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The optimal cutting parameter design of rough cutting process in side milling

H.-S. Lu, J.-Y. Chen*, Ch.-T. Chung
Department of Mechanical and Computer-Aided Engineering,
National Formosa University, 64, Wun-Hun Road, Huwei, Yunlin 632, Taiwan
* Corresponding author: E-mail address: jychen@nfu.edu.tw

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ABSTRACT

Purpose: This paper is focused on the optimal cutting parameters design of rough cutting processes in side milling for SKD61 tool steels.
Design/methodology/approach: The fuzzy logics can be a proper basis to perform the optimization procedure with complicated multiple performance characteristics in this paper. Using this approach combined with the grey-relational analysis, the design algorithm is transformed into optimization of a single and simple grey-fuzzy reasoning grade rather than multiple performance characteristics. The Taguch method is also adopted to search for an optimal combination of cutting parameters for this rough cutting process in side milling.
Findings: The improvement of tool life and metal removal rate from the initial cutting parameters to the optimal cutting parameters are 54% and 9.7%. Hence, this reveals that the proposed approach in this study can effectively improve the cutting performance.
Research limitations/implications: In this paper only four cutting parameters are taken into consideration. Many other parameters such as tool geometric shape are not applied to this study.
Practical implications: It is believed that this optimal result can be applied to practical processes to effectively reduce manufacturing cost and greatly enhance manufacturing efficiency.
Originality/value: A systematic and effective optimization method is presented in this paper. Using this method can effectively acquire an optimal combination of the cutting parameters.
Keywords: Machining; Side milling; Grey-fuzzy logics; Optimization

1. Introduction

Taguchi method is one of the simple and effective solutions for parameter design and experimental planning [1, 2]. It analyzes the influence of parameter variation to performance characteristics. Thereby, an optimal result can be obtained so that the sensitivity of performance characteristics respect to parameter variation. Nowadays, several researchers have successfully applied this method to investigate the performance characteristics of processes. However, Taguchi method has shown some defects in dealing with the problems of multiple performance characteristics [3-7].

The grey system theory proposed by Deng [8] in 1982 has been proven to be useful for dealing with poor, insufficient, and uncertain information. The grey relational analysis based on this theory can further be adopted for solving the complicated inter-relationships among multiple performance characteristics [9, 10].

The theory of fuzzy logics, initiated by Zadeh in 1965 [11], has proven to be useful for dealing with uncertain and vague information. Since the definition of performance characteristics used for this research such as lower-the-better, higher-the-better, and nominal-the-better contains a certain degree of uncertainty and vagueness. Hence, fuzzy logics can be a proper basis to perform the optimization procedure with complicated multiple performance characteristics in this study [12-15]. Using this approach combined with the grey-relational analysis, the design algorithm is transformed into optimization of a single and simple grey-fuzzy reasoning grade rather than multiple performance characteristics. The Taguchi method is also adopted to search for an optimal combination of cutting parameters for this rough cutting process in side milling.

2. Experimental apparatus and design

The test workpieces are made of SKD61 tool steel and 200 mm×80 mm×80 mm in size. The hardness of the workpiece material was measured to be 53 HRC. The end mill served as cutting tools are made of tungsten carbide and coated with AlTin under a major specification such as: diameter of 10 mm, 4 flutes, helix angle of 45°, negative radial rake angle of 8°, and radial relief angle of 8°. The overhang length of the tools is fixed at about 45 mm, and radial run-out was maintained at less than 10 μm. The experiments were carried out on a Papers B8 CNC machining center using up milling operation with air blow.

This paper is focused on the optimal cutting parameters design of rough cutting processes in side milling for SKD61 tool steels. For rough cutting process in side milling operations, tool life and metal removal rate are selected as indexes to evaluate cutting performance. In practice, the longer tool life is, the smaller tool wear rate is. Therefore, tool wear rate (TWR) coupled with metal removal rate (MRR) is selected as two performance characteristics in this study. Basically, the smaller tool wear rate in the side milling process is, the better the cutting performance is. Hence, tool wear rate is a lower-the-better performance characteristics.

