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Multi-Response Optimization of Milling Parameters on AISI 304 Stainless Steel using Grey-Taguchi Method

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Abstract

In today's world AISI 304 stainless steel contributes to almost half of the world's production and consumption for industrial purposes. Austenitic steels are hard materials to machine due to their high strength, high ductility and low thermal conductivity. This paper reports an experimental study on performance characteristics of AISI 304 stainless steel during CNC milling process. In milling process the surface roughness (SR) and material removal rate (MRR) are the most important performance characteristics, which are influenced by many factors like cutting speed, feed rate and depth of cut. The selection of these parameters at optimum level plays a vital role in getting minimum surface roughness and maximum MRR. This paper presents multi-objective optimization of milling process parameters using Grey-Taguchi method in machining of AISI 304 stainless steel. The experiments are conducted based on Taguchi's L27 orthogonal array by taking cutting speed, feed rate and depth of cut at three levels. The Grey relational analysis is used to obtain the relation between the machining parameters and performance characteristics. The complete experimental results are discussed and presented in this paper.

Keywords: *CNC milling, AISI stainless steel, surface roughness, material removal rate (MRR), Grey relational analysis, Taguchi method, Tungsten carbide end mill.*

1. Introduction

Austenitic stainless steels are grades of chromium-nickel steels exhibiting a very high corrosion resistance in addition to a wide range of excellent mechanical properties not offered by any other alloy. Austenitic stainless steels cannot be hardened by traditional heat treatment processes but they can be strengthened by cold working [1]. AISI 304 steel is hard to machine due to their high strength, high ductility and low thermal conductivity, high tensile strength, high fracture toughness and high work hardening rate [2, 3].

The surface roughness and material removal rate have been identified as quality attributes and are assumed to be directly related to performance of mechanical pieces, productivity and production costs. For these reasons there has been research and development with the objective of optimizing cutting conditions, to obtain a desired machinability. Bagci and Aykut [4] conducted Taguchi experiments for minimising surface roughness in terms of cutting parameters (feed rate, cutting speed and depth of cut) on face milling of the cobalt-based alloy (stellite 6) material. El-Tamimi and El-Hossainy [5] investigated the machinability of austenitic AISI 302 stainless steel under oblique cutting. They have studied the surface roughness at different cutting conditions and nose radius. Julie et al. [6] performed optimization of surface roughness in an end-milling operation using the Taguchi method. Maintaining good surface quality usually involves additional manufacturing cost or loss of productivity. Bhattacharya et al. [7] presented Taguchi and ANOVA techniques to analyse the effect of cutting parameters on surface finish and power consumption during high speed machining of AISI 1045 steel. Moshat et al. [8] studied on optimization of CNC milling process parameters using PCA based Taguchi method that had served the purposes of optimization but not simultaneously optimize the surface roughness and the material removal rate in the study. Kadirgama and Noor et al. [9] highlighted about optimization of the surface roughness when milling Aluminium alloys (AA6061-T6) with carbide coated inserts using Response Surface Method (RSM) and Radian Basis Function Network (RBFN) to predict thrust force and surface roughness. Abele and Frolich [10] have compiled the case study of high speed milling of titanium alloys and have provided base for different metallurgical and machining conditions to be taken into account for the study. The case study of titanium based alloys were conducted for the high speed milling process for sets of input parameters with moderate cutting speeds and feed rate to get better material removal of aircraft materials. Lou et al. [11] developed the prediction technique for the surface roughness of the CNC end milling process but focused only on the roughness average but not at the material removal rate. Thangarasu et al. [12] established the relationship with the basic parameters to the responses namely Surface roughness and Material Removal Rate. They adopted Taguchi based Box-Behnken RSM (Response Surface Methodology) method and Multi Objective Genetic Algorithm (MOGA) for optimization of CNC milling process. Kaladhar et al. [13] studied surface roughness in turning of AISI 202 austenitic stainless steel using CVD coated cemented carbide tools. They have observed feed is the most significant factor that influences the surface roughness followed by nose radius. Kechagias et al. [14] brought out the influence of cutter geometry and cutting parameters during end milling on the surface texture of aluminium alloy 5083 that was experimentally investigated using Taguchi L18 standard orthogonal array. Jenarthanan et al. [15] develop a mathematical model for surface roughness and delamination through response surface methodology (RSM) and analyse the influences of the entire individual input machining parameters (cutting speed, fibre orientation angle, depth of cut and feed rate) on the responses in milling of glass fibre reinforced plastics (GFRP) composites with solid carbide end mill cutter coated with PCD. Naresh et al. [16] established the relationship between the process parameters and responses namely surface roughness, machining force and delamination factor for GFRP composites using solid carbide end mill. Philip Selvaraj and Chandramohan [17] brought out the influence of cutting parameters like cutting speed, feed rate and depth of cut on the surface roughness of AISI 304 austenitic stainless steel bars during dry turning.

