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Multi-Objective Optimization of End-Milling Process Parameters Using Grey-Taguchi Approach

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ABSTRACT

The present work analyses different parameters of end milling to minimize the surface roughness for AISI D2 steel. D2 Steel is generally used for stamping or forming dies, punches, forming rolls, knives, slitters, shear blades, tools, scrap choppers, tyre shredders etc. Surface roughness is one of the main indices that determines the quality of machined products and is influenced by various cutting parameters. In machining operations, achieving desired surface quality by optimization of machining parameters, is a challenging job. In case of mating components the surface roughness become more essential and is influenced by the cutting parameters, because, these quality structures are highly correlated and are expected to be influenced directly or indirectly by the direct effect of process parameters or their interactive effects (i.e. on process environment). In this work, the effects of selected process parameters on surface roughness and subsequent setting of parameters with the levels have been accomplished by Taguchi's parameter design approach. The experiments have been performed as per the combination of levels of different process parameters suggested by L16 orthogonal array. Experimental investigation of the end milling of AISI D2 steel with carbide tool by varying feed, speed and depth of cut and the surface roughness has been measured using surface roughness tester. Analyses of variance have been performed for mean and signal-to-noise ratio to estimate the contribution of the different process parameters on the process.

Keywords: *End milling process, Grey relational Analysis, Taguchi Approach..*

1. INTRODUCTION

Milling is one of the most widely used metal removal processes in industry and milled surfaces are largely used to mate with other parts in die, aerospace, automotive, and machinery design as well as in manufacturing industries. Surface roughness is an important measure of the quality of a production and also influences the machining cost. The mechanism behind the formation of surface roughness is very dynamic, complicated, and process dependent; it is difficult to calculate surface roughness value through theoretical analysis. Therefore, usually most of machine operators applied “trial and error” approaches to set- up milling machine cutting conditions in order to achieve the desired surface roughness. However, it is not effective and efficient and the success rate for repetitive desirable value is very low. The dynamic nature and widespread usage of milling operations in practice have raised a need for a systematic approach that can help to set-up milling operations in comparatively lesser time and also achieve the desired surface roughness quality. Due to high tolerances and good surface finish values that milling can deal, it is ideal for adding precision features to a part whose basic shape has already been formed.

Fig. 1 End Millling Operation On AISI D2 Steel

The Taguchi parameter design had been done in order to identify the optimum surface roughness performancewith a particular combination of cutting parameters in an end-milling operation. Taguchi optimization methodology was employed to optimize cutting parameters in end milling while machining AISI D2 steel with CVD coated carbide insert tool with TiAlN coating, under semi-finishing and finishing conditions of high speed cutting considering the milling parameters - cutting speed, feed rate and depth of cut. Grey-Taguchi method combined the orthogonal array (OA) design of experiments (DOE) with grey-relational analysis(GRA), which enabled the determination of the optimal combination of milling parameters for multiple process responses.
Grey relational analysis was performed to combine the multiple responses in to one numerical score, rank these scores, anddetermine the optimal machine parameter settings. Confirmation tests were performed by using experiments. ANOVA wasperformed to investigate the more influencing parameters on the multiple performance characteristics.

2. LITERATURE REVIEW

Tsai et al. [1] stated that the feed rate, cutting speed, depth of cut, cutter geometry, and cutter run out, tool wear, and the cutter force and vibration under dynamic cutting conditions were found to be possible factors affecting surface finish. **Fuh and Wu [2]** included cutting speed, feed rate, depth of cut, tool nose radius, and flank as control factors for the creation of a statistical model to predict surface roughness for aluminum parts in end milling operations using Taguchi design . **Ghani et al. [3]** conducted a study to optimize cutting conditions for hardened steel under semi-finish and finish conditions. Applying cutting speed, feed rate, and depth as control factors, they used measured responses (i.e., surface roughness and resultant cutting force) and their calculated signal-to-noise ratio to determine the optimal cutting condition.**Bouzid et al. [4]** did research to obtain optimal cutting parameters such as cutting speed, feed per tooth, and cutting depth for surface roughness in down face milling operations by using duplex stainless steel and carbon steel compositions as samples.**Lakshmi and Venkata Subbaiah [5]** conducted experimental investigations on surface finish and material removal rate during the high speed end milling of EN24 alloy steel in order to develop an appropriate roughness prediction model and optimize the cutting parameters using RSM. **Jaya Krishna et al.[6]** adopted principal component analysis (PCA) based neural networks for predicting the surface roughness in CNC end milling of P20 mould steel.**Babu and Sunny [7]** conducted study with a view to determine optimal machining parameters in drilling of GFRP composite materials.**Palanikumar et al.[8]** studied the effect of cutting parameters on surface roughness on machining of GFRP composites by Polycrystalline Diamond (PCD) tool by developing a second order model for predicting the surface roughness average.

