target materials with a small number of FEM simulations, identifying five parameters of the Johnson-Cook law.

1. Introduction

To successfully simulate machining processes, the material behaviour must be described correctly. However, it is difficult to correctly determine material parameters under the conditions encountered in machining because strains can exceed 200% and strain rates may be of the order of 10^6 /s if cutting speeds are high. These conditions cannot be reproduced with standard testing methods. It is of course possible to measure material parameters at lower strains and strain rates, but the required extrapolation then assumes that the flow stress law used is valid in a very wide range of conditions.

One possibility to circumvent this problem is to use the machining process itself to determine material parameters [1]. An inverse parameter identification method can be used, varying the material parameters until agreement between predicted and observed quantities (like cutting force or shear angle) is reached. This method requires the ability to predict observables from a set of material parameters. This can be done using models of the machining process (see, for example [1,2]). These models, however, are not easy to implement, especially if the chip formation process is complicated, for example by chip segmentation. One alternative approach is to use finite element models to predict the observables, but standard inverse identification methods (like evolutionary or swarm algorithms [3] or gradient-based methods [4]) require a large number of iterations and thus a large number of finite element simulations. Therefore, this method has seldomly been used in the past.

Recently, a new method to determine material parameters with an inverse method has been proposed that needs only a comparatively small number of finite element simulations to correctly determine material parameters [5]. This new method uses intermediate quantities, called descriptors, to implement physical knowledge of the relation between experimentally observable quantities and material parameters. The method has been demonstrated for simple test cases (forging of a plastic material and indentation of a hyperelastic material). In this contribution, the method is applied to the parameter identification in a machining process.

The final goal of any parameter identification method is of course to determine parameters from experiments. In this paper, however, simulations have been used to provide the target values. There are three reasons for this: (i) using simulations ensures that there actually is a parameter set that can faithfully reproduce the target values; (ii) if experimental values were used, it would be difficult to see whether problems in identification are due to a problem of the algorithm itself or to the fact that the material law (or the friction coefficient or other...
conditions) is not suitable to describe the material, so that evaluating the performance of the method itself is difficult; (iii) the target material parameters can be varied in a wide range without problems to test the robustness of the algorithm.

| Nomenclature |
|---------------|
| $\alpha$ | Ratio of yield stress to hardening |
| $A$ | Yield stress |
| $B$ | Hardening prefactor |
| $c$ | Mean slope of stress-strain curve set |
| $C$ | Strain rate dependence |
| $\varepsilon$ | Strain |
| $\dot{\varepsilon}$ | Strain rate |
| $\varepsilon_0$ | Reference strain rate |
| $F$ | Cutting force |
| $k$ | Material point number |
| $m$ | Temperature exponent |
| $n$ | Hardening exponent |
| $p$ | Set of material parameters |
| $q$ | Johnson-Cook prefactor |
| $\sigma$ | Stress |
| $\sigma_0$ | Hardening exponent |
| $T_{\text{melt}}$ | Melting temperature |
| $T_{\text{ref}}$ | Reference temperature |
| $v_c$ | Cutting speed |
| $V_i$ | Material point volume |
| $W$ | Work |

After a brief introduction of the finite element model used for the calculation, the method and its adaptation to a machining problem are explained. The method is then employed for a set of 12 different identification tasks (three target sets with four initial values each). It is shown to be able to predict material parameter sets that yield machining results very close to the target set. However, it is also shown that this does not always mean that the material parameters themselves are identified because different material parameters can lead to almost identical chip shapes and cutting forces (see also [6]).

2. FE model

An explicit finite-element model was created using a python script in Abaqus [7], see Fig. 1, allowing to change the rake angle and cutting speed. The mesh was intentionally chosen to be coarse in order to keep CPU times small since this study is not directly concerned with detailed modelling of the chip formation process, but rather with proving the feasibility of the identification algorithm. The model was three-dimensional to allow the use of the generalised contact feature in Abaqus; however, the number of elements in the third dimension was set to 1, and movement in this direction was constrained so that the model was effectively a plane strain model. Coulombian friction between tool and work piece was assumed with a friction coefficient of 0.2. This value is at the lower end of the range given as typical in [8], but is higher than that found when using coated tools [9] and thus seems a reasonable choice. The tool was modelled as a rigid surface without any thermal properties to keep CPU times low.

