Multi-response Optimization Of Machining Parameters In End Milling CNC Machine of AISI H13 Hot Die Steel By Using Grey Relational Analysis

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Abstract – *In this study a Research is carried out for the optimization of End milling process of AISI H-13 hot die steel material with multiple performance characteristics based on the orthogonal array with taguchi-grey relational analysis method. Surface roughness and material removal rate are optimized by consideration of the performance characteristics like cutting speed, feed rate and depth of cut. A comparative study has been done with coolant condition and compressed air condition by using carbide coated end milling cutter tool. A grey relational grade obtained from the grey relational analysis is used to solve the end milling process with multiple performance characteristics. An analysis of variance (ANOVA) is applied to identify the most significant factor and its percentage influence on output parameter. At last confirmation tests are performed to make comparison between the experimental results and developed model.*

Key Words: End milling, AISI H-13, carbide coated tool, taguchi design of experiments, grey relational analysis and optimisation.

1. INTRODUCTION

Milling is the name given to machining process in which the metal removal takes place due to cutting action of a revolving cutter. Milling is the machining process that uses rotary cutters to remove material from the workpiece by advancing in a direction with some angle along the axis of the tool. The cutter rotates at high speed and because of the multiple cutting edges it removes metal at very fast rate. It covers a wide variety of different operations and machines, on scales from small individual parts to large heavy-duty gang milling operations. It is one of the most commonly used processes in industry and machine shops today for machining parts to precise sizes and shapes. [1]

1.1 End Milling

The end milling may be considered as the combination of peripheral and face milling operation. The cutter has teeth both on the end face and on the periphery. [1] End milling is commonly used in most of the manufacturing industries due to its ability of producing complex geometric edges with reasonable accuracy and surface finish. However, with the inventions of CNC milling machine, the flexibility has been adopted along with versatility in end milling process. Cutting parameters as spindle speed, feed, depth of cut, type and flow of cutting fluid affects the surface finish of the product. Thus optimizing the process parameters for the minimum surface roughness is important in CNC end milling process.

With the more precise demands of modern engineering products and competition to supply best quality of the products, the surface finish together with dimensional accuracy plays a very vital role. It has been observed that 'surface texture' greatly influences the functioning of the machined parts. Whatever may be the manufacturing process that used for manufacturing it is not possible to produce perfectly smooth surface. Hence, the improved qualities of product and the economics of the manufacturing operation are very important consideration to produce product having the functional and visual appeal. The end mill cutting operation is as shown in fig 1.1

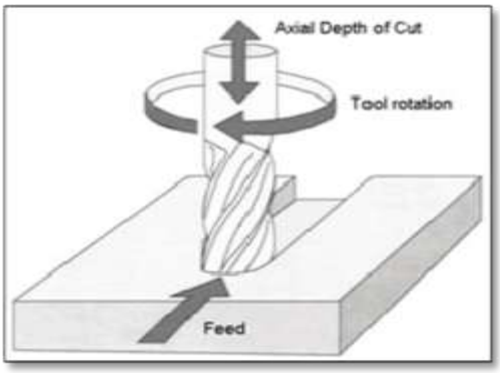

Fig -1: End milling operation

2. EXPERIMENATL SET UP

A. MATERIAL

The material used for this study is H13 hot 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: percentage wise composition

Chemical Composition of AISI H-13			
C	0.36	**S**	0.010
Mn	0.27	**P**	0.018
Cr	5.05	**Si**	0.94
Ni	0.26	**V**	0.86
Mo	1.22		

Mechanical properties and chemical composition of H13 hot die steel material used in the experiments has been tested at SN Metallurgical Services MIDC Waluj, Aurangabad.

B. Machining setup

End milling operation was carried out on a BFW SURYA VF 30 CNC VS. 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 8x20x76 mm manufactured by Totem-Forbes.

C. Metal Removal Rate Calculation

The Material Removal Rate in mm^3/ min was calculated by using this formula:

MRR = W×t×fm

Where,

W = Width of cut

t = Depth of cut

fm= Table (machine) Feed

D) 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 Taylor Hobson Surface roughness tester. An average of three measurements of the surface roughness was taken to use in the multi-criteria optimization.

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[4] and their levels for experimentation were selected from carrying out OVAT (one variable at a time) analysis.

