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Research Article

Optimization of Machining Parameters in End Milling of AISI H11 Steel Alloy by Taguchi based Grey Relational Analysis

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Abstract

This study investigated the effects of the machining parameters by end milling operation on the AISI H11 steel alloy. Metal machining has been a very significant activity in manufacturing. Surface quality is one of the most common concern is to satisfy customer needs in which the major indication of surface quality on machined parts is surface roughness. It has long been recognized that the machining conditions, such as cutting speed, feed and depth of cut affect the performance of the operation to a high extent. Surface roughness and material removal rate should be taken into consideration. This can be achieved using design of experiments (DOE). It is used in the manufacturing industries for making die casting moulds, extrusion dies, moulds for glass industry, punches, etc. In the present study the machining experiments were conducted on CNC vertical milling machine whose maximum speed was 6000 RPM. Design of experiments based on Taguchi grey relational analysis with three independent factors (cutting speed, feed rate and depth of cut), three levels L27 orthogonal array has been used to develop relationships for predicting surface roughness and metal removal rate. The surface roughness was measured using surface roughness tester (Mitutoyo surftest-4) and the averages were calculated to obtain the surface roughness of the samples. Material removal rate was calculated using the formula in terms of width of cut, depth of cut and table feed rate.

Keywords:*Grey Relation Analysis, ANOVA, DOE, Surface Roughness and Material Removal Rate*

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. In order to build up a bridge between quality and productivity and to achieve the same in an economic way, the present study highlights optimization of CNC end milling process parameters to provide good surface finish and high material removal rate (MRR). The surface finish of the machined surface has been identified as quality attribute whereas MRR has been treated as performance index directly related to productivity. Attempt has been made to optimize quality and productivity in a manner that these multi-criterions could be fulfilled simultaneously up to the expected level. Multi-objectives related to quality and productivity has been accumulated to evaluate an equivalent single quality index (called grey relational grade); which has been optimized finally by Taguchi based Grey relational method (Moshat *et al*. 2010).

2. Experimental Setup

A. Material

The specification of work piece used is AISI H11 steel alloy having 115 mm in length, 80 mm in width and 20 mm in thickness.

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Figure 1: Work piece

B. Chemical Composition

The chemical composition of **AISI** H11 steel alloy is as:

Table 1: Chemical composition of AISI H11, % weight

Element	C	Mn	Si	Cr	Mo	V	P	S
%	0.25	0.36	0.85	5.14	1.20	0.87	0.014	0.010

Figure 2: Surya VF 30 CNC VS Milling Machine

C. CNC Machine

End milling operation was carried out on a BFW SURYA VF 30 CNC VS in dry 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 end mill with mechanically attached carbide insert having 16 mm diameter.

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 (Kadirgama, K., Noor. M.M., Zuki.N.M, Rahman, M.M., Rejab M.R.M, Daud, R., K. Abou-El-Hossein, A., 2008). The most accepted parameter is centerline average (CLA) surface roughness value (R_a). Mathematically, R_a is the arithmetic value of the departure of the profile from centerline along sampling length. in the present study, surface roughness of the work pieces after milling was measured by using surface roughness tester (Mitutoyosurftest - 4).

Figure 3 MitutoyoSurftest – 4

E.Metal Removal Rate Calculation

MRR = volume removed / cutting time = $W \times t \times f_m$

Where $f_m = f_t \times n \times N$
N = RPM of Cutter
n = Number of Teeth on Cutter
W = Width of cut
T = Depth of cutter
f_m= Table (machine) Feed
f_t= Feed/tooth of cutter

F. Selection of cutting parameters

The selection of cutting parameters and orthogonal need an important consideration in experimental research work . The cutting parameters selected are:

1. Cutting speed 2. Feed 3. Depth of cut

Table 2: Process control parameters and their levels according to TGRA

Parameter	Units	Symbol	Level 1	Level 2	Level 3
Speed	(rpm)	A	400	800	1100
Feed	(mm/tooth)	B	0.12	0.20	0.30
Depth of cut	(mm)	C	0.20	0.40	0.60

3. Methodology

A. Taguchi based Grey relation analysis

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 (BalaMurganGopalsamy, BiswanathMondal, Sukumal Ghosh,2009, ;D. Philip Selvaraj, P. Chandramohan ,2010;Ross, P. J. ,1998.). Signal to Noise ratios are also calculated for analyzing the effect of machining parameters more accurately.