It can be observed from the above review of literatures that the surface quality (surface roughness) and material removal rate is strongly dependent on cutting parameters, tool geometry and cutting forces. Therefore this paper focuses on the effect CNC milling parameters on surface roughness and material removal rate are reported using grey based Taguchi method.

2. Grey Based Taguchi Method

The integrated grey based Taguchi method combines the algorithm of Taguchi method and grey relational analysis to determine the optimum process parameters for multiple responses.

The concept of the Taguchi method is that the parameters design is performed to reduce the sources of variation on the quality characteristics of product, and reach a target of process robustness [18]. It utilizes the orthogonal arrays from experimental design theory to study a large number of variables with a small number of experiments [19, 20]. The experiments are conducted based on orthogonal arrays, which provide a set of well balanced (minimum) experiments. Taguchi's Signal-to-Noise ratios (S/N), which are log functions of desired output, serve as objective functions for optimization, help in data analysis and prediction of optimum results. The standard S/N ratios generally used are as follows: - Nominal-is-Best (NB), Lower-is-Better (LB) and Higher-is-Better (HB). The optimal setting is the parameter combination which has the highest S/N ratio. The objectives of the present work are lower surface roughness (SR) and higher material removal rate (MRR), hence the S/N ratio for surface roughness is lower is better (LB) and for MRR is higher is better (HB). The loss function (L) for objective of LB and HB are defined using the following equations:

$$L_{LB} = \frac{1}{n}\sum_{i=1}^{n} y^2{}_{SR} \cdots\cdots\cdots (1)$$

$$L_{HB} = \frac{1}{n}\sum_{i=1}^{n} \frac{1}{y^2{}_{MRR}} \cdots\cdots\cdots\cdots (2)$$

Where y is response variable and L is loss function

The S/N ratios are the logarithmic transformation of the loss function, the S/N ratio for surface roughness and MRR are given in below equations,

S/N ratio for SR $= -10\log_{10}(L_{LB})$ ....(3)

S/N ratio for MRR $= -10\log_{10}(L_{LB})$ ....(4)

The grey relation analysis is used to convert the multiple response optimization problems into a single response optimization problem. In the present work the objectives are to obtain lower surface roughness and higher MRR, the grey relation analysis convert this multi-objective problem into single objective problem by using overall grey relation grade. The optimal parametric combination is then evaluated by maximising the overall grey relational grade. The overall grey relation grade is an average of grey relational coefficients of each selected response. The grey relational coefficient represents the correlation between the desired and actual experimental data. The grey relational coefficient is calculated based on experimental results of each selected response. In calculating the grey relational coefficient first the experimental data i.e. the quality characteristics of surface roughness and material removal rate are normalized ranging from zero to one, this process is known as grey relational generation. The experimental data for each quality characteristic is converted into S/N ratio. These S/N ratios for each quality characteristics are normalized using the following grey relational generation equations [21, 22, 23]

The normalized data corresponding to lower-the-better (LB) criterion can be expressed as:

$$x_i(k) = \frac{\max y_i(k) - y_i(k)}{\max y_i(k) - \min y_i(k)} \ldots\ldots (5)$$

The normalized data corresponding to higher-the-better (HB) criterion can be expressed as:

$$x_i(k) = \frac{y_i(k) - \min y_i(k)}{\max y_i(k) - \min y_i(k)} \ldots\ldots (6)$$

Where,

i = 1, 2, 3,...... m, m = number of experimental runs in Taguchi orthogonal array, in the present work L_{27} orthogonal array is selected then m = 27.

k = 1, 2,..... n, n = number of quality characteristics or process responses, in the present work surface roughness and material removal rate are selected, then n = 2.

y_i (k) is the S/N ratio based on the experimental data.

min y_i (k) is the smallest value of y_i (k) for the k^{th} response.

max y_i (k) is the largest value of y_i (k) for the k^{th} response.

x_i (k) is normalized S/N ratios.

