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Optimization of cutting parameters in milling based on tool wear model

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Abstract

High accuracy and machining capability are the main requirements for metal cutting operations, and high cutting speed and feed rate increase machining accuracy and material removal rate, but lower tool life. In this paper, a tool wear life model is developed during milling and a method is proposed to determine the cutting parameters that maximize the tool wear life under certain metal removal rates. The tool wear model is constructed by a polynomial regression model using simulation data from Deform 3D and the cutting parameters are optimized using Matlab's fmincon function. The proposed method is verified through cutting of high temperature alloy Ti6Al4V and can be applied to determine cutting parameters that maximize tool life in machining various hard-working materials.

Keywords: Tool Wear; Cutting parameters; Deform3D; Optimization

1. Introduction

High cutting speed and feed rate increase machining accuracy and metal removal, but increase tool temperature, accelerate wear and shorten tool life. Since both material removal rate and tool life are related to cutting parameters, the cutting parameters should be chosen appropriately ^[1].

Hence, many studies have been carried out to clarify the relationship between tool wear and cutting conditions and to optimize cutting conditions.

A mathematical model about the tool wear life and cutting parameters was investigated for two different tool materials (CBN, ceramics) by means of an empirical method when turning high-hardness steel ^[2] and an empirical model about tool life and cutting parameters was established and the cutting parameters were optimized based on experiments and linear regression models for high-speed milling of titanium alloys ^[3]. The study shows that the tool life increases with decreasing cutting speed and increasing depth of cut at constant efficiency.

A tool wear prediction model and a cutting parameter optimization model were developed using an improved BP neural network based on genetic algorithm ^[4] and an experimental study was carried out for turning operations using the TSK fuzzy modelling for the multi-sensor information integration with wear information ^[5]. The modelling rules were generated directly from the data acquired by the sensors.

In ^[6, 7] mathematical models for the tool wear prediction were formulated using the Response Surfaces Methodology, in which wear is expressed as a function of the process parameters. The Analysis of Variance was then applied to verify the adequacy of the model and its parameters.

The effects of cutting parameters on tool life of PVD TiAlN-coated carbide tools and volume of workpiece material removed during the machining of the N-155 iron-nickel-base superalloy were evaluated ^[8] and the relationships between machining parameters and output variables were modelled by using response surface methodology (RSM). ANOVA was performed to check the adequacy of the mathematical model and its respective variables.

A multiple response optimization of tool life and volume of removed material for achieving maximum productivity was carried out using the desirability function approach.

In ^[9], the grey relation based Taguchi method was applied for the multiple performance characteristics of turning operation. A grey relational analysis of the material removal rate and the tool wear ratio obtained from the Taguchi method reduced from the multiple performance characteristics to a single performance characteristic which is called the grey relational grade.

An advanced hybrid multi output optimization technique by applying weighted principal component analysis (WPCA) incorporated with response surface methodology (RSM) was presented ^[10].

This investigation was carried out through a case study in CNC turning of Aluminum alloy 63400 for surface roughness (Ra) and tool vibration (db) optimization.

In [11], a comprehensive review concerning analytical and empirical modelling of tool wear and forces of CBN tool in hard turning, was presented. In this paper, an optimization procedure for the productivity maximization by resorting to a multi-objective optimization with a deterministic objective function, in compliance with a stochastic constraint represented by tool wear, is presented.

In other work [12], cutting force measurement was performed for the prediction of tool wear evolution. It was found a relationship between wear curve and cutting force variations that shows the transitions in tool wear evolution.

The different cutting conditions are compared to reduce tool wear using lubrication and additive during turning AISI 1045 steel [13]. Using lubrication and additive contained lubrication reduced tool wear in rate of 25% and 40% respectively.

A sensor based monitoring system is used to provides information about tool wear development during turning of Ti6Al4V [14]. The developed system can be useful when integrated with numerical controller for recon-struction of tool wear.

