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Interpolation and Milling Optimization of Titanium Alloy Based on Machine Learning and Multi-objective Algorithm

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Abstract: With the continuous progress of the society, the manufacturing industry is facing greater challenges and opportunities. Complex, diverse and customized requirements demand greater flexibility and faster response times in manufacturing process systems. As a machining method that can quickly remove metal materials, insert milling has attracted much attention in recent years, and has been widely used in aerospace and die manufacturing industries. In this paper, the interpolation and milling optimization of titanium alloy based on machine learning and multi-objective algorithm is studied. In this paper, taking milling TC4 titanium alloy as an example, a machining optimization model based on multi-objective optimization is proposed to improve the quality and improve the efficiency. DDQN is used to optimize and model the parameters (satisfying the minimum surface roughness, maximum material removal rate and optimal milling force stability). Finally, the effectiveness of the multi-objective algorithm is verified by comparing with the empirical parameters.

1. Introduction

The aero-engine integral disc and the centrifugal compressor integral impeller are the core components of aero-engine and centrifugal compressor. The working conditions of such parts are poor, and the materials are generally difficult to be machined, such as titanium alloy, all kinds of stainless steel and high temperature alloy, and more than 60% of the blank materials need to be cut in the cutting stage [1-2]. Under the existing conditions, the production cycle of the integral blade disk and the integral impeller is relatively long and the production cost is very high. It is of great significance to improve the production efficiency and reduce the production cost for the national defense industry and chemical industry. The cutting of large mold cavities in the automobile

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industry is also a type of processing with large amount of metal removal. The cold-working die steel of the mold used for stamping automobile shell sheet has high hardness, good wear resistance and poor machinability, so the production cost of a set of molds is very high and the production cycle is relatively long [3-4]. With the continuous development of economy and technology in the new century, the difficulties encountered by the manufacturing industry include how to respond to the market demand quickly, develop the technology of new products and develop new manufacturing process. As a processing method that can quickly remove metal materials, interpolation and milling can significantly improve the processing efficiency and shorten the manufacturing cycle of products [5]. If insertion and milling technology can be applied to the processing process of the above parts, the international competitiveness in the production and manufacturing of such parts in China will be greatly improved [6].

The different combination of process parameters in the processing process will directly affect the quality of processed parts, machine tool processing efficiency, production cost and production energy consumption. Generally, the processing optimization objectives in intelligent manufacturing can be selected according to the production needs and technical constraints of enterprises [7]. In recent years, the study of process parameter optimization has gradually attracted the attention of experts and scholars. Researchers have conducted a series of studies on process parameter optimization and proposed various solutions. The solution methods can be divided into two categories: one is to conduct processing experiments to comprehensively evaluate the decision variables and optimization objectives, for example, to directly obtain results through correlation ranking [8]. Another kind of method is to seek the optimal solution or equilibrium point in multiple objectives, especially in multiple objectives with opposite optimization direction, through intelligent optimization algorithm to solve the optimization problem [9]. For the second type of methods, the Pareto solution set of the optimization objective is usually used for evaluation. Pareto solution, also known as non-dominated solution, may lead to the deterioration of other targets when optimizing a certain target in the processing, and a better solution cannot be obtained in the direction of a single target [10]. At this time, the solution set composed of machining parameters and optimization objectives is called Pareto solution set, and the set of these solutions is called Pareto optimal solution set [11]. Meta-heuristic algorithm is one of the commonly used methods to solve multi-objective optimization problems in the processing process and obtain Pareto solution sets. It is developed by simulating natural phenomena according to intuitive or empirical construction and combining with biological evolution or optimization behavior to adapt to environmental changes [12].

Reasonable cutting parameters can significantly improve machining performance indexes, improve machining efficiency and reduce production costs and energy consumption. Optimizing cutting parameters is of great significance to play the advantages of interpolation and milling.

