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Abstract

Finite element simulation of metal machining requires accurate constitutive models to characterize the material stressstrain response in plastic deformation processes. An optimization methodology using genetic algorithms was developed to determine the Johnson–Cook material model for Ti–6Al–4V alloy. The optimization of the parameters resulted in lower errors between the calculated flow stress and the experimental values obtained through the split Hopkinson pressure bar tests at different temperatures (ranging from 25 °C to 900 °C) and strain rates (2000 and 2500s⁻¹). Optimized Johnson–Cook constitutive parameters were used to calculate the flow stress under various conditions. The calculated results showed excellent agreement with the experimental values, with errors lower than 4%. In addition, Ti–6Al–4V alloy orthogonal cutting experiments were carried out to validate the finite element simulation results. The experimental chip morphology was compared with the simulation results obtained by the optimized Johnson–Cook model (M2) and the original Johnson–Cook model (M1). The simulated results (including chip morphology and cutting force) were affected by the flow stress model. Comparison of the experimental and simulated results revealed that the optimized Johnson–Cook model can provide relatively good prediction results for the titanium alloy machining process, especially for chip morphology prediction.

Keywords

Titanium alloy, Johnson–Cook constitutive model, optimization, machining simulation

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Introduction

Titanium alloys have become popular materials in aerospace and medical industries because of their combined properties, such as high stiffness, low density, excellent corrosion and oxidation resistance.¹ Titanium alloys are difficult-to-machine materials because of the high flow stress at elevated temperatures and the sensitivity of these materials to the processing parameters of the forming process.² Therefore, understanding the machining mechanics and improving machining efficiency have become increasingly important for the industrial application of titanium alloy. The finite element (FE) method has recently emerged as an essential modeling methodology because of its efficiency and usefulness to decrease the cost of experiments in machining. This method is also a convenient technique to acquire the machining parameters that are difficult

to obtain experimentally, such as stress, strain, temperature, etc. Metal cutting always involves large strain (1–10), high strain rate $(10^3-10^6 s^{-1})$ (Jaspers and Dautzenberg³) and a wide range of temperatures. A material constitutive equation plays a key role in characterizing the deformation behavior in machining. Several material models have been developed to determine the deformation behavior under high strain rate conditions. Cockroft and Latham⁴ developed the

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Chengzu Ren, Key Laboratory of Advanced Ceramic and Machining Technique (Tianjin University), Ministry of Education, Tianjin 300072, China. Email: renchz@tju.edu.cn Cockroft-Latham model according to the density of strain energy. Johnson and Cook⁵ presented the Johnson-Cook (J-C) model, considering the influence of strain, strain rate and temperature on flow stress. Zerilli and Armstrong⁶ developed the Zerilli-Armstrong model based on the dislocation mechanics theory. Recently, Calamaz et al.¹ presented the hyperbolic tangent (TANH) model considering the effect of strain softening. Some of these models are considered as semi-empirical constitutive models that are widely used in existing FE simulation of metal cutting processes.⁷ The material parameters of the J–C model, one of the most widely used models,8 are commonly obtained through split Hopkinson pressure bar (SHPB) tests. This experimental technique is commonly used to assess the deformation behavior at strain rates ranging from 10^2 s^{-1} to 10^4 s^{-1} , so the J–C model parameters obtained by SHPB tests can be applied to simulate machining processes under high strain rate conditions.

Many studies have applied the J–C model in machining simulation. Umbrello et al.¹⁰ used the J–C constitutive equation with different J–C parameters to simulate AISI 316L steel machining and found that the residual stresses are very sensitive to the J–C model parameters. Özel¹¹ applied the J–C model in a three-dimensional FE model to simulate the AISI 4340 turning process and investigated the influence of the micro-geometry edge on forces, stress and tool wear of polycrystalline cubic boron nitride (PCBN) inserts. Chen et al.¹² presented a ductile failure FE model based on the J–C constitutive model to simulate Ti–6Al–4V alloy high-speed machining.

