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OPTIMIZATION OF MACHINING PARAMETER FOR TURNING OF EN 16 STEEL USING GREY BASED TAGUCHI METHOD

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ABSTRACT

This paper presents the optimization of CNC turning parameters for EN 16 steel bar using the Grey Taguchi Method. A plan of experiments based on Taguchi's L_{27} orthogonal array was established and turning experiments were conducted with prefixed cutting parameters for EN 16 steel bar using tungsten carbide tool. The turning parameters are cutting speed, feed rate and depth of cut and the responses are surface finish and material removal rate. Taguchi's signal-to-noise (S/N) ratio are determined based on their performance characteristics. A grey relational grade is obtained by using S/N ratio. Based on grey relational grade value, optimum levels of parameters have been identified by using response Table and response graph and the significant contributions of controlling parameters are estimated using analysis of variances (ANOVA).

Keywords: CNC turning, EN 16 steel, surface roughness, MRR, grey Taguchi method, and ANOVA

INTRODUCTION

EN 16 is low alloy and high tensile steel and finds its typical applications in manufacturing of automobile, welded construction in structural components, air craft fittings, aerospace components and components for severe chemical environments. Properties of EN16 steel, like low specific heat, good resistance to shock, resistance to wear and excellent ductility. The machining of EN16 steel and its alloys is generally cumbersome owing to several inherent properties of the material.

In machining, turning is a most widely used process in which a single point cutting tool removes material from surface of a rotating cylindrical workpiece. Surface roughness (SR) and material removal rate (MRR) have been identified as quality attributes and are assumed to be directly related to performance of mechanical process, productivity and production costs. Both the surface roughness and material removal rate greatly vary with the change of cutting process parameters. It is important to choose the best machining parameters for achieving optimum performance characteristics for machining process. The desired machining parameters are usually selected with the help of referred handbooks, past experience and various trails. However, the selected machining parameters may not be optimal or near optimal machining parameters. Taguchi method can be applied for optimization of process parameters to produce high quality products with lower manufacturing costs [1]. Taguchi's parameter design is one of the important tools for robust design, which offers a systematic approach for parameters optimization in terms of performance, quality and cost [2-6]. Taguchi technique had been applied to optimize machining process parameters for turning process of different grade of EN materials like EN-8 and EN-3 with TiN-coated cutting tools [3]. The same methodology had been used by yang *et al*., [4] to find the optimal cutting parameters, i.e. cutting speed, feed rate and depth of cut for surface roughness in turning operation based on experimental results done on S45C steel bars using tungsten carbide cutting tools. Kopac *et al*., [5] also used Taguchi orthogonal array for finding optimum cutting parameters, i.e. cutting speed, cutting tool materials, feed rate and depth of cut on surface roughness in machining C15 E4 steel on a lathe. Further, design optimization for quality was carried out by Asilturk *et al*. [6] to find the optimal cutting parameters in turning process for hardened AISI 4140 steel bars using coated carbide cutting tools by orthogonal array and analysis of variance. Thus, Taguchi methodology can be effectively used to optimize process parameters for single performance characteristic only. However, the optimizations of multiple performance characteristics find more applications and it is also an interesting research program.

Many authors [7-10] have been proposed different methods for solving multiple performance characteristic problems. Naveen Sait *et al*. studied flank wear, crater wear, surface roughness and machining force on turning glass-fibre reinforced plastic (GFRP) pipes using desirability function analysis [7]. Ramanujam *et al*. [8] also used desirability function analysis for optimizing multiple performance characteristics namely surface roughness and power consumption in turning Al-15%SiC_p metal matrix composites. Gopalsamy *et al*., [9] used grey relational analysis to investigate machinability study of hardened steel and to obtain optimum process parameters. Also applied analysis of variance (ANOVA) to study the performance characteristics of machining process parameters such as cutting speed, feed, depth of cut and width of cut with consideration of multiple responses, i.e. volume of material removed, surface finish, tool wear and tool life. Taguchi method integrated with grey relation theory for solving multi-objective optimization problem has been proposed by Sanjit *et al*., [10]. They have adopted entropy measurement technique to calculate individual response weights according to their relative priority.