Based on the normalized S/N ratios of the experimental data the grey relation coefficient can be calculated using the following equation:

The grey relational coefficient,

$$\xi_i(k) = \frac{\Delta_{min} + \psi\, \Delta_{max}}{\Delta_{0i}(k) + \psi\, \Delta_{max}} \ldots\ldots\ldots (7)$$

Where,

$\Delta_{0i} = \| x_0(k) - x_i(k) \|$ = difference of absolute value $x_0(k)$ and $x_i(k)$.

$x_0(k)$ is reference sequence k^{th} quality characteristics.

ψ is distinguishing coefficient lies between 0 to 1 $(0 \leq \psi \geq 1)$, in general it is set to 0.5 [24].

Δ_{min} = The smallest value of Δ_{0i} = $\forall j^{min} \in i\ \forall k^{min} \| x_0(k) - x_i(k) \|$

Δ_{max} = the largest value of Δ_{0i} = $\forall j^{max} \in i \forall k^{max} \| x_0(k) - x_i(k) \|$

The grey relation coefficient values are used to find the grey relation grade. The grey grade for each experimental run can be obtained by accumulation the grey relation coefficient of each quality characteristic. The average grey grade for the ith experimental run for all 'n' responses is given by

$$\gamma_i = \frac{1}{n} \sum_{k=1}^{n} \xi_i(k) \ldots\ldots\ldots\ldots \quad (8)$$

Where,

i = 1,2,3 ... 27, [L_{27} orthogonal array is selected]

$\xi_i(k)$ is the grey relational coefficient of k^{th} response in i^{th} experiment

n = Number of responses.

The higher grey relational grade means that the corresponding parameter combination is closer to the optimal. In the equation 8 for finding grey relational grade, all the quality features are considered as equally important.

3. Determination of optimal machining parameters

3.1. Experimental details

The experimental investigation presented here was carried out on a CNC milling (KENT Ind. Co. Ltd., Taiwan) with 7.5 kW power and maximum spindle speed of 8000 rpm. The work material selected for the study was AISI 304 stainless steel with high strength, high ductility and low thermal conductivity. The selection of the AISI 304 stainless steel was made taking into account its use in almost all industrial applications for approximately 50% of the world's stainless steel production and consumption. The important characteristics responsible for the commercial popularity of this material are its ability to resistance to corrosion and staining. Low maintenance, relatively low cost and familiar lustre make it an ideal base material for a host of commercial applications. The chemical composition of the work piece material is given in Table 1. The dimension of the work piece used in the experiment was 460 mm X 100 mm X 10 mm. The cutting tool is made up of tungsten carbide end mill with 4 flutes of 10 mm diameter. A schematic diagram of the experimental set-up used in this study is shown in Fig. 1.

The responses considered in this study are surface roughness and material removal rate. The surface roughness was evaluated using stylus type profilometer Mitutoyo SJ-201. Material removal rate is used to evaluate a machining performance. Material removal rate is expressed as the amount of material removed under a period of machining time and is calculated using the equation.

$$MRR = \frac{Volume\ of\ material\ removed\ from\ work\ piece (mm^3)}{Machining\ time (sec)}$$

Where,

Volume of material removed from work piece (mm^3) = Depth of cut (mm) * breadth of the work piece (mm) * groove width (mm)

Table 1. Chemical composition of AISI 304 Stainless Steel

Element	Wt %
C	0.02
Mn	1.31
Si	0.32
Cr	16.38
Ni	12.17
P	0.3
S	0.2

Fig 1: Fixation of AISI 304 stainless steel plate by using clamps in the machining center

To perform the experimental design, three levels of machining parameters cutting speed, feed rate and depth of cut are selected and are shown in Table 2. To select an appropriate orthogonal array for the experiments, the total degrees of freedom need to be computed. The degrees of freedom for the orthogonal array should be greater than or equal to those for the process parameters. In this study, an L_{27} orthogonal array is used because it has 26 degrees of freedom more than the 8 degrees of freedom in the machining parameters. The experimental combinations of the machining parameters using the L_{27} orthogonal array are presented in Table 3. Based on the designed orthogonal array combination milling operations are performed on AISI 304 stainless steel. The experimental results are summarized in Table 3.

