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Research on Optimization of Cutting Force of TC4 Titanium Alloy Based on Support Vector Machine

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Abstract: Titanium alloy TC4 has excellent mechanical properties and corrosion resistance, and is widely used in aerospace, medical devices and other fields. However, its difficult machinability leads to large cutting forces and severe tool wear. Its inherent low thermal conductivity, low elastic modulus and work hardening characteristics easily cause problems such as cutting overheating and poor surface machining quality during the cutting process, affecting processing efficiency and quality. Based on support vector machine (SVM) technology and through orthogonal experimental design, this paper selects appropriate design parameter sample points to design a prediction model, builds a cutting force prediction model for TC4 titanium alloy, and optimizes the cutting parameters. The research results show that the SVM model can effectively predict cutting force, and the optimized cutting parameters significantly reduce cutting force and improve processing efficiency.

1. Introduction

Scholars at home and abroad have conducted extensive research on the cutting force of TC4 titanium alloy. For instance, Sun Lin et al. analyzed the influence of cutting parameters on cutting force through Deform-3D software simulation [1]; Chen Bo et al. studied the influence law of cutting parameters on cutting force by using the response surface method [2]; Huang Zhengtao et al. proposed an optimization model of milling parameters based on stability constraints [3-4]. However, most of the existing studies are based on traditional statistical methods and lack in-depth exploration of nonlinear relationships. As a powerful machine learning tool, support vector machine can effectively handle nonlinear problems and provide new ideas for the optimization of cutting force.

This paper uses the finite element analysis simulation software DEFORM-3D to conduct simulation analysis on aspects such as cutting force, surface integrity, and stress-strain during the cutting process. Meanwhile, it proposes a prediction analysis of cutting parameters based on the MATLAB support vector machine model, and conducts error rate and significance tests and analyses on the predicted values and experimental values. Through the research methods proposed in this paper, researchers and technical staff can have a more comprehensive understanding and application of cutting process parameters in production practice.

2. Establishment of Finite Element Analysis Model for High-Speed Milling of 2 Titanium Alloys

2.1 Geometric Model and Grid Division

For example, in this article, a simplified model is established to replace more complex cutting workpieces and tools. In the finite element simulation research process, the workpiece is selected as the outer blank material close to the tool, while the tool only contacts the tip of the workpiece surface as the research object. A tool model with a front angle of 10° and a back angle of 6° was established for the simulated workpiece blank size of 60 × 30 × 10 in this article. Figure 1 show the complete geometric model required for cutting simulation and machining. The geometric model of the cutting tool is shown in Figure 2. For DEFORM-3D software, a special tetrahedral mesh is usually used to locally refine the mesh in simulating cutting processes. According to actual needs, the mesh for areas with small changes in physical quantities such as stress, strain, and temperature can be sparse, while the mesh for areas with severe changes in field quantities needs to be dense. (1) Workpiece mesh division: The number of unit meshes is roughly determined based on the size and cutting depth of the workpiece. The mesh corresponding to all cutting depths of 3-4mm selected in this simulation is shown in Figure 3. (2) Tool mesh division: The tool in contact with the workpiece only has the tip area, and the other parts of the tool have little physical field change during the cutting process. Therefore, when dividing the mesh, it is necessary to refine the front and rear cutting surfaces of the tip area, as shown in Figure 4 [5-7].

