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Investigation of Optimum Cutting Parameters for End Milling of H13 Die Steel using Taguchi based Grey Relational Analysis

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Abstract

In today's industrial scenario to remain competitive in the market, manufacturers rely on their engineers to quickly and effectively set up manufacturing processes for new products to achieve good quality. Due to this surface finish & material removal rate becomes very important. This paper presents the study of the parameter optimization of end milling operation for H13 die steel with multi-response criteria based on the Taguchi L9 orthogonal array with the grey relational analysis. Surface roughness and material removal rate are optimized with consideration of performance characteristics namely cutting speed, feed rate and depth of cut. A grey relational grade obtained from the grey relational analysis is be used to solve the end milling process with the multiple performance characteristics. Additionally, the analysis of variance (ANOVA) is to be applied to identify the most significant factor. Finally, confirmation tests are performed to make a comparison between the experimental results and developed model.

Keywords: *End Milling, Taguchi Design of Experiments, Grey relational analysis, Optimization*

1. Introduction

End milling is one of the important machining operations, widely used in most of the manufacturing industries due to its capability of producing complex geometric surfaces with reasonable accuracy and surface finish. The effect of cutting parameters is reflected on surface roughness, surface texture and dimensional deviations of the product. Surface roughness, which is used to determine and to evaluate the quality of a product, is one of the major quality attributes. Surface roughness and material removal rate are measures of the technological quality of a product and a factor that greatly influences manufacturing cost.

Attempts have been made to optimize quality and productivity in a manner that these multi-criterions could be fulfilled simultaneously up to the expected level. Sandeep kumar et.al used the optimized vale of Input Parameters to increase the productivity & quality in end milling of H13 by Taguchi technique [16]. Upinder Kumar et.al investigated optimum values of input parameters in high speed turning of H13 in dry conditions. Taguchi's L9 orthogonal array and analysis of variance (ANOVA) are used for individual optimization [20]. J.C. Outeiro examined the residual stresses induced by dry turning of AISI H13 tool steel. He used modelling and optimization procedure based in Artificial Neural Network (ANN) and Genetic Algorithm (GA) [11]. The effects of various milling parameters such as spindle speed, feed rate, depth of cut and coolant flow on the surface roughness (Ra) of finished products were studied by Avinash A. Thakre [1]. Lohithaksha M Maiyar et.al investigated the parameter optimization of end milling operation for Inconel 718 super alloy with multi-response criteria based on the Taguchi orthogonal array with the grey relational analysis [12]. Optimization of Machining Parameters in End Milling of AISI H11 Steel Alloy was carried out by Nikhil Aggarwal and Sushil Kumar Sharma using Taguchi based Grey Relational Analysis [14]. E. Kuram et.al discussed an application of Taguchi experimental method for investigating the influence of milling parameters and cutting fluid types on the tool wear and forces during milling of AISI 304 stainless steel [6]. Optimization of process parameters for pulsed laser milling of micro-channels on AISI H13 tool steel was studied by Daniel Teixidor et.al. Their study focuses on understanding the influence of laser milling process parameters on the final geometrical and surface quality of micro-channel features fabricated on AISI H13 steel [4]. From above literature we can say that input machining parameters play an important role in production and manufacturing. Selection the optimal levels of parameters can lead us to higher productivity within same set of resources. Also there are number of optimization techniques available for generating a model which will lead us towards best output results. In the similar way present study will go step by step towards better and best results for surface finish and material removal rates.

2. Experimental Setup

A) Material

The material used for this study is premium high grade H13 die steel. It contains strengthening agents such as vanadium and molybdenum. These steels are resistant to softening at elevated temperatures due to the presence of chromium content. Since increased hardness slows down the formation of heat checking cracks, improved tool performance can be expected. The composition of H13 is given in following table:

Table 1. Composition of H13

Alloying Elements	C	Si	Mn	Cr	Mo	V
Percentage	0.36	1	0.4	5	1.2	0.9

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B) Machining setup

End milling operation was carried out on a BFW SURYA VF 30 CNC VS in wet conditions. The CNC milling machine equipped with AC variable speed spindle motor up to 6000 rpm and 3.7KW motor power was used for the present experimental work. The cutter used in this work was mechanically attached regular carbide Proton plus coated end mill cutter with dimensions 12x22x120 mm manufactured by Totem-Forbes.

