Proc. of the 9th Intl. Conf. of Asian Society for Precision Engg. and Nanotechnology (ASPEN 2022)
15–18 November 2022, Singapore. Edited by Nai Mui Ling Sharon and A. Senthil Kumar
doi://10.3850/978-981-18-6021-8_OR-09-0138

A tool protection strategy for digital turning process based on simulation data

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KEYWORDS: Turning titanium alloy, Simulated cutting force, Simulated temperature, Optimization algorithm

This paper presents a tool protection strategy for turning titanium alloy. The orthogonal table ($L5^3$) is taken as the simulation sample point in the design space, and the actual cutting force is compared through experiments to verify the reliability of the simulation results. A reliable response surface model (R_f^2=0.980, RMS_f=0.047, R_t^2=0.948, RMS_t=0.024) was obtained by extracting the simulated cutting force and the simulated tool tip temperature as the inputs of the surrogate model. The embedded Non-dominated Sorting Genetic Algorithms (NSGA-II) takes the minimum force and temperature as the objective, so as to realize the optimization of cutting parameters input and the minimization control of cutting force and tool tip temperature under different material removal rates. The results show that the strategy is effective and can be used as a reference module to help the transformation of digital manufacturing industry.

NOMENCLATURE

MRR = material removal rate
HRSM = hybrid response surface model

1. Introduction

Titanium alloys are widely used in the aerospace field because of their high specific strength, high temperature thermal strength and corrosion resistance. Meantime, the low thermal conductivity and high-temperature chemical activity of titanium alloy lead to the early failure of high-temperature tool adhesion during machining. Many researchers are committed to improving various cutting environments to avoid or reduce their difficult machinability. In particular, intelligent manufacturing has attracted much attention in the case of irreversible digital manufacturing.

In the past, numerical theory and statistical analysis based on physical model have laid a digital foundation for real objects and can preliminarily predict cutting temperature and optimize cutting parameters[1]. Taguchi method based on statistics and variance analysis have been used to investigate and predict the performance of titanium alloy turning[2]. With the continuous breakthroughs in computer science, meta heuristic optimization algorithm and artificial intelligence can better adapt to today's intelligent interconnected big data manufacturing environment. Various machine learning algorithms of regression and classification have been proved to have better prediction and optimization results, showing more future advantages of soft computing[3].

This paper is devoted to digital exploration. The finite element model is used to transparent the cutting performance of titanium alloy, and NSGA-II multi-objective algorithm is embedded to optimize the design space surrogate model. The results show that appropriate cutting parameters can be found at all levels of material removal rate to minimize the cutting force and cutting temperature.

2. Model construction and correlation

2.1 Simulation and experimental data

Select the coated tungsten carbide tool to turn the titanium alloy (Ti-6Al-4V) bars (D30mm, L150mm). The force measuring instrument (Kistler type 9257) is installed on the CNC lathe table (DC-2CNC, Daegu Heavy Industry Co. Ltd.) to measure the actual cutting force data. $L5^3$ orthogonal table is used for sampling. The simulation data of AdvantEdge software and the real experimental data are shown in Figure 1.

It can be seen from the figure that the trend of cutting force of simulation and experiment is consistent, and the error is about 10N. Therefore, the results of the finite element model are proved to be reliable. Secondly, the simulation results of cutting temperature are indirectly proved to be of reference value, because it is difficult to measure the temperature of the cutting area in the actual cutting process. The next section will discuss the generation of surrogate model and optimization through this data.

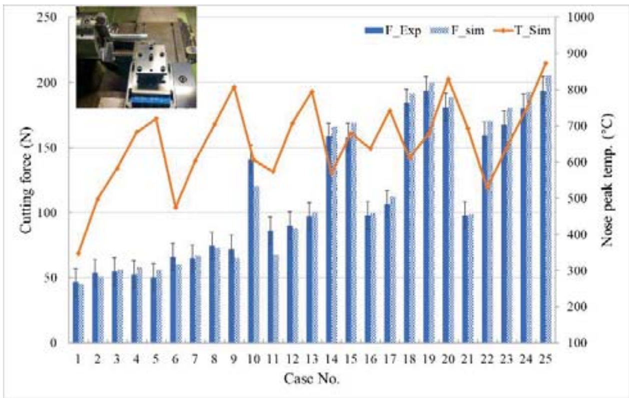

Fig. 1 Actual cutting force, simulated cutting force and simulated temperature sampled by L5^3 orthogonal table

2.2 Embed NSGA-II into the generated surrogate model

The parameter ranges and details of the design space are shown in the table in Figure 2. Response surface model (RSM) is selected as the surrogate model of design space, so as to avoid the long calculation time of cutting process simulation and realize rapid deployment and prediction. RSM takes cutting speed, feed and cutting depth as input parameters, simulates cutting force and simulates temperature as output parameters. Cross validation (5 points) is used to evaluate the reliability of the model. The R square (R^2) and root mean square (RMS) of the surface model of force and temperature are 0.980, 0.047, 0.948 and 0.024 respectively. The numerical formula of material removal rate and the quadratic RSM model are fused and defined as hybrid RSM (HRSM). So far, the digital display plate of titanium alloy turning in the design space has been completed.

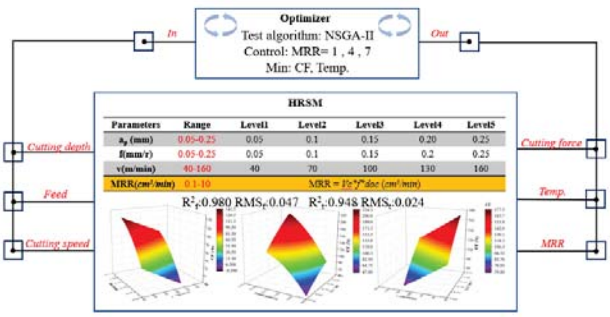

Fig. 2 Integrated deployment scheme of HRSM and optimizer

As a typical multi-objective optimization algorithm, Non-dominated Sorting Genetic Algorithm II (NSGA-II) implements global optimization by embedding HRSM connection input and output. Considering the actual production demand, MRR fast (7), medium (4) and slow (1) grades are set respectively to find the minimum cutting force and temperature within the conditions to ensure the minimum load of the tool and realize tool protection and sustainable machining.

The final optimization result is shown in Table 1. The weight of force and temperature is set equal, and the first value at the front of the Pareto is selected as the result. The output opt. MRR can be close to the preset value, minimizing the force and temperature on the tool. The real cutting force is basically consistent with the model results, which confirms the accuracy of the model. Finally, the optimized input parameters can be used as a feasible reference for the selection of machining parameters.

Table 1 Final optimization result

NSGA-II optimized input			
MRR (cm3/min)	V (m/min)	Doc (mm)	Feed (mm/rev)
1	60	0.24	0.07
4	120	0.22	0.15
7	140	0.25	0.21
NSGA-II optimized output			
Opt. MRR (cm3/min)	Temp. (°C)	CF (N)	Real force (N)
1.01	514	131	132
3.96	754	147	151
7.35	856	174	182

3. Conclusions

The tool protection strategy proposed in this paper has been proved to be an effective digital sustainable machining method.

ACKNOWLEDGEMENT

This research was supported by the Basic Science Research through the National Research Foundation of Korea (NRF) funded by the Ministry of Science, ICT, and Future Planning (grant number NRF-2020R1A2B5B02001755).

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