There are 2 Signal-to-Noise ratios of common interest for optimization of static problems used in present study as are:

(I) Smaller-the-Better:

$$\eta = -10 \log 1/n\sum_{i=1}^{n} y_i^2 \quad (1)$$

(II) Larger-the-Better:

$$\eta = -10 \log \sum_{i=1}^{n} 1/y_i^2 \quad (2)$$

Where, η- Signal to Noise (S/N) Ratio,
y_i– i^{th}observed value of the response,
n - Number of observations in a trial,
y - Average of observed values (responses)

Regardless of the category of the performance characteristics, the higher S/N ratio corresponds to a better performance. Therefore, the optimal level of the process parameters is the level with the highest S/N value. The statistical analysis of the data is performed by analysis of variance (ANOVA) to study the contribution of the various factors and interactions and to explore the effects of each process on the observed values. The use of Taguchi method with grey relational analysis to optimize the end milling operations with multiple performance characteristics includes the following steps:

1. Identify the performance characteristics and cutting parameters to be evaluated.
2. Determine the number of levels for the process parameters.
3. Select the appropriate orthogonal array and assign the cutting parameters to the orthogonal array.
4. Conduct the experiments based on the arrangement of the orthogonal array.
5. Normalize the experiment results of surface roughness and metal removal rate.
6. Perform the grey relational generating and calculate the grey relational coefficient.

7. Calculate the grey relational grade by averaging the grey relational coefficient.
8. Analyze the experimental results using the grey relational grade and statistical ANOVA.
9. Select the optimal levels of cutting parameters.

B. Data Pre Processing

In grey relational analysis, the data pre-processing is the first step performed to normalize the random grey data with different measurement units to transform them to dimensionless parameters. Thus, data pre-processing converts the original sequences to a set of comparable sequences. Experimental data i.e. measured features of quality characteristics of the product are first normalized ranging from zero to one. This process is known as grey relational generation. (C. C. Tsao, 2009; NihatTosun, 2006).

In grey relational generation, the normalized data corresponding to lower-the-better (LB) criterion can be expressed as:

$$x_i(k) = \max y_i(k) - y_i(k) / \max y_i(k) - \min y_i(k) \quad (3)$$

For higher-the-better (HB) criterion, the normalized data can be expressed as:

$$x_i(k) = y_i(k) - \min y_i(k) / \max y_i(k) - \min y_i(k) \quad (4)$$

Here x_i (k) is the value after the grey relational generation, min y_i (k) is the smallest value Of y_i (k)for the kth response, and max y_i(k) is the largest value of y_i (k) for the kth response. An ideal sequence x_o (k) is for the responses. The purpose of grey relational grade is to reveal the degrees of relation between the sequences say, [$x_{o\ (k)}$ and x_i (k), i=1,2,3…………,27)

C. Grey Relational Coefficient and Grey Relational Grade

Next, based on normalized experimental data, grey relational coefficient is calculated to represent the correlation between the desired and actual experimental data. Then overall grey relational grade is determined by averaging the grey relational coefficient corresponding to selected responses. The overall performance characteristic of the multiple response process depends on the calculated grey relational grade. 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.

The grey relational coefficient ξ_i(k):

$$= \Delta_{min} + \psi\ \Delta_{max} / \Delta_{0i}(k) + \psi\ \Delta_{max} \quad (5)$$

Here deviation sequence, Δ_{0i} (k) :

$$= || x_0(k) - x_i(k) || \quad (6)$$

is difference of the absolute value x_o (k) and x_i (k) and ; ψ is the distinguishing coefficient $0 \le \Psi \le 1$;Δ_{min}= the smallest value of Δ_{oi}; and Δ_{max} = largest value ofΔ_{oi}. After averaging the grey relational coefficients, the grey relational gradeγ_i can be computed as:

$$\gamma_i = i/n \sum_{k=1}^{n} \xi i(k) \quad (7)$$

Here n= number of process responses. The higher value of grey relational grade corresponds to intense relational degree between the reference sequence x_0 (k) and the given sequence x_i (k) The reference sequence x_0 (k) represents the best process sequence. Therefore, higher grey relational grade means that the corresponding parameter combination is closer to the optimal. Different weightages have to be assigned to different responses. If different priority weightages have been assigned to different responses, the equation for calculating overall grey relational grade becomes:

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

Here γ_i , is the overall grey relational grade for i^{th}experiment. is the grey relational coefficient of k^{th} response in i^{th} experiment and w_k is the weightage assigned to the i^{th}response.