From the exhaustive literature review, it has been observed that there is a need of finding the optimal machining parameter setting at which the MRR is maximum and both surface roughness and parallelism are minimum for machining of AISI D2 steel using end milling process. Therefore, in this paper, an attempt has been made to optimize the end milling process parameters using Grey-Taguchi approach.

3. EXPERIMENTATION

The experimental region has been decided as per Taguchi design approach. The number of levels for each controllable process parameter has been defined by Table 3. A wide experimental region has been covered so that sensitivity to noise factors does not alter with small changes in these factors settings and to obtain optimum regions for the process parameters. Therefore, each parameter was analysed at different levels of the process parameters. The work-piece has been machined to the size of 100×100×25 mm by cutter. Three main machining parameters are considered to predict surface roughness of D2 material using carbide tool. The machining is carried out by selecting proper spindle speed and feed rate during each experimentation as per OA selected. Taguchi's designs aimed to allow greater understanding of variation than did many of the traditional designs. Taguchi contended that conventional sampling is inadequate here as there is no way of obtaining a random sample of future conditions. Taguchi projected extending experimentation with an outer array or orthogonal array should simulate the random atmosphere. In the present work the experiments have been performed on the combinations of levels of factors defined by L16 orthogonal array. Taguchi orthogonal array is designed with three levels of three milling parameters. Orthogonal array design of experiment has been found suitable in the present work. It considers three process parameters (without interaction) to be varied in three discrete levels.

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The calculation of S/N ratio depends on the quality characteristics of the product or process to be optimized. The equation for calculating S/N ratios for "larger is better" (HB), "smaller is better" (LB) and "nominal is best" (NB) types of characteristics are as follows:

- For larger is better

$$(S/N)_{HB} = -10\log\left[\frac{1}{n}\sum_{i=1}^{n}(1/y_i^2)\right]$$

- For smaller is better

$$(S/N)_{LB} = -10\log\left[\frac{1}{n}\sum_{i=1}^{n}(y_i^2)\right]$$

- For nominal the better

$$(S/N)_{NB} = -10\log\left[\frac{1}{n}\sum_{i=1}^{n}(y_i - y_0)^2\right]$$

Where, y_i = experimental value in the i^{th} test

y_0 = target value and

n = number of replications

The signal-to-noise (S/N) ratio for each level of process parameters are computed. The optimum setting of the process parameters contributes the minimization of the effect of noise. It means that the level of process parameters with the highest S/N ratio corresponds to the optimum level of process parameters.

3.1Design of Experiment

In this work, four levels and three factors such as speed. Feed and depth of cut are considered for the experiment. The factors and levels are shown in Table 1.

Table 1Factors and Levels

Factors	Level 1	Level 2	Level 3	Level 4
Speed(rpm)	2700	2900	3100	3300
Feed(mm/min)	1000	1150	1300	1450
Depth of cut(mm)	0.10	0.13	0.16	0.20

Table 2L16 Orthogonal Array

Experimental Runs	Factor 1	Factor 2	Factor 3
1	1	1	1
2	1	2	2
3	1	3	3
4	1	4	4
5	2	1	2
6	2	2	1
7	2	3	4
8	2	4	3
9	3	1	3
10	3	2	4
11	3	3	1
12	3	4	2
13	4	1	4
14	4	2	3
15	4	3	2
16	4	4	1

3.2 Data Pre-processing

The application of GRA is carried out in the following steps:

Different methods are employed to pre-process grey data depending upon the quality characteristics of the original data. If the original sequence data has quality characteristic as 'larger-the-better' then the original data is pre-processed as 'larger the best':

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

If the original data has the quality characteristic as 'smaller- the-better than the original data is pre-processed as 'smaller- the-best':

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

Here $x_i(k)$ is the value after grey relational generation, min $y_i(k)$ is the smallest value of $y_i(k)$ for the k^{th} response, and max $y_i(k)$ is the largest value of $y_i(k)$ for the k^{th} response.

