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JOHNSON-COOK PARAMETER IDENTIFICATION FROM MACHINING SIMULATIONS USING AN INVERSE METHOD

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Abstract. The Johnson-Cook model is a material model which has been widely used for simulating the chip formation processes. It is a simple 5 parameter material model which predicts the flow stress at large strains, strain-rates and at high temperatures. These parameters are usually identified by determining the flow stress curves experimentally, and then using curve fitting techniques to find the optimal parameters to describe the material behaviour. However the state-of-the-art experimental methods can only rely on data obtained from strains of up to 50% and strain-rates of the order of 10^3 per second, whereas in machining processes strains of more than 200% are reached at strain-rates of the order of 10^6 or more. Therefore, the parameters obtained at much milder conditions have limited applicability when simulating machining.

In this paper an inverse method of material parameter identification from machining simulations is described. It is shown that by using the observables of a machining process such as the chip shape and cutting forces, the underlying material parameters can be identified. In order to achieve this, a finite element model of the machining process is created and simulation is carried out using a known standard parameter set from literature. The objective of the inverse method is to reidentify this set by using the chip shape and cutting forces. An error function is created using the non-overlap area of the chip shapes and the difference in the cutting forces. The Levenberg-Marquardt algorithm is used to minimise the error function.

It has been shown before that multiple sets of Johnson-Cook parameter sets exist which might give rise to indistinguishable chip shapes and cutting forces. In order to identify the

parameter set uniquely, simulations are performed at widely varying cutting conditions such as differing rake angles, cutting speeds and non-adiabatic conditions. Thus, material parameters which represent the material behaviour over a wide range can be identified.

1 INTRODUCTION

In a conventional machining process the material from a workpiece is removed using a harder tool material. Simulation of the material removal process by machining has been extremely challenging due to the complex character of the process. The removed material undergoes large plastic deformation (strains of more than 200%), at very high strain rates ($\sim 10^6$ s^{-1} or more) and is accompanied by a temperature rise of hundreds of degrees in the deformation zone. A number of material models have been suggested which take into account the before mentioned issues. Identification of material parameters for such models is usually done by material tests at varying strains, strain rates and temperatures. Split Hopkinson Bar tests are widely used for conducting high strain rate tests. The data obtained from such tests are used for parameter identification using curve fitting techniques. However due to physical constraints the material is usually deformed only upto 50% of plastic strain and at strain rates of the order of $\sim 10^3$ - 10^4 s^{-1}. Therefore when simulating the chip formation process, strains and strain rates are extrapolated over several orders of magnitudes leading to erroneous simulation results.

The issue of material parameter determination for machining process has been addressed by different researchers. Jaspers and Dautzenberg [1] had proposed using Split Hopkinson Bar data for determining material parameters. However, the shortcomings of this method have been discussed in the previous paragraph. The approach of Tounsi et al.[2] and Shatla et al. [3] depends on using a theoretical model for estimating the material parameters. Howeve,r the problem with this approach is that theoretical models are difficult to verify under the extreme conditions of large strains, strain rates and high temperatures. Another problem in such an approach is that material parameters can be varied to obtain a good match between the simulation results and experiments for a particular set of cutting conditions. However, when the cutting conditions are varied widely, the results fail to match outside the domain where they have been explicitly matched.

In this paper a method for inverse determination of material parameters is proposed. In Section 2 the Johnson-Cook material model is briefly described. In Section 3 the inverse identification problem is explained along with the description of the error function to be minimised and the finite element model that is used. The results are presented in Section 4. Finally conclusions are drawn in Section 5 and the line of future work is also suggested.

2 JOHNSON-COOK MATERIAL MODEL

The Johnson-Cook Model [4] is a five parameter material model which is used to describe material behaviour over a large range of strains, strain rates and temperatures.