D. The 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. Major part of this portion has been taken from (Montgomery, 2005 &Mahajan, 2008). 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.

4. Analysis of Results

Table 3: Experimental design and collected response data

Expt. No.	Speed (A) (rpm)	Feed (B) (mm/tooth)	Depth of cut (C) (mm)	R_a (µm)	MRR (mm^3/sec)
1	400	0.12	0.2	4.53	4.16
2	400	0.12	0.4	3.87	8.32
3	400	0.12	0.6	4.50	12.48
4	400	0.20	0.2	4.9	6.93
5	400	0.20	0.4	4.74	13.8
6	400	0.20	0.6	6.50	20.8
7	400	0.30	0.2	6.74	10.4
8	400	0.30	0.4	6.78	20.8
9	400	0.30	0.6	5.41	31.2
10	800	0.12	0.2	2.19	8.32
11	800	0.12	0.4	1.76	16.64
12	800	0.12	0.6	1.78	24.96
13	800	0.20	0.2	1.64	13.8
14	800	0.20	0.4	2.12	27.7
15	800	0.20	0.6	2.41	41.6

16	800	0.30	0.2	2.38	20.8
17	800	0.30	0.4	3.7	41.6
18	800	0.30	0.6	3.9	62.4
19	1100	0.12	0.2	2.25	11.44
20	1100	0.12	0.4	2.24	22.88
21	1100	0.12	0.6	2.22	34.32
22	1100	0.20	0.2	2.48	19.06
23	1100	0.20	0.4	2.47	38.13
24	1100	0.20	0.6	2.2	57.2
25	1100	0.30	0.2	2.9	28.6
26	1100	0.30	0.4	2.23	57.2
27	1100	0.30	0.6	2.28	85.8

A. Optimal solution of single objective optimization

1. Minimization of the surface roughness

Table 4: Mean effect on surface roughness

Level	Speed (A) (rpm)	Feed (B) (mm/tooth)	Depth of cut (C) (mm)
1	5.33	**2.8155**	3.3344
2	2.4311	3.2733	**3.3233**
3	**2.3633**	4.0355	3.4666
Average	3.3747	3.3747	3.3747
(Max. – Min.)	2.9667	1.22	0.1322
Rank	1	2	3

It is clear that desired optimum condition for surface roughness is ‘A3 B1 C2’

2. Maximization of material removal rate

Table 5: Mean effect on material removal rate

Level	Speed (A) (rpm)	Feed (B) (mm/tooth)	Depth of cut (C) (mm)
1	14.3211	15.9466	13.7233
2	28.6466	26.5577	27.4522
3	**39.4033**	**39.8666**	**38.0177**
Average	27.457	27.457	26.3977
(Max. – Min.)	25.0822	23.92	24.2944
Rank	1	3	2

It is clear that desired optimum condition for material removal rate becomes ‘A3 B3 C3’

B. Optimal solution of bi-objective optimization (surface roughness and material removal rate taken together)

Table 6: S/N ratio calculations for R_a and MRR

Expt No.	R_a (μm)	S/N Ratio	MRR (mm^3/sec)	S/N Ratio
1	4.53	-13.122	4.16	12.38187
2	3.87	-11.7542	8.32	18.40247
3	4.50	-13.0643	12.48	21.92429
4	4.9	-13.8039	6.93	16.81466
5	4.74	-13.5156	13.8	22.79758
6	6.50	-16.2583	20.8	26.36127
7	6.74	-16.5732	10.4	20.34067
8	6.78	-16.6246	20.8	26.36127
9	5.41	-14.6639	31.2	29.88309
10	2.19	-6.80888	8.32	18.40247
11	1.76	-4.91025	16.64	24.42307
12	1.78	-5.0084	24.96	27.94489
13	1.64	-4.29688	13.8	22.79758
14	2.12	-6.52672	27.7	28.8496
15	2.41	-7.64034	41.6	32.38187
16	2.38	-7.53154	20.8	26.36127
17	3.7	-11.364	41.6	32.38187
18	3.9	-11.8213	62.4	35.90369
19	2.25	-7.04365	11.44	21.16852
20	2.24	-7.00496	22.88	27.18912
21	2.22	-6.92706	34.32	30.71095
22	2.48	-7.88903	19.06	25.60246
23	2.47	-7.85394	38.13	31.62534
24	2.2	-6.84845	57.2	35.14792
25	2.9	-9.24796	28.6	29.12732
26	2.23	-6.9661	57.2	35.14792
27	2.28	-7.1587	85.8	38.66975