Table 2. Process Parameters and their Levels

		Levels		
Process parameters	Units	1	2	3
Cutting speed (A)	m/min	63	79	95
Feed rate (B)	mm/min	600	700	800
Depth of cut (C)	mm	0.4	0.6	0.8

Table 3. Experimental design using L_{27} orthogonal array and their responses.

Exp. No.	A	B	C	Surface Roughness, SR (µm)	Material Removal Rate, MRR (mm^3/sec)
1	1	1	1	0.32	120
2	1	1	2	0.3	150
3	1	1	3	0.34	160
4	1	2	1	0.39	140
5	1	2	2	0.42	165
6	1	2	3	0.32	180
7	1	3	1	0.56	115
8	1	3	2	0.47	150
9	1	3	3	0.46	170
10	2	1	1	0.38	140
11	2	1	2	0.44	180
12	2	1	3	0.46	200
13	2	2	1	0.57	160
14	2	2	2	0.6	180
15	2	2	3	0.52	200
16	2	3	1	0.64	145
17	2	3	2	0.56	155
18	2	3	3	0.57	170
19	3	1	1	0.49	160
20	3	1	2	0.58	165
21	3	1	3	0.61	200
22	3	2	1	0.7	140
23	3	2	2	0.74	170
24	3	2	3	0.59	210
25	3	3	1	0.88	135
26	3	3	2	0.73	180
27	3	3	3	0.75	200

3.2. Optimization of machining parameters

Initially, the S/N ratios for a given responses are computed using equation (3) and (4) because the surface roughness is lower-the-better criterion and material removal rate is higher-the-better criterion.

The normalized values for each response S/N ratios are estimated using equation (5) & (6) and the normalized values of S/N ratios are shown in Table 4.

Grey relational coefficient for each response has been calculated using equation (7). The value for ψ is taken as 0.5 since both the responses are of equal weight. The results are shown in Table 4. The grey relational grade can be calculated by using equation (8), which is the overall representative of both the responses shown in Table 4. Now, the multi-response optimization problem has been transformed into a single equivalent objective function optimization problem using this approach. Basically, the larger the grey relational grade, the better is the multiple performance characteristic. However, the relative importance among the machining parameters for the multiple performance characteristics still needs to be known, so that the optimal combinations of the machining parameter levels can be determined more accurately. The mean response table for overall grey relational grade is shown in Table 5 and is represented graphically in Fig. 2. With the help of the Table 5 and Fig. 2, the optimal parameter combination (The Optimal Selected Levels are bolded in Table 5) has been determined. The optimal factor setting becomes A3 (cutting speed, 95m/min), B3 (feed rate, 800mm/min) and C3 (depth of cut, 0.8mm).

Table 4. S/N ratios and Grey relational coefficient of responses and Grey relational grade

Exp. No.	S/N ratio		Normalised values of S/N ratios		Grey relational coefficient of		Grey relational grade
	SR	MRR	SR	MRR	SR	MRR	
1	9.8970	41.5836	0.0600	0.0707	0.3472	0.3498	0.3485
2	10.4576	43.5218	0.0000	0.4412	0.3333	0.4722	0.4027
3	9.3704	44.0824	0.1163	0.5484	0.3613	0.5254	0.4433
4	8.1787	42.9226	0.2438	0.3267	0.3980	0.4261	0.4120
5	7.5350	44.3497	0.3127	0.5995	0.4211	0.5552	0.4881
6	9.8970	45.1055	0.0600	0.7440	0.3472	0.6614	0.5043
7	5.0362	41.2140	0.5800	0.0000	0.5435	0.3333	0.4384
8	6.5580	43.5218	0.4172	0.4412	0.4618	0.4722	0.4670
9	6.7448	44.6090	0.3972	0.6491	0.4534	0.5876	0.5205
10	8.4043	42.9226	0.2197	0.3267	0.3905	0.4261	0.4083
11	7.1309	45.1055	0.3559	0.7440	0.4370	0.6614	0.5492
12	6.7448	46.0206	0.3972	0.9190	0.4534	0.8606	0.6570
13	4.8825	44.0824	0.5964	0.5484	0.5533	0.5254	0.5393
14	4.4370	45.1055	0.6441	0.7440	0.5842	0.6614	0.6228
15	5.6799	46.0206	0.5111	0.9190	0.5056	0.8606	0.6831
16	3.8764	43.2274	0.7041	0.3849	0.6282	0.4484	0.5383
17	5.0362	43.8066	0.5800	0.4957	0.5435	0.4978	0.5206
18	4.8825	44.6090	0.5964	0.6491	0.5533	0.5876	0.5704
19	6.1961	44.0824	0.4559	0.5484	0.4789	0.5254	0.5021
20	4.7314	44.3497	0.6126	0.5995	0.5634	0.5552	0.5593
21	4.2934	46.0206	0.6595	0.9190	0.5949	0.8606	0.7277
22	3.0980	42.9226	0.7873	0.3267	0.7015	0.4261	0.5638
23	2.6154	44.6090	0.8390	0.6491	0.7564	0.5876	0.6720
24	4.5830	46.4444	0.6285	1.0000	0.5737	1.0000	0.7868
25	1.1103	42.6067	1.0000	0.2663	1.0000	0.4053	0.7026
26	2.7335	45.1055	0.8263	0.7440	0.7422	0.6614	0.7018
27	2.4988	46.0206	0.8514	0.9190	0.7709	0.8606	0.8157