Due to its simplicity and the low number of free parameters, this model is widely used in machining simulations. The flow stress σ is expressed as

$$\sigma = \underbrace{(A + B\varepsilon^n)}_{Elasto-Plastic\ term} \underbrace{\left[1 + C \ln\left(\frac{\dot{\varepsilon}}{\dot{\varepsilon}_0}\right)\right]}_{Viscosity\ term} \underbrace{\left[1 - \left(\frac{T - T_{room}}{T_{melt} - T_{room}}\right)^m\right]}_{Thermal\ softening\ term} \tag{1}$$

where ε is the plastic strain, $\dot{\varepsilon}$ is the strain rate, $\dot{\varepsilon}_0$ is the reference strain rate. T is the temperature of the material, T_{melt} is the melting point of the material and T_{room} is the room temperature. The empirical constants are as follows: A is the yield stress, B is the pre-exponential factor, C is the strain rate factor, n is the work-hardening exponent and m is the thermal-softening exponent.

3 INVERSE IDENTIFICATION PROBLEM

The cutting force, chip shape, chip temperature etc are observables in a machining process. These quantities are a function of the material behaviour and the cutting conditions. Using finite element simulations and keeping the cutting conditions identical to the machining experiment, it might be possible to inversely determine the material parameters. In order to test this hypothesis, a standard material parameter set is inversely reidentified using machining simulations. A standard simulation is done using a material parameter set from literature and while keeping the cutting conditions constant, test simulations are carried out in order to identify the standard parameter set. This methodology was also adopted because this way it was possible to keep the cutting conditions the same in case of standard simulations and the test simulations.

The material parameters for the test simulations were systematically varied during the inverse identification process. The inverse identification was conducted in two stages where the goal is to minimise the error function which is expressed as a sum of squares of non-linear functions. In the first optimisation stage the Levenberg-Marquardt algorithm was used and the converged set from this stage is used as the starting set during the second stage for which the Simplex algorithm is used. In a Levenberg-Marquardt algorithm, the parameters are changed in the direction of the steepest descent which is determined by evaluating a Jacobian. The amount of variation in this direction is determined by a damping parameter which is reduced during the course of the optimisation process so as to have a faster convergence and is increased when close to the minimum so that the steps become smaller and the minimum is not overstepped. In case of the Simplex algorithm, a simplex crawls towards the minimum using a set of reflection, expansion, contraction and reduction steps. An exhaustive explanation of the two algorithms can be found in literature [5, 6, 7].

3.1 Error Function

The aggregate error function takes into account the chip shape and the cutting force. The area of non-overlap between two chips is used as a measure of the chip shape error. The difference in the cutting force between the standard case and the test case is the measure of the cutting force error. In order to find the chip shape error, the standard chip and the test chip are superimposed and the region of interest where non-overlap is to be found is bound by a window. This region is then discretised by a number of horizontal lines. The intersection of the horizontal lines with the chip outlines is found out which gives the length of the line intercepted between the chip outlines. Using the distance between the discretising lines and the intercepted length, the elemental area of non-overlap is found which is summed over all the elemental areas to give the chip overlap error (Figure 1). The chip overlap error and the cutting force error are combined using a weighting factor w, which is used to balance the contribution of the two factors in the overall optimisation, to give an aggregate error function $\phi_i(\mathbf{x})$ (Equation 2). The value of w used in this paper is $1/500\ \mathrm{mm}^2\,\mathrm{N}^{-1}$. The error function $\chi^2(\mathbf{x})$ is obtained by summing the square of the aggregate error functions over all the observations (Equation 3).

$$\phi_i(\mathbf{x}) = \left|e_i^A(\mathbf{x})\right| + w.\left|e_i^F(\mathbf{x})\right| \tag{2}$$

$$\chi^2(\mathbf{x}) = \frac{1}{2}\sum_{i=1}^{N}\phi_i^2(\mathbf{x}) = \frac{1}{2}\sum_{i=1}^{N}\left(\left|e_i^A(\mathbf{x})\right| + w.\left|e_i^F(\mathbf{x})\right|\right)^2 \tag{3}$$

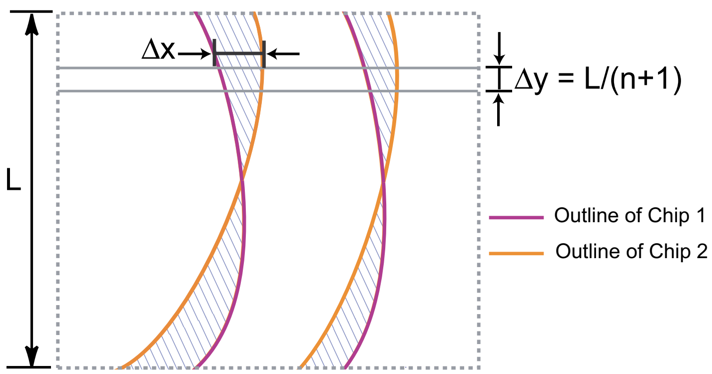


Figure 1: Estimation of chip overlap error. The region of interest is discretised by n lines.