Table 7: Data pre-processing results

Expt.No.	Response values (normalized)	
	R_a	MRR
1	0.7160	0.000000
2	0.6051	0.229026
3	0.7113	0.362997
4	0.7713	0.168625
5	0.7479	0.396217
6	0.9703	0.531781
7	0.9958	0.302756
8	1.0000	0.531781
9	0.8410	0.665753
10	0.2040	0.229026
11	0.0502	0.458051
12	0.0582	0.592023
13	0.0000	0.396217
14	0.1812	0.626438
15	0.2715	0.760807
16	0.2627	0.531781
17	0.5735	0.760807
18	0.6105	0.894778
19	0.2231	0.334247
20	0.2201	0.563273
21	0.2137	0.697244
22	0.2917	0.502916
23	0.2886	0.732028
24	0.2067	0.866029
25	0.4010	0.637003
26	0.2164	0.866029
27	0.2318	1.000000

Table 8: Deviation sequence

Expt. No.	Deviation sequence	
	R_a 1.0000	MRR 1.0000
1	0.284	1
2	0.3949	0.770974
3	0.2887	0.637003
4	0.2287	0.831375
5	0.2521	0.603783
6	0.0297	0.468219
7	0.0042	0.697244
8	0	0.468219
9	0.159	0.334247
10	0.796	0.770974
11	0.9498	0.541949
12	0.9418	0.407977
13	1	0.603783
14	0.8188	0.373562
15	0.7285	0.239193
16	0.7373	0.468219
17	0.4265	0.239193
18	0.3895	0.105222
19	0.7769	0.665753

20	0.7799	0.436727
21	0.7863	0.302756
22	0.7083	0.497084
23	0.7114	0.267972
24	0.7933	0.133971
25	0.599	0.362997
26	0.7836	0.133971
27	0.7682	0

C. Calculated Grey relational coefficients and Grey relational grades

1: General machining$W_1 = W_2 = 0.5$

Table 9: Calculated Grey relational coefficients and Grey relational grades for $W_1 = W_2 = 0.5$

ExptNo.	Grey relational coefficient		Grade for $W_1= W_2=$ 0.5	Grade order
	R_a	MRR		
1	0.637755	0.333333	0.485544	17
2	0.558722	0.393399	0.47606	18
3	0.633955	0.439753	0.536854	12
4	0.686153	0.375552	0.530853	9
5	0.664805	0.452988	0.558896	11
6	0.943931	0.516412	0.730171	2
7	0.99167	0.417626	0.704648	3
8	1	0.516412	**0.758206**	1
9	0.758725	0.599343	0.679034	5
10	0.385802	0.393399	0.389601	27
11	0.344875	0.47987	0.412373	25
12	0.346789	0.550675	0.448732	23
13	0.333333	0.452988	0.393161	26
14	0.379133	0.572369	0.475751	20
15	0.407	0.676413	0.541707	13
16	0.404106	0.516412	0.460259	21
17	0.539665	0.676413	0.608039	10
18	0.562114	0.826144	0.694129	6
19	0.391573	0.428907	0.41024	24
20	0.390656	0.533773	0.462214	19
21	0.388712	0.622855	0.505783	16
22	0.413805	0.501462	0.457633	22
23	0.412746	0.651066	0.531906	14
24	0.386608	0.788679	0.587643	8
25	0.454959	0.579376	0.517168	15
26	0.389529	0.788679	0.589104	7
27	0.39426	1	0.69713	4

2: Rough machining $W_1 = 0.2$, $W_2 = 0.8$

Table 10: Calculated Grey relational coefficients and Grey relational grades for $W_1= 0.2$, $W_2= 0.8$