The experiment includes four cutting parameters. Each parameter is set to three levels. The degree of freedom is defined as the number of comparisons among process parameters needed to optimize the parameters. In the present study, there are totally eight degrees of freedom owing to considering three levels for each cutting parameter and neglecting the interaction amid the parameters. Thereby, a L_9 orthogonal array is used. The experimental layout is shown in Table 1. According to the listed combinations of cutting conditions, workpieces of SKD61 tool steel are continuously cut for 70 m long. Then, the cutting time is counted and the flank wear of peripheral cutting edge is measured. Finally, the values of tool wear rate and metal removal rate are listed in Table 2.

Table 1.
Experimental layout

No.	V (rpm)	F (mm/t)	Da (mm)	Dr (mm)	Cutting time (min)
1	2700	0.046	7	0.1	140.90
2	2700	0.065.	10	0.2	99.72
3	2700	0.084	13	0.3	44.09
4	3200	0.046	10	0.3	67.93
5	3200	0.065	13	0.1	84.13
6	3200	0.084	7	0.2	65.10
7	3700	0.046	13	0.2	102.82
8	3700	0.065	7	0.3	72.77
9	3700	0.084	10	0.1	56.31

V: spindle speed; F: Feed per tooth; Da: Depth of cut; Dr: Radial depth of cut

Table 2.
Experimental results

No.	Tool wear (mm)	TWR (mm/min)	MRR (mm^3/s)
1	0.0387	2.7466x10-4	5.796
2	0.0301	3.0195x10-4	23.400
3*	0.0353	8.0064x10-4	58.968
4*	0.0558	8.2143x10-4	29.440
5	0.0259	3.0786x10-4	18.027
6	0.0342	5.2535x10-4	25.088
7	0.0325	3.1609x10-4	29.501
8	0.0555	7.6268x10-4	33.670
9	0.0309	5.4875x10-4	20.720

*: Cutting edge breakage

3. Analysis and discuss

As mentioned earlier, tool wear ratio is selected as the first criterion (*i.e.* i=1) in termed of a lower-the-better characteristic that can be expressed as

$$\eta_{ij} = -10\log\left(\tfrac{1}{n}\sum_{j=1}^{n} y_{ij}^2\right) \tag{1}$$

where y_{ij} is the ith experiment at the jth test and n is the total number of the tests.

The second criterion (*i.e.* i=2) is metal removal rate regarded as a higher-the-better characteristic and is expressed as

$$\eta_{ij} = -10\log\left(\tfrac{1}{n}\sum_{j=1}^{n} \frac{1}{y_{ij}^2}\right) \tag{2}$$

Based on Eq. (1) and Eq. (2), Table 3 shows the S/N ratio of the tool wear rate and metal removal rate.

The grey relational analysis initially generates a data preprocessing to normalize the raw data. Here, the S/N ratio is linearly normalized in the range between 0 and 1, which is also called grey-relational generating.

A linear date preprocessing method of the S/N ratio can be expressed as:

$$x_i(k) = \frac{\eta_i(k) - \min \eta_i(k)}{\max \eta_i(k) - \min \eta_i(k)} \tag{3}$$

where $x_i(k)$ is the value obtained from the grey relational generating; $\max \eta_i(k)$ is the largest value of $\eta_i(k)$; $\min \eta_i(k)$ is the smallest value of $\eta_i(k)$.

In addition, the grey relational coefficient is expressed as

$$\gamma(x_o(k), x_i(k)) = \frac{\Delta_{\min} + \zeta \cdot \Delta_{\max}}{\Delta_{oi}(k) + \zeta \cdot \Delta_{\max}} \tag{4}$$

where

a. $\Delta_{oi}(k) = \| x_o(k) - x_i(k) \|$ is the absolute value of the difference between $x_o(k)$ and $x_i(k)$

b. (b) $\Delta_{\min} = \min\limits_{\forall i} \min\limits_{\forall k} \Delta_{oi}(k)$

c. (c) $\Delta_{\max} = \max\limits_{\forall i} \max\limits_{\forall k} \Delta_{oi}(k)$

d. (d) ζ : distinguishing coefficient, $\zeta \in [0,1]$. ζ is set as 0.5 in this study.

The purpose of defining this coefficient is to show the relational degree between the ideal sequence $x_o(k)$ and the calculated nine sequences $x_i(k)$,where i=1, 2…, 9 and k=1, 2. Calculated based on Table 3 and Eqs. (3) and (4), the results of Table 4 show the grey relational coefficients for each experiment using the L_9 orthogonal array.