Figure 1. Workpiece model

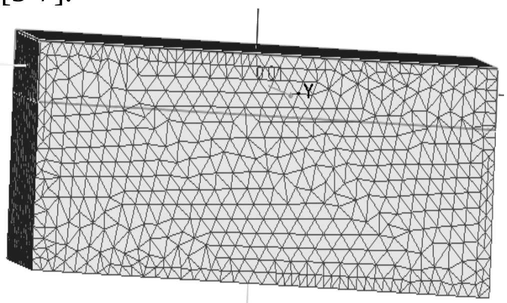

Figure 2. Artifacts grid

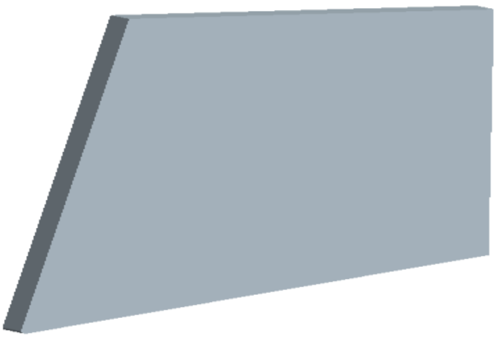

Figure3. Tool model

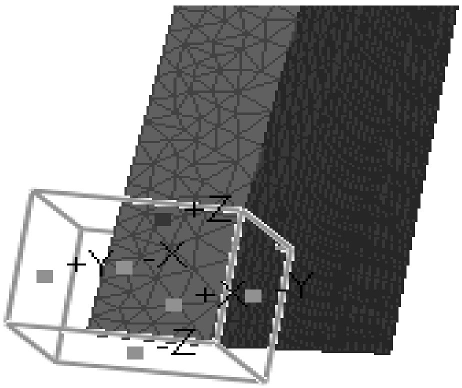

Figure 4. Tool grid

2.2 Material Constitutive Model and Related Parameters

For the material constitutive relationship of titanium alloy Ti6Al4V, this paper adopts Johnson Cook's constitutive model of high strain, high strain rate, and high temperature deformation, which is suitable for the martensitic crystal structure. Let A be the yield strength of the material; B is the hardening strength of the material; n is the strain hardening index of the material; C is the strain rate strengthening coefficient of the material; m is the temperature softening coefficient of the material; T_r is the reference temperature for room temperature; T_m is the melting point temperature; **σ** represents the yield stress of the material; ε represents the equivalent strain of the material; ε' is the strain rate; ε_0 is the reference strain rate, which generally takes the form of [8-10]:

$$\sigma = \left(A + B\varepsilon^n\right)\left[1 + C\ln\left(\frac{\varepsilon'}{\varepsilon_\circ}\right)\right]\left[1 - \left(\frac{T - T_r}{T_m - T_r}\right)^m\right] \tag{1}$$

The first bracket on the right side of the equation explains the effect of strain ε on yield stress σ, the second explains the relationship between strain rate ε0 and yield stress σ , and the last part is about the relationship between yield stress σ and temperature T. The 7 model parameters of Johnson Cook model are shown in Table 1.

Table 1. Ti6Al4V Johnson - Cook7 model parameters

parameter	*A*/MPa	*B*/MPa	*n*	*c*	*m*	T_0/℃	T_m/℃
coefficient	973.08	617.1	0.144	0.001	0.72	20	1560

The titanium alloy material selected is Ti6Al4V material, whose basic characteristic quantities include density, elastic modulus, thermal conductivity, specific heat capacity, etc., as shown in Table 2.

Table 2. The materials properties of titanium alloy Ti6Al4V parameters

density (g/cm3)	Elastic modulus(GPa)	thermal conductivity(W/m ·K)	Specific heat capacity (J/kg ·K)	Poisson's ratio
4.45	103	6.8	611	0.34

In this article, DEFORM-3D simulation cutting simulation is used, and the tool material is selected as hard alloy WC material, which has good electrical and thermal conductivity. Adding an appropriate amount of metal materials such as titanium carbide and cobalt can reduce the brittleness of WC material. At the same time, its chemical properties are very stable, making it a good material suitable for cutting tools. The basic properties of WC hard alloy materials are shown in Table 3. Complete material loading of workpieces and tools in DEFORM-3D software. [11-12]

Table 3. Carbide WC material characteristic parameters

density (g/cm3)	Elastic modulus(GPa))	thermal conductivity(W/m ·K)	melting point(℃)	Specific heat capacity (J/kg ·K)	Poisson's ratio
15.63	71	5.9	2870	0.02	0.25

3. Principle of Support Vector Regression Machine

For the sample set, $D = \{(x_i, y_i) | \ i = 1,2,...l\}$,where $x_i \in R^n$ is the input quantity ,and $y_i \in R$ is the output quantity. Support vector regression mainly fits sample points using the following regression function based on training samples. [13-14]

$$f(x) = w.x + b \tag{2}$$

In order to obtain better regression fitting results, by assuming that all training values can generate a linear fit with an accuracy of ε, the regression estimation function becomes overly focused on finding the minimum $\|\omega\|$ problem, which can be expressed in the form of a convex optimization problem as follows:

$$\begin{cases} \min \ \frac{1}{2}\|\omega\|^2 \\ s.t \quad \begin{cases} \omega.x_i + b - y_i \le \varepsilon \\ y_i - \omega.x_i - b \le \varepsilon \end{cases} \end{cases} \tag{3}$$