Taguchi method based on L⁹ orthogonal array is presented to find out the best cutting conditions and the most effective parameter on flank wear in turning of AISI 4340 steel [15]. The results showed that depth of cut, cutting speed and feed rate has 46%, 34% and 15% contribution on flank wear respectively. Manivel and Gandhinathan carried out an experimental work for optimization on hard turning operation using ANOVA and S/N ratio analysis [16]. They found that cutting speed has highest contribution with 50% followed by feed rate with 30%.

Debnath carried out an experimental work for deter-mining of the best parameters in CNC turning of mild steel [17]. According to the results, cutting speed has highest contribution with 43% but feed rate have the least contribution with 7% on tool wear.

Sel-varaj applied Taguchi optimization method for machining of special stainless steel [18]. It is found that cutting speed and feed rate affect tool wear 91-92% and 7-8% respectively. In these works, it was seen that Taguchi based optimization methods have been used successfully for reduced production time and costs.

In this paper, the optimization of cutting parameters during milling of titanium alloys is carried out. A polynomial regression equation is used to construct the tool wear model using simulation data from Deform3D finite element program. The cutting tests were carried out with different cutting parameters and different geometries of the milling cutters. Based on this model, the cutting parameters in the machining center are optimized to improve the machining efficiency and tool life during machining of titanium alloy.

2. Modeling of milling cutter wear life

In general, operators choose cutting parameters based on experience, thus reducing the cutting efficiency. To increase the cutting efficiency and improve the tool life, the cutting parameters should be chosen appropriately.

Therefore, a relational model between tool wear life and cutting parameters should be developed.

2.1. An empirical model of milling wear life

Taylor studied the influence of cutting parameters and tool

materials on tool life and presented an empirical formula to determine the cutting parameters.

$$T^m = \frac{C_T K_T}{v a_p^x f_z^y a_e^z} \quad T^m = \frac{C_T K_T}{v a_p^x f_z^y a_e^z} \quad (2-1)$$

Here, m is an index that indicates of influence of v on T , reflects the cutting performance of the tool material, and the higher the value, the smaller the effect of cutting speed on the tool life.

C_T-cutting parameter coefficient

K_T -Other factors are the correction factors that affect the tool life, including the machining mode, workpiece and tool material, workpiece surface parameter, principal plane angle, auxiliary plane angle, and principal plane arc radius. Depending on the research objective, factors affecting tool life are added to this equation or those with small effects are eliminated. The cutting parameters (cutting speed, feed per tooth, axial depth of cut, radial depth of cut) during milling have a significant effect on the tool life and the formula is expressed in exponential form depending only on the cutting parameters as follows

$$T = C a_p^{b_1} a_e^{b_2} v^{b_3} f_z^{b_4} \quad (2-2)$$

Here, T - tool life (min), v - cutting speed (m/min), f_z - feed per tooth (mm/z), a_p - axial depth of cut (mm), and a_e - radial depth of cut (mm).

The linearization by converting the above expression is

$$\ln T = \ln C + b_1 \ln a_p + b_2 \ln a_e + b_3 \ln v + b_4 \ln f_z \quad (2-3)$$

Converting the variable $y = \ln T, b_0 = \ln C, x_1 = \ln a_p, x_2 = \ln a_e, x_3 = \ln v, x_4 = \ln f_z$, the above expression is expressed as

$$y = b_0 + b_1 x_1 + b_2 x_2 + b_3 x_3 + b_4 x_4 \quad (2-4)$$

The experimental results of the four variables are y and have a linear relationship. Since there is an error ε_i for 16 experiments, the simultaneous equation of tool life is

$$y_1 = \beta_0 + \beta_1 x_{11} + \beta_2 x_{12} + \beta_3 x_{13} + \beta_4 x_{14} + \varepsilon_1$$

$$y_2 = \beta_0 + \beta_1 x_{21} + \beta_2 x_{22} + \beta_3 x_{23} + \beta_4 x_{24} + \varepsilon_2$$

$$y_{16} = \beta_0 + \beta_1 x_{16,1} + \beta_2 x_{16,2} + \beta_3 x_{16,3} + \beta_4 x_{16,4} + \varepsilon_{16}$$