Expt.No.	Grey relational coefficient		Grade for $W_1= 0.2$, $W_2= 0.8$	Grade order
	R_a	MRR		
1	0.637755	0.333333	0.394217	26
2	0.558722	0.393399	0.426464	25
3	0.633955	0.439753	0.478593	20
4	0.686153	0.375552	0.437672	22
5	0.664805	0.452988	0.495351	19
6	0.943931	0.516412	0.601916	11
7	0.99167	0.417626	0.532435	14
8	1	0.516412	0.61313	9
9	0.758725	0.599343	0.631219	8
10	0.385802	0.393399	0.39188	27
11	0.344875	0.47987	0.452871	21
12	0.346789	0.550675	0.509898	16
13	0.333333	0.452988	0.429057	24
14	0.379133	0.572369	0.533722	13
15	0.407	0.676413	0.62253	7
16	0.404106	0.516412	0.493951	18
17	0.539665	0.676413	0.649063	5
18	0.562114	0.826144	0.773338	2
19	0.391573	0.428907	0.42144	23
20	0.390656	0.533773	0.50515	15
21	0.388712	0.622855	0.576026	10
22	0.413805	0.501462	0.483931	17
23	0.412746	0.651066	0.603402	6
24	0.386608	0.788679	0.708265	4
25	0.454959	0.579376	0.554493	12
26	0.389529	0.788679	0.708849	3
27	0.39426	1	0.878852	1

3: Finish machining $W_1= 0.8$, $W_2 = 0.2$

Table 11: Calculated Grey relational coefficients and Grey relational grades for $W_1= 0.8$, $W_2 = 0.2$

Expt. No.	Grey relational coefficient		Grade for $W_1= 0.8$, $W_2= 0.2$	Grade order
	R_a	MRR		
1	0.637755	0.333333	0.576871	8
2	0.558722	0.393399	0.525657	9
3	0.633955	0.439753	0.595115	7
4	0.686153	0.375552	0.624033	5
5	0.664805	0.452988	0.622442	6
6	0.943931	0.516412	0.858427	3
7	0.99167	0.417626	0.876861	2
8	1	0.516412	0.903282	1
9	0.758725	0.599343	0.726849	4
10	0.385802	0.393399	0.387321	24
11	0.344875	0.47987	0.371874	26
12	0.346789	0.550675	0.387566	25
13	0.333333	0.452988	0.357264	27
14	0.379133	0.572369	0.41778	22
15	0.407	0.676413	0.460883	14
16	0.404106	0.516412	0.426567	19
17	0.539665	0.676413	0.567015	11
18	0.562114	0.826144	0.61492	10
19	0.391573	0.428907	0.39904	23
20	0.390656	0.533773	0.419279	21
21	0.388712	0.622855	0.435541	18
22	0.413805	0.501462	0.431336	20
23	0.412746	0.651066	0.46041	17
24	0.386608	0.788679	0.467022	16
25	0.454959	0.579376	0.479842	13
26	0.389529	0.788679	0.469359	15
27	0.39426	1	0.515408	12

Table 12: Results of ANOVA for surface roughness

Factor	Sum of Squares	Mean Squares	F-ratio	Percet Contribution	F > F table
Speed (S)	58.11044	28.3602	54.7566	0.8231151	Significant
Feed (F)	3.155556	1.09766	2.89644	0.0272551	Insignficant
Depth of Cut(D)	0.113355	0.05167	0.10566	0.0015217	Insignficant
S × F	0.565089	0.12372	0.24700	0.0070270	
F × D	0.750588	0.17267	0.34789	0.0907572	
S × D	0.541155	0.11802	0.24402	0.0750694	
Error	3.306722	0.33834			
Total	66.54291	30.2622			
$F_{0.05(2,8)}$	4.4590				
$F_{0.05(4,8)}$	3.8378				

Table 13: Results of ANOVA for Material removal rate

Factor	Sum of Squares	Mean Squares	F-ratio	Percet Contribution	F > F table
Speed (S)	3895.410	1849.710	19.4704464	0.38215821	Significant
Feed (F)	2255.301	1079.650	11.7726874	0.22232922	Significant
Depth of Cut(D)	2729.775	1456.482	15.1438770	0.28834415	Significant
S × F	236.5333	59.65823	0.59688833	0.024996	
F × D	180.6311	46.90511	0.46893360	0.019606182	
S × D	310.0721	78.01222	0.78909460	0.032193805	
Error	802.2543				
Total	10410				
$F_{0.05(2,8)}$	4.4590				
$F_{0.05(4,8)}$	3.8378				