From this, the linear fitting function expression of the regression machine can be obtained:

$$f(x) = w.x + b = \sum_{i=1}^{n} \left(\alpha_i - \alpha_i^*\right)\left\langle x_i, x_j \right\rangle + b \tag{4}$$

By utilizing the knowledge of general functions, it can be known that the inner product operation of projecting training data onto high-dimensional feature regions is equivalent to a kernel function substitution of the original low dimensional region $K\left(x_i, x_j\right)$, that is, replacing the inner product algorithm in linear problems through kernel functions in high-dimensional feature regions

$$K\left(x_i, x_j\right) = \varphi\left(x_i\right)\varphi\left(x_j\right) \tag{5}$$

At the end, the support vector machine fitting relationship is obtained as follows:

$$f(x) = \sum_{i=1}^{n} \left(\alpha_i - \alpha_i^*\right) K\left(x_i, x_j\right) + b \tag{6}$$

4. Cutting Force Prediction Based on Support Vector Machine Model

4.1 Regression orthogonal experimental design

In the construction process of the prediction model, the first step is to select the correct training points. Obtain the relationship between design variables and response variables from a limited number of data sample points, and then obtain the relevant physical quantities in the prediction model. Orthogonal experimental design can obtain richer information about the overall experimental situation with the least number of tests, and analyze the variance of the experimental results to predict the relative weights of various factors and analyze their interactions; Regression analysis is an effective method for data processing. By using established regression equations, experimental conclusions can be predicted and optimized. Orthogonal experimental design combines regression analysis and orthogonal experiments to select appropriate experimental points within the experimental range of factors, construct high-precision and statistically superior regression equations with fewer experiments, and also process optimization related to experiments [15-17].

Orthogonal table is a highly regular table constructed based on orthogonal Latin using combinatorial number theory. It is an effective way to handle experiments and experimental results in orthogonal experimental design. This article analyzes the effect of cutting speed, width, and depth on cutting force. Using the principle of regression orthogonal experiment, a simulation method is designed to select 3 factors and 4 levels as shown in Table 4:

Table 4. Cutting simulation test factors level table

Factor level	Cutting Speed(mm/s)	Cutting Depth(mm)	Cutting width(mm)
I	300	0.1	0.3
II	600	0.2	0.4
III	900	0.3	0.5
IV	1200	0.4	0.6

If the overall simulation cutting plan is made according to Table 4, the workload will be 4^3 times and the simulation cutting time will increase. Therefore, in order to shorten the time and obtain reliable and accurate simulation results, the regression orthogonal experimental design method is adopted. The general orthogonal table can be represented by symbol $L_n(r^m)$, where L is the orthogonal table code; n represents the number of rows in the orthogonal table. r is the factor level number; m is the column count of the orthogonal table . Design an orthogonal table $L_{16}(4^3)$ with 3 factors and 4 levels as shown in Table 5. For the analysis of each group, it is necessary to follow the operation stroke of the analysis to ensure that the simulation of each group does not include the three factors of cutting speed, cutting width, and cutting depth. Other external interference reasons should be as uniform as possible to improve the accuracy of the simulation results. Record the cutting force values generated during the simulation process and fill them into the orthogonal experimental simulation table.

Table 5. L_{16} (4^3) orthogonal cutting force simulation results

number	Cutting Speed(mm/s)	Cutting Depth(mm)	Cutting width(mm)	cutting force(N)		
				Fx	Fy	Fz
1	300	0.1	0.3	726.31	1.78	114.91
2	300	0.2	0.4	912.93	1.69	127.67
3	300	0.3	0.5	887.21	1.42	135.72
4	300	0.4	0.6	587.53	2.67	142.63
5	600	0.1	0.3	656.71	2.65	105.54
6	600	0.2	0.4	622.78	2.49	119.41
7	600	0.3	0.5	739.69	3.21	127.53
8	600	0.4	0.6	598.16	2.91	133.38
9	900	0.1	0.3	613.23	2.57	121.16
10	900	0.2	0.4	774.58	2.29	149.36
11	900	0.3	0.5	683.87	2.63	136.72
12	900	0.4	0.6	776.71	2.19	143.23
13	1200	0.1	0.3	865.23	2.89	139.69
14	1200	0.2	0.4	913.15	2.18	145.13
15	1200	0.3	0.6	989.52	1.08	125.63
16	1500	0.4	0.6	813.75	0.99	135.36

A support vector machine model was established based on MATLAB software, and cutting force prediction analysis was conducted using multiple cutting simulation test factors as shown in Table 4. The simulation results data in Table 4 were substituted into the established model for prediction, and the Fx and Fz prediction results were compared with the experimental values shown in Table 6. However, the values in the Fy direction were not considered because they were too small.