Representing in matrix form

$$Y = X\beta + \varepsilon \quad (2-5)$$

Here,

$$Y = [y_1 y_2 \dots y_{16}]^T, X = \begin{bmatrix} 1 & x_{11} & \dots & x_{14} \\ 1 & x_{21} & \dots & x_{24} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & x_{16,1} & \dots & x_{16,4} \end{bmatrix}, \beta = [\beta_0 \beta_1 \dots \beta_4], \varepsilon = [\varepsilon_1 \varepsilon_2 \dots \varepsilon_{16}]^T$$

Using the regression coefficient, the least squares

approximation of the coefficient is calculated, and the regression equation is

$$\hat{y} = b_0 + b_1x_1 + b_2x_2 + b_3x_3 + b_4x_4 \quad (2-6)$$

The regression coefficient is calculated by the following equation:

$$b = (X^T X)^{-1} X^T Y \quad (2-7)$$

2.2. Polynomial regression model of tool wear life

The Taylor tool life formula has narrow coverage since only four cutting variables reflect the effect on tool life. When the tool is coated or the workpiece is hard-working, there is a quadratic effect between tool life and four cutting parameters, and there is an interaction between the four variables. Based on statistical theory, any function can be expressed as the sum of infinite higher order powers of all variables. Therefore, by polynomial regression, the relationship between tool wear life and cutting parameters is expressed as

$$T = a_0 + a_1a_p + a_2a_e + a_3v + a_4f_z + a_5a_pa_e + a_6a_pv + a_7a_pf_z + a_8a_e v + a_9a_ef_z + a_{10}vf_z + a_{11}a_p^2 + a_{12}a_e^2 + a_{13}v^2 + a_{14}f_z^2 \quad (2-8)$$

Here,

$$a_p = x_1, a_e = x_2, v = x_3, f_z = x_4, a_pa_e = x_5, a_pv = x_6, a_pf_z = x_7,$$

$$a_e v = x_8, a_ef_z = x_9, vf_z = x_{10}, a_p^2 = x_{11}, a_e^2 = x_{12},$$

$$v^2 = x_{13}, f_z^2 = x_{14}.$$

$a_0 \sim a_{14}$ are the regression coefficient.

i.e.

$$y = a_0 + a_1x_1 + a_2x_2 + a_3x_3 + a_4x_4 + a_5x_5 + a_6x_6 + a_7x_7 + a_8x_8 + a_9x_9 + a_{10}x_{10} + a_{11}x_{11} + a_{12}x_{12} + a_{13}x_{13} + a_{14}x_{14} \quad (2-9)$$

Through the experiments, the linear regression equation can be constructed and the regression coefficient can be found.

$$Y = XA + \varepsilon \quad (2-10)$$

Here, ε_i is the experimental random error, x_{ij} , y_j are the experimental measurements.

$$Y = [y_1 y_2 \cdots y_{16}]^T, X = \begin{bmatrix} 1 & x_{11} & \cdots & x_{14} \\ 1 & x_{21} & \cdots & x_{24} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & x_{16,1} & \cdots & x_{16,4} \end{bmatrix}, A = [a_0 a_1 \cdots a_{14}], \varepsilon = [\varepsilon_1 \varepsilon_2 \cdots \varepsilon_{16}]^T \quad (2-11)$$

If the effect of random error is not taken into account, the regression coefficient matrix can be calculated from the least squares principle.

$$A = (X^T X)^{-1} X^T Y \quad (2-12)$$

3. Simulation of the wear behavior of milling cutter by deform 3D

3.1. Simulation environment determination

To develop the tool wear life model, the tool wear life data must be obtained through experiments. However, milling is a complex process with many influencing factors, and simple cutting tests are not only time consuming, material consuming, labor consuming and cost-increasing, but also difficult to obtain accurately in real time temperature, deformation, tool wear, etc. during cutting. Deform3D is an engineering simulation analysis program, which is an ideal program to analyze the influence of tool design and machining parameters on machining performance.