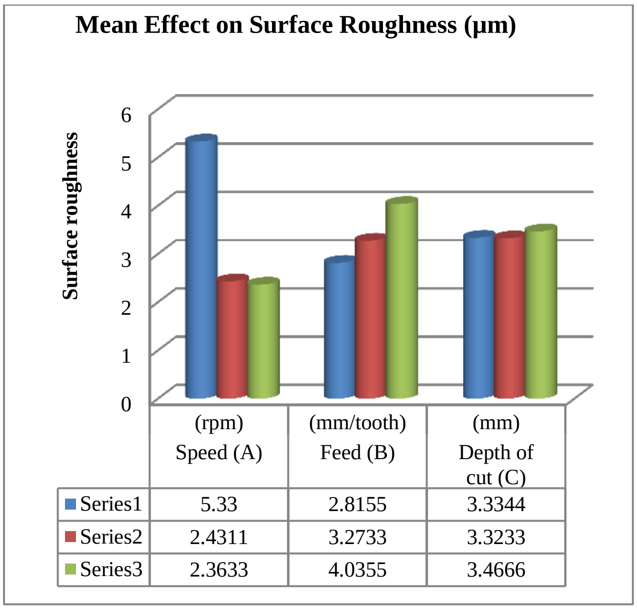

Figure 4 Graphical representation of mean effect on surface roughness

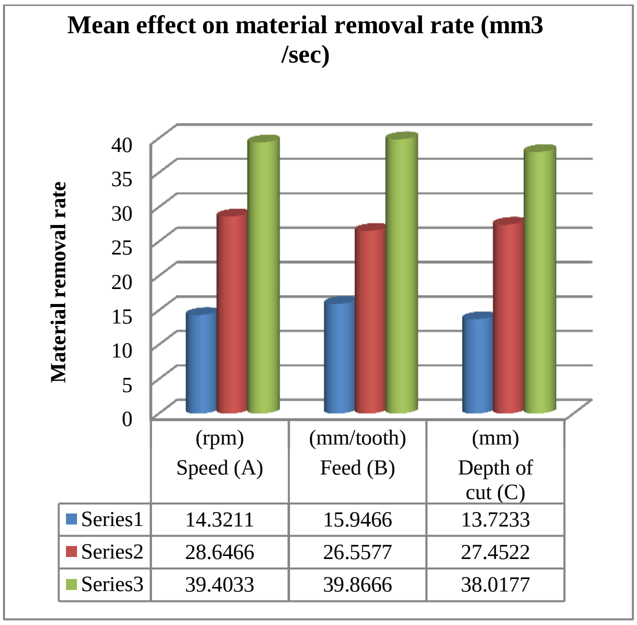

Figure 5 Graphical representation of mean effect on material removal rate

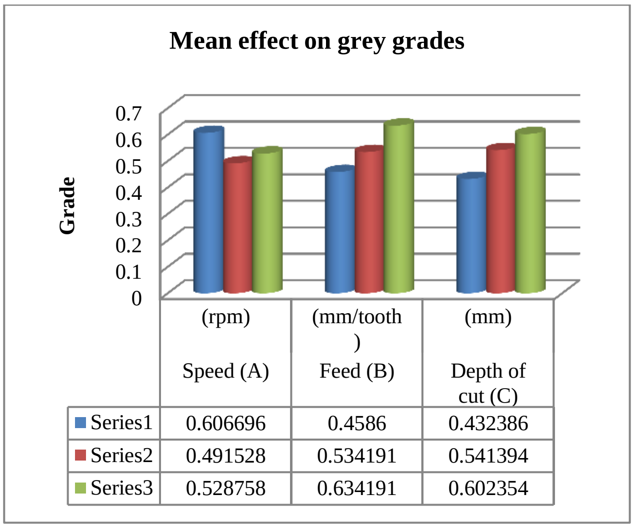

Figure 6 Grey relational grades with varying input parameters for $W_1 = W_2 = 0.5$