3.2 Finite Element Model

The two-dimensional adiabatic finite element model for machining simulation was made using the commercial finite element software ABAQUS 6.9-1 and consisted of a rigid tool meshed with R2D2 elements and a workpiece meshed with four node CPE4R elements

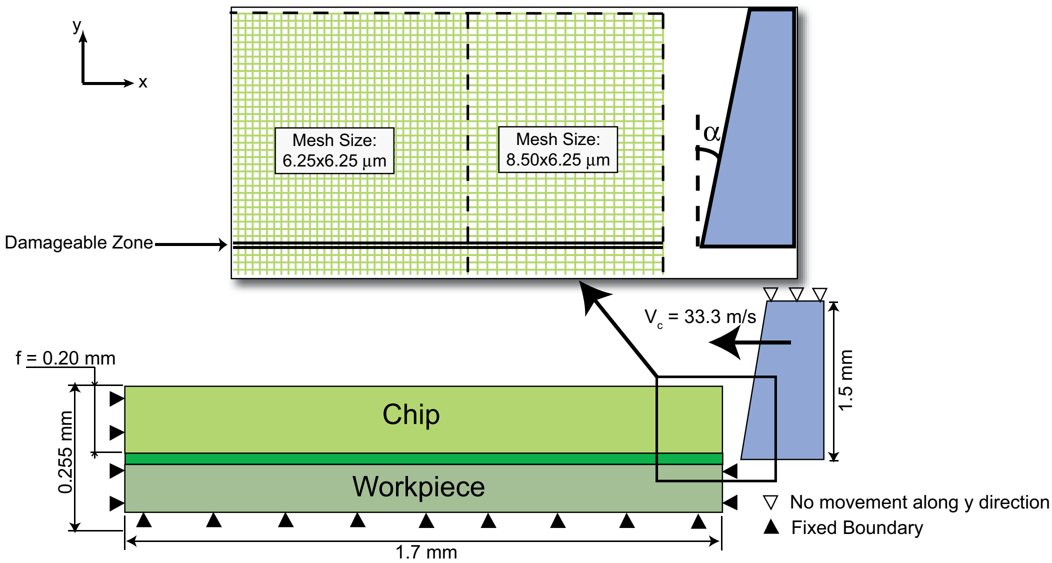


Figure 2: Finite Element Model showing the boundary conditions and the non uniform meshing

(Figure 2). The workpiece was partitioned into three regions such that the top region formed the chip, the bottom region the machined workpiece and the intermediate region comprised of damageable elements which were removed from the simulation after a critical shear strain of 2.0 is exceeded. The cutting speed is fixed at 33.3 m/s and the simulation is conducted for 0.040 ms during which 500 frames are recorded. Friction is neglected throughout the simulation. In order to ensure that the optimisation takes into account a wider range of cutting conditions, two different values of rake angles were used, viz. 1° and 10°. The material properties used for the simulation have been shown in Table 1 and Table 2. The thermal properties of the material have been taken from [8].

$$C_P = 92.78 + 0.7454T + \frac{12404 \times 10^3}{T^2} \mathrm{J\,kg^{-1}\,K^{-1}} \tag{4}$$

Table 1: Material properties for HY 100 steel [9, 10, 11]

Density [$\mathrm{kg\,m^{-3}}$]	7860
Young's Modulus [GPa]	205
Poisson's Ratio	0.28

Table 2: Johnson-Cook parameters for HY 100 steel [9, 10, 11] used in the standard simulation

A [MPa]	B [MPa]	C	m	n	T_{melt} [K]	T_{room} [K]	$\dot{\varepsilon}_0$ [$\mathrm{s^{-1}}$]
316	1067	0.0277	0.7	0.107	1500	300	3300

The elements on the workpiece after coming in contact initially with the tool get badly crushed thereby reducing the characteristic length of such elements. This in turn reduces the stable time increment and thus increases the total simulation time. As a solution to this problem, the first 10% length of the workpiece is meshed with rectangular elements of dimensions 8.5 × 6.25 µm. The rest of the workpiece is meshed with square elements of dimensions 6.25 × 6.25 µm. The workpiece is finely meshed with 32 elements across the uncut chip thickness. A C++ code is written to read the deformed chip shape coordinates and the cutting force values. The values thus obtained are used with the minimisation algorithms which are available in the GNU Scientific Library [12]. From the two simulations which are conducted for the different rake angle values 15 observations, from frames 486 to 500, are taken from each to evaluate the error function.

