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Optimize Multiple Responses for Thin Wall Milling Process Using Taguchi Method Based on GRA Theory

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Abstract: *Machining thin-walled parts is a key process in the aerospace industry. The part deflection caused by the cutting force is difficult to predict and control. The distortion of the thin-walled part is significantly affected by the accuracy of the finished part. In this study, the Taguchi method based on the grey relational analysis theory was selected to optimize multi-responses for the thin wall milling process as the deflection of workpieces and the surface roughness. The grey relational index (GRI) were determined from the experimental results (the deflection of workpieces and the surface roughness) by using the grey relational analysis theory. Then the optimal condition – (V=350m/min, fz=0.04mm/tooth, a=0.6mm and b=12mm) was determined by Taguchi's method through the mean value and ratio (S/N).*

Keywords: *Thin wall, Aluminum, Surface roughness, GRA, Taguchi*

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I. INTRODUCTION

With the higher demands on the speed and performance of the modern aircraft, the thin-walled aluminum alloy parts have been used broadly in aeronautics. Due to the large area and low rigidity, the thin-walled plates are always machined in numerical control (NC) end milling process. However, owing to various reasons in the machining process, the thin-walled plates are very easy to deform under the cutting force, which will influence the accuracy and quality. In end milling process, the thickness of the plates is reduced gradually, which makes it even more difficult to control the accuracy of machining. The end milling of such plates is complicated, where periodically varying milling forces excite the flexible plate structures both statically and dynamically and leading to significant deformations [1]. Kuang and Wu (1995) found that cutting speed, feed amount, and tip radius have a significant effect on residual stress [2]. Coto et al. (2011) showed that increasing toolpath will increase tensile residual stress, however by increasing shear speed will reduce tensile residual stress [3]. Navas et al. (2012) note that by reducing the amount of feed and increasing the cutting speed, it is possible to reduce the tensile residual stress when machining AISI4340 steel [4].

Thus, it is very difficult to control the form and magnitude of residual stress of the machined surface. And there are no clear rules given when using different processing materials and with different technological parameters. For example, Mohammadpour et al. (2010) showed that the maximum value of surface layer residual stress (MMSRS) is 680MPa, and the depth of shear corresponding to the maximum compressive residual stress is 200 millimeters [5]. Liang and Su (2007) measured the MMSRS as 900 MPa, the DMCRS ranging from 25 to 100 micrometers [6]. However, Ulutan et al. (2007) found the MMSRS to be 1200 MPa and the DMCRS to be even smaller than 10 micrometers [7]. The influence of factors on different structures during heat reduction is studied and calculated. Robinson et al. (2011) discussed the mechanism of redistribution of residual stress after machining for Al7449 material after heating [8]. By removing the material in layers, the effect of residual stress redistribution on strain is discussed. While there is no indication of stress reduction, and the model is limited to the cubic rule. In summary, all studies are based on the thickness of each layer (equal or nearly equal) of the work piece, so it is difficult to apply to the machining of thin-walled parts, where the depth variable machining. Therefore, it is necessary to further analyze the redistribution of residual stress of thin-walled parts with different cutting depths during machining, thereby reducing the deformation of thin-walled parts.

In this research, a grey relational index (GRI) was calculated by the grey relational analysis to solve the thin wall milling operations with multiple performance features. Optimal cutting parameters can then be determined by the Taguchi method using the grey relational index. The deflection of workpieces and surface roughness are important characteristics in the thin wall milling process. Using these characteristics of the cutting conditions, including cutting speed, feed per tooth, radial depth of cut and Axial depth of cut are optimized in this study.

II. EXPERIMENT AND METHOD

The machining process is carried out on the Mazak 530 C machining center manufactured by Japan. The experimental devices are shown on the figure 1.Using end mills made of uncoated bits material with 3 cutting teeth, helix angle 450 of Korean YG company with code 36588. This is a specialized cutting tool for machining aluminum alloys and non-ferrous alloys, used for finishing with high surface quality. The workpieces are made by the aluminum alloys 6061 and have thin wall 3mm. The deflection of workpieces are measured by the Mitutoyo's Digital indicator gauge in the milling process. The surface roughness is measured by Mitutoyo's SJ210 roughness gauge.

Figure 1. The experimental devices

III. OPTIOMIZATION METHOD

A. Grey relation analysis theory

Grey relation analysis (GRA) is a experimental analysis method based on the grey system theory developed by China Professor. GRA is widely used in experimental data analysis and multi-objective optimization [9] [10] [11]. From the experimental data set with different units (tool wear and surface roughness), GRA allows synthesis into a single coefficient.