In this paper, the tool wear of milling tools is simulated and analyzed using Deform3D finite element software, and the tool wear model is constructed from the result. The geometric parameters of the cemented carbide end mill are given in Table 3.1.

Table 3.1: Geometric parameters of end mills

Variable	Value
cutter diameter (mm)	20
number of teeth (z)	3
rake angle (°)	10
clearance angle (°)	15
helix angle (°)	30
core radius (mm)	12.4
strip width (mm)	1
cutting edge length (mm)	32
pitch (mm)	108.8
number of turns	0.27
insert material	YT15
hardness (HRA)	91

The main components and physical properties of Ti6Al4V alloy are listed in the table.

Table 3.2: Chemical composition of titanium alloys

Element	Ti	Al	V	Fe	O	C	N	H
Content	rest	5.5~6.75	3.5~4.5	≤0.25	≤0.2	≤0.08	≤0.05	≤0.01

Table 3.3: Physical properties of titanium alloys

Density (kg/m ³)	4430
hardness (HB)	349
Tensile yield strength (MPa)	880
Shear yield strength (MPa)	550
Elongation(%)	14
Elastic modulus (GPa)	113.8
Poisson's ratio	0.342
Shear strength (MPa)	550
Thermal expansion coefficient (μm/(m·°C))	8.6
Specific heat (J/(kg·°C))	526.3
Thermal conductivity (W/(m·°C))	6.7
Melting point (°C)	1604~1660
βphase transition temperature (°C)	980

In the present simulation, the rigid plastic finite element method is used. That is, when importing the geometry of the tool and the workpiece, the tool is set to rigid and the workpiece to plastic. Grid partitioning of both tool and workpiece uses a relative type. The tool element size is expressed by the number of 50,000 relative grids and the mesh of the tool tip is subdivided in a 10:1 size ratio to increase the accuracy. That is, the tool grid is roughly divided and the grid of the edge is subdivided by 10%. Therefore, the element size of the tool model consists of 53033 element grids and 12204 nodes. Also, if the

workpiece material is subdivided into 10:1 dimensions, the workpiece element size is represented by 30,000 relative

grids, including 31367 element grids and 7235 nodes. The meshing state of the tool and workpiece is shown in Fig.3.1.

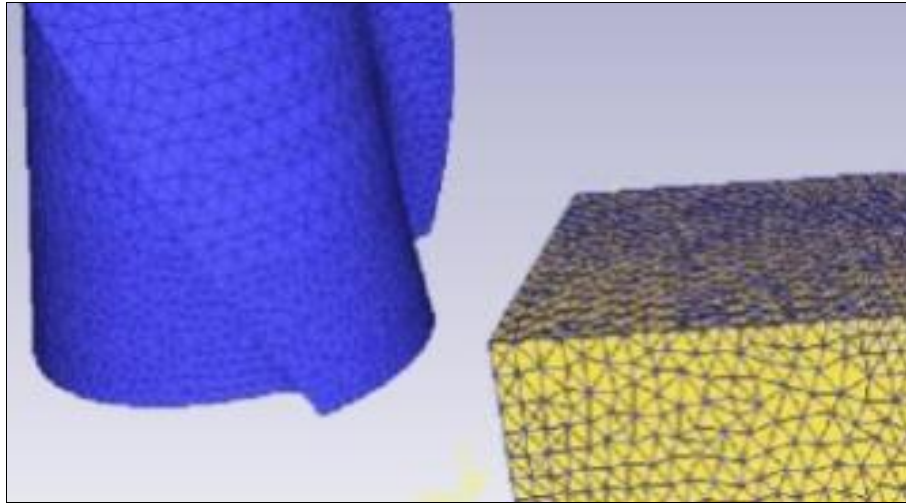


Fig 3.1: Mesh of tool and workpiece

The initial temperature of the tool is set to 20 °C. The rigid plastic finite element solves the large deformation problem by incremental method, and the size of incremental step directly affects the accuracy and efficiency of the finite element solution. The step is setted usually determined by the size of the grid, and the smaller the grid, the smaller the step. Here, we use a combination of minimum and isotime step. That is, if the isotime step does not converge within a given iteration order, it automatically converts to a sub-

iteration of the minimum time step. The isotime step is set as the distance the tool advances along each step and is 0.065 mm in size. Metal cutting is considered to be highly nonlinear, so the N-R method is used, convergence is judged as a displacement criterion, and the solver chooses Sparse. In SolidWorks, model the tool and workpiece, save it in STL format, and open the STL file in Deform3D environment (Figure 3.2).