C) Surface roughness measurement

Surface roughness is defined as the finer irregularities of the surface texture that usually form nucleation sites for cracks or corrosion. Surface roughness of the machined samples was measured with Mitutoyo make Surface roughness tester (SJ-210). An average of 3 measurements of the surface roughness was taken to use in the multi-criteria optimization.

D) Metal Removal Rate Calculation

The Material Removal Rate, MRR (mm^3/ min) was calculated using formula:

$$MRR = W \times t \times fm$$

Where,

W = Width of cut

t = Depth of cut

fm= Table (machine) Feed

E) Selection of cutting parameters and their levels

From the literature review and industrial survey, most influential parameters affecting on surface roughness and MRR are selected. Their levels for experimentation were selected from carrying out OVAT (one variable at a time) analysis. The results and selected levels of parameters are shown in table below:

Table 2. OVAT analysis results

Expt . no.	Speed (rpm)	Feed (mm/revo)	Depth of cut (mm)	Ra avg (µm)
1	2000	0.2	0.3	0.2455
2	**2500**	0.2	0.3	0.261
3	**3000**	0.2	0.3	0.201
4	**3500**	0.2	0.3	0.219
5	4000	0.2	0.3	0.225
6	2000	0.2	0.3	0.2455
7	2000	**0.3**	0.3	0.246
8	2000	**0.4**	0.3	0.2155
9	2000	**0.5**	0.3	0.208
10	2000	0.6	0.3	0.283
11	2000	0.2	0.3	0.2455
12	2000	0.2	**0.6**	0.2705
13	2000	0.2	**0.9**	0.2345
14	2000	0.2	**1.2**	0.224
15	2000	0.2	1.5	0.3165

Table 3. Levels of input parameters

Parameters	Levels		
	A	B	C
Speed (rpm)	2500	3000	3500
Feed (mm/revo)	0.3	0.4	0.5
Depth of cut (mm)	0.6	0.9	1.2

3. Design Of Experiment

A) Taguchi method of DOE

Experiments are designed using Taguchi method so that effect of all the parameters could be studied with minimum possible number of experiments. Taguchi method uses a special design of orthogonal arrays to study the entire parameter space with a small number of experiments. Signal to Noise (S/N) ratios are also calculated for analyzing the effect of machining parameters more accurately.

Based on Taguchi design L9 orthogonal array has been selected for the experiments in MINITAB 14. All these data are used for the analysis and evaluation of the optimal parameters combination. The selected L9 orthogonal array is shown below:

Table 4. L9 Orthogonal Array

Expt. no.	Speed	Feed	Depth of cut
1	2500	0.3	0.6
2	2500	0.4	0.9
3	2500	0.5	1.2
4	3000	0.3	0.9

5	3000	0.4	1.2
6	3000	0.5	0.6
7	3500	0.3	1.2
8	3500	0.4	0.6
9	3500	0.5	0.9

B) Grey Relational Analysis

In the Grey relational analysis the quality characteristics are first normalized, ranging from zero to one. This process is known as Grey Relational Generation. The Grey Relational Coefficient based on normalized experimental data is calculated to represent the correlation between the desired and the actual experimental data. Then overall grey relational grade is determined by averaging the grey relational coefficient corresponding to selected responses. This approach converts a multiple- response- process optimization problem into a single response optimization situation, with the objective function is overall grey relational grade. The optimal parametric combination is then evaluated by maximizing the overall grey relational grade.

In Grey relational generation, the normalized MRR should follow the larger-the-better (LB) criterion, which can be expressed as:

$$xij = \frac{yij - min\, yij}{max\, yij - \min yij} \qquad (1)$$

The normalized Ra should follow the smaller-the-better (SB) criterion which can be expressed as:

$$xik = \frac{max\, yik - yik}{max\, yik - \min yik} \qquad (2)$$

Where, *xij* and *xik* are the value after Grey Relational Generation for LB and SB criteria. *Max yij* is the largest value of *yij* for *jth* response and *min yik* is the minimum value of *yik* for the *kth* response.

Next, the grey relational coefficient is calculated to express the relationship between the ideal (best) and the actual normalized experimental results. The grey relational coefficient ξij can be expressed as:

$$\xi ij = \frac{\Delta min + \xi \Delta \max}{\Delta oi(j) + \xi \Delta \max} \qquad (3)$$

Where,

$\Delta oi\ (j) = |xo(i)-xi(j)|$; $\Delta max = \max \Delta oi\ (j)$; $\Delta min = \min \Delta oi\ (j)$ and *xoi* is the ideal normalized results for the *ith* performance characteristics and is the distinguishing coefficient which is defined in the range $0< \xi >1$. In the present study the value of is assumed as 0.5.