The first, the deflection of workpieces and surface roughness in the thin wall milling process are standardized in the range from 0 to 1. The formula determining data standardization depends on the characteristics of an experimental data sequences. In this research, the smaller - the better quality parameters were choosen to caculate the grey relational grade for the deflection of workpieces and surface roughness. With the smaller –the better, data standardization can be expressed by:

$$x^*_{i(k)} = \frac{\max\ x^0_i(k) - x^0_i(k)}{\max\ x^0_i(k) - \min\ x^0_i(k)} \qquad (1)$$

Where

i=1…m ; k=1….n

m is number of experimental data

n is the number of parameters;

$x^0_i(k)$ is the original sequence,

$x^*_i(k)$ is the sequences after data preprocessing,

Min $x^0_i(k)$ and max $x^0_i(k)$ are the smallest and the largest value of $x^0_i(k)$

Next, the grey relational coefficient is determined from the standardized data to indicate the relationship between the desired and actual characteristics such as the deflection of workpieces and surface roughness. The grey relational coefficients were caculated by Eq. (2) [9]:

$$\xi_i(k) = \frac{\Delta\min + \xi.\Delta\max}{\Delta_{0,1}(k) + \xi\Delta\max} \qquad (2)$$

where,

Δ_{0i} deviation sequences of the reference and comparability sequence

$$\Delta_{0,i} = \|x^*_0(k) - x^*_i(k)\| \qquad (3)$$

$$\Delta_{\min} = \min_{\forall j \in i} \min_{\forall k} \left\| x^*_0(k) - x^*_j(k) \right\|$$

$$\Delta_{\max} = \max_{\forall j \in i} \max_{\forall k} \left\| x^*_0(k) - x^*_j(k) \right\|$$

$x^*_0(k)$ the reference sequence, and $x^*_i(k)$ is the comparative sequence.

ζ is known as distinguishing coefficient with $\zeta \in [0,1]$, which can be selected to better identify between standardized reference sequences and standardized comparative sequences. In this research, Normal level ζ (0.5) is selected to moderately distinguish the effect. From the calculation, the values of minΔ and maxΔ are respectively 0 and 1. Then The grey relational coefficients were caculated by Eq. (4):

$$\xi_i(k) = \frac{0.5}{\Delta_{0,1}(k) + 0.5} \qquad (4)$$

After the grey relational coefficient is calculated, grey relational index (GRI) is determined by averaging the value of the grey relational coefficients. The existing GRI between two series is always distributed between 0 and 1. Grey relational indexs can be determined using formula below:

$\gamma_i = \frac{1}{n}\sum_{k=1}^{n}\xi_i(k)$ (5)

where γ_i represents GRI; the level of correlation between the reference sequence and the comparability sequence.

B. Taguchi experiment design

Influences of the cutting parameters on the deflection of workpieces and surface roughness were analyzied by using the Taguchi experimental design in the thin wall milling process. The L9 orthogonal array was chosen and shown in table 1. In Taguchi method, the S/N ratio is used to consider the influence of the input factors on the output factor. The greater value of the S/N ratio, the less the impact of the noise parameters. The S/N ratio as determined as follows:

$S/N = -10\mathrm{Log}10[\mathrm{MSD}]$ (6)

Where MSD is the mean square error for output factors. The MSD values can be determined by three types of the S/N ratio characteristics: nominal the better, smaller the better, and greater the better. In this paper, the theory of GRA method were used to convert the tool wear and surface roughness of the slide milling process a Grey relational index. The higher – the better quality parameters were choosen to caculate the S/N ratio for the grey relational index of the slide milling process.

The mean-square deviation (M.S.D.) for the-higher-the-better quality characteristic can be expressed as: $\mathrm{MSD} = \frac{1}{n}\sum_{i=1}^{n} y_i^2$ (7)

Where: yi is the grey relational index.
n is the number of experiments

Table 1 Experimental design based on L9 orthogonal array

Exp. No	V (m/min)	fz (mm/tooth)	a (mm)	b (mm)	Ra (µm)	x (µm)
1	250	0.02	0.3	8	0.217	60
2	250	0.04	0.6	12	0.112	48
3	250	0.06	1.2	16	0.267	174
4	300	0.02	0.6	16	0.203	97
5	300	0.04	1.2	8	0.176	30
6	300	0.06	0.3	12	0.144	63
7	350	0.02	1.2	12	0.250	42
8	350	0.04	0.3	16	0.133	32
9	350	0.06	0.6	8	0.229	5

IV. RESULT AND DISCUSSION

The normalised input parameters were caculated for the deflection of workpieces and surface roughness by formula (3), shown in table 2. The deviation sequences of the absolute value between xo(k) and xi(k), the grey relational coefficient for the deflection of workpieces (x) and surface roughness (Ra) were determined by equation (2) & (3), shown in table 3. And then, the grey relational grades were calculated by equation (5). The Table 4 shows the experimental results for the grey relational grade and order using the experimental layout. The higher value of the grey relational grade means that the corresponding cutting conditions is closer to optimal.