The material model used was a standard Johnson-Cook law for the flow stress $\sigma$ as function of strain $\varepsilon$, strain rate $\dot{\varepsilon}$, and temperature $T$, written as

$$\sigma = q (1 + \alpha \varepsilon) (1 + C \ln \dot{\varepsilon}/\dot{\varepsilon}_0) \left(1 + \frac{T - T_{\text{ref}}}{T_{\text{melt}} - T_{\text{ref}}} \right)^m, \quad (1)$$

where $q$ is the overall flow stress, $\alpha$ is the ratio of initial yield stress to the strain hardening, $n$ is the hardening exponent, $C$ is the strain rate hardening factor, $\varepsilon_0$ is the reference strain rate (chosen as 3 300/s), $T_{\text{ref}}$ is the reference temperature (chosen to be 0°C), and $T_{\text{melt}}$ is the melting temperature. Usually, the first term is written in the equivalent form $(A + B \varepsilon^n)$; the form used here is more convenient because there is only one variable that sets the overall stress level. The Taylor-Quinney coefficient (the amount of plastic work converted to heat) was set to 0.9.

Elements were allowed to fail (and were deleted upon failure) if they were cut by the tool tip when their strain increased a critical value of 1.2. (Since only an element that is directly cut by the tool is allowed to fail, the exact value of the critical strain does not strongly affect the simulation result.)

The simulation time was adapted to the cutting speed so that a cutting length of ten times the cutting depth was simulated. After this time, the cutting force and the shear angle reached a stationary value. Forces and shear angles were averaged over the final ten frames of the simulation.

3. Identification algorithm

On trying to re-identify a given set of Johnson-Cook parameters using machining simulations, it cannot be expected that the original parameters will always be found with a small error, even if the identification is successful. The reason for this is that different Johnson-Cook parameters can produce chip shapes and cutting forces that are almost indistinguishable, as shown in [6]. This can already be seen by only looking at the term $A + B \varepsilon^n$, using, for example, the parameter values $(130, 100, 0.5)$.
and (100, 130, 0.3) for \((A, B, n)\). For strains between 0 and 1.5, the resulting curves are very close, differing by less than 6 MPa, except at very small strains, see Fig. 2. Even the parameter set \((163, 65, 0.7)\) yields similar stresses except at small strains. The chip formation process is more sensitive to the overall shape of the stress-strain curve, but not to the details of the curve in a small strain region, so that these different flow stress laws will lead to very similar chips. In addition, strain hardening may also be compensated by increased thermal softening. Thus, a perfect identification cannot always be expected and the only valid criterion to judge whether an identification was successful is good agreement of the observable quantities like cutting forces or shear angles.

### 3.1. Idea of algorithm

Usually, inverse identification algorithms consider the process itself as a “black box” – observables are calculated from material parameters, but no physical knowledge about the correlation between the observables and the material parameters is employed. If a finite element model is involved, the material parameters are changed in the simulation and the resulting observables (for example, cutting forces) are calculated. The basic idea of the new method is to use the physical knowledge of the process to improve the identification process.

The following example illustrates the idea: Consider the mean cutting force (in forming a continuous chip) as an observable quantity that is to be matched to a target value. Start with a given set of material parameters and calculate the resulting cutting force. Each material point in the FEM simulation deforms given a set of material parameters and calculate the resulting cuttable quantity that is to be matched to a target value. Start with a mean cutting force (in forming a continuous chip) as an observable quantity that is to be matched to a target value. Start with a

\[ W_{\text{current}} = \sum \int \sigma(p_{\text{current}}; \epsilon, T, \dot{\epsilon}, \ldots) \, dV_k. \quad (2) \]

where \(W_{\text{current}}\) is the current work, \(k\) denotes the material points with corresponding volume \(V_k\), \(\epsilon\) is the equivalent plastic strain and \(\sigma\) denotes the flow stress as function of the current material parameters \(p_{\text{current}}\) of the strain, and other variables like temperature \(T\) and strain rate \(\dot{\epsilon}\). In a stationary process, this work is proportional to the cutting force. Thus, if the current cutting force \(F_{\text{current}}\) is too small by a certain factor (compared to the target value \(F_{\text{target}}\)), the total area under the stress-strains curves of the material points should be increased by this factor:

\[ W_{\text{new}} = W_{\text{current}} \frac{F_{\text{target}}}{F_{\text{current}}}. \quad (3) \]

The stress-strain curves in eq. (2) thus should be changed so that the work is equal to \(W_{\text{new}}\).