Table -2: Process parameters and their levels

Parameters	Levels		
	1	**2**	**3**
Cutting Speed (rpm)	3000	4000	5000
Feed (mm/rev)	0.1	0.2	0.3
Depth Of Cut (mm)	0.3	0.4	0.5

3. DESIGN OF EXPERIMENT

A. Taguchi Method of DOE

These Experiments are designed by 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 and Signal to Noise (S/N) ratios are also calculated for analyzing the effect of machining parameters more accurately.[2] On the basis of Taguchi design L9 orthogonal array has been selected for the experiments in MINITAB 17software. All these data are used for the evaluation and analysis of the optimal parameters combination. Following table shows the selected L9 orthogonal array.

Table -3: L9 Orthogonal array

Expt. No	Cutting speed (rpm)	Feed(mm/rev)	Depth of cut(mm)
1	3000	0.1	0.3
2	3000	0.2	0.4
3	3000	0.3	0.5
4	4000	0.1	0.4
5	4000	0.2	0.5
6	4000	0.3	0.3
7	5000	0.1	0.5
8	5000	0.2	0.3
9	5000	0.3	0.4

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.[3] In GRA, data pre processing is the first step performed to normalize the random grey data with different measurement units to transform them into dimensionless parameters.[10] Thus data pre processing converts original sequence to a set of comparable sequence. The grey relational coefficients based on normalized experimental data are calculated to represent the correlation between desired and actual experimental data. Then overall grey relational grade is determined by averaging the grey relational coefficient corresponding to selected response.

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 [6]

$$xij = \frac{yij - min\ yij}{max\ yij - \min yij} \qquad (1.1)$$

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

$$xik = \frac{maxyik - yik}{max\ yik - \min yik} \qquad (1.2)$$

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:

$$\xi ij = \frac{\Delta min + \xi \Delta \max}{\Delta oi\,(j) + \xi \Delta \max} \qquad (1.3)$$

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< ξ >1. In the present study the value of is assumed as 0.5. [6] 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.

$$\gamma j = \frac{1}{m}\sum_{i=1}^{m} \xi ij \qquad (1.4)$$

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 is the statistical treatment most generally applied to the results of the experimental to determine percent contribution of each factor. 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 [6]

$$SST = \sum_{j=1}^{p} (\gamma j - \gamma m)^2 \qquad (1.5)$$

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 -4: Experimentally collected response data under coolant condition

Expt.no	Speed	Feed	DOC	Ra	MRR
1	3000	0.1	0.3	0.98	725
2	3000	0.2	0.4	1.20	1922
3	3000	0.3	0.5	1.25	3608
4	4000	0.1	0.4	0.88	1278
5	4000	0.2	0.5	0.96	3209
6	4000	0.3	0.3	1.12	2884
7	5000	0.1	0.5	0.81	2009
8	5000	0.2	0.3	0.91	2412
9	5000	0.3	0.4	1.14	4802

Table -5: normalized value and GRC data under coolant condition

Expt.no	Normalized value		GRC	
	Ra	MRR	Ra	MRR
1	0.6136	0.0000	0.5641	0.3333
2	0.1136	0.2936	0.3606	0.4145
3	0.0000	0.7071	0.3333	0.6306
4	0.8409	0.1356	0.7586	0.3665
5	0.6591	0.6093	0.5946	0.5614
6	0.2955	0.5296	0.4151	0.5153
7	1.0000	0.3149	1.0000	0.4219
8	0.7727	0.4138	0.6875	0.4603
9	0.2500	1.0000	0.4000	1.0000

Table -6: Grey relational grades data for coolant condition

Expt. no	GRG	Rank
1	0.4487	8
2	0.3876	9
3	0.4820	6
4	0.5626	5
5	0.5780	3
6	0.4652	7
7	0.7110	1
8	0.5739	4
9	0.7000	2

Table -7: Grey relational grades for individual factor levels under coolant condition

Factors	Grey Relational Grades at Optimum Factor Levels			Optimum levels of parameters
	1	2	3	
Speed (A)	0.4394	0.5353	0.6616	**5000 rpm**
Feed (B)	0.5741	0.5132	0.5491	**0.1 mm/rev**
DOC (C)	0.4959	0.5501	0.5903	**0.5 mm**