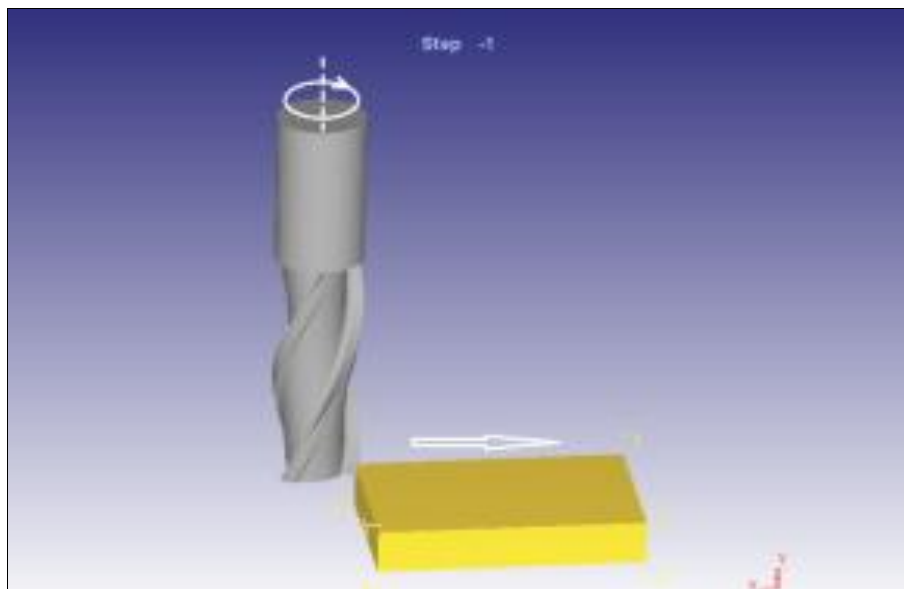


Fig 3.2: Tool and workpiece model

3.2. Simulation and results analysis

The cutting parameters levels for the orthogonal

experiments are listed in Table 3.4 and the orthogonal experimental scheme is listed in Table 3.5.

Table 3.4: Cutting parameter level

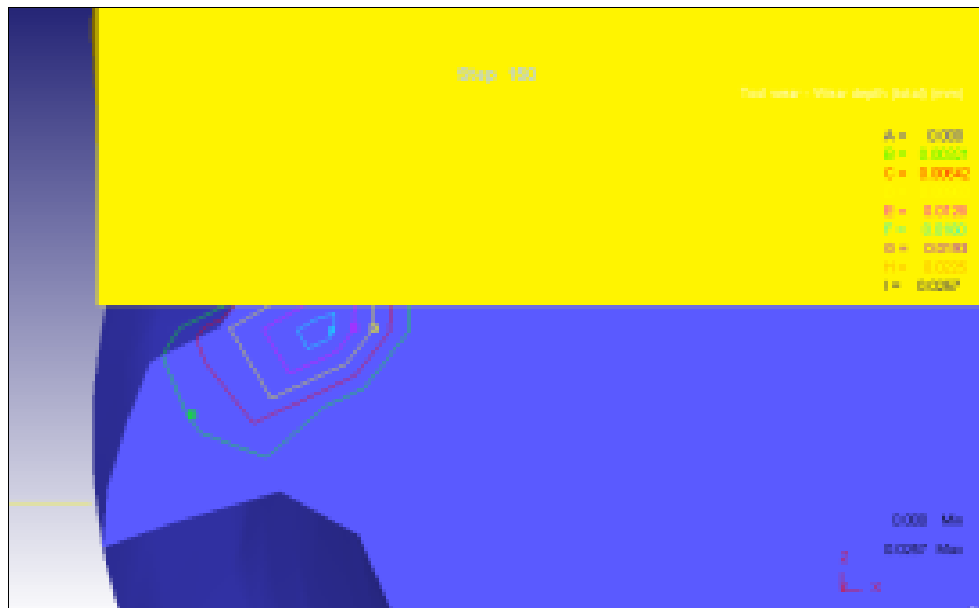
Level	$v_c(\text{m/min})$	$f_z(\text{mm/z})$	$a_e(\text{mm})$	$a_p(\text{mm})$
1	60	0.02	5	0.2
2	80	0.06	8	0.6
3	100	0.1	11	1
4	120	0.14	14	1.4