The material parameters are crucial to the accuracy of the J–C model. The J–C parameters are usually fitted according to the strain–stress curves obtained through SHPB tests.¹³ Seo et al.⁹ determined the J–C parameters using SHPB tests at 1400 s⁻¹ strain rate and from room temperature to 1000 °C. Lee and Lin¹⁴ fitted J–C model parameters using SHPB tests to study the high-temperature deformation behavior of Ti–6Al– 4V alloy under different strain rates. However, the fitting method for the J–C model parameters was not discussed in the article. According to the study of Karpat,¹⁵ the flow stress calculated from the J–C model parameters listed in Lee and Lin¹⁴ do not agree very well with the experimental data at a strain rate of 800 s^{-1} and at room temperature.

Optimization technologies were developed to determine constitutive model parameters using various objective functions to assess the difference between experimental and computed data. Dusunceli et al.¹⁶ applied the genetic algorithm (GA) optimization technique to determine the parameters for the viscoplasticity model based on overstress (VBO model) by minimizing the errors between experimental and simulated stress. Besides, Cao and Lin¹⁷ developed an optimization technique focused on objective function to determine material constants in creep/viscoplastic constitutive equations based on experimental data. Similarly, Anaraki et al.¹⁸ presented an inverse method to determine the material constants for AZ61 magnesium alloy by minimizing the errors between calculated and experimental results.

Very few studies have focused on the optimization of constitutive model parameters under high strain rate conditions. Lin and Yang¹⁹ applied a GA-based multiobjective optimization technique to determine the viscoplastic constitutive equations for titanium alloy with low strain rates $(5 \times 10^{-5} - 1 \times 10^{-3} \text{ s}^{-1})$ at 927 °C. Recently, Özel and Karpat²⁰ applied the cooperative particle swarm optimization (CPSO) method to identify the J-C parameters by SHPB tests in Lee and Lin,²¹ considering the influence of different temperatures at a strain rate of 2000 s⁻¹. Although optimization techniques are currently widely used to obtain a material constitutive model, very few studies have reported on the application of model optimization results. As the J-C model is commonly applied to characterize the material deformation behavior in machining, it is necessary to use machining simulation to validate the optimized J-C constitutive parameters.

There is a similarity in the deformation behaviors of SHPB tests and machining under high strain rate conditions. Therefore, a GA-based optimization technique is presented in the current study to calculate the J–C parameters according to the SHPB tests under different high strain rates and temperatures. Afterwards, the optimized J–C model parameters are applied in machining simulations to validate the optimization results.

Johnson–Cook model

To model the plastic behavior of Ti–6Al–4V alloy, the J–C constitutive model was employed, which can be represented by the following equation⁵

$$\bar{\sigma} = \left[A + B(\bar{\varepsilon})^n\right] \left[1 + C \ln\left(\frac{\dot{\varepsilon}}{\dot{\varepsilon}_0}\right)\right] \left[1 - \left(\frac{T - T_{room}}{T_{melt} - T_{room}}\right)^m\right]$$
(1)

where \bar{e} is the equivalent plastic strain, $\dot{\bar{e}}$ is the equivalent plastic strain rate, \dot{e}_0 is the reference strain rate, T_{room} is the room temperature (25 °C), T_{melt} is the melting temperature of workpiece material (1660 °C for Ti–6Al–4V in this work). The parameter A is the quasistatic yield strength of the material (MPa), B is the hardening modulus (MPa), n is the hardening index, C is the strain rate sensitive coefficient and m is the thermo-softening index.

Some J–C parameter sets for Ti–6Al–4V alloy are listed in Table 1. Although some of these sets are based on the same SHPB test data, the calculated J–C parameters vary in a wide range owing to the possible differences in microstructures and/or the mathematical techniques applied in calculation.¹⁵ Different material parameters will lead to different simulation results when the J–C model is applied in machining simulation. Umbrello et al.¹⁰ studied the influence of J–C parameters on the results of AISI 316L steel machining

Source	A/MPa	B/MPa	n	С	т	$\dot{\varepsilon}_0/s^{-1}$	Method
Seo et al. ⁹ in 2005	997.9	653.I	0.45	0.0198	0.7	I	SHPB
Lee and Lin ¹⁴ in 1998	724.7	683.I	0.47	0.035	I	10^{-5}	SHPB
Özel and Karpat ²⁰ in 2007	987.8	761.5	0.41433	0.01516	1.516	2000	Orthogonal cutting
Lee and Lin ²¹ in 1998	782.7	498.4	0.28	0.028	I	10 ⁻⁵	SHPB
Meyer and Kleponis ²² in 2001	862.5	331.2	0.34	0.012	0.8	I.	SHPB
Pittalà and Monno ²³ in 2011	0	1508	0.049	0.067	0.71	1000	milling

Table 1. J-C model parameters for Ti-6AI-4V alloy.