4 RESULTS AND DISCUSSIONS

In order to keep the problem moderately difficult, only 3 Johnson-Cook parameters, viz. A, B and n, are reidentified. Three different starting parameter sets are chosen for inverse identification. The first set is reasonably close to the standard parameter set, the second and the third sets are far from the standard parameter set (refer Table 3).

Table 3: Standard and Starting parameter sets

	A	B	n
Standard Set	316	1067	0.107
Starting Set Case 1	250	900	0.020
Starting Set Case 2	800	50	0.400
Starting Set Case 3	50	50	0.400

For the first stage of optimisation the Levenberg-Marquardt algorithm is chosen as it gives faster convergence towards the standard set. Transformed optimisation parameters are used as they were found to give better convergence [13].

4.1 Optimisation parameters

During a high speed machining process the material heats up due to the plastic work done. Since the process is very fast, the heat cannot be conducted away from the shear zone sufficiently quickly. The effective material behaviour due to the continuous heating of the material can be expressed by using adiabatic stress-strain curves, which can be drawn after taking into account the adiabatic heating of the material. The adiabatic stress-strain curves can be used to explain the chip formation process [14] and therefore they can also aid in determining the optimisation parameters for inverse determination.

Johnson-Cook parameters A and B can be varied from the standard values A_s and B_s in order to estimate the deviations between the corresponding adiabatic stress-strain

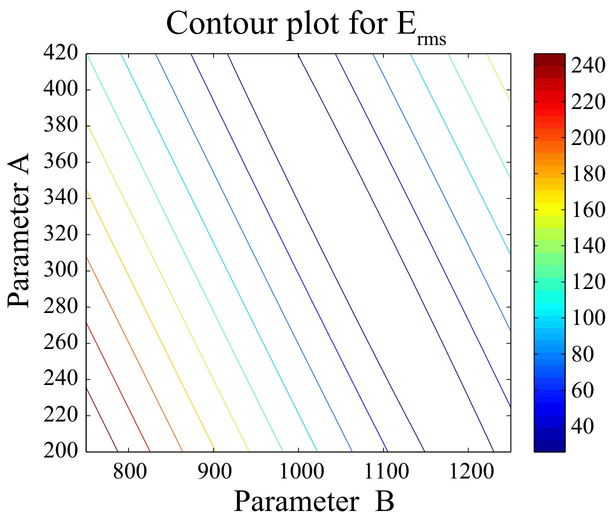


Figure 3: Contour plot for E_{rms}

curves. The root mean squared error (Equation 5) between the curves expressed as

$$E_{rms}(A, B) = \frac{||\sigma_{adia}(A, B) - \sigma_{adia}(A_s, B_s)||}{\sqrt{M}} \tag{5}$$

is a measure of such deviations. Here $\sigma_{adia}(A, B)$ is the set of points lying on the adiabatic stress-strain curve from parameters A and B, A_s and B_s are the target Johnson-Cook parameters and M is the total number of points. $|| \bullet ||$ is the Euclidean norm.

On plotting E_{rms} w.r.t parameters A and B, a valley containing the minimum is seen to run in the direction of $(A - B)$ (Figure 3). Consequently the direction $(A + B)$ is the direction of steepest ascent. New parameters K and L are defined such that

$$K = A + B \tag{6a}$$
$$L = A - B \tag{6b}$$

Using the transformed parameters (Equations 6a and 6b), the Johnson-Cook equation can be rewritten as

$$\sigma = \left(\frac{K + L}{2} + \frac{K - L}{2} \varepsilon^n \right) f(\dot{\varepsilon}, T) \tag{7}$$