Table 3.5: Orthogonal cutting experiment scheme

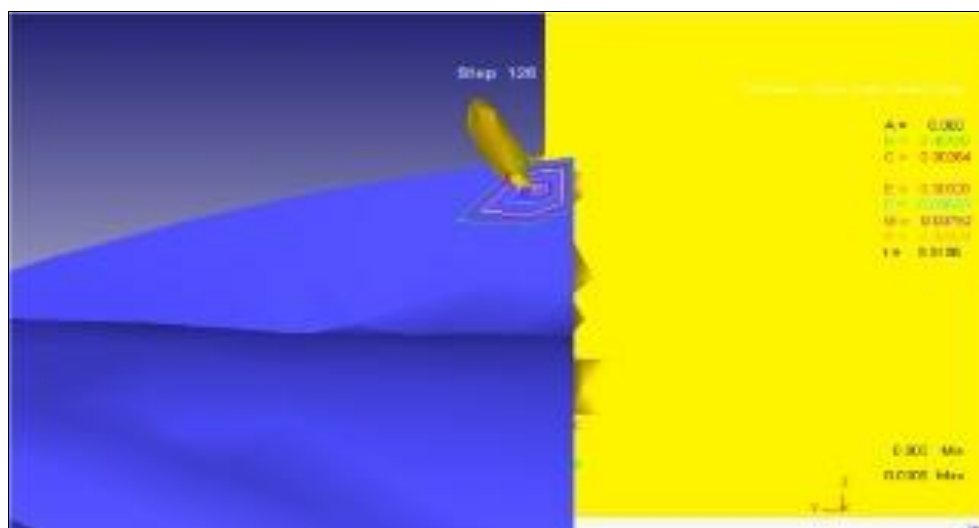
No	v_c (m/min)	f_z (mm/z)	a_e (mm)	a_p (mm)
1	100	0.06	11	1.4
2	80	0.14	5	1.4
3	120	0.02	8	1.4
4	60	0.1	14	1.4
5	60	0.06	8	1
6	120	0.14	14	1
7	80	0.02	11	1
8	100	0.1	5	1
9	60	0.14	11	0.6
10	120	0.06	5	0.6
11	80	0.1	8	0.6
12	100	0.02	14	0.6
13	100	0.14	8	0.2
14	80	0.06	14	0.2
15	120	0.1	11	0.2
16	60	0.02	5	0.2

The tool wear process is simulated from the instant when the tool is inserted into the workpiece to steady state. Figure

3.3 shows the simulation results for experiments 4 and 8.



No. 4 simulation



No. 8 simulation

Fig 3.3: Tool wear diagram

From the simulation results, tool wear is the most severe at the edge, and the maximum wear height at the flank reflects the tool wear rule. Therefore, the maximum wear height

(H_{max}) at the flank is used to estimate the tool wear (Fig. 3.4).