SHPB: split Hopkinson pressure bar.



Figure 1. The flow stress calculated by J–C parameters of Lee and Lin 14 and the SHPB test results at 800 s $^{-1}$ and 25 $^\circ C.$

simulation. Besides, Umbrello²⁴ investigated the effect of J-C model parameters on the predicted segmented chip morphology in Ti-6Al-4V alloy orthogonal cutting simulation. These previous studies have demonstrated that material constitutive parameters have a significant impact on simulation results, such as residual stresses, forces and chip morphology. Lee and Lin¹⁴ performed the SHPB tests at different temperatures and strain rates, and they developed a set of J-C parameters according to the test results. However, the stress calculated by the J-C parameters presented in the article did not agree very well with the experimental data, i.e. the stress at $800 \,\mathrm{s}^{-1}$ strain rate and at $25 \,^{\circ}\mathrm{C}$ (Figure 1). Thus, the main objective of this study is to acquire a set of accurate J-C model parameters using an optimization method according to the experimental results of SHPB tests in Lee and Lin.14

Determination of constitutive parameters by genetic algorithm

Objective function

Optimization techniques can be applied to identify material parameters by minimizing a particular norm of the errors between the calculated and the experimental results without any conversion.²⁵ Two objective functions are defined in the present study in terms of a particular form of difference between the calculated and experimental data for a stress–strain curve.

$$f_1(\mathbf{x}) = \sum_{j=1}^{n_1} \sqrt{\sum_{i=1}^{m_1} (\sigma_{i,j}^c - \sigma_{i,j}^e)^2}$$
(2)

$$f_2(\mathbf{x}) = \sum_{l=1}^{n_2} \sqrt{\sum_{k=1}^{m_2} (\sigma_{k,l}^c - \sigma_{k,l}^e)^2}$$
(3)

where $f_1(\mathbf{x})$ and $f_2(\mathbf{x})$ are the sums of error functions under two strain rates, 2000 and $2500 \,\mathrm{s}^{-1}$, respectively. $\mathbf{x} = [A, B, n, C, m]$ represents the design variables, i.e. the J–C parameters. m_1 is the number of stress–strain data for each temperature j at strain rate of $2000 \,\mathrm{s}^{-1}$, whereas n_1 is the number of temperature setting considered; while m_2 is the number of stress-strain data for each temperature *l* at strain rate of $2500 \,\mathrm{s}^{-1}$, whereas n_2 is the corresponding number of temperature values considered. $\sigma_{i,i}^c$ and $\sigma_{i,i}^e$ are the computational and experimental stresses, respectively, for the same strain level iand temperature j at strain rate of $2000 \,\mathrm{s}^{-1}$; $\sigma_{k,l}^c$ and $\sigma_{k,l}^{e}$ are the computational and experimental stresses, respectively, for the same strain level k and temperature *l* at strain rate of 2500 s⁻¹. In addition, $\sigma_{i,j}^c$ and $\sigma_{k,l}^c$ are calculated using the J–C model equation (1); $\sigma_{i,j}^e$ and $\sigma_{k,l}^{e}$ are obtained using the experimental results of Lee and Lin.¹⁴ Lee and Lin¹⁴ applied the form of

$$\sigma = A + B\varepsilon^n \tag{4}$$

to represent the measured stress-strain relationship under each strain rate and temperature condition. Therefore, $\sigma_{i,j}^e$ and $\sigma_{k,l}^e$ are obtained by providing the strain data into equation (4) at specific strain rates and temperatures.