3.3 Deviation Sequencing

Deviation sequencing is calculated for the obtained pre- processing data by considering ideal value 1. Deviation sequencing can be calculated by using the following formula:

$$\Delta 0i=1-x_i(k)$$

Where

$\Delta 0i$ = Deviation sequencing for the k^{th} process data

$x_i(k)$ = k^{th} pre-process value

3.4 Calculation of Grey Relational Coefficient

In the next step coefficient ξi is calculated for all the obtained deviational sequencing data individually, Grey relational coefficient ξi(k) is calculated using the following formula:

$$\xi_i(k)=\frac{\Delta\min.+\psi\,\Delta\max}{\Delta 0_i(k)+\psi\,\Delta\max}$$

3.5 Computation of Grey Relational Grade

Grey relational grade is calculated by the following formula:

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

Where n is the number of process responses.

The higher value of grey relational grade corresponds to intense relational degree between the reference sequence x0(k) and the given sequence xi(k). The reference sequence x0(k) represents the best process sequence; therefore, higher grey relational grade means that the corresponding parameter combination is closer to the optimal.

4. RESULT AND ANALYSIS

The following results have been obtained using Grey-Taguchi method. Table 3 shows the computed values of MRR, surface roughness and parallelism. Table 4 shows the Normalized values for MRR, surface roughness and parallelism. Grey relational loss and grey relational co-efficient have been calculated and presented in Table 5 and Table 6 respectively. Consequently, the overall grey relational grade of each experimental run are computed and the obtained values are shown in Table 7.

Table 3 Experimental runs for MRR, Surface Roughness and Parallelism

Sl. No	Process Parameters			Responses		
	Speed (rpm)	Feed(mm/min)	Depth of cut(mm)	MRR(mm^3/min)	Ra(µm)	Parallelism (mm)
1	2700	1000	0.10	0.155	1.805	0.099
2	2700	1150	0.13	0.149	2.689	0.025
3	2700	1300	0.16	0.331	1.743	0.021
4	2700	1450	0.20	0.477	2.328	0.021
5	2900	1000	0.13	0.184	1.733	0.109
6	2900	1150	0.10	0.149	1.556	0.100
7	2900	1300	0.20	0.436	1.777	0.007
8	2900	1450	0.16	0.415	1.91	0.005
9	3100	1000	0.16	0.254	2.543	0.031
10	3100	1150	0.20	0.671	1.714	0.233
11	3100	1300	0.20	0.210	1.328	0.026

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12	3100	1450	0.13	0.567	1.887	0.018
13	3300	1000	0.20	0.311	1.793	0.204
14	3300	1150	0.16	0.273	1.049	0.024
15	3300	1300	0.13	0.314	1.058	0.015
16	3300	1450	0.10	0.303	1.082	0.017

Table 4 Normalized values for MRR, Surface Roughness & Parallelism

Experimental runs	Normalized MRR	Normalized Ra	Normalized Parallelism
1	0.01149425	0.53902439	0.58771929
2	0	0	0.91228070
3	0.34865900	0.57682926	0.92982456
4	0.62835249	0.22012195	0.92982456
5	0.06704980	0.58292682	0.54385964
6	0	0.69085365	0.58333333
7	0.54980842	0.55609756	0.99122807
8	0.50957854	0.475	1
9	0.20114942	0.08902439	0.88596491
10	1	0.59451219	0
11	0.11685823	0.82987804	0.90789473
12	0.80076628	0.49512195	0.94298245
13	0.31034482	0.54634146	0.12719298
14	0.23754789	1	0.91666666

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15	0.31609195	0.99451219	0.95614035
16	0.29501915	0.97987804	0.94736842

Table 5Grey relational loss

Experimental runs	Δ_{MRR}	Δ_{Ra}	$\Delta_{Parallelism}$
1	0.98850575	0.46097561	0.41228071
2	1	1	0.0877193
3	0.651341	0.42317074	0.07017544
4	0.37164751	0.77987805	0.07017544
5	0.9329502	0.41707318	0.45614036
6	1	0.30914635	0.41666667
7	0.45019158	0.44390244	0.00877193
8	0.49042146	0.525	0
9	0.79885058	0.91097561	0.11043509
10	0	0.40548781	1
11	0.88314177	0.17012196	0.09210527
12	0.19923372	0.50487805	0.05701755
13	0.68965518	0.45365854	0.87280702
14	0.76245211	0	0.08333334
15	0.68390805	0.0054878	0.04385965
16	0.70498085	0.02012196	0.05623158