Table 2. Data normalization of each performance characteristics

Exp. No	V (m/min)	fz (mm/tooth)	a (mm)	b (mm)	Ra (μm)	Normalization of Ra	x (μm)	Normalization of x
1	250	0.02	0.3	8	0.217	0,322581	60	0,674556
2	250	0.04	0.6	12	0.112	1	48	0,745562
3	250	0.06	1.2	16	0.267	0	174	0
4	300	0.02	0.6	16	0.203	0,412903	97	0,455621
5	300	0.04	1.2	8	0.176	0,587097	30	0,852071
6	300	0.06	0.3	12	0.144	0,793548	63	0,656805
7	350	0.02	1.2	12	0.250	0,109677	42	0,781065
8	350	0.04	0.3	16	0.133	0,864516	32	0,840237
9	350	0.06	0.6	8	0.229	0,245161	5	1

Table 3 Grey relational coefficient

Exp. No	V (m/ min)	fz (mm/ tooth)	a (mm)	b (mm)	Deviation sequences of Hs	Deviation sequences of Ra	Grey Coe. of Hs	Grey Coe. of Ra
1	250	0.02	0.3	8	0,325444	0,677419	0,605735	0,424658
2	250	0.04	0.6	12	0,254438	0	0,662745	1
3	250	0.06	1.2	16	1	1	0,333333	0,333333
4	300	0.02	0.6	16	0,544379	0,587097	0,478754	0,459941
5	300	0.04	1.2	8	0,147929	0,412903	0,771689	0,547703
6	300	0.06	0.3	12	0,343195	0,206452	0,592982	0,707763
7	350	0.02	1.2	12	0,218935	0,890323	0,695473	0,359629
8	350	0.04	0.3	16	0,159763	0,135484	0,757848	0,786802
9	350	0.06	0.6	8	0	0,754839	1	0,398458

Further, optimization of the multiple responses for the thin wall milling process can be converted into optimization of a single grey relational index. The grey relational indexes (GRI) were analyzed by the software Minitab 18.

Table 4. Grey relational index and its order

No.	A (%)	B (m/min)	GRI	S/N of GRI	Order
1	0.0	25	0.515196	-5.76055	7
2	0.0	30	0.831373	-1.60409	1
3	0.0	35	0.333333	-9.54243	9
4	0.2	25	0.469347	-6.57012	8
5	0.2	30	0.659696	-3.61312	4
6	0.2	35	0.650373	-3.73676	5
7	0.4	25	0.527551	-5.55471	6
8	0.4	30	0.772325	-2.24400	2
9	0.4	35	0.699229	-3.10761	3

The influence of the cutting parameters on the GRI values of the milling of aluminum alloy thin-walled parts was analyzed using Minitab. The analysis results show that the average value of the GRI values corresponds to different levels for each survey parameter and the order of influence of the parameters on the GRI values is shown in table 5. The analysis results show that among the investigated parameters, the feed per tooth is the parameter that has the strongest influence on the average value of the GRI values.

Table 5. Response Table for Means

Level	Cutting speed	Feed per tooth	Radial depth of cut	Axial depth of cut
1	0.1986	0.2234	0.1649	0.2076
2	0.1743	0.1404	0.1811	0.1687
3	0.2042	0.2132	0.2311	0.2009
Delta	0.0299	0.0830	0.0662	0.0389
Rank	4	1	2	3

The influence of the cutting parameters of the machined surface on the the GRI values is shown in Figures 2. The results show that: When increasing the cutting speed from 250 m/min to 350 m/min, the GRI value increases. The feed per tooth also strongly affects the GRI values. the GRI reaches the strongest value with feef per tooth (fz) 0.04mm. Meanwhile radial depth of cut and the axial depth of cut increase, the GRI value also decreases.