2. Interpolation and Milling Optimization Based on Multi-objective Optimization Algorithm

2.1. Interpolation and Milling Machining Mode and Modeling

(1) Processing mode

Interpolation milling is one of the most efficient machining methods for metal cutting. The intercalation and milling stage is mainly divided into three stages. The intercalation and milling stage is when the intercalation and milling cutter is fed along the axis and cut to a certain depth. Cutting tool along the axis, for the rising stage then the tool continues to deviate from the horizontal direction for a distance, which is the deviating stage, and so on and so on [13].

Interpolation milling is often used to remove material allowance quickly, complex surface of parts, difficult materials and long tool overhang. In the cutting tool length to diameter is large and complex curved surface parts processing, the conventional method of milling cutter are prone to deformation, able to withstand the radial cutting force is small, in order to avoid the flutter, affect the machining accuracy and other negative effect to adopt conservative cutting parameters, such as reducing cutting speed, cutting depth and cutting width, this limits the processing efficiency. In the process of interpolation and milling, the tool is fed along the spindle direction, and the rigidity of the cutting system is large, which can better avoid chatter, make the machining quality of parts more stable, and improve the cutting parameters appropriately to improve the material removal rate [14-15].

In addition, intercalation and milling can quickly remove a large amount of workpiece materials with a large cutting width, feed per tooth, cutting step distance and appropriate spindle speed, which makes the intercalation and milling have low requirements on the machine tool and thus can obtain high processing efficiency on the machine tool with insufficient power [16].

(2) Geometric modeling

The cutting edge of milling cutter is directly involved in the cutting of workpiece material, and the movement track of the cutting edge is related to the shape of the tool and milling parameters. The tool motion can be decomposed into rotation around the central axis of the tool and feed motion vertically downward along the central axis [17]. In order to simplify the research, the cutting edge is discretized into countless points, and the trajectory of a single point is first analyzed, and then the motion trajectory of these points is set to form the motion trajectory of the cutting edge. Assuming that the horizontal distance between any point i on the cutting edge and the center point of the tool is the radius Ri, the parameter equation of the motion trajectory of this point in the three-dimensional cartesian coordinate system can be expressed as formula (1).

$$
\begin{aligned}
x &= R_i \cos(\omega t) \\
y &= R_i \sin(\omega t) \\
z &= v_f t
\end{aligned}
\tag{1}
$$

In Equation (1), ω represents the angular velocity of tool rotation, vf represents the axial feed velocity of tool, and t is time.

It is assumed that the tool is rigid, the edge of the tool is not rounded, and the intersection of the main cutting edge and the secondary cutting edge is the tool point. The tool tip point is a special point of the cutting edge of the tool. Here, the tool tip point is used to represent the points on the cutting edge, and its motion track is studied. If the horizontal distance between the tool tip point and the tool center point is R, the following relationship (2) can be obtained.

$$
\begin{aligned}
\omega &= 2\pi n \\
v_f &= z n f_z
\end{aligned}
\tag{2}
$$

Taking R=16mm two-tooth milling cutter as an example, assuming that the spindle speed n=1000r/min and the feed rate of each tooth fz=0.1mm/z, the geometric model of the trajectory of the corresponding tool tip was established.

The geometry of cutting tool and workpiece is called cutting geometry. It can represent the relative position, cutting order and cutting way of cutting tool and workpiece. It is the basis of further research on cutting mechanism. The shape and nature of the cutting geometry affect the way of cutting material allowance and the distribution of cutting load for each cutter tooth on the cutting tool, which has an important impact on the formulation of machining technology and the performance indexes such as cutting force, tool life and machining efficiency in the cutting process [18].

2.2. Multi-Objective Optimization Based on Dual Deep Q Network

Dual Deep Q network (DDQN) is a value-based reinforcement learning algorithm, in which the value of all actions is output and the action is selected according to the highest value.