Table 6. Comparison experimental and predicted values

number	Cutting Speed (mm/s)	Cutting Depth (mm)	Cutting width (mm)	Fx(N)			Fy(N)	Fz(N)		
				Test Value	Estimate Value	relative error(%)	Test Value	Estimate Value	relative error(%)	relative error(%)
1	300	0.1	0.3	726.31	730.91	0.55	1.78	114.91	112.76	1.93
2	300	0.2	0.4	912.93	923.12	1.21	1.69	127.67	128.93	1.02
3	300	0.3	0.5	887.21	886.31	0.10	1.42	135.72	137.75	1.48
4	300	0.4	0.6	587.53	585.05	0.42	2.67	142.63	141.57	-0.75
5	600	0.1	0.3	656.71	652.93	0.58	2.65	105.54	113.92	-1.13
6	600	0.2	0.4	622.78	631.19	1.35	2.49	119.41	121.54	1.67
7	600	0.3	0.5	739.69	745.71	0.81	3.21	127.53	128.05	1.18
8	600	0.4	0.6	598.16	597.17	-0.16	2.91	133.38	135.25	1.57
9	900	0.1	0.3	613.23	609.86	0.55	2.57	121.16	122.55	1015
10	900	0.2	0.4	774.58	765.75	1.03	2.29	149.36	143.18	1.26
11	900	0.3	0.5	683.87	676.01	1.14	2.63	136.72	137.31	0.44
12	900	0.4	0.6	776.71	769.45	0.94	2.19	143.23	141.58	-1.18
13	1200	0.1	0.3	865.23	861.12	0.47	2.89	139.69	136.95	-1.97
14	1200	0.2	0.4	913.15	901.03	1.32	2.18	145.13	146.47	0.89
15	1200	0.3	0.5	989.52	985.36	0.42	1.08	125.63	126.58	0.80
16	1200	0.4	0.6	813.75	806.78	0.86	0.99	135.36	137.12	1.33

From Table 6, it can be seen that the trend of changes in the experimental and predicted values is consistent, and the average relative error of the data is within 2%. The reason for the error is that: 1) there are differences between the actual machining and the tool tool in the simulation model; 2) In the actual machining process, the tool may experience wear, but in the simulation prediction model, the tool is treated as a rigid body; 3) The actual machining process is affected by various external conditions such as continuous vibration of the machine tool and indoor temperature, but the simulation prediction model is made in an ideal environmental atmosphere for machining. Overall, it can be seen that the simulation predicted values and experimental values of milling force have a relatively ideal fitting effect, demonstrating the feasibility of the established prediction model.

5. Conclusion

The article conducted a large number of simulation cutting experiments on the characteristics of cutting force and residual stress in the production process of typical titanium alloy Ti6Al4V material, and finally optimized the simulation results using MATLAB. The main work and corresponding conclusions of the entire article are summarized as follows:

(1) An introduction was given to the cutting principle and the formation process of chips, clarifying the changes that occur in the workpiece at which processing stage and the impact on the quality of the processed workpiece; Explanations were made on cutting force and surface integrity, laying the foundation for the analysis of simulation results.

(2) Perform cutting simulation through DEFORM-3D software;

Establish a support vector machine model to predict and analyze cutting forces, and conclude that support vector regression machine is more suitable for predicting and analyzing small sample data; By conducting regression orthogonal experiments on cutting forces and forming a design scheme for L16 (43), the efficiency of cutting simulation was improved

(3) The genetic algorithm toolbox provided by MATLAB software was used for parameter optimization and the results were obtained. The optimization results were validated using the support vector machine model established earlier, and the final optimization results were

determined. This provides a theoretical basis for selecting appropriate cutting parameters for milling in the actual production process.

(4) The TC4 titanium alloy cutting force prediction model based on support vector machine has high prediction accuracy and reliability. The optimized cutting parameters significantly reduce cutting forces and improve machining efficiency.

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