Also similar experimentation has been performed under compressed air condition

Table -8: Experimentally collected response data under compressed air condition

Exp.no	Speed	Feed	DOC	Ra	MRR
1	3000	0.1	0.3	0.87	726
2	3000	0.2	0.4	1.09	1918
3	3000	0.3	0.5	1.14	3612
4	4000	0.1	0.4	0.77	1269
5	4000	0.2	0.5	0.85	3218
6	4000	0.3	0.3	1.01	2878
7	5000	0.1	0.5	0.71	2012
8	5000	0.2	0.3	0.80	2408
9	5000	0.3	0.4	1.03	4805

Table -9: normalized value and GRC data under Compressed air condition

Expt.no	Normalized value		GRC	
	Ra	MRR	Ra	MRR
1	0.6279	0.0000	0.5733	0.3333
2	0.1163	0.2922	0.3614	0.4140
3	0.0000	0.7075	0.3333	0.6309
4	0.8605	0.1331	0.7819	0.3658
5	0.6744	0.6109	0.6056	0.5624
6	0.3023	0.5276	0.4175	0.5142
7	1.0000	0.3153	1.0000	0.4220
8	0.7907	0.4124	0.7049	0.4597
9	0.2558	1.0000	0.4019	1.0000

Table -10: Grey relational grades data for compressed air condition

Expt. no	GRG	Rank
1	0.4532	9
2	0.4962	6
3	0.4821	7
4	0.5739	5
5	0.5840	3
6	0.4659	8
7	0.7111	1
8	0.5823	4
9	0.7010	2

Table -11: Grey relational grades for individual factor levels under compressed air condition

Factors	Grey Relational Grades at Optimum Factor Levels			Optimum levels of parameters
	1	2	3	
Speed (A)	0.4772	0.5413	0.6648	**5000 rpm**
Feed (B)	0.5794	0.5542	0.5497	**0.1 mm/rev**
DOC (C)	0.5005	0.5904	0.5924	**0.5 mm**

5. Result and Discussion

A. Analysis of Variance (ANOVA) and Main Effect Plot

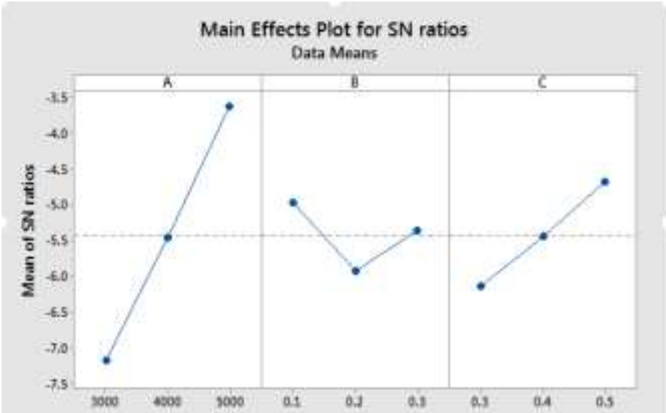

Chart-1: Main Effects Plot for GRG for coolant condition

Optimization From the graph, it can be said that finest combination values for maximizing the multiple performance characteristics or grey relational grade were cutting speed 5000rpm, feed rate 0.1 mm/rev and depth of cut 0.5mm.

Table -12: results of ANOVA analysis for Grey relational grades for coolant condition

Source	DF	Adj SS	Adj MS	F	P	%
Speed	2	18.906	9.4532	12.37	0.075	75.5213
Feed	2	1.417	0.7086	0.93	0.519	5.6603
DOC	2	3.182	1.5908	2.08	0.325	12.7107
Error	2	1.529	0.7643			6.1077
Total	8	25.034				

Similarly same steps performed for compressed air condition

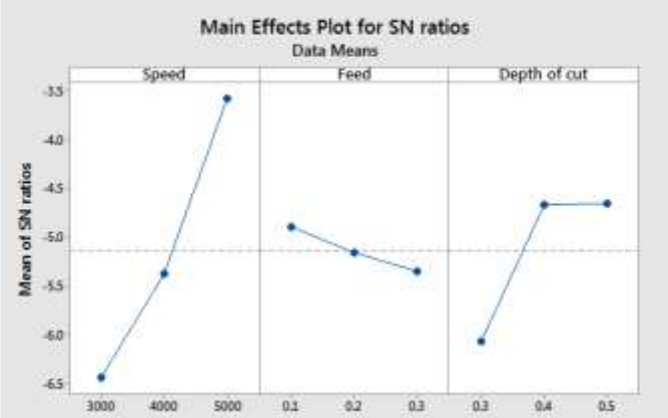

Chart-2: Main Effects Plot for GRG for Compressed air condition

Here also from graph it can be said that finest combination values for maximizing the multiple performance characteristics were cutting speed 5000rpm, feed rate 0.1 mm/rev and depth of cut 0.5mm.