The ultimate objective is to acquire a set of appropriate parameters to minimize $f_1(\mathbf{x})$ and $f_2(\mathbf{x})$ simultaneously. This is a multiple objective optimization problem. However, there is no obvious conflict in optimizing the stress-strain responses at different temperatures and strain rates. The stress-strain responses at different strain rates can be considered as a set of curves, which are similar to those at different temperatures. Hence, for simplicity, this multiple objective optimization problem is translated into a simple objective

problem, and the penalty function method²⁶ is also induced. The ultimate objective function is given by

$$\phi(\mathbf{x}) = c_1 f_1(\mathbf{x}) + c_2 f_2(\mathbf{x}) \tag{5}$$

$$function(A, B, n, C, m) = Min\{\phi(\mathbf{x})\}$$
(6)

where c_1 and c_2 are weight coefficients for $f_1(\mathbf{x})$ and $f_2(\mathbf{x})$.

Computation procedure

Compared with the conventional optimization methods, the GA has the advantage of solving the constrained non-linear optimization problem. This technique is a stochastic search method based on evolution and genetics, exploiting the concept of survival of the fittest.²⁷ A fitness function F(x) derived from the objective function is used in the successive genetic operations. Individuals with high fitness will survive to the next generation. In the current study, optimization is a minimization problem, so the fitness is defined as

$$\mathbf{F}(\mathbf{x}) = C_0 - \boldsymbol{\phi}(\mathbf{x}) \tag{7}$$

where C_0 is a predefined constant to ensure that the fitness function has a positive value.

The schematic of the GA optimization procedure is shown in Figure 2. The step-by-step optimization process is outlined as follows.

1. The design variables of the optimization are chosen and the domains of material parameters are inputted. The population size k, maximum number of generation g_m , crossover probability λ_c and mutation probability λ_m are defined before the optimization program is started.



Figure 2. The schematic of GA optimization procedure.

- 2. The initial population is generated randomly.
- 3. Each individual \mathbf{x}_i in the population is evaluated by the fitness function.
- 4. The optimization procedure is terminated if the fitness function related stopping criterion (the weighted average change of the fitness function value is less than function tolerance over a specified generations) is satisfied, i.e. the mean fitness of the population does not evolve after a finite number of generations. Otherwise, if $g_i > g_m$, then optimization is terminated.
- If the stopping criteria are not satisfied, then the 5. genetic operators, such as reproduction, crossover and mutation on the population are executed (Figure 3). The individuals in population P_i are ranked according to the values of fitness function in the reproduction process. Some parent individuals with high fitness values are selected as elite children (EC), which are automatically survived to the next generation \mathbf{P}_{i+1} (Figure 3). In addition, there are two other types of children, namely, crossover children (CC) and mutation children (MC), which are both produced by parent individuals. The individuals that have high fitness values are usually selected as parent individuals in the GA optimization. The CC are created by combing the chromosome (e.g. binary string) of the parent individuals. The mutation operator is used to reduce the probability of a premature loss of genetic material caused by reproduction and crossover.¹⁹ The MC are created by changing one variable on a chromosome, selected at random, from a single parent individual.
- 6. The children population is generated by reproduction, crossover and mutation operations. The number of generations is set as $g_i = g_i + 1$. Step 3 is repeated until one of the termination criteria is satisfied.

The GA technique can overcome the difficulty of choosing the correct initial values for the constants that exist in traditional optimization techniques.¹⁹ The



Figure 3. The genetic operators of the GA optimization. EC: elite children; MC: mutation children; CC: crossover children.

domains of design variables (J–C parameters) and the variables of optimization are specified at the beginning: the population size k = 1000, maximum number of generation $g_m = 100$, crossover probability $\lambda_c = 0.8$ and mutation probability $\lambda_m = 0.06$. The domains of J–C parameters are defined as 700 MPa $\leq A \leq 1000$ MPa, 600 MPa $\leq B \leq 1000$ MPa, $0 \leq n \leq 1$, $0 \leq C \leq 1$ and $0.5 \leq m \leq 1.5$. The initial population is generated within the domains. The GA procedure begins with the initial population that is composed of random individuals, i.e. the design variables. Then, the optimal design variables are determined by computing the fitness function, generation by generation until one of the termination criteria is reached.