The present study aims to achieve an optimum combination of machining process parameters considering two responses namely surface roughness and material removal rate. The traditional Taguchi method focused on

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one characteristic to optimize and obtain a combination of parameter conditions. As the present study deals with more than one quality characteristic, the traditional Taguchi method is not suitable to optimize the problem and higher signal/noise (S/N) ratio of one response may corresponds to lower S/N ratio of the other. So a single performance index is needed which may represent all the responses. The extended grey based Taguchi method can effectively solve the correlation problem. Here, Grey relational analysis is adopted to convert the multivariate problem in to a single performance index then Taguchi method is employed to find the optimum parameter combination.

EXPERIMENTAL PROCEDURE

The experimental investigation was carried out on a computer numerical control (CNC) turning machine shown in Figure-1 (Manufactured by Jarng Yeong Enterprise Co., Ltd., Taiwan), with 3.75 kW power and maximum spindle speed of 6000 rpm. The work material selected for the study was EN16 steel bars of diameter 38 mm and length 200 mm. The selection of the EN16 steel was made taking into account its use in almost all industrial applications for approximately 50% of the world's steel production and consumption. The chemical composition of the workpiece material and its physical and mechanical properties are given in Table-1 and Table-2. The cutting tool selected for machining was tungsten carbide tool. The responses considered in this study were surface roughness and material removal rate. Surface roughness can generally be described as the geometric features of the surface. The surface roughness was evaluated using a Mitutoyo Surf test 211 with the cut-off length set as 2.5 mm. Each trail was repeated for three times and the average roughness values were obtained. 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 formula given in equation (1).

$$MRR\ (mm^3/min) = \frac{W_i -}{\rho\ \cdot} \quad (1)$$

where, W_i and W_f are the initial and final weight of the workpiece in grams, ρ is the density of the workpiece in gm/mm^3 and t is the machining time in min.

Table-1. Chemical composition of EN16 steel.

Element	% Composition
C	0.35
Si	0.25
Mn	1.50
Mo	0.30
S	0.02
P	0.02

Table-2. Physical and mechanical properties of EN16 steel.

Property	Value
Tensile stress (MN/m^2)	695
Yield stress (MN/m^2)	605
Young's modulus (GN/m^2)	210
Density (kg/m^3)	7833
% Elongation	16

Figure-1. CNC turning centre.

To perform the experimental design, a total of three parameters namely cutting speed (A), feed rate (B) and depth of cut (C) were chosen for the controlling factor, and each parameter is designed to have three levels, namely low, medium, and high, denoted by 1, 2 and 3, as shown in the Table-3. It was also decided to study the two factor interaction effects on multiple performance characteristics. The selected interactions were between cutting speed and feed rate (A×B), between cutting speed and depth of cut (A×C), and between feed rate and depth of cut (B×C). To select an appropriate orthogonal array for the experiments, the total degrees of freedom (DOF) need to be computed. With three parameters each at three levels and three second-order interactions the total degree of freedom required is 18, since a three level parameter has 2 DOF and each second order interaction has 4 DOF (product of DOF of interacting parameters). As per Taguchi's method, the DOF for the orthogonal array should be greater than or equal to the total DOF required for the experiment. In this study, an L_{27} orthogonal array (a standard 3-level orthogonal array) having 26 DOF (No. of trials -1) was selected. The experimental combinations of the machining parameters using the L_{27} orthogonal array are presented in Table-4. Based on the designed orthogonal array, twenty seven experiments were conducted on EN 16 steel. The experimental results are summarized in Table-4.

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Table-3. Process parameters and their levels.

Factors	Process parameters	Units	Level 1	Level 2	Level 3
A	Cutting speed	m/min	150	200	250
B	Feed rate	mm/rev	0.10	0.15	0.20
C	Depth of cut	mm	0.2	0.4	0.6

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.

