

One-pass milling machining parameter optimization to achieve mirror surface roughness

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Abstract: In this paper, the possibility of just using general machine centres in one-pass milling process to finish an aluminium plate with the mirror surface roughness is studied. In particular, how to find the optimal setting of machining parameters is presented. In this optimization problem, to evaluate whether the surface roughness meets the average criterion of a mirror surface requires real cutting experiments, and it is desirable to find the optimal machining parameters using as few experiments as possible. The 'sequential neural network approximation method' was used to find the optimal machining parameters, including the spindle speed, feed rate, depth of cut, and number of inserted blades in the cutter to maximize the metal removal rate while the surface roughness meets the average criterion of a mirror surface.

Keywords: mirror surface roughness, machining parameter optimization, sequential neural network method

1 INTRODUCTION

Mirror surfaces based on a metal matrix intended for application on reflectors and optical parts have been expected to become true in mass production. The cost of mirror quality fabrication of metal surface using superprecision machines or multi-loop machining is still high. On the other hand, for cheap and fast mass production, the possibility of just using general machine centres in a one-pass milling process to finish an aluminium plate with the desired mirror surface roughness is studied. In particular, how to find the optimal setting of machining parameters for one-pass milling of metal mirror surfaces is presented in this paper.

The effect of various machining parameters (such as spindle speed, feed rate, depth of cut, and different types of cutter) on the surface roughness has been well studied [1–4], but few researchers have paid special attention to mirror surface machining with a one-pass milling simple procedure. This paper describes the process of optimizing the machining

parameters in a one-pass milling process by a general machine centre for mass production of aluminium alloy 6061-T6 plates. The purpose is to maximize the metal volume removal rate while the finished surface will pass the desired average roughness of the mirror surface. The spindle speed, feed rate, depth of cut, and number of inserted blades in the cutter are the design variables to be decided.

The spindle speed of the computer numerical control machine centre used in this research ranges from 40 to 7100 r/min (cutting speed, 20–3560 m/min), with a feed increment of 0.001 mm. The cutting tool was a Mapal face miller, 160 mm in diameter, with one to ten diamond face milling blades inserted. A non-contact cut-off light-type Taylor–Hobson microscope with 0.02 µm resolution of a pick-up diamond probe was used to measure the cutting surface roughness. The workpiece was 55 mm³ aluminium alloy 6061-T6 material.

The metal removal rate Q (cm³/min) can be calculated as

$$Q = \frac{w_c d_c v_f}{1000} \quad (1)$$

where w_c is the width of cut (mm), d_c is the depth of cut (mm), and v_f is the feed speed (mm/min).

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Moreover,

$$v_f = v_s z r_f \quad (2)$$

where z is the number of blades or cutter teeth and r_f is the feed per cutter tooth (mm/tooth). In this case, $w_c = 55$ mm, and the objective is to maximize the metal removal

$$\text{maximize } Q = 0.055 d_c v_s r_f z \quad (3)$$

At the same time the surface roughness measured by the Taylor–Hobson microscope has to pass the criterion of a mirror surface. In general, for a mirror surface, the center-line average roughness R_a is defined by

$$R_a = \frac{\sum_{i=1}^n y_i}{n} \leq 0.05 \mu\text{m} \quad (4)$$

where y_i is the measured roughness height according to each individual division from the average centre-line, and n is the total number of divisions.

This is a typical engineering optimization problem that cannot be solved by directly applying the existing numerical optimization algorithms. In this optimization problem, the mirror surface constraint is the so-called ‘implicit constraint’ [5]. It cannot be expressed as an analytical function in terms of the design variables. Many factors can affect the surface roughness of a workpiece, and it is hard to analyse the surface roughness and to establish a theoretical form using cutting theory. To evaluate whether the surface roughness meets the average criterion of a mirror surface requires real cutting experiments. It is desirable to find the optimal machining parameters using as few experiments as possible.

There has been considerable interest in the area of non-linear discrete optimization. Some reviews and survey articles on the algorithms for nonlinear optimization problems with mixed discrete variables have been published [6, 7]. Among these methods, the branch and bound method, simulated annealing, and genetic algorithm are suitable implementations for problems with non-differentiable functions, but these methods require many function evaluations, which may not be suitable for engineering optimization problems with implicit constraints.