Optimization results

The objective function is calculated using equations (2) to (6) to minimize the difference between the experimental and calculated stresses. The experimental data are obtained by SHPB tests from Lee and Lin.¹⁴ The stress–strain data at different temperatures ($25 \,^{\circ}$ C, $300 \,^{\circ}$ C, $500 \,^{\circ}$ C, $700 \,^{\circ}$ C, $900 \,^{\circ}$ C and $1100 \,^{\circ}$ C) are considered in the objective function. The strain rate in machining processes is high and varies with cutting speeds. Therefore, two different strain rates, 2000 and $2500 \, \text{s}^{-1}$, are also involved in the objective function. The referenced experimental flow stress curves are shown in Figure 4. Although the flow stress is affected by temperature and strain rate, the effect of temperature is more pronounced than that of strain rate.

The flow stress of the J–C model is calculated using equation (1). The objective function of the GA-optimized result is shown in Figure 5. The design variables (M2) obtained by the GA optimization and the fitted J–C model (M1) given by Lee and Lin¹⁴ are listed in Table 2.

Using the GA technique, the value of the objective function decreases rapidly within the first ten generations, i.e. the difference between the experimental and calculated flow stress is minimized markedly in the first ten generations compared with subsequent generations. Afterwards, the value of the objective function decreases gradually toward a stable value, until it reaches 542.6 when the optimization is terminated. That is, the specified error (calculated by equations (2) to (5)) between the experimental and calculated stress using the optimized J–C model M2 (Table 2) is 542.6, whereas the error between the experimental and calculated stress using the J–C model M1 (Table 2) is 7836.2. Therefore, the flow stress calculated using J–C model M2 is closer to the experimental flow stress than that calculated using model M1 at the specified temperatures and strain rates as mentioned above.

The experimental and calculated flow stress at different temperatures is shown in Figure 6(a) and (b). The calculated values are obtained using the optimized J–C model M2. The errors between experimental and calculated stress (given by equation (8)) at different temperatures are shown in Figure 7(a) and (b). The calculated flow stress shows excellent agreement with the experimental values, except for a few data at the deformation initiation when $\varepsilon < 0.01$. The error is lower than 4% at a strain rate of 2000 s^{-1} , whereas the error is lower than 3% at a strain rate of 2500 s^{-1} , when $\varepsilon \ge 0.01$.

$$Error_{i,j} = \frac{\sigma_{i,j}^e - \sigma_{i,j}^c}{\sigma_{i,j}^e} \times 100\%$$
(8)

In order to see the optimized results at different strain rates (2000 and $2500 \,\mathrm{s}^{-1}$), the flow stress calculated by the J–C model with two sets of parameters (M1 and M2 in Table 2) and the experimental results obtained by the SHPB test at 300 °C and 900 °C are shown in Figure 8(a) and (b). A strain rate hardening phenomenon is evident, both in the experimental and calculated curves. A higher strain rate leads to higher stress at identical temperatures. However, the sensitivity of the strain rate hardening is weak at the two aforementioned strain rates, especially for the calculated results. For instance, the maximum distance of



Figure 4. Stress-strain responses based on the data of Lee and Lin¹⁴ at different temperatures and strain rates.



Figure 5. The objective function result of the optimization procedure.

Model	A/MPa	B/MPa	n	С	m	ė₀/s ^{−1}
M1: Lee and Lin ¹⁴ in 1998	724.7	683.1	0.47	0.035	l	10 ⁻⁵
M2: Optimized result	888.5	600	0.21	0.007	1.012	10 ⁻⁵

Table 2. Comparison of the two sets of J-C model parameters.



Figure 6. Comparison of experimental¹⁴ and calculated flow stress obtained by optimized J–C model M2 at different temperatures: (a) strain rate = 2000 s^{-1} ; (b) strain rate = 2500 s^{-1} . J–C: Johnson–Cook.



Figure 7. Errors between experimental¹⁴ and calculated flow stress obtained by optimized J–C model M2 at different temperatures: (a) strain rate = 2000 s^{-1} ; (b) strain rate = 2500 s^{-1} .

experimental stress at the two different strain rates is 20 MPa, whereas that of calculated stress using M2 is 2 MPa, at a temperature of 900 °C. This phenomenon may be related to the objective function of the GA procedure, which aims to minimize the errors between experimental and calculated stresses at the two different strain rates. On the other hand, the stress calculated by model M2 is closer to the experimental results than that calculated by M1 at temperatures of 300 °C and 900 °C (Figure 8).