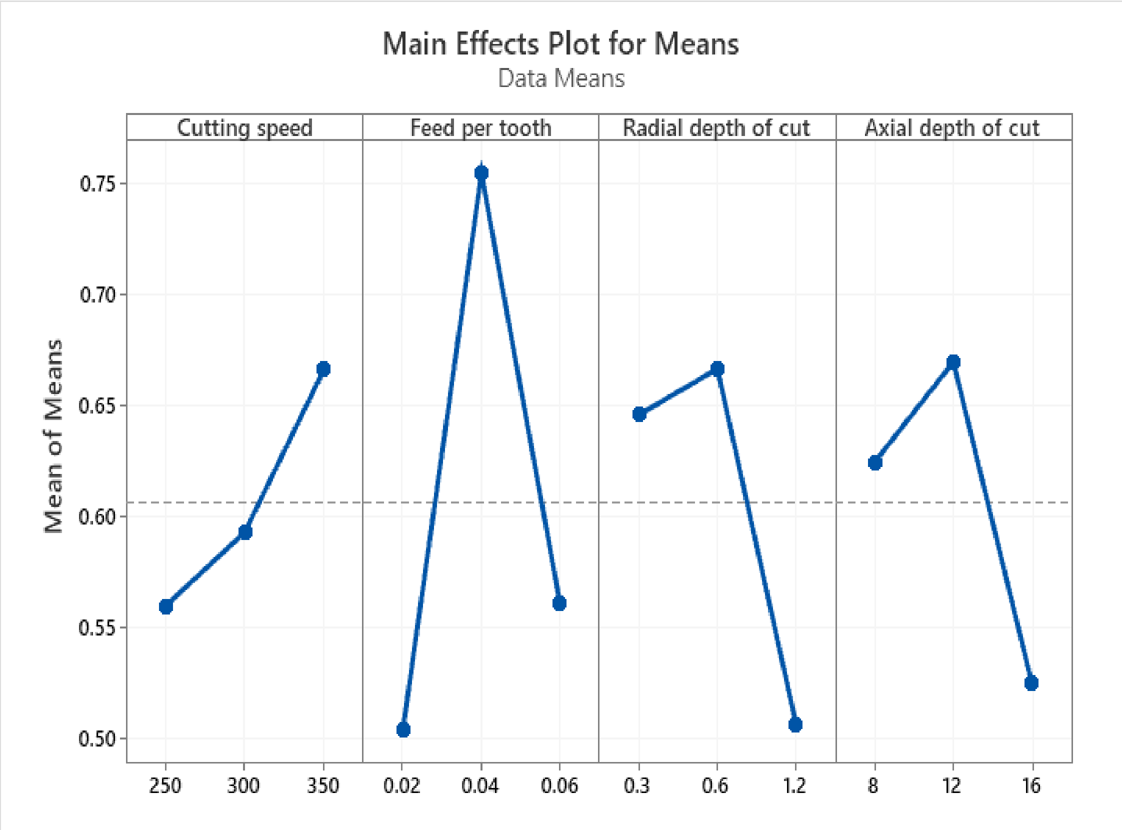

Figure 2. Main effects plot for the GRI value

Using Minitab software, analyze the influence of cutting parameters on the signal-to-noise ratio S/N calculated for the surface roughness. The analysis results show that the signal-to-noise ratio for the GRI value corresponds to different levels for each survey parameter and the order of influence of the parameters on the S/N ratio value of the GRI value. The analysis results in table 6 show that among the investigated parameters, the feed per tooth and the radial depth of cut are the parameters that have the strongest influence on the S/N ratio of the GRI valuein the thin wall milling process. The influence of the cutting parameters on the S/N ratio of the GRI value for optimizing multi response of the milling thin wall part is shown in Figure 3. The results show that the S/N ratio of GRI value reached the maximum value with the parameter set V=350m/min, fz=0.04mm/tooth, a=0.6mm and b=12mm.

Table 6. Response Table for Signal to Noise Ratios

Smaller is better				
Level	Cutting speed	Feed per tooth	Radial depth of cut	Axial depth of cut
1	14.59	13.05	15.86	13.71
2	15.26	17.21	15.24	15.97
3	14.28	13.71	12.86	14.28
Delta	1.15	4.15	3.00	2.26
Rank	4	1	2	3

Figure 5. Main effects plot for the S/N ratio of GRI value

V. CONCLUSION

Grey relational analysis is the effective and efficient method for optimizing multi response process parameters. The cutting parameters for the thin wall milling process using Taguchi method and grey relational analysis. A single GRI value was determined by using a GRA theory and Taguchi method to optimize multiple responses in the thin wall milling process using nanofluids. The research results show that the feed per tooth are the great effect factor to the GRI index by using Taguchi method based on GRA theory with in the thin wall milling process. The optimum parameter values for different control parameters have been suggested as V=350m/min, fz=0.04mm/tooth, a=0.6mm and b=12mm.

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