Table 5. Response table (mean) for overall grey relational grade.

Factors	Level-1	Level-2	Level-3
A	0.4472	0.5654	**0.6702**
B	0.5109	0.5858	**0.5861**
C	0.4948	0.5537	**0.6343**

The results obtained from the experiments were analyzed using Analysis of Variance to find the significance of each input parameter on the measures of process performances, surface roughness and material removal rate. Using the grey relational grade value, ANOVA is formulated for identifying the significant factors. The results of ANOVA are presented in Table 6. From ANOVA, it is clear that cutting speed (56.90%) influences more on milling of AISI 304 stainless steel followed by depth of cut (22.43%) and feed rate (8.58%).

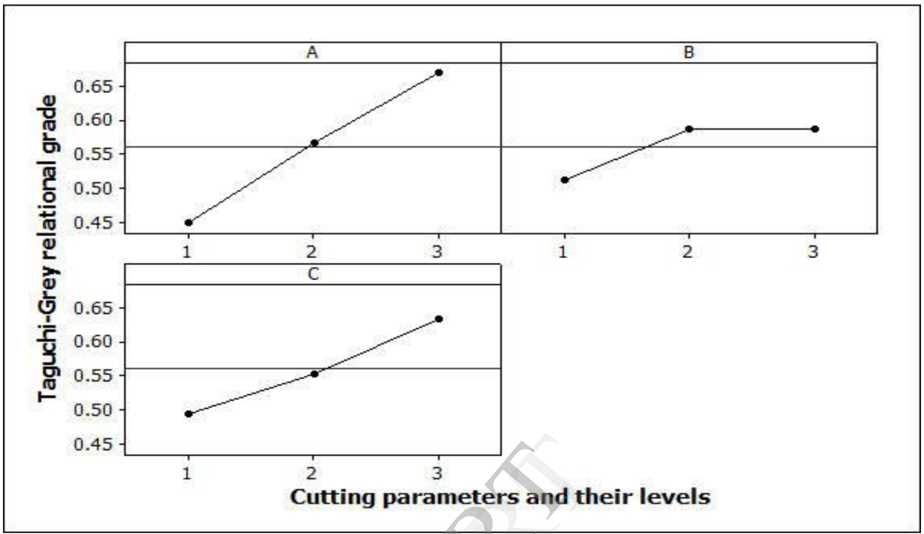

Fig 2: The response graph for each level of machining parameters

Table 6. Results of the ANOVA

Factors	DOF	Sum of squares	Mean square	F value	% Contribution
A	2	0.2240	0.1120	46.66	56.90
B	2	0.0338	0.0169	7.04	8.58
C	2	0.0883	0.0441	18.37	22.43
Error	20	0.0476	0.0024	-	12.09
Total	26	0.3937	-	-	100

4. Conclusions

Experiments are designed and conducted on CNC milling machine with tungsten carbide end mill and AISI 304 stainless steel as work material to optimize the milling parameters. The surface roughness and material removal rate are the responses. The proposed Grey based Taguchi method is constructive in optimizing the multi-responses. It is identified that cutting speed (56.90%) influences more on milling of AISI 304 stainless steel followed by depth of cut (22.43%) and feed rate (8.58%). The optimal 'process parameters' based on Grey Relational Analysis for the milling of AISI 304 stainless steel include a 95 m/min cutting speed, 800 mm/min feed rate and 0.8mm depth of cut.

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