Ti-6Al-4V alloy machining simulation for model parameters validation

Ti-6AI-4V alloy orthogonal cutting experiments

A set of FE simulation and titanium alloy orthogonal cutting experiments were developed to evaluate the accuracy of the optimized J–C model parameters in describing material deformation behavior of the machining process. In this work, three different tests (Test1: v = 60 m/min, f = 80 µm/rev; Test2: v = 80 m/min,



Figure 8. Comparison of experimental¹⁴ and calculated flow stress obtained by J–C models M1 and M2 at different strain rates: (a) T = 573 K; (b) T = 1173 K.

 $f = 100 \,\mu\text{m/rev}$; and Test3: $v = 130 \,\text{m/min}$, $f = 100 \,\mu\text{m/}$ rev) were performed for a Ti–6Al–4V alloy orthogonal dry cutting experiment and FE simulation.

The orthogonal cutting experiments were performed on a vertical machining center type NEXUS410B-HS. The workpiece was composed of Ti–6Al–4V alloy disks 100 mm in diameter and 2.03 mm thick. The experiment set-up is shown in Figure 9. The cutting tool was an uncoated carbide insert type TPGN 110304 (Kennametal Inc.) with 3° rake angle, 8° clearance angle and 0° inclination angle. The cutting edge radius was approximately 5 μ m. The cutting forces were monitored by a dynamometer (Kistler 9257A) and a charge amplifier (Kistler 5070A). A new insert was used for each test to avoid tool wear in the cutting process.

FE modeling

A two-dimensional (2D) FE model was developed to validate the optimized J-C model parameters by

comparing the experimental and simulated results. The geometry of the 2D FE model is shown in Figure 10. The workpiece was meshed with 8000 plane strain thermally coupled quadrilateral elements (type CPE4RT), and the tool was meshed with 255 elements. The characteristic dimensions of the tool were in accordance with the experimental condition: rake angle $\alpha = 3^{\circ}$, clearance angle $\beta = 8^{\circ}$ and edge radius $r = 5 \,\mu$ m. The workpiece was fixed, meanwhile, a velocity along the *X* direction was exerted on the tool to accomplish the cutting process.

The J–C plastic material model (equation (1)) and an energy density-based ductile failure criterion, which was illustrated in a previous work,¹² were applied to the FE model in the cutting simulation. Besides the energy density failure criterion, a shear failure criterion is assigned to a separation layer to separate the chip from the workpiece (Figure 10). The failure parameters were identical to those of the previous work.¹²



Figure 9. Schematic diagram of the orthogonal cutting experiment set-up.

The cutting conditions of the simulation were in accordance with those in the orthogonal cutting



Figure 10. The geometry of the cutting FE model ($f = 80 \,\mu$ m/rev).



Figure 11. Comparison of experimental chip morphology (Exp.) and simulation results (Sim.) obtained by J–C models M1 and M2 in various cutting conditions.

experiments. The J–C model M1 and the optimized model M2 (Table 2) were both applied in the cutting simulation to compare the original and optimized J–C model parameters. Except for the changes of J–C model parameters, the other parameters remained unchanged to study the effect of material parameters on the machining simulation.

Simulation results and discussion

The predicted and experimental chip morphology is shown in Figure 11, in which Figure 11(a)–(c) are predicted using model M1, whereas Figure 11(a')–(c') are predicted using model M2.

Obvious segmented chip morphology exists both in the predicted and experimental results. The predicted temperature distribution is illustrated in the simulation results. Many studies have discussed the mechanism of segmented chip formation. Calamaz et al.¹ classified the mechanism of chip formation into two groups: 1) the thermoplastic instability; 2) the crack initiation and propagation. Hua and Shivpuri²⁸ developed the titanium alloy machining simulation and stated that crack initiation and propagation are the main causes of segmented chip. On the other hand, Komanduri and Hou²⁹ developed a thermal model for the thermoplastic instability and stated that thermoplastic instability caused by thermal softening along the adiabatic shear band is one of the main factors that leads to a segmented chip. In addition, the thermoplastic instability theory was also proved by the relationship of strain and temperature along shear bands in the Ti–6Al–4V alloy machining simulation.³⁰

Chip morphology was characterized by the average dimension of peak, valley and pitch (Figure 11(a)) to compare the experimental chip morphology with the simulation results using model M1 and M2. Each dimension value was measured three times to reduce the measurement error. The measured average dimensions of the segmented chip are given in Table 3.