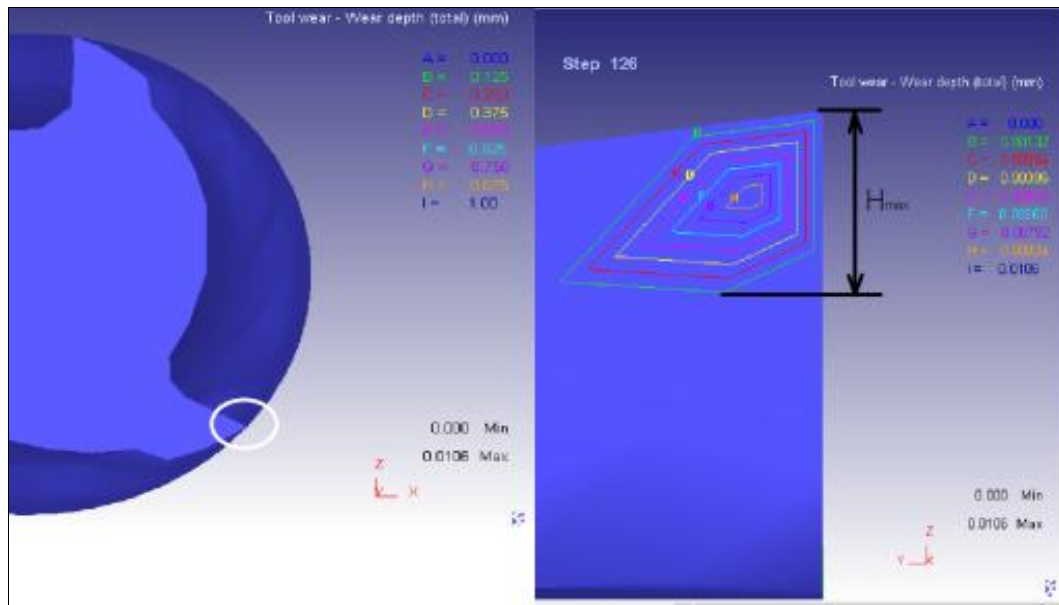


Fig 3.4: Measurement of tool wear

When the tool enters the normal wear stage, the flank wear amount is proportional to the cutting time. The 40 mm cutting time at experiment No. 4 is 3.59 s, and the measurement of Deform3D is 0.0059 mm when measuring the maximum flank wear height. Hence, when the maximum flank wear height reaches the tool failure criterion ($VB = 0.6$ mm), the tool wear life is 6.1 min. Likewise, tool wear life can be predicted under different cutting parameters in the other groups (Table 3.6).

Table 3.6: Test parameters and results

No	v_c (m/min)	f_z (mm/z)	a_e (mm)	a_p (mm)	T (min)
1	100	0.06	11	1.4	7.12
2	80	0.14	5	1.4	4.3
3	120	0.02	8	1.4	43.4
4	60	0.1	14	1.4	6.1
5	60	0.06	8	1	24.65
6	120	0.14	14	1	0.49
7	80	0.02	11	1	222.26
8	100	0.1	5	1	5.66
9	60	0.14	11	0.6	6.77
10	120	0.06	5	0.6	16.58
11	80	0.1	8	0.6	13.02
12	100	0.02	14	0.6	91.37
13	100	0.14	8	0.2	36.59
14	80	0.06	14	0.2	126.39
15	120	0.1	11	0.2	23.01
16	60	0.02	5	0.2	5740.5

Based on the above tool prediction model theory and test results, the regression coefficient values are calculated using matlab. The obtained tool life experience formula is as follows :

$$T = 1224898 a_p^{-1.494} a_e^{-0.949} v^{-2.347} f_z^{-2.053} \quad (3-1)$$

The tool life polynomial is

$$T = 100000 \times (0.0801 - 0.0261a_p - 0.0257a_e + 0.0023v - 0.6775f_z + 0.0012a_p a_e - 0.0003a_p v - 0.0013a_p f_z + 0.0001a_e v + 0.0733a_e f_z - 0.0043f_z v + 0.0219a_p^2 + 0.0005a_e^2 - 0.00001v^2 + 1.4426f_z^2) \quad (3-2)$$

From the formula, it can be seen that the feed per tooth and the cutting speed have a great influence on the tool life. Increasing cutting speed accelerates tool wear and reduces tool life due to rapid increase in tool temperature, which leads to increased tool work hardening and adhesion.