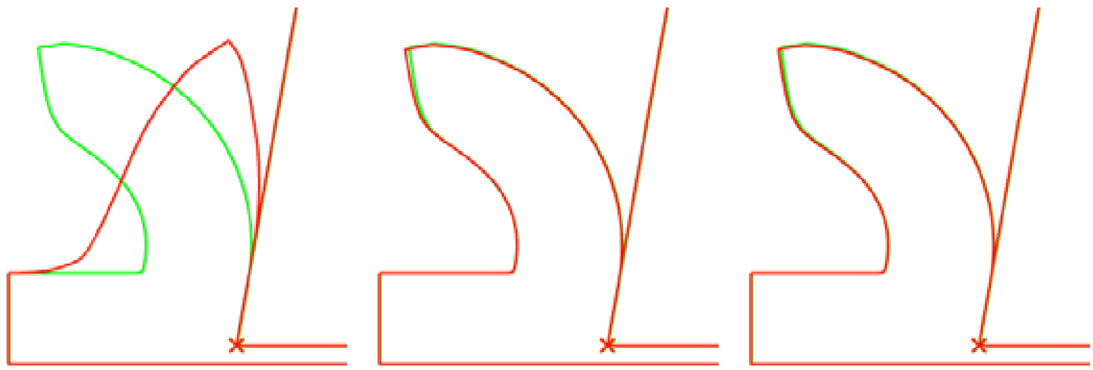
where

$$f(\dot{\varepsilon}, T) = \left[1 + C \ln \left(\frac{\dot{\varepsilon}}{\dot{\varepsilon}_0} \right) \right] \left[1 - \left(\frac{T - T_{room}}{T_{melt} - T_{room}} \right)^m \right] \tag{8}$$

The effectiveness of using such modified optimisation parameters has been shown in earlier papers [13, 15].

4.2 Simulation results

The starting parameter sets for the inverse identification have been shown in Table 3. In the first stage of optimisation Levenberg-Marquardt algorithm was used. The initial chip shapes and cutting forces are different from the standard chip shapes and cutting forces (specially in Case 3). The chip shapes at the end of each optimisation stage has been shown in Figure 4 and Figure 5. The standard chip is represented in green and the test chip in red. At the end of the first stage the chip shapes (Figure 4(a), 4(b) and 5(a), 5(b)) and cutting forces (Figure 6(a) and 6(b)) show substantial improvement. This was found to work consistently well with all the three cases. The test adiabatic stress-strain curves are also seen to come closer towards the standard adiabatic stress-strain curve (Figure 7(a), 7(b) and 7(c)). At the end of the first stage the solution could not be further improved by using the Levenberg-Marquardt algorithm.



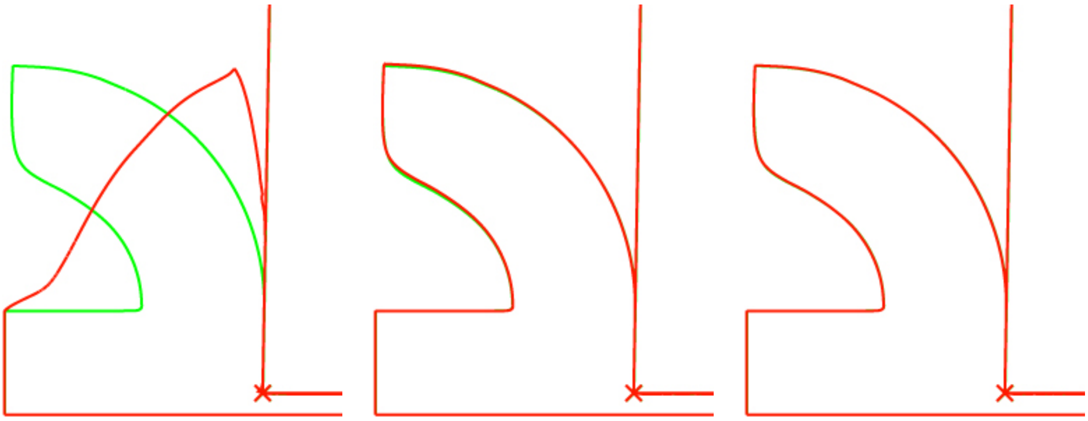
(a) Starting set (b) Stage 1 (c) Stage 2