The average peak dimensions of M1 and M2 agree well with the experimental results in Tests 1 to 3, with relative errors lower than 15%, and they are similar with each other. The errors between the predicted (M1 and M2) and experimental valley dimensions (in Tests 1 to 3) are also lower than 15%, except for M1 (20.7% in Test 1). The predicted valley of the M2 model is closer to the experimental results than that of the M1 model in Tests 1 and 2. In addition, the average valley dimension of M1 is smaller than that of M2. This phenomenon may be caused by the material plastic flow along the shear bands. The density of material ductile failure energy G_{ε} defined by equation (9) is constant during the material failure process. Therefore, if the stress of M1 $(\sigma_{\nu 1})$ is larger than that of M2 $(\sigma_{\nu 2})$ (Figure 8), then the variation of plastic strain along the shear band $\Delta \varepsilon_1$ in M1 will be smaller than $\Delta \varepsilon_2$ in M2. Hence, model M1 is easier to reach the state of complete failure from failure

Cutting condition	Model	Peak (µm)	Valley (µm)	Pitch (µm)
Testl	Exd.	123.5	92.3	37.5
v = 60 m/min	Sim. MI (error)	109.8 (11.1%)	73.2 (20.7%)	44.9 (-19.7%)
f=80 μm/rev	Sim. M2 (error)	108.3 (12.3%)	81.2 (12%)	37.4 (0.26%)
Test2	Exp.	144 `´´	101.3	79.4 `´
v = 80 m/min	Sim. MI (error)	134.5 (6.6%)	94 (7.2%)	53.8 (32.2%)
f=100 μm/rev	Sim. M2 (error)	133.2 (7.5%)	98.8 (2.5 [°] %)	52.7 (33.6%)
Test3	Exp.	128	82.2	76.6
v = 130 m/min	Sim. MI (error)	125.8 (1.7%)	89 (-8.3%)	44.7 (41.6%)
f=100 μm/rev	Sim. M2 (error)	131.2 (–2.5%)	93 (–I3.I%)	57 (25.59%)

Table 3. Comparison of measured chip dimensions in experiments and simulations.

initiation, which will lead to a larger plastic deformation along the shear band in M1, inducing a relatively small chip valley dimension

$$G_{\varepsilon} = \int_{\bar{\varepsilon}_{oi}}^{\bar{\varepsilon}_{f}^{ol}} \sigma_{y} d\bar{\varepsilon}$$
⁽⁹⁾

Comparing with the peak and valley dimensions, larger relative errors exist for the pitch dimension, as illustrated in the results of Tests 2 and 3. The pitch dimensions of model M2 are closer to the experimental results than those of M1, except Test 2. Although there is no distinct difference between M1 and M2 in the prediction of peak and valley dimensions, the pitch sizes of M2 are closer to the experimental results than those of M1. Thus, the optimized J–C model M2 is more appropriate to be applied in the titanium alloy machining simulation.

The predicted (M1 and M2) and experimental principle cutting forces of Tests 1 to 3 are shown in Figure 12. The predicted forces of M1 are larger than the experimental results, contrary to the relatively small predicted forces of M2. Based on the stress–strain curves of M1 and M2 models (Figure 8), higher stress will lead to a higher cutting force in the same FE model under the same strain condition. Although the predicted forces using M1 are closer to the experimental results, the errors of Tests 1 to 3 are 6.8%, 5.7% and 7.9%,



Figure 12. The predicted (with model M1 and M2) and experimental principle cutting forces.

respectively, the errors between M2 and experiment are lower than 15% (12.9%, 13.3% and 10.2% for Tests 1 to 3, respectively). As the measurement error and the differences of material physical behavior exist in the FE model and actual machining, the predicted forces can be considered as reasonable for model M1 and M2.