Table 3.
S/N ratio of the each individual quality characteristic

No.	S/N ratio (dB)	
	TWR	MRR
1	71.22	15.26
2	70.40	27.38
3	61.93	35.41
4	61.71	29.38
5	70.23	25.12
6	65.59	27.99
7	70.00	29.40
8	62.35	30.54
9	65.21	26.33

Table 4.
The grey relational coefficient and the grey-fuzzy reasoning grade

No	grey relational coefficient		grey-fuzzy reasoning grade
	TWR	MRR	
1	1.0000	0.3333	0.6591
2	0.9831	0.5565	0.7393
3	0.3388	1.0000	0.6614
4	0.3333	0.6255	0.4831
5	0.8277	0.4899	0.6481
6	0.4579	0.5759	0.5191
7	0.7958	0.6263	0.6532
8	0.3490	0.6741	0.5089
9	0.4417	0.5260	0.4612

A fuzzy logic unit comprises a fuzzifier, membership functions, a fuzzy rule base, an inference engine, and a defuzzifier. In the fuzzy logic analysis, the fuzzifier uses membership functions to fuzzify the grey relational coefficient first. Next, the inference engine performs a fuzzy reasoning on fuzzy rules to generate a fuzzy value. Finally, the defuzzifier converts the fuzzy value into a grey-fuzzy reasoning grade.

The function of the fuzzifier is to convert outside crisp sets of input data into proper linguistic fuzzy sets of information. The input variables of the fuzzy logic system in this study are the grey relational coefficients for tool wear rate x_1 and metal removal rate x_2. They are converted into linguistic fuzzy subsets using membership functions of a triangle form, that is shown in Fig. 1, and is uniformly assigned into three fuzzy subsets small (S), medium (M), and large (L) grade.

The fuzzy rule base consists of a group of if-then control rules to express the express the inference relationship between input and output. A typical linguistic fuzzy rule called Mamdani is described as

Rule 1: if x_1 is A_1 and x_2 is B_1 then y is C_1 else
Rule 2: if x_1 is A_2 and x_2 is B_2 then y is C_2 else
……………………………………………..
Rule n: if x_1 is A_n and x_2 is B_n then y is C_n else

A_i, B_i, and C_i are fuzzy subsets defined by the corresponding membership functions, ie., μ_{Ai}, μ_{Bi}, and μ_{Ci}.

The output variable is the grey-fuzzy reasoning grade y_0, and also converted into linguistic fuzzy subsets using membership functions of a triangle form, that are shown in Fig. 2. Unlike the input variables, the output variable is assigned into relatively subtle five subsets, i.e., very small (VS), small (S), medium (M), large (L), very large (VL) grade. Then, considering the conformity of two performance characteristics for input variables, nine fuzzy rules are defined.

The fuzzy inference engine is the kernel of a fuzzy system. It can solve an problem by simulating the thinking and decision pattern of human being using approximate or fuzzy reasoning. In this paper, the max-min compositional operation of Mamdani is adopted to perform calculation of fuzzy reasoning. Supposing that x_1 and x_2 are the input variables of the fuzzy logic system, the membership function of the output of fuzzy reasoning can be expressed as

$$\mu_{C_o}(y) = (\mu_{A_1}(x_1) \wedge \mu_{B_1}(x_2) \wedge \mu_{C_1}(y)) \vee \ldots (\mu_{A_n}(x_1) \wedge \mu_{B_n}(x_2) \wedge \mu_{C_n}(y)) \tag{5}$$

where $\wedge$ is the minimum operation and $\vee$ is the maximum operation.

Finally, a defuzzification method, called the center-of-gravity method, is utilized here to transform the fuzzy inference output μ_{C_o} into a non-fuzzy value y_o, i.e.

$$y_o = \frac{\sum_{i=1}^{k} y_i \mu_{C_o}(y_i)}{\sum_{i=1}^{k} \mu_{C_o}(y_i)} \tag{6}$$

where $\mu_{C_o}(y_i)$ is the membership value of y_i belonging to the fuzzy subset C_o.

In this paper, the non-fuzzy value y_o is called a grey-fuzzy reasoning grade. Based on the above discussion, the larger the grey-fuzzy reasoning grade is, the better the performance characteristic is. Based on Table 4 and Eqs. (5) and (6), the results of fuzzy inference is shown in Table 4.