4. Optimization of cutting parameters

After the workpiece and tool are selected, cutting parameters are the main factors affecting the machining efficiency. Taking the cutting speed v , feed per tooth f_z , axial depth of cut a_p and radial depth of cut a_e as design variables, we have

$$X = (x_1, x_2, x_3, x_4)^T$$

When solving a multi-objective optimization problem, the most important objective is to optimize the objective, and the rest can be solved with constraints. The objective function that is aimed at optimizing the tool life is:

$$T = 100000 \times (0.0801 - 0.0261x_1 - 0.0257x_2 + 0.0023x_3 - 0.6775x_4 + 0.0012x_1 x_2 - 0.0003x_1 x_3 - 0.0013x_1 x_4 + 0.0001x_2 x_3 + 0.0733x_2 x_4 - 0.0043x_3 x_4 + 0.0219x_1^2 + 0.0005x_2^2 - 0.00001x_3^2 + 1.4426x_4^2) \quad (4-1)$$

The constraints are as follows :

-Machine speed limit.

$$G_1(x) = \frac{\pi D n_{min}}{1000} - x_4 \leq 0 \quad G_1(x) = \frac{\pi D n_{min}}{1000} - x_4 \leq 0 \quad (4-2)$$

$$G_2(x) = x_4 - \frac{\pi D n_{\max}}{1000} \leq 0 \quad G_2(x) = x_4 - \frac{\pi D n_{\max}}{1000} \leq 0 \quad (4-3)$$

- Feedrate limit.

$$\frac{v_{f \min}}{n_{\max} z} = f_{z \min} \leq f_z \leq f_{z \max} = \frac{v_{f \max}}{n_{\min} z}$$

$$G_3(x) = f_{z \min} - x_3 \leq 0 \quad (4-4)$$

$$G_4(x) = x_3 - f_{z \max} \leq 0 \quad (4-5)$$

- Limitations on metal removal rates

$$G_5(x) = \frac{1000 x_1 x_2 x_3 x_4}{\pi D} - Q = 0 \quad (4-6)$$

Hence, the cutting parameter optimization model is expressed as

$$\max T(x) \quad (4-7)$$

$$x = (x_1, x_2, x_3, x_4)^T$$

Using Matlab's `fmincon` function, we can solve the maximum problem as a minimum problem. The metal removal rate per unit time Q (mm³/min) is 300, 400, 500, and 600, respectively.

By obtaining the optimum cutting parameters at different metal removal rates and entering this into the tool life model, the predicted tool wear life is obtained and simultaneous simulation with the optimal cutting parameters is carried out to obtain the experimental tool wear life (Table 4.1).

Table 4.1: Experimental verification of parameter optimization

Q	v	f_z	a_c	a_p	Prediction $T_{a \min}$	Experimental $T_{c \min}$	Percentage Error %
300	41	0.11	7.9	0.55	1255	1106	13.5
400	47	0.087	8.7	0.71	2306	2104	9.6
500	50	0.081	9.3	0.83	2838	2536	11.9
600	54	0.073	10	0.96	3710	3203	15.8

Conclusions

In this paper, a method is proposed to determine the cutting parameters at which the tool wear life is maximum for a constant metal removal rate. The tool wear model was constructed by a polynomial regression model from the simulation data obtained by Deform3D finite element software, and the optimization solution was performed using Matlab's `fmincon` function. The effectiveness of the proposed method was verified through cutting of high temperature alloy Ti6Al4V and improved machining accuracy and machining time of machining center. The error range of tool wear life prediction is between 9.6% and 15.8%, indicating that this method can optimize cutting parameters for tool wear life.

The proposed method can be applied to determine the cutting parameters that maximize the tool life for machining various hard-working materials.

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Conflict of interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

Disclosure statement

No potential conflict of interest was reported by the authors.

Data Availability

The data that support the findings of this study are available within the article.

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