Conclusions

A genetic algorithm was proposed to minimize the errors between the flow stress obtained through the J–C constitutive model parameters and the SHPB experimental results in Lee and Lin¹⁴ at different temperatures ($25 \,^{\circ}$ C to 1100 °C) and high strain rates (2000 and $2500 \, \text{s}^{-1}$). In addition, Ti–6Al–4V alloy orthogonal cutting experiments and the corresponding FE simulations were performed to validate the optimized J–C model parameters. In summary, the following conclusions can be drawn.

- 1. The GA technique can be applied to minimize the difference between experimental and calculated material flow stress.
- 2. The flow stress obtained through the optimized J–C model M2 is closer to the experimental data than that of model M1. The percentage differences between the flow stress of the J–C model M2 and the experimental data at 2000 and 2500 s⁻¹ are lower than 4% and 3%, respectively. Therefore, the flow stress obtained through the J–C model at different temperatures and strain rates can characterize the material flow stress obtained in the SHPB tests.
- 3. The experimental chip morphology and the FE simulation results obtained by the two sets of the J–C model (M1 and M2) showed no distinct difference between models M1 and M2 for peak and valley dimensions. In addition, the valley dimension of the segmented chip is greatly dependent on the J–C model parameters. At a constant density of material ductile failure energy in the material failure process, higher stress will lead to a shorter failure process, and thus cause a smaller valley dimension. The predicted pitch dimensions of the J–C model M2 are closer to the experimental results than those of M1. Thus, the GA-optimized material parameters M2 are more appropriate for

the simulation of the titanium alloy machining process than model M1.

- 4. The percentage errors between the predicted (M1 and M2) and experimental principle cutting forces are lower than 15%. Hence, the predicted forces can be regarded as reasonable for both M1 and M2 models.
- The optimized J–C model M2, which considers different temperatures (25 °C to 1100 °C) and strain rates (2000 and 2500 s⁻¹), can be used to characterize the Ti–6Al–4V alloy deformation mechanism in machining simulation.

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Conflict of interest

The authors declare that there is no conflict of interest.

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Appendix		α	rake angle		
Notations		β	clearance angle		
INOLULIONS		3	strain		
A	initial yield stress	Ē	equivalent plastic strain		
В	hardening modulus of J–C flow stress model	$\overline{\varepsilon}_{f}^{pl}$	equivalent plastic strain at complete failure		
С	coefficient of strain rate of J–C flow stress	$\overline{\varepsilon}_{oi}$	equivalent plastic strain at onset of failure		
-	model	$\frac{1}{3}$	equivalent plastic strain rate		
C_0	predefined constant	$\dot{\varepsilon}_0$	reference strain rate		
c_1, c_2	weight coefficient for $f_1(\mathbf{x})$ and $f_2(\mathbf{x})$	λ_{c}	crossover probability		
$\mathbf{F}(\mathbf{x})$	fitness function of the genetic algorithm	$\lambda_{ m m}$	mutation probability		
$f_1(\mathbf{x}), f_2(\mathbf{x})$	sums of the error functions	σ	stress		
G_{ε}	density of the ductile failure energy	$ar{\sigma}$	flow stress at non-zero strain rate		
g_i	number of generations	$\sigma_{i,j}^c$	computational stress for the same strain		
$g_{\rm m}$	maximum number of generation		level <i>i</i> and temperature <i>j</i> at strain rate		
K M1	population size		2000 s		
M1 M2	J-C model parameters in Lee and Lin	$\sigma_{k,l}^{c}$	computational stress for the same strain		
IVI Z	optimization		level k and temperature l at strain rate $2500 \mathrm{s}^{-1}$		
т	thermo-softening index for J–C flow stress model	$\sigma^{e}_{i,j}$	experimental stress for the same strain level <i>i</i> and temperature <i>j</i> at strain rate		
m_1, m_2	number of stress-strain data at each		$2000 \mathrm{s}^{-1}$		
	temperature with strain rate 2000 and 2500 s^{-1} , respectively	$\sigma^{e}_{k,l}$	experimental stress for the same strain level k and temperature l at strain rate		
п	hardening index for J–C flow stress model		$2500 \mathrm{s}^{-1}$		
n_1, n_2	number of temperature at strain rate 2000 and $2500 \mathrm{s}^{-1}$, respectively	$\sigma_y \ \phi(\mathbf{x})$	Mises yield stress objective function of the genetic algorithm		