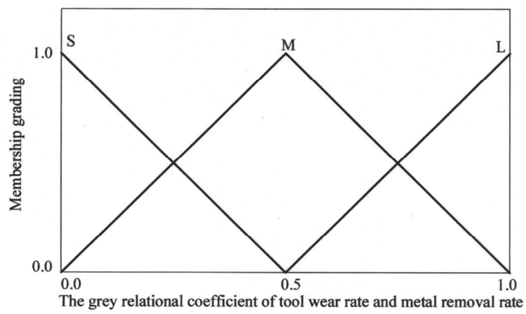

Fig. 1. Membership functions for TWR and MRR

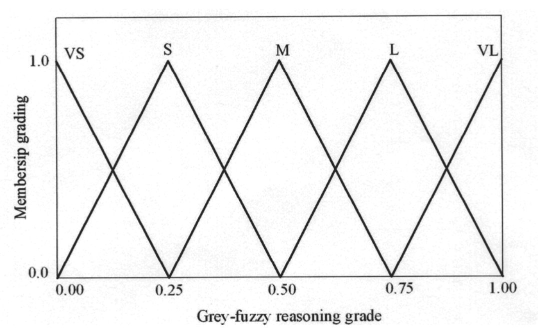

Fig. 2. Membership functions for multi-response output

Table 5.
Response table for the grey-fuzzy reasoning grade

Cutting parameter	Level 1	Level 2	Level 3	Max-Min
V	0.6866	0.5501	0.5411	0.1455
F	0.5985	0.6321	0.5472	0.0849
Da	0.5597	0.5612	0.6542	0.0945
Dr	0.5895	0.6372	0.5511	0.0861

Table 6.
Comparison between initial and optimal level

	Best combination	Tool life (min)	Total metal removal volumes (mm^3)	Metal removal rate (mm^3/s)
Initial design	V2F2Da2Dr2	84.13	140000	27.73
Optimal design	V1F2Da3Dr2	128.21	234000	30.42
Final gain		44.08	94000	2.69

Since the design of this experiment is orthogonal in view of the grey-fuzzy analysis, it is then possible to separate out the effect of each cutting parameter on the grey-fuzzy reasoning grade at different levels. The mean values of grey-fuzzy reasoning grade for each level of the cutting parameters are summarized in Table 5. Basically, the larger the grey-fuzzy reasoning grade is, the closer the product quality is to the ideal value. Thus, higher values for the grey-fuzzy reasoning grade is desirable. Based on the Table 5, the cutting parameters with the best level are spindle speed at level 1 (*i.e.* 27000 rpm), feed per tooth at level 2 (*i.e.* 0.065 mm/t), axial depth of cut at level 3 (*i.e.*13 mm) and radial depth of cut at level 2 (*i.e.* 0.2 mm).

Once the optimal level of the cutting parameters is identified, the following step is to verify the improvement of the performance characteristics using this optimal combination. Table 6 shows the comparison of the experiment results using the initial combination of the cutting parameters with the optimal one. The definition of tool life, shown in Table 6, is the total cutting time before the breakage of peripheral cutting edge of the tool or, that is, as the flank wear of the peripheral cutting edge reaches 0.2 mm. As shown in Table 6, tool life increases form 84.13 min to 128.31 min; total metal removal volumes increase from 140000 mm^3 to 234000 mm^3; metal removal rate increase from 27.73 mm^3/s to 30.42 mm^3/s. Based on the results above, it is clearly shown that tool life and metal removal rate are greatly improved through this study.

4. Conclusions

This paper presents an application of the Taguchi method with grey-fuzzy logics for optimizing the cutting parameters of rough cutting process in side milling operation for SKD61 tool steel. The results reveal that the proposed method provides a systematic and efficient methodology for the optimization design of the cutting parameters. The results of the confirmation tests prove that the performance characteristics of the side milling process such as tool life and metal removal rate are improved simultaneously through the optimal combination of the cutting parameters obtained from the proposed method. The improvement of tool life and metal removal rate from the initial cutting parameters to the optimal cutting parameters are 54% and 9.7%. Hence, it is believed that this optimal result can be applied to practical processes to effectively reduce manufacturing cost and greatly enhance manufacturing efficiency.

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