One important category of numerical optimization algorithms is the sequential approximation methods. The basic idea of sequential approximation methods is to use a ‘simple’ subproblem to approximate the hard exact problem. By a ‘simple’ subproblem is meant the type of problem that can be readily solved by existing numerical algorithms. For example, linear programming subproblems are widely used in sequential approximation methods. The solution point of the simple subproblem is then used to form a better approximation to the hard exact

problem for the next iteration. In an iterative manner, it is expected that the solution point of the simple approximate problem will become closer to the optimum point of the hard exact problem. One major disadvantage of the existing sequential approximation methods is that they are usually derivative-based approximation methods, which require at least the first derivatives of the constraints with respect to the design variables.

2 THE SEQUENTIAL NEURAL NETWORK APPROXIMATION METHOD

In this paper, the ‘sequential neural network approximation (SNA) method’ [8, 9] is used to solve the problem. In this method, first a back-propagation neural network is trained to simulate the feasible domain formed by the implicit constraints using a few representative training data. The ‘exact optimization model’ equations (3) and (4) can be approximated as

$$\begin{aligned} \min[f(x)] \\ \text{s.t. } \text{NN}(x) = 1 \end{aligned} \quad (5)$$

where $f(x) = -Q$. The binary constraint $\text{NN}(x) = 1$ approximates the feasible domain of the implicit surface roughness constraint equation (4). If $\text{NN}(x) = 1$, the design point x (a set of values for the machining parameters) is feasible; if $\text{NN}(x) = 0$, the design point x is infeasible; i.e. the surface roughness obtained by the set of values for the machining parameters x cannot meet the average criterion of a mirror surface.

Table 1 shows the possible discrete values of the design variables. The set of initial training points should reasonably represent the whole design domain. Various types of matrix are commonly used for planning experiments to study several input

Table 1 Possible discrete values of machining parameters for the mirror surface

Training point	v_s (10^3 r/min)	r_f (mm/tooth)	d_c (mm)	z (teeth)
1	2	0.5	0.025	2
2	2.5	1.0	0.03	4
3	3	1.5	0.035	6
4	3.5	2.0	0.04	8
5	4	2.5	0.045	10
6	4.5	3.0	0.05	
7	5	3.5	0.055	
8	5.5	4.0	0.06	
9	6	4.5	0.065	
10	6.5		0.07	
11	7		0.075	
12			0.08	
13			0.085	

Table 2 The set of initial training data using the L_9 orthogonal array

Training point	L_9 orthogonal array				v_s (r/min)	r_f (mm/tooth)	d_c (mm)	z (teeth)	Q (cm ³ /min)	R_a (μm)	Feasible
1	1	1	1	1	2000	0.5	0.025	2	0.00275	0.08627	No
2	1	2	2	2	2000	2.5	0.055	6	0.09075	0.04587	Yes
3	1	3	3	3	2000	4.5	0.085	10	0.42075	0.04786	Yes
4	2	1	2	3	4500	0.5	0.055	10	0.06806	0.02997	Yes
5	2	2	3	1	4500	2.5	0.085	2	0.10519	0.05580	No
6	2	3	1	2	4500	4.5	0.025	6	0.16706	0.05088	No
7	3	1	3	2	7000	0.5	0.085	6	0.09818	0.04744	Yes
8	3	2	1	3	7000	2.5	0.025	10	0.24063	0.06227	No
9	3	3	2	1	7000	4.5	0.055	2	0.19058	0.10546	No

variables. Orthogonal arrays are highly popular in industrial applications because they are geometrically balanced in the coverage of experimental region with just a few representative experiments. The orthogonal array is also adopted in this research to form the set of initial training data. A training datum consists of two pieces of information: a design point and whether this design point is feasible or infeasible. Table 2 shows the set of initial training points using the L_9 (3^4) orthogonal array. Note that four initial training points are feasible ($R_a \leq 0.05 \mu\text{m}$), and training point 3 (2000, 4.5, 0.085, 10) has the maximum metal removal rate.

The size of the input layer of the three-layer network depends on the number of variables and the number of discrete values of each variable. Figure 1 shows the representation of training point 2 [(2000, 2.5, 0.055, 6), feasible] in Table 2. In this example, a total of 38 neurons are used in the input layer. Each neuron represented in Fig. 1 with a circle or a cross in the input layer has the value 1 or 0 respectively to represent the discrete value in the sequence corresponding to each variable. There is only one single neuron in the output layer to represent whether this design point is feasible (the output neuron has the value 1) or not (the output neuron has the value 0).