To first order, the effect of a change in material parameters on the flow stress can be calculated by assuming that \(T\) and \(\dot{\epsilon}\) are not affected. Thus, the improved material parameter set \(p_{\text{new}}\) should fulfill the following equation:

\[ W_{\text{new}} = \sum \int \sigma(p_{\text{new}}; \epsilon, T, \dot{\epsilon}, \ldots) \, dV_k. \quad (4) \]

This equation yields one condition for the new parameter set. Although the equation is implicit in \(p_{\text{new}}\), it can be solved by inverse iteration methods without a finite element simulation. The problem of identifying material parameters is thus split into two parts: (i) calculating new quantities for variables that can be related to the material parameters as in eq. (3) (these variables, e.g. the work done, are called descriptors) and (ii) calculate a new set of material parameters that match these descriptors. Descriptors are calculated in the finite element model and need not to be observable experimentally, but they are assumed to be related to experimentally observable variables as in equation (5). These observables are called proxies.

### 3.2. Descriptors for machining

As described in the previous section, the total work done can be related to the area under the stress-strain curve of material points. In a realistic machining process, part of the work done by the tool is dissipated by friction, but as long as the work is dominated by the plastic work, the method should still converge, as shown for other examples in [5].

As shown in eq. (4), each descriptor provides one implicit equation to determine the material parameters. In principle, one could use the cutting force five of different cutting experiments (with varying cutting speed or rake angle) to set five conditions on the material parameters. However, the cutting force itself is often not very sensitive to a change in material parameters because an increase in hardening causes an increase in temperature with subsequent thermal softening [10].

The shear angle is another observable quantity that can be measured experimentally (using the chip compression of a continuous chip [11]). It is well-known [1] that the shear angle decreases with increasing hardening of the material. Since the stress-strain history is stored in the finite element model at each material point, effective stress-strain curves can be used to calculated a mean slope \(c\), see figure 3. Since the slope can change its sign if the material softens, it is converted to a number that is always positive by calculating \(\exp \left( -c / \bar{\sigma} \right)\), where \(\bar{\sigma}\) is the mean stress of all stress-strain curves in the strain interval considered.
3.3. Improvements of the algorithm

The basic idea of the algorithm was explained in section 3.1 and in [5]. In equation (3) it was assumed that the proxy and the descriptor (for example the cutting force and the plastic work done) are proportional. This assumption can be improved after several iterations of the algorithm have been performed because values for descriptors and proxies are then known. Therefore, instead of simply using a proportional scaling, the already known descriptor-proxy pairs can be fitted with a linear function and the new value of the descriptor can be calculated using this function. This is especially helpful if friction is present because there will always be an offset between the cutting force and the amount of plastic work due to dissipation.

A second improvement has been made with respect to the prediction of the material behaviour when parameters are changed: A change in the flow stress will also affect the temperature field. If the process were adiabatic, this change could be calculated directly from the flow stress; however, at lower cutting speeds this is not true. Therefore, in each finite element simulation, an adiabaticity parameter is calculated at each time step and each material point that is defined as the ratio of the actual temperature change to the change expected if the process were adiabatic. This parameter is then used in re-calculating the descriptors as in eq. (4).

3.4. Finding parameters from descriptors

As explained at the beginning of this section, the relation between material parameters and observable quantities in machining (proxies) cannot always be assumed to be unique. This may cause problems in trying to identify material parameters from the descriptors (i.e., solving eq. (4)) because inverse identification algorithms may get stuck in a local minimum of the fitness landscape.