The grey relational grade is computed by averaging the grey relational coefficient corresponding to each performance characteristics. The overall evaluation of the multiple performance characteristics is based on the grey relational grade.

$$\gamma j = \frac{1}{m}\sum_{i=1}^{m} \xi ij \qquad (4)$$

Where γj is the grey relational grade for the *jth* experiment and *m* is the number of performance characteristics. This approach converts a multiple- response process optimization problem into a single response optimization situation; the single objective function is the overall grey relational grade. The optimal parametric combination is then evaluated by maximizing the overall grey relational grade.

C) Analysis of Variance (ANOVA)

The analysis of variance (ANOVA) is the statistical treatment most generally applied to the results of the experiment to determine the percent contribution of each factor. Study of the ANOVA table for a given analysis determines, whether a factor requires control or not. Once the optimum condition is determined, it is usually a good practice to run a confirmation experiment. The analysis of variance (ANOVA) test establishes the relative significance of the individual factors and their interaction effects. First, the total sum of the squared deviations SST from the total mean of the grey relational grade γj can be calculated as:

$$SST = \sum_{j=1}^{p} (yj - ym)^2 \qquad (5)$$

Where p is the number of experiments in the orthogonal array, yj is the grey relational grade for the *jth* experiment and ym is mean grey relational grade.
The percentage contribution of each of the machining parameter in the total sum of the squared deviations *SST* can be used to evaluate the importance of the machining parameter change on the performance characteristic.

4) Data Analysis

A) Data pre-processing

Table 5. Experimentally collected response data

Expt. No.	Speed rpm	Feed mm/ revo	Depth of cut mm	Ra avg µm	MRR mm^3/sec
1	2500	0.3	0.6	0.2557	1.2
2	2500	0.4	0.9	0.2715	2.4
3	2500	0.5	1.2	0.280	4.0
4	3000	0.3	0.9	0.2665	1.8
5	3000	0.4	1.2	0.271	3.2
6	3000	0.5	0.6	0.272	2.0
7	3500	0.3	1.2	0.255	2.4
8	3500	0.4	0.6	0.278	1.6
9	3500	0.5	0.9	0.365	3.0

Table 6. S/N ratio calculations for Ra and MRR

Expt. No.	Ra (µm)	S/N ratio	MRR (mm^3/sec)	S/N ratio
1	0.2557	11.8454	1.2	1.5836
2	0.2715	11.3246	2.4	7.6042
3	0.280	11.0568	4.0	12.0412
4	0.2665	11.4861	1.8	5.1055
5	0.271	11.3406	3.2	10.1030
6	0.272	11.3086	2.0	6.0206
7	0.255	11.8692	2.4	7.6042
8	0.278	11.1191	1.6	4.0824
9	0.365	8.7541	3.0	9.5424

Table 7. Data pre-processing results

Experiment No.	Normalized response values	
	Ra	MRR
1	0.9936	0
2	0.8500	0.428
3	0.7727	1

4	0.8955	0.214
5	0.8555	0.714
6	0.8455	0.286
7	1.0000	0.428
8	0.7909	0.143
9	0.0000	0.643

Table 8. Deviation Sequence

Experiment No.	Deviation Sequence	
	Ra	MRR
1	0.0064	1
2	0.1500	0.572
3	0.2273	0
4	0.1045	0.786
5	0.1445	0.286
6	0.1545	0.714
7	0.0000	0.572
8	0.2091	0.857
9	1.0000	0.357

B) Calculations for Grey relational coefficients and grey relational grades

Table 9. Grey Relational Coefficients

Experiment No.	Grey Relational Coefficients	
	Ra	MRR
1	0.9874	0.333
2	0.7692	0.466
3	0.6875	1
4	0.8271	0.389
5	0.7758	0.636
6	0.7639	0.412
7	1.0000	0.466
8	0.7051	0.368
9	0.3333	0.583