There are 12 neurons in the hidden layer in this example. The transfer functions used in the hidden

and output layers of the network are both log-sigmoid functions. The neuron in the output layer has the range [0, 1]. After the training is completed, a threshold value of 0.25 is applied to the output layer when simulating the boundary of the feasible domain. In other words, given a discrete design point in the search domain, the network always has the output 0 (if the output neuron's value is less than the given threshold) or 1 (otherwise) to indicate whether this discrete design point is feasible or not.

The computational effort required in the neural network training is critical. If the computation required is larger than that of evaluating the implicit constraints, then the SNA method will lose its advantage. Here all the training data are represented in a clear 0–1 pattern, which make the training process relatively faster. A quasi-Newton algorithm is used for the training. In our numerical experience, the error goal of 10^{-6} is usually met within 2000 epochs, even for cases with many training points.

A search algorithm then searches for the 'optimal point' in the feasible domain simulated by the neural network, starting from the best feasible design point in the initial training set [2000, 4.5, 0.085, 10], $Q = 0.421 \text{ cm}^3/\text{min}$. This search algorithm is specially designed for the SNA method and has been described in detail in reference [7]. When the 'optimal point' is found, a cutting experiment is performed to evaluate whether this point is feasible, i.e. whether the surface roughness meets the average criterion of a mirror surface. The new training data are then added to the training set. The neural network is trained again with these added trained data, hoping that the network will better approximate the boundary of the feasible domain of the exact optimization model. This process continues in an iterative manner until the same design point is obtained repeatedly and no new training point is generated.

Table 3 and Fig. 2 show the iteration history of this problem. The SNA method terminates after six iterations. The final optimal machining parameters are as follows: spindle speed $v_s = 2500 \text{ r/min}$; feed

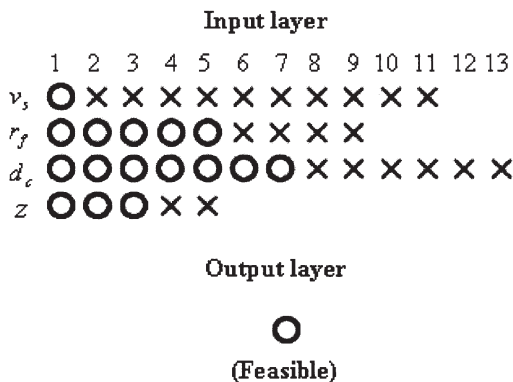


Fig. 1 Representation of training point [(2000, 2.5, 0.055, 6), feasible]

Table 3 Iteration history

Iteration	v_s (r/min)	r_f (mm/tooth)	d_c (mm)	z (teeth)	Q (cm ³ /min)	R_a (μ m)	Feasible
Start point	2000	4.5	0.085	10	0.420 75	0.047 86	Yes
1	3500	4.5	0.085	10	0.736 31	0.064 59	No
2	3500	3.5	0.085	10	0.752 69	0.056 25	No
3	2500	4.5	0.085	10	0.525 94	0.052 30	No
4	2500	4.5	0.080	10	0.495 00	0.048 78	Yes
5	3000	4.5	0.080	10	0.594 00	0.053 91	No
6	2500	4.5	0.080	10	0.495 00	0.048 78	Yes
7 (restart)	7000	4.5	0.085	10	1.472 63	0.143 41	No
8	7000	4.5	0.080	10	1.386 00	0.135 82	No
9	7000	4.0	0.080	10	1.232 00	0.124 39	No
10	7000	3.0	0.080	10	0.924 00	0.101 47	No
11	5000	2.0	0.065	10	0.357 50	0.044 01	Yes
12	6000	4.5	0.065	10	0.965 25	0.091 50	No
13	5500	3.0	0.075	10	0.680 63	0.068 04	No
14	5000	4.5	0.065	10	0.804 38	0.071 47	No
15	4500	3.0	0.080	10	0.594 00	0.058 43	No
16	7000	3.5	0.055	10	0.741 13	0.087 66	No
17	7000	2.5	0.085	10	0.818 13	0.095 55	No
18	7000	2.5	0.075	10	0.721 88	0.084 94	No
19	7000	2.0	0.085	10	0.654 50	0.083 54	No
20	7000	2.0	0.080	10	0.616 00	0.078 50	No
21	7000	2.5	0.065	10	0.625 63	0.076 36	No
22	6000	2.5	0.065	10	0.536 25	0.060 68	No
23	5500	2.5	0.070	10	0.529 38	0.057 22	No
24	5000	2.5	0.065	10	0.446 88	0.049 53	Yes
25	5000	2.5	0.080	10	0.550 00	0.057 73	No
26	5000	2.5	0.075	10	0.515 63	0.054 49	No
27	5000	2.5	0.065	10	0.446 875	0.049 53	Yes
28 (restart)	2500	4.5	0.080	10	0.495 00	0.048 78	Yes
29	2500	4.5	0.080	10	0.495 00	0.048 78	Yes
30 (restart)	2500	4.5	0.080	10	0.495 00	0.048 78	Yes
Optimum	2500	4.5	0.080	10	0.495 00	0.048 78	Yes