Table -13: results of ANOVA analysis for Grey relational grades for compressed air condition

Source	DF	Adj SS	Adj MS	F	P	%
Speed	2	12.4648	6.2324	42.49	0.023	73.123
Feed	2	0.3273	0.1637	1.12	0.473	1.9201
DOC	2	3.9607	1.9804	13.50	0.069	23.235
Error	2	0.2934	0.1467			1.7212
Total	8	17.0463				

B. Comparative Study of Ra and MRR

Two different conditions were taken to study their effects on surface roughness and material removal rate. These two conditions are

a) Coolant condition
b) Compressed air condition
c)

To check effect of these two condition on surface roughness and material removal rate. The machining observations of AISI H-13 are tabulated in table 4 and table 8 respectively The values obtained after the experimentation for both condition it is clear that there is no significant change in material removal rate. There is only 0-0.013% reduction of MRR in compressed air condition but the surface roughness is better in compressed air condition as compared to coolant condition the table shows that better performance is achieved in Compressed air condition only rather than coolant condition. It also shows its percentage reduction.

Table -14: percentage reduction in Ra

Condition	Range of Ra	% Reduction of Ra in compressed air
Coolant	0.81 – 1.25	0-11 %
Compressed Air	0.71-1.14	

C. Confirmation Experiment

Once the optimal level of machining parameters is selected the final step is to predict and verify the improvement of the performance characteristics using the optimal level of machining parameter. The predicted grey relational grade can be calculated by using following equation. [16]

$$\gamma_{predicted} = \gamma_m + \sum_{i=1}^{n}(\gamma_i - \gamma_m) \qquad 1.6$$

Where, γ_m is the total mean for GRGs, γ_i is the mean GRGs at optimal level, n is the number of machining parameters that significantly affect the multiple performance quality characteristics. Based on equation 1.6 estimated grey relational grade using the optimal machining parameters can be obtained. Table 15 shows the results of confirmation experiment using the optimal machining parameters. The surface roughness Ra is improved from 0.98 to 0.81 µm and Material removal rate 725 to 2009mm³/min in case of coolant condition. Also in case of compressed air condition Ra is improved from 0.87 to 0.71 µm and material removal rate 726 to 2012 mm³/min respectively. Thus, it can be concluded that the quality of the product can be considerably improved through this study. A confirmatory test was conducted to validate the findings and an improvement of 0.2623 in GRG coolant condition and 0.2578 in compressed air condition observed.

Table -15: Results of machining performance using initial and optimal machining parameters for coolant condition

	Initial machining parameters Predicted	Optimal machining parameters experiment	
	A1B1C1	A3B1C3	A3B1C3
Ra	0.98		0.81
MRR	725		2009
GRG	0.4487	0.7107	0.7110

Improvement in grey relational grade 0.2623

Table -16: Results of machining performance using initial and optimal machining parameters for compressed air condition

	Initial machining parameters Predicted	Optimal machining parameters experiment	
	A1B1C1	A3B1C3	A3B1C3
Ra	0.87		0.71
MRR	726		2012
GRG	0.4532	0.7109	0.7111

Improvement in grey relational grade 0.2578

6. 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 AISI H13 Hot 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 coolant condition as well as in compressed air condition lies at 5000 rpm for cutting speed, 0.1 mm/revolution for feed rate and 0.5 mm for depth of cut.

3. Analysis of variance shows that in case of coolant condition, Cutting speed is the most significant machining parameter followed by Depth of cut, affecting selected response characteristics i.e. surface roughness and material removal rate, with 75.52% and 12.71% influence respectively.

4. Under compressed air condition Analysis of variance shows that Cutting speed is the most significant machining parameter followed by Depth of cut, affecting selected response characteristics i.e. surface roughness and material removal rate, with 73.12% and 23.23% influence respectively.

5. There is a reduction of 0-11% in surface roughness using compressed air as a coolant compared to coolant condition.

6. Here result shows that carbide coated end mill cutter performs better in compressed air condition as compared to coolant condition.

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