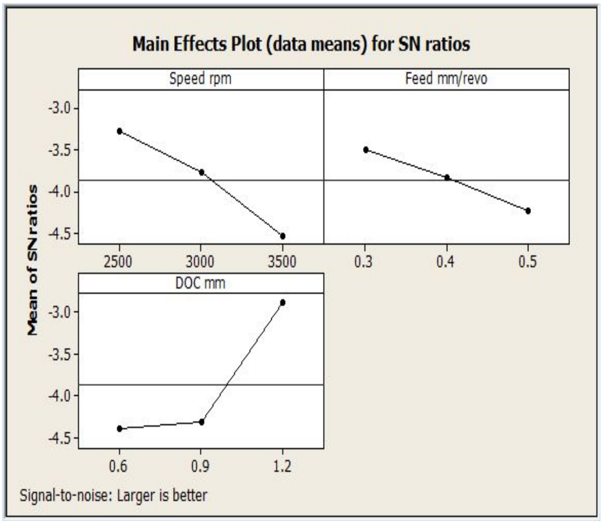
Table 9. Grey Relational Grades

Experiment No.	Grey Relational Grades	Ranks
1	0.6702	4
2	0.6476	6
3	**0.7437**	**1**
4	0.648	5
5	0.7259	2
6	0.5779	7
7	0.686	3
8	0.5665	8
9	0.5381	9

Table 10. Grey relational grades for individual factor levels

Factors	Grey Relational Grades at Optimum Factor Levels		
	1	2	3
Speed	**0.6872**	0.6506	0.5986
Feed	**0.6680**	0.6466	0.6199
Depth of cut	0.6048	0.6112	**0.7185**

From graph 1 below it is seen that S/N ratio plot for the grey grades are showing similar results as that of predicted levels from grey relational analysis proving the validity of experiment.



Graph 1. Main effects plot of S/N ratios for grey grades

C. Analysis of variance

The total sum of the squared deviations *SST* is decomposed in to two sources: the sum of the squared deviations *SSd* due to each machining parameter and the sum of the squared error *SSe*. The percentage contribution of each of the machining parameter in the total sum of the squared deviations *SST* can be used to evaluate the importance of the machining parameter change on the performance characteristic. In addition, the Fisher's F- test can also be used to determine which machining parameters have a significant effect on the performance characteristic. Table below shows the results of ANOVA analysis.

Table 11. Results of ANOVA analysis for Grey Relational Grades

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Speed	2	0.0123	0.0123785	0.0061892	34.05	0.029
Feed	2	0.0034	0.0034944	0.0017472	9.610	0.094
DOC	2	0.0244	0.0244739	0.0122370	67.31	0.01
Error	2	0.0003	0.0003636	0.0001818		
Total	8	0.0407				

S = 0.0134829 R-Sq = 99.11%

R-Sq(adj) = 96.43%

D. Predicted optimum condition

The predicted values of GRG at the optimal levels are calculated by using the relation:

$$\check{n} = nm + \sum_{i=1}^{o}(nim - nm) \qquad (6)$$

Where, $\check{n}$ = Predicted value after optimization.

nm = Total mean value of quality characteristic.

nim = Mean value of quality characteristic at optimum level of each parameter.

o = Number of main machining parameters that effects the response parameters.

E. Confirmation Experiment

The confirmation experiment is conducted at the optimum settings to verify the quality characteristics for milling of H13 die steel. The optimum combinations for the predicted milling parameters were set, and trial was conducted. In order to assess the closeness of the observed value with that of the predicted value, the confidence interval (CI) value for the optimum factor level combination at a 90% confidence level is determined.

Following table 13 shows comparison between predicted and experimental machining parameters. It gives error below 10% which is an acceptable limit. Hence it proves confirmation of the test readings.

Table 13. Comparison of machining performance from predicted and experimental results

Response Factors	Initial factors (optimal GRG trial) A1B2C2	Optimal factor levels		Error (%)
		Predicted A1B1C3	Experi-mental A1B1C3	
Surface roughnes	0.28	0.24	0.253	5.14
Material removal rate	2.40	2.62	2.40	8.4
Grey relational grade	0.8437	0.8571		1.57

5. Conclusions

The present work has successfully demonstrated the application of Taguchi based grey relational analysis for multi response optimization of process parameters in End milling of H13 die steel.

The important conclusions drawn from the present work are summarized as follows:

1) Multi-response problem was successfully converted into single response problem i.e. grey grade successfully which helped in optimization of both parameters simultaneously.

2) The optimal cutting parameters for the machining process lies at 2500 rpm for cutting speed, 0.3 mm/revolution for feed rate and 1.2 mm for depth of cut.

3) Analysis of variance shows that depth of cut is the most significant machining parameter followed by cutting speed, affecting selected response characteristics i.e. surface roughness and material removal rate, with 60.11% and 30.40% influence respectively.

4) Taguchi grey relational analysis does not involve any complicated mathematical theory or computation and thus can be employed by the engineers without a strong statistical background.

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