Table 6Grey relational co-efficient

Experimental run	ξ_{MRR}	ξ_{Ra}	$\xi_{Parallelism}$
1	0.33590733	0.52030456	0.54807691
2	0.33333333	0.33333333	0.85074626
3	0.43427620	0.54161162	0.87692307
4	0.57362637	0.39066221	0.87692307
5	0.34893047	0.54521276	0.52293577
6	0.33333333	0.61793518	0.54545454
7	0.52620967	0.52971576	0.98275862
8	0.50483558	0.48780487	1
9	0.38495575	0.35436473	0.81908790
10	1	0.55218854	0.33333333
11	0.36149584	0.74613283	0.84444443
12	0.71506848	0.49757281	0.89763778
13	0.42028985	0.52429667	0.36421725
14	0.39605462	1	0.85714284
15	0.42233009	0.98914355	0.91935483
16	0.41494435	0.96131299	0.89890617

Table 7Grey relational grade

Experimental runs	Gi	Rank
1	0.46809626	15
2	0.50580430	12
3	0.61760363	9
4	0.61373721	10
5	0.47235966	14
6	0.49890768	13
7	0.67956135	5
8	0.66421348	6
9	0.51946946	11
10	0.62850729	8
11	0.65069104	7
12	0.70242602	4
13	0.43626792	16
14	0.75106582	3
15	0.77694282	1
16	0.76033975	2

Response Table for Means

Level	A	B	C
1	0.5513	0.4740	0.5945
2	0.5788	0.5961	0.6144
3	0.6253	0.6812	0.6381

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4	0.6812	0.6852	0.5895
Delta	0.1298	0.2111	0.0486
Rank	2	1	3

Analysis of Variance for Means R-Sq = 85.7%   R-Sq(adj) = 64.2%

Source	DF	Seq SS	Adj SS	Adj MS	F	P
A	3	0.038854	0.038854	0.012951	2.87	0.126
B	3	0.117580	0.117580	0.039193	8.67	0.013
C	3	0.005858	0.005858	0.001953	0.43	0.738
Residual Error	6	0.027116	0.027116	0.004519		
Total	15	0.189408				

S = 0.06723   R-Sq = 85.7%   R-Sq(adj) = 64.2%

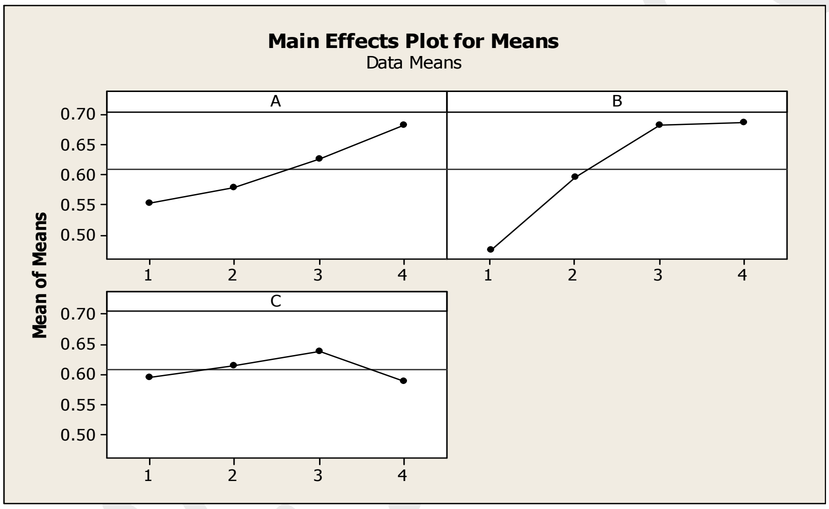

Fig. 2Main effect plot for means

4. CONCLUSION

The study proposes an integrated optimization approach using Taguchi method and Grey Analysis Approach . Optimum combination of process parameters (MRR, Ra & Parallelism) for minimum surface roughness has been calculated using Taguchi methods. The result also matches with the analysis in the Taguchi Analysis Table where S/N ratio is minimum (1.669) for the said combination. It has been found that the depth of cut contributes more than 21% in minimization of surface roughness, whereas, feed and speed affects the surface roughness to 17.8% and 16.7% respectively. The predicted range of surface finish lies at 95% consistency level for optimum combination of process parameters. Three conformational experiments have also been performed at the optimum combination of process parameters and all the results are found within the calculated range of surface roughness. From this observation, it is found that, optimal parameter setting is speed at level 4, feed at 4 and depth of cut at 3.

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Taguchi parameter design can provide a systematic procedure that can effectively and efficiently identify the optimum surface roughness in the process control of individual end milling machines. It also allows industry to reduce process or product variability and minimize product defects by using a relatively small number of experimental runs and costs to achieve superior-quality products. This research only demonstrates how to use Taguchi parameter design for optimizing machining performance for minimum surface roughness. This approach can be recommended for continuous quality improvement and off-line quality of any production process.

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