TAGUCHI METHOD

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 [11]. It utilizes the orthogonal arrays from experimental design theory to study a large number of variables with a small number of experiments [12, 13]. Taguchi's Signal-to-Noise ratios (S/N), indicates the degree of predictable performance of a product or process in the presence of noise factors. Process parameter settings with the highest S/N ratio always yield optimal quality with minimum variance. Taguchi categorized the performance characteristics of a system into three different kinds based on the type of performance: the nominal the best, the smaller the better, and the larger the better. In this study, smaller the better principle was considered to minimize the surface roughness (SR) and larger the better was considered for material removal rate (MRR). The corresponding loss function can be expressed as follows:

For smaller the better-

$$L_{ij} = \frac{1}{n}\sum_{k=1}^{n} y_{ijk}^2 \quad (2)$$

For larger the better-

$$L_{ij} = \frac{1}{n}\sum_{k=1}^{n} \frac{1}{y_{ijk}^2} \quad (3)$$

In Equations (2) and (3), n represents the number of repeated experiments, L_{ij} is the loss function of the i^{th} performance characteristic in the j^{th} experiment, and y_{ijk} is the experimental value of the i^{th} performance characteristic in the j^{th} experiment at the k^{th} test. The loss function is further transformed into an S/N ratio. The S/N ratio $\square_{ij}$ for the i^{th} performance characteristic in the j^{th} experiment can be calculated from the following expression:

$$\square_{ij} = -10 \log(L_{ij}) \quad (4)$$

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Table-4. Experimental plan with response (s).

Exp. No.	Process parameters			Responses	
	A	B	C	Surface roughness, SR (μm)	Material removal rate, MRR (mm^3/min)
1	1	1	1	0.290	0725.33
2	1	1	2	0.347	1529.86
3	1	1	3	0.367	3077.06
4	1	2	1	0.620	0887.56
5	1	2	2	0.753	1953.97
6	1	2	3	0.617	3789.67
7	1	3	1	0.970	1532.21
8	1	3	2	0.757	1925.33
9	1	3	3	0.990	3795.95
10	2	2	1	0.670	1063.20
11	2	2	2	0.863	2642.40
12	2	2	3	0.753	5174.00
13	2	3	1	0.800	1527.84
14	2	3	2	1.043	3129.57
15	2	3	3	0.917	6015.91
16	2	1	1	0.357	0941.38
17	2	1	2	0.317	1734.55
18	2	1	3	0.347	2813.41
19	3	3	1	1.603	1749.32
20	3	3	2	1.093	3649.09
21	3	3	3	1.083	6903.25
22	3	1	1	0.330	1088.37
23	3	1	2	0.270	1859.94
24	3	1	3	0.317	3449.90
25	3	2	1	0.567	0517.04
26	3	2	2	0.520	1963.36
27	3	2	3	0.697	0903.43

GREY RELATIONAL ANALYSIS

The grey relational analysis is used to convert the multi-response characteristics into single-response characteristic. As a result, optimization of the complicated multi-response characteristics can be converted into optimization of a single response characteristic called grey relational grade. The multi-responses such as surface roughness and material removal rate are combined as grey relational grade using grey relational analysis. In the present work the objectives are to minimize the surface roughness and maximize the MRR. The grey relational grade is an average of grey relational coefficients of each response characteristic. The grey relational coefficient is calculated based on experimental results of each response characteristic. In calculating grey relational coefficient, first the experimental data for each response characteristics are normalized ranging from zero to one. 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 equations [14-16].

The normalized data corresponding to smaller-the-better criterion can be expressed as:

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

The normalized data corresponding to larger-the-better criterion can be expressed as:

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

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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,

$$\chi_i(k) = \frac{\Delta_{min} + \xi \Delta_{max}}{\Delta_{0i}(k) + \xi \Delta_{max}} \quad (7)$$

Where,
$\Delta_{0i} = \| x_0(k) - x_i(k) \|$ = difference of absolute value $x_0(k)$ and $x_i(k)$. $x_0(k)$ is the reference sequence of k^{th} quality characteristics. ξ is distinguishing coefficient lies between 0 to 1 ($0 \le \xi \ge 1$), in general it is set to 0.5 [17].

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

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

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 i^{th} experimental run for all 'n' responses is given by:

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

Where, i = 1,2,3 ... 27, [L_{27} orthogonal array is selected]
$\chi_i(k)$ is the grey relational coefficient of k^{th} response in i^{th} experiment and n is the number of responses.