Figure 4: Chip shapes (rake +10°) at different stages of optimisation for Case 3

In order to further improve the solution and checking the feasibility of reidentifying the parameters robustly, a second stage of optimisation was carried out using the downhill simplex algorithm. At the end of the optimisation, the chip shapes (refer Figure 4(c) and 5(c)), the cutting forces and the adiabatic stress-strain curves were found to match exactly (Figure 7(a), 7(b), 7(c)). Despite having a near perfect match of chip shapes, cutting forces and adiabatic stress-strain curves, the converged Johnson-Cook parameter sets are not unique [16]. Some non-unique parameter sets can be eliminated by using wide ranges of cutting conditions.

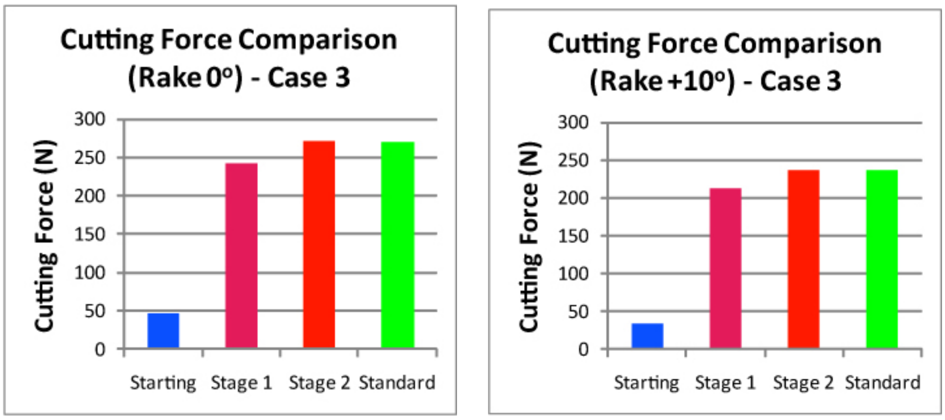
5 CONCLUSION

In this paper a two stage inverse material parameter determination method was discussed. An error function was defined by taking into account the chip shape and the cutting force. Levenberg-Marquardt and Downhill Simplex methods were used for the minimisation of the error function. The two stage optimisation process is found to be



(a) Starting set (b) Stage 1 (c) Stage 2

Figure 5: Chip shapes (rake 0°) at different stages of optimisation for Case 3

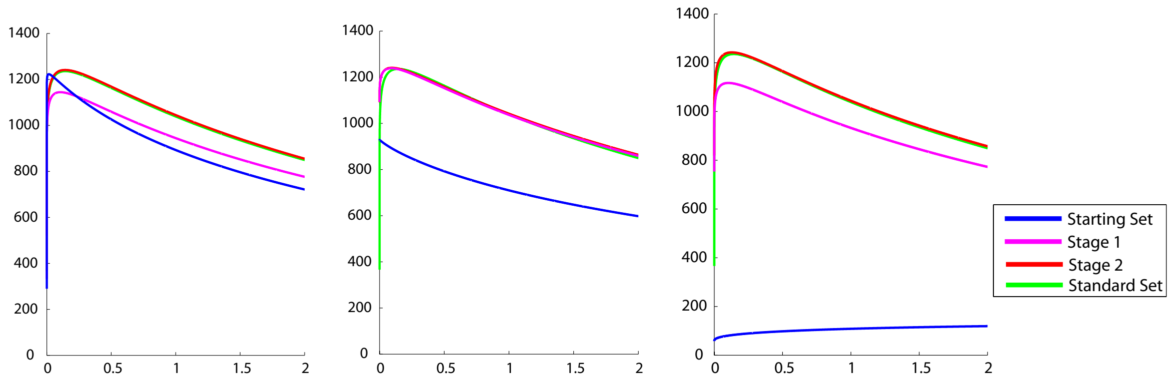


(a) Rake angle = 0° (b) Rake angle = 10°

Figure 6: Cutting force at the end of different stages of optimisation

Table 4: Converged parameter sets at the end of stage 1 and stage 2

	Case 1			Case 2			Case 3		
	A	B	n	A	B	n	A	B	n
Stage 1	287.11	935.36	0.080	943.6	435.6	0.306	650.6	549.3	0.151
Stage 2	449.4	943.9	0.126	942.4	445.3	0.309	707.7	684.4	0.180



(a) Case 1 (b) Case 2 (c) Case 3

Figure 7: Adiabatic stress-strain curves at different stages of optimisation

robust as the original chip shape and cutting force can be reidentified after starting from substantially different initial parameter sets. It is also observed that after optimisation, the adiabatic stress-strain curve of the converged parameter set matches that of the standard parameter set. It was also observed that the converged parameter sets were not unique.