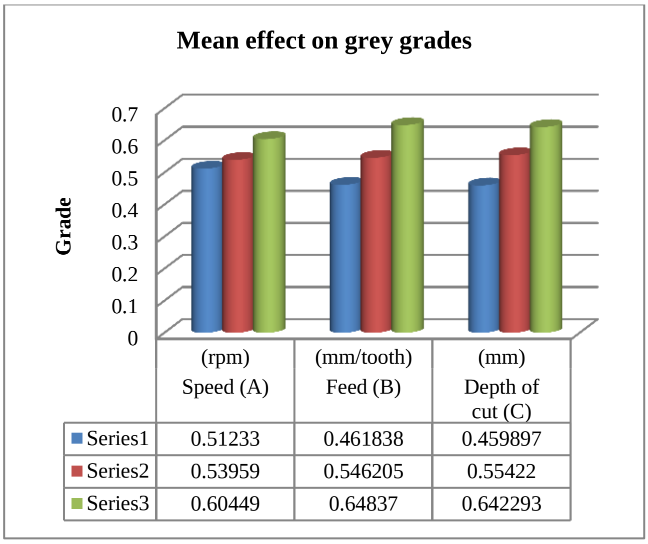

Figure 7 Grey relational grades with varying input parameters for $W_1 = 0.2$, $W_2 = 0.8$

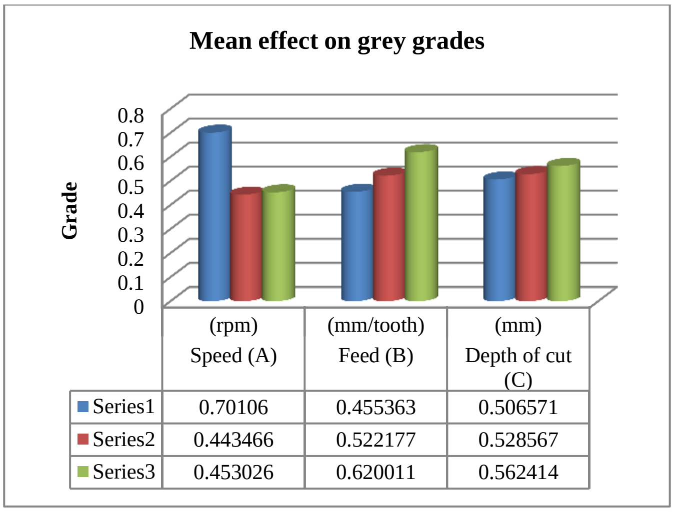

Figure 8 Grey relational grades with varying input parameters for $W_1 = 0.8$, $W_2 = 0.2$

C. Predicted optimum condition

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

$$\check{n} = nm + \sum_{i=1}^{o}(nim - nm) \quad (9)$$

Where ň= 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

D. Confirmation Experiment

The confirmation experiment is conducted at the optimum settings to verify the quality characteristics for milling of AISI H11 steel alloy. The optimum combinations for the predicted milling parameters were set, and two trials were 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 95% confidence level is determined.

Table 14: Predicted and confirmed results at optimum setting

Case A: General machining W_1= W_2= 0.5			
	Predicted	Confirmed	%improvement
Setting level	A1 B3 C2	A1 B3 C3	1.89
Grade	0.758	0.772	
Case A: General machining W_1= 0.2,W_2= 0.8			
	Predicted	Confirmed	%improvement
Setting level	A1 B3 C2	A1 B3 C3	1.09
Grade	0.7858	0.7944	
Case A: General machining W_1= 0.8,W_2= 0.2			
	Predicted	Confirmed	%improvement
Setting level	A1 B3 C2	A1 B3 C3	0.62
Grade	0.815	0.82	

Conclusion

The present work has successfully demonstrated the application of Taguchi based grey relational analysis for multi response optimization of process parameters in End milling AISI H11 steel alloy.
The important conclusions drawn from the present work are summarized as follows:
1. Cutting speed is the only significant machining parameter for surface roughness.
2. The increase in cutting speed produces better surface finish (i.e., surface roughness reduces). The surface roughness decreases from level one to level two and subsequently increases to level three with depth of cut, whereas with increase in feed rate the surface roughness increases throughout.
3. For rough machining conditions the most influencing parameters in decreasing order are feed rate, depth of cut and cutting speed.
4. Out of three parameters considered feed rate is identified as the most significant and influential machining parameter followed by cutting speed. Whereas depth of cut has the least influence on surface roughness and MRR for general machining conditions.
5. For finish machining conditions the significant parameters are cutting speed and feed rate.
6. An increase in the value of predicted weighted GRG confirms the improvement in the performance of milling process using optimal values of process parameters.
7. The optimal combination of the cutting parameters obtained for maximizing MRR is the set with A3, B3 and C3.
8. 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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