To alleviate this problem, a rather complex method was used to identify material parameters from descriptors by only changing some material parameters at any given time. The method was again based on the understanding of how different material properties affect the descriptors and proxies. For example, if the cutting force is underestimated at low cutting speeds and overestimated at high cutting speeds (or vice versa) at the same rake angle, it can be assumed that m or C need to be adapted because both change the rate dependence of the force (the parameter C directly, the parameter m because at higher speeds the process is more adiabatic and thus thermal softening increases). Similarly, the shear angle is mostly affected by the hardening parameter n.

To find parameters in the suboptimisation problem, a Fletcher-Reeves conjugate gradient method and a Broyden-Fletcher-Goldfarb-Shannon algorithm [4] were used in alternation. If these methods did not lead to success, an evolutionary method [12] was used.

Due to space restrictions and because this part of the algorithm does not affect the overall method (in principle, an exhaustive search of parameter space could be performed because this part of the method does not involve performing finite element simulations), details of the identification algorithm are not presented here.

3.5. Overview of the algorithm

In summary, the algorithm proceeds as follows:

1. Target values for the proxies (cutting force and shear angles) are calculated using finite element simulations with given target parameters.
2. Start with an initial guess for the material parameters.
3. Do machining simulations with the current set of material parameters. Calculate proxies and descriptors. If convergence is achieved (current proxies and target proxies are sufficiently close), stop.
4. Calculate new descriptor values either by simple scaling as in eq. (3) (in the first iterations) or by using a linear fit (see section 3.3).
5. Calculate the new material parameter set for the new descriptors as explained in section 3.4. Go to step (3).

If any of the material parameters is calculated to be outside of the bounds listed in table 1, it is set to the upper or lower limiting value.

4. Results

The algorithm was tested not against experimental data, but against target simulations with different values of the material parameters. This has the advantage of being able to check how well material parameters have been identified and of avoiding problems due to other parameters that are difficult to ascertain.
experimentally (like the friction coefficient). To test the algorithm, three different sets of target parameters with four different starting values (listed in table 2) were performed. Each simulation step consisted of three finite element simulations with the following cutting conditions: (i) speed $v_i = 33$ m/s, rake angle $15^\circ$, (ii) $v_i = 5.0$ m/s, rake angle $15^\circ$, and (iii) $v_i = 33$ m/s, rake angle $-5^\circ$. For each simulation, the mean cutting force and the shear angle were calculated, resulting in six proxies that could be used for the optimisation.

To determine the quality of a material parameter set, the root mean square of the relative deviation between the current simulation and the target simulation was calculated. Convergence was assumed to be reached when this value becomes smaller than 3% because shear angle and cutting force [13] cannot be measured to higher precision in practice.

As shown in table 2, 10 out of 12 calculations reached the set error limit within less than 10 iterations and thus less than 10 sets of finite element simulations (each set consisting of three simulations for the three cutting parameter sets). Compared to gradient methods, where each iteration step requires $N+1$ FE simulations or to evolutionary methods, where usually populations consisting of several individuals evolve over dozens of generations, this is a rather small number of iterations and shows that the method is efficient.

One simulation converged only after 18 iterations; another one did not converge at all. In this latter simulation, all material parameters were estimated in the first step to lie outside the parameter range covered by the process does not affect the predictive value of the parameters.

Although the error is small in almost all cases after less than 10 iterations, the target parameters themselves have not been identified to high precision. This is due to the non-uniqueness already discussed in section 3. This can also be seen in the fourth run, which reached an error of 0.70% after 10 iterations but with strongly differing parameters, identifying (261.4 MPa, 0.581, 0.571, 0.888, 0.00789) for a target of (200 MPa, 0.5, 0.5, 1.5, 0.015). In general, the chip formation process is not very sensitive to the initial yield stress, so that the parameter $\alpha$ is difficult to determine. Similarly, high speed processes also lead to higher temperature, so that a correct simultaneous identification of $C$ and $m$ is also problematic.

This problem, however, is not a problem of the identification algorithm itself, but rather of the general task of identifying (Johnson-Cook) material parameters from machining experiments alone. It could be alleviated if additional experimental observables are available, for example the temperature of the chip, because this would allow to specify the amount of thermal softening. (To add this observable to the algorithm, the predicted temperature of the material points due to the deformation could be used as a descriptor.) However, since measuring the chip temperature reliably requires a rather large experimental effort.