per cutter tooth, $r_f = 4.5$ mm/tooth; depth of cut, $d_c = 0.08$ mm; number of blades or cutter teeth, $z = 10$. The maximum volume cut-off is 0.495 cm³/min, increasing by 17.6 per cent. Using this set of machining parameters in the cutting experiment, $R_a = 0.048 78$ μ m, which meets the average criterion

of a mirror surface. Note that a total of 15 design points out of $11 \times 9 \times 13 \times 5 = 6435$ possible combinatorial combinations (0.23 per cent) were evaluated by real cutting experiments.

To ensure a better chance of reaching a global optimum, the searching process was restarted from three

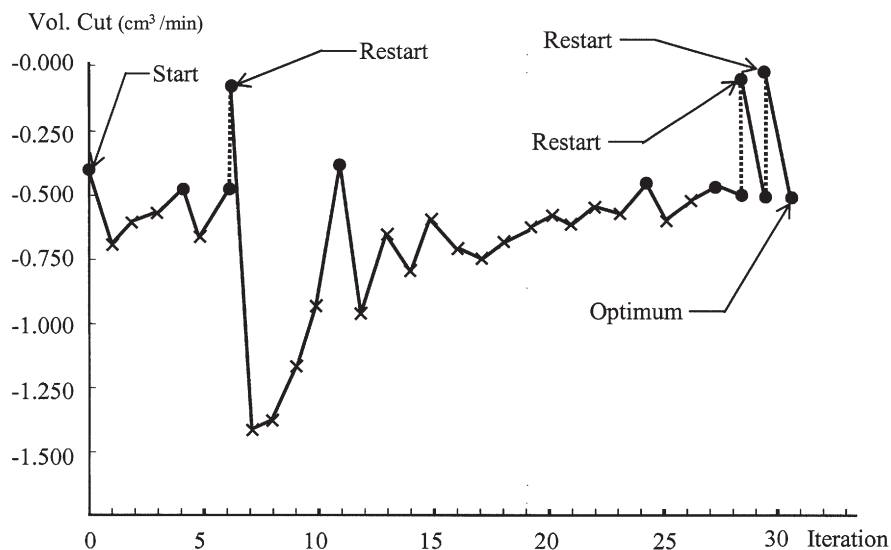


Fig. 2 Iteration history

other feasible points in the set of initial training data in Table 2. As shown in Table 3 and Fig. 2, after a total of 30 iterations, the same optimal machining parameters were obtained. Note that the final optimal design point is close to the starting point obtained by the L_9 orthogonal array, which is commonly used for planning experiments to study several input variables, while the metal removal rate Q increases by 17.6 per cent.

3 CONCLUSION

This paper demonstrates how to use the SNA method for one-pass milling machining parameter optimization to achieve mirror surface roughness. Among the four parameters, the number of blades, z , appeared to be insensitive and stayed at ten throughout the optimization process. Using the multiple-blade cutter, there is an 'optimum' spindle speed v_s (cutting speed). A high spindle speed (cutting speed) will increase R_a due to the chatter problem. As expected, a reduced depth of cut, d_c , and feed per cutter tooth, r_f , will result in a better surface finish but will also reduce the metal removal rate. In the optimization process, the optimum d_c and r_f were chosen to maximize the metal removal rate, while maintaining the desired surface finish. The same optimization process can be directly extended to find the optimal parameters in other manufacturing processes using the least number of experiments.

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APPENDIX

Notation

- d_c depth of cut
 Q metal removal rate
 r_f feed per cutter tooth
 R_a centre-line average roughness
 v_f feed speed
 w_c width of cut
 y_i measured roughness height
 z number of blades or cutter teeth

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