According to the idea of multi-objective optimization, reasonable design variables are the primary consideration for machining parameter optimization. In general, the basic processing parameters with great influence on the target are selected as design variables, while the variables with little influence on the target or predetermined according to actual needs can be treated as constants. When solving complex problems, the appropriate selection criteria should be considered. In addition, in order to reduce the difficulty of optimization, the number of variables should be minimized. Therefore, the basic milling parameters are selected as the decision variables of the model, namely, the spindle speed n, the feed rate f, the axial cutting depth ap and the radial cutting depth ae (see Equation 3).

$$\begin{aligned} &\min Y = F(x) = \{ f_{Ra,} 1/ f_{MRR}, f_{FDS} \} \\ &X = [n, f, a_e, a_p] \end{aligned} \tag{3}$$

The objective function is an index to select and evaluate the optimization objective. In actual production, different optimization objective functions are usually established according to different processing needs. In order to achieve the best surface quality, machining efficiency and machining performance in milling, it is necessary to select the appropriate combination of process parameters. Therefore, the relationships between surface roughness Ra, milling force stability FDS, material removal rate MRR and milling parameters were denoted as objective functions (fRa, fFDS, fMRR). Ra and FDS are established through DDQN.

The larger MRR is, the better the processing efficiency is. The reciprocal of MRR (1/MRR) is taken for the convenience of calculation and result presentation. Y is used to represent the minimum total optimization objective, as shown in Equation (3). In addition, various constraints (machine tool performance, machining quality and tool parameters, etc.) should be fully considered to optimize the machining parameters, so that the optimized parameters have practical significance.

Using reinforcement learning to solve machining parameters optimization essence is in the processing environment to obtain the optimal parameters of multi-objective under collection, state through access to a range of different processing parameters, and use the corresponding evaluation index to evaluate the stand or fall of the action, then feedback to the value network to obtain more quickly find the optimal parameters of the decision. Finally, the Pareto front is obtained by selecting the observed states.

The internal value network of DDQN in the multi-objective optimization task uses the fully connected network to estimate the value function. ReLu activation function is used for nonlinear transformation, and RMSProp optimizer is used to control the historical information by stochastic gradient descent. The 300 sets of processing parameter combinations obtained in the training are used as the input samples for training, and the output is the executed action. The multi-objective optimization of processing parameters is carried out here. The multi-objective optimization task is more complex and requires more iteration which is set as 50000 here.

3. Parameter Optimization Experimental Setting

3.1. Titanium Alloy TC4

Titanium alloys are widely used in key aerospace components. The TC4 studied in this paper belongs to α+β titanium alloy and is composed of Ti-6Al-4V. Its chemical composition is shown in Table 1, and its mechanical properties at room temperature are shown in Table 2.

Table 1. Chemical composition of TC4 titanium alloy w (%)

A1	V	Fe	N	C	O	H	Ti
6.0	4.0	0.3	0.05	0.1	0.2	0.0125	Other

Table 2. Mechanical properties of TC4 titanium alloy

Density (g/cm^3)	Thermal conductivity (W/(m K))	Elastic modulus GPa	Tensile strength MPa	Elongation %
4.42	8.37	115	932	13

3.2. Parameter Optimization

The milling parameter optimization method in this paper is optimized according to the multi-objective algorithm and optimized based on the established objective function and preset constraints. The specific optimization process is as follows:

The initial population was established by the combination of four processing parameters: spindle speed, axial cutting depth, radial cutting depth and feed per tooth. Set the objective function of milling parameter optimization; Set constraints for milling parameter optimization.

Because MATLAB has a complete genetic algorithm toolbox, so the above objective function and constraints are written into m file, through MATLAB multi-objective genetic algorithm toolbox for calculation.

4. Analysis of Experimental Results

4.1. Pareto Optimal Solutions

According to the optimization results, five groups of Pareto optimal solutions with high fitness are derived, and the set of optimal solutions is shown in Table 3 below.