On the other hand, the uniqueness problem may not be too severe in practice. If material parameters are found that can describe the material behaviour correctly for a wide range of cutting conditions, the non-uniqueness of these parameters that is basically due to a redundancy in the mathematical model in the parameter range covered by the process does not affect the predictive value of the parameters.

5. Conclusion and Outlook

A new method to determine material parameters directly from machining simulations was presented. The method requires only the knowledge of easily measurable experimental variables (cutting force and shear angle). It relies on physical knowledge of a relation between observable quantities (proxies) and parameters that can be used to describe the material behaviour (descriptors). In most cases, the new method requires only a small amount of finite element simulations to find material parameters that lead to good agreement of the observable quantities with the target values.

In the future, the method will be applied to observables directly obtained from experiments instead of target simulations. Furthermore, many materials form segmented chips, especially at high cutting speeds. Segmented chips offer additional proxies (like the degree of segmentation), although it may be difficult to find descriptors that can exploit detailed knowledge of these proxies.

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Table 2. Results of the parameter identification runs

| Target parameters | Initial parameters | Final parameters | Iter. |
|-------------------|--------------------|-----------------|-------|
| $q$ | $n$ | $m$ | $\alpha$ | $C$ | $q$ | $n$ | $m$ | $\alpha$ | $C$ | $q$ | $n$ | $m$ | $\alpha$ | $C$ | Iter. |
| 200 | 0.5 | 0.5 | 1.0 | 0.015 | 100 | 0.3 | 0.7 | 0.5 | 0.04 | 327.1 | 0.714 | 0.530 | 0.601 | 0.005 | 9 |
| 200 | 0.5 | 0.5 | 1.0 | 0.015 | 200 | 0.1 | 0.3 | 2.0 | 0.01 | 167.3 | 0.502 | 0.437 | 2.011 | 0.0225 | 3 |
| 200 | 0.5 | 0.5 | 1.0 | 0.015 | 500 | 0.7 | 0.8 | 0.5 | 0.01 | 315.3 | 0.652 | 0.781 | 0.499 | 0.005 | 6 |
| 200 | 0.5 | 0.5 | 1.0 | 0.015 | 500 | 0.8 | 0.1 | 0.2 | 0.0277 | 256.6 | 0.557 | 0.622 | 0.888 | 0.005 | 6 |
| 300 | 0.3 | 0.7 | 1.0 | 0.0277 | 100 | 0.3 | 0.7 | 0.5 | 0.04 | 435.4 | 0.528 | 0.555 | 0.514 | 0.0310 | 2 |
| 300 | 0.3 | 0.7 | 1.0 | 0.0277 | 200 | 0.1 | 0.3 | 2.0 | 0.01 | 249.2 | 0.298 | 0.455 | 1.983 | 0.0232 | 3 |
| 300 | 0.3 | 0.7 | 1.0 | 0.0277 | 500 | 0.7 | 0.8 | 0.5 | 0.01 | 425.5 | 0.503 | 0.602 | 0.539 | 0.0180 | 5 |
| 300 | 0.3 | 0.7 | 1.0 | 0.0277 | 500 | 0.8 | 0.1 | 0.2 | 0.0277 | no convergence |
| 400 | 0.7 | 0.2 | 0.5 | 0.02 | 100 | 0.3 | 0.7 | 0.5 | 0.04 | 616.6 | 0.743 | 0.105 | 0.571 | 0.0187 | 6 |
| 400 | 0.7 | 0.2 | 0.5 | 0.02 | 200 | 0.1 | 0.3 | 2.0 | 0.01 | 201.6 | 0.326 | 0.186 | 2.068 | 0.0334 | 7 |
| 400 | 0.7 | 0.2 | 0.5 | 0.02 | 500 | 0.7 | 0.8 | 0.5 | 0.01 | 441.6 | 0.564 | 0.152 | 0.653 | 0.0112 | 5 |
| 400 | 0.7 | 0.2 | 0.5 | 0.02 | 500 | 0.8 | 0.1 | 0.2 | 0.0277 | 248.7 | 0.378 | 0.120 | 1.280 | 0.0234 | 18 |

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