Thus using inverse identification techniques, it is possible to identify material parameters. In order to eliminate some of the non-unique parameter sets, the cutting conditions must be varied widely. Further work must be done in order to find the good search directions which lead to quicker identification of material parameters. Such improved optimisation strategies can substantially reduce the computational costs.

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REFERENCES

[1] Jaspers, S. P. F. C., Dautzenberg, J. H., Material behaviour in conditions similar to metal cutting: flow stress in the primary shear zone, *Journal of Materials Processing Technology*, (2002), **122**, Issues 2-3, pp 322-330.

[2] Tounsi, N., Vincenti, J., Otho, A., Elbestawi, M. A., From the basic mechanics of orthogonal metal cutting toward the identification of the constitutive equation, *International Journal of Machine Tools and Manufacture*, (2002), **42**, Issue 12, September 2002, pp. 1373-1383.

[3] Shatla, M., Kerk, C., Altan, T., Process modeling in machining. Part I: determination of flow stress data, *International Journal of Machine Tools and Manufacture*, (2001),

41, Issue 10, Pages 1511-1534.

[4] Johnson, G.R., Cook, W.H., A constitutive model and data for metals subjected to large strains, high strain rates and high temperatures, *In: 7th International Symposium on Ballistics* (1983), p. 514.

[5] Levenberg, K., A method for the solution of certain nonlinear problems in least squares, *The Quarterly of Applied Mathematics*, (1944), **2**, p. 164.

[6] Marquardt, D., An algorithm for least-squares estimation of nonlinear parameters,*Journal of the Society for Industrial and Applied Mathematics*, (1963),**11**, No. 2., p. 431.

[7] Nelder, J. A. and Mead, R., A Simplex Method for Function Minimization, *The Computer Journal*, (1965), **7**, pp. 308-313.

[8] Taljat, B.,Radhakrishnan, B., Zacharia, T., Numerical Analysis of GTA Welding Process with Emphasis on Post-Solidification Phase Transformation Effects on Residual Stresses *Materials Science and Engineering A*, (1998) **246**, Issues 1-2, p. 45.

[9] Batra, R.C., Kim, C.H., Effect of viscoplastic flow rules on the initiation and growth of shear bands at high strain rates, *Journal of the Mechanics and Physics of Solids*, (1990) **38**, Issue 6, p. 859.

[10] Goto, D.M., Bingert, J.F., Chen, S.R., Gray, G.T., Garrett, R.K., The Mechanical Threshold Stress Constitutive-Strength. Model Description of HY-100 Steel, *Metallurgical and Materials Transactions A*, (2000), **31**, issue 8, p. 1985.

[11] Durrenberger, L., Molinari, A., The Mechanical Threshold Stress Constitutive-Strength. Model Description of HY-100 Steel, *Experimental Mechanics*, (2009), **49**, Issue 2 , p. 247.

[12] Press, W.H., Teukolsky, S.A., Vetterling, W.T., Flannery, B. P., *Numerical recipes in C (2nd ed.): the art of scientific computing* (1992), Cambridge University Press, New York, USA.

[13] Shrot, A. and Bäker, M., How To Identify Johnson-Cook Parameters From Machining Simulations, *AIP Conference Proceedings*, (2011), **1353**, pp. 29-34.

[14] Bäker, M. *Finite Element Simulation of Chip Formation*, (2004), Shaker Verlag, Aachen.

[15] Shrot, A. and Bäker, M., Inverse Identification of Johnson-Cook Material Parameters from Machining Simulations, *Advanced Materials Research*, (2011),**223**, pp. 277-285.

[16] Shrot, A. and Bäker, M., Is it possible to identify Johnson-Cook law parameters from machining simulations?,*International Journal of Material Forming*, (2010),**3**, No. 0., p. 443.