Table 3. Pareto optimal solution set for milling parameter optimization

	Feeding (mm/z)	Axial depth of cutting (mm)	Radial cutting depth (mm)	Surface roughness (μm)	Material removal rate (mm^3/min)	Spindle speed (r/min)
1	0.32	3.26	0.20	0.18	1054	1328
2	0.24	3.21	0.20	0.18	873	1296
3	0.28	3.29	0.20	0.18	972	1279
4	0.15	3.28	0.20	0.18	617	1252
5	0.27	3.55	0.20	0.185	1059	1241

By considering the objective function comprehensively, the higher the material removal rate is, the better the surface roughness is. Therefore, a set of milling parameters are optimized as shown in Table 4.

Table 4. Machining the optimal solution of the selected milling parameters

Feeding (mm/z)	Axial depth of cutting (mm)	Radial cutting depth (mm)	Surface roughness (μm)	Material removal rate (mm^3/min)	Spindle speed (r/min)
0.27	3.55	0.20	0.185	1059	1241

4.2. Verification of Parameter Optimization Effect

According to the factory survey, the empirical parameters for stable milling of titanium alloy are as follows: n =1850/ min, fz=0.02mm /z, ap =1.8mm, ae = 0.2mm. The effectiveness of the optimization is verified by comparing the corresponding objective functions of the front and rear milling parameters.

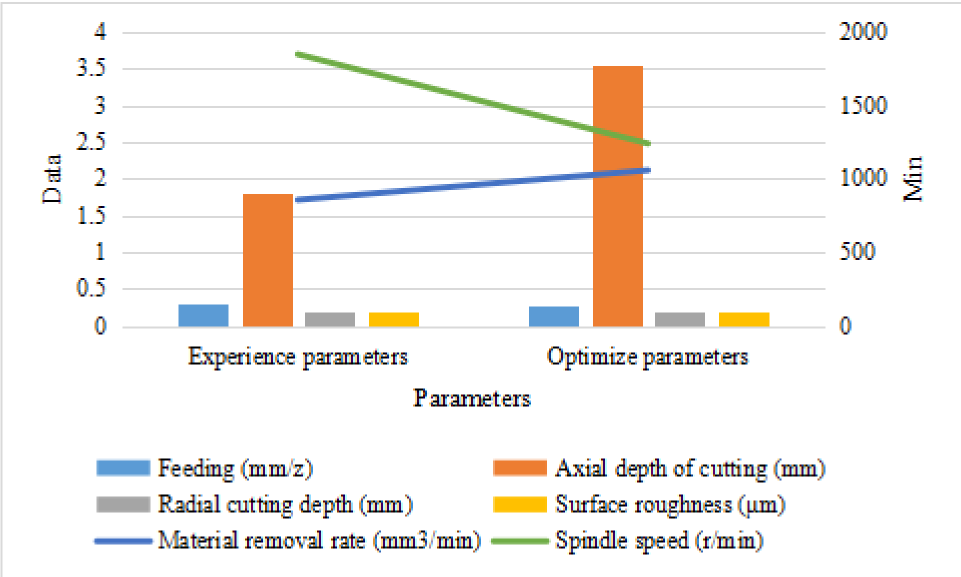

Figure 1. Machining selected milling parameters optimization results

As shown in Figure 1, compared with the empirical parameters, the optimization parameters obtained by the multi-objective optimization algorithm can improve the material removal rate on the basis of reducing the surface roughness of the processed workpiece, which is significant to a certain extent.

5. Conclusion

In this paper, the modeling and optimization of milling force in insert milling process of titanium alloy are studied. Firstly, the principle and characteristics of insertion and milling are introduced briefly, and then the trajectory of the tool tip and the geometric model of the undeformed chip are established. In this paper, DDQN is used to solve the proposed multi-objective optimization problem of machining parameters by using the established surrogate model. Combined with the research results of this paper and the current research status in this field, further research can be carried out in the following aspects: Multi-objective problem of this study was to define the processing parameters, the decision variables used in common processing parameters, and have a lot of input variables in the actual processing in the machining process can be considered, such as cutting tool Angle (after cutting tool rake Angle, cutting tool Angle, the Angle and blade Angle of tools) and machining properties have important influence on the quality of parts.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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