The optimum level of the process parameters is the level with the highest grey relational grade. In the equation 8 for finding grey relational grade, all the quality features are considered as equally important.

RESULTS AND DISCUSSIONS

In the CNC turning process, lower surface roughness and higher material removal rate are indications of better performance. Taguchi's L_{27} orthogonal array was used for experimental investigation. The experimentally collected data were subjected to Grey relational analysis and ANOVA for optimization of machining parameters. For data pre-processing in the grey relational analysis process, surface roughness is taken as the "smaller is better" and material removal rate is taken as the "larger is better".

Initially, the S/N ratios for a given responses are computed using equation (4) and (5) 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 (6) and (7) and the normalized values of S/N ratios are shown in Table-5.

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Table-5. S/N ratios and grey relational coefficient of responses and grey relational grade.

Exp. No.	S/N ratio		Normalized values of S/N ratios		Grey relational coefficient of		Grey relational grade
	SR	MRR	SR	MRR	SR	MRR	
1	10.7520	57.2107	0.0401	0.1306	0.3425	0.3651	0.3538
2	9.1934	63.6930	0.1409	0.4186	0.3679	0.4624	0.4151
3	8.7067	69.7627	0.1723	0.6882	0.3766	0.6159	0.4962
4	4.1522	58.9640	0.4667	0.2085	0.4839	0.3871	0.4355
5	2.4641	65.8184	0.5758	0.5130	0.5410	0.5066	0.5238
6	4.1943	71.5720	0.4640	0.7686	0.4826	0.6836	0.5831
7	0.2646	63.7064	0.7180	0.4192	0.6394	0.4626	0.5510
8	2.4181	65.6901	0.5788	0.5073	0.5428	0.5037	0.5232
9	0.0873	71.5864	0.7294	0.7692	0.6488	0.6842	0.6665
10	3.4785	60.5323	0.5102	0.2782	0.5051	0.4092	0.4571
11	1.2798	68.4400	0.6524	0.6295	0.5899	0.5744	0.5821
12	2.4641	74.2765	0.5758	0.8887	0.5410	0.8179	0.6794
13	1.9382	63.6816	0.6098	0.4181	0.5617	0.4621	0.5119
14	-0.3657	69.9097	0.7587	0.6947	0.6745	0.6209	0.6477
15	0.7526	75.5860	0.6864	0.9469	0.6145	0.9040	0.7592
16	8.9466	59.4753	0.1568	0.2312	0.3722	0.3941	0.3831
17	9.9788	64.7837	0.0901	0.4670	0.3546	0.4840	0.4193
18	9.1934	68.9847	0.1409	0.6536	0.3679	0.5907	0.4793
19	-4.0987	64.8574	1.0000	0.4703	1.0000	0.4856	0.7428
20	-0.7724	71.2437	0.7850	0.7540	0.6993	0.6702	0.6847
21	-0.6926	76.7811	0.7798	1.0000	0.6942	1.0000	0.8471
22	9.6297	60.7355	0.1127	0.2872	0.3604	0.4122	0.3863
23	11.3727	65.3900	0.0000	0.4940	0.3333	0.4970	0.4151
24	9.9788	70.7561	0.0901	0.7323	0.3546	0.6513	0.5029
25	4.9283	54.2705	0.4165	0.0000	0.4615	0.3333	0.3974
26	5.6799	65.8600	0.3679	0.5148	0.4416	0.5075	0.4745
27	3.1353	59.1179	0.5324	0.2153	0.5167	0.3892	0.4529

Grey relational coefficient for each response has been calculated using equation (8). The value for ψ is taken as 0.5 since both the responses are of equal weight. The grey relational grade can be calculated by using equation (9), which is the overall representative of both the responses shown in Table-5. 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-6 and is represented graphically in Figure-2. Basically, the larger the composite desirability, the better is the multiple performance characteristics. From the response graph and response Table the optimal parameter combination (The optimal selected levels are bolded in Table-6) has been determined. The optimal factor setting becomes A2 (cutting speed, 200m/min), B1 (feed rate, 0.1mm/rev) and C3 (depth of cut, 0.6mm). The interaction plots for grey relational grade is shown in Figure-3 are between cutting speed and feed rate (A B), between cutting speed and depth of cut (A C), and between feed rate and depth of cut (B C). It is observed from the interaction plots for grey relational grade that there is a more interaction between cutting speed and feed rate (A B) and there is very slight interaction between all the other process

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parameter in affecting multiple performance characteristics.

Table-6. Response table (mean) for overall grey relational grade.

Factors	Level-1	Level-2	Level-3
A	0.5054	**0.5466**	0.5449
B	**0.5843**	0.5295	0.4830
C	0.4688	0.5206	**0.6074**

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-7. From ANOVA, it is clear that the interaction between cutting speed and feed rate (60.71%) influences more on turning of EN 16 steel followed by depth of cut (20.04%) and feed rate (10.49%).

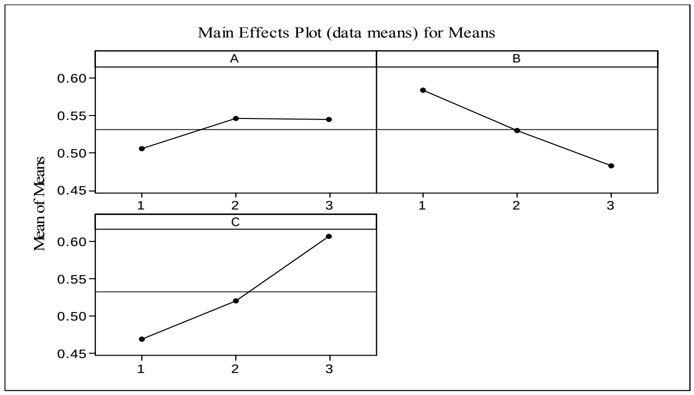

Figure-2. The response graph for grey relational grade.

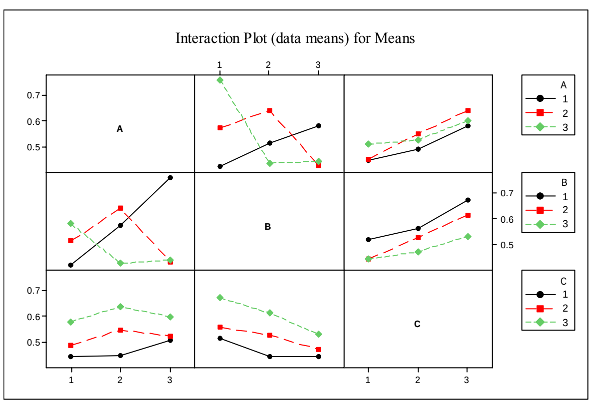

Figure-3. Interaction plots for grey relational grade.

CONCLUSIONS

Experiments are designed and conducted on CNC turning machine with tungsten carbide tool and EN 16 steel as work material to optimize the turning parameters. The surface roughness and material removal rate are the responses. The proposed Grey based Taguchi method is constructive in optimizing the multi-responses. The optimal 'process parameters' based on grey relational analysis for the turning of EN 16 steel include a 200 m/min cutting speed, 0.1 mm/rev feed rate and 0.6mm depth of cut. From ANOVA, it is identified that the interaction parameter between cutting speed and feed rate (60.71%) influences more on turning of EN 16 steel followed by depth of cut (20.04%) and feed rate (10.49%).

Table-7. Results of the ANOVA.

Factors	**Sum of square** (SS)	**Degree of freedom**	**Mean square** (MS)	**F- test**	**% Contribution**
A	0.00978	2	0.00489	2.92	2.22
B	0.04622	2	0.02311	13.77	10.49
C	0.08832	2	0.04416	26.32	20.04
A*B	0.26748	4	0.06687	39.85	60.71
A*C	0.00849	4	0.00212	1.27	1.93
B*C	0.00687	4	0.00172	1.02	1.56
Error	0.01342	8	0.00168		3.05
Total	0.44059	26			100
S = 0.04096 R-Sq = 96.95% R-Sq (adj) = 90.10%					

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