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Optimization of Multiple process parameter of Milling (multi-objective) on AISI 202 stainless steel using Taguchi based grey relational analysis

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Abstract
In the current competitive landscape prevailing in the manufacturing industry, it is has become crucial to focus on the quality and productivity aspects at a low cost to remain competitive. To achieve a competitive advantage by focusing on improvement activities on how the product is manufactured is crucial. The two most crucial machining characteristics considered here are surface roughness and material removal rate. These two contradict objectives where (Ra) has to be lower, and (MRR) has to be higher. The paper gives a methodology that figures out the optimal cutting or control parameters that satisfy both the objectives mentioned above parallelly. Taguchi grey relational analysis is carried out to obtain to optimize the two objectives. The operation done is face milling on AISI 202 Stainless steel with L27 OA each. Experiments have been done concerning Taguchi grey relational analysis methods with 3 control parameters, say, Feed (f), Speed(v), Depth of cut(d) with 3 levels on each of these. To find out the most significant process parameter on MRR and Ra, Analysis of variance(ANOVA) was used.

Keywords:
Gray relational analysis, L27 Orthogonal Array, Optimization, ANOVA, Machining

I. INTRODUCTION

Surface roughness has turned out to be the most crucial factor when it comes to technical requirements in the manufacturing space. Of late, the manufacturing industries have specifically started paying special attention to the product's surface finish. Traditionally the industry practice uses the handbook to find the optimal control parameters or cutting parameters to have the desired surface finish. The practice followed conventionally paves the way to improper surface finish and lower productivity issues due to the machine's sub-optimal capability utilization. Which leads to comparatively undesirable product quality and higher cost of manufacturing. Along with SR, the high Material removal rate is also aimed for by the industries. Consequently, the requirement to optimize the control parameters to attain the expected output machining characteristics by using a systemic approach is prevailing. Design of Experiments, also known as DOE, is one of TQM's proven tools for making high-quality systems by reducing manufacturing costs. Taguchi's approach aids in lessening the numerous experiment runs when the number of process parameters is on the increase. Researchers have worked a lot on optimizing the single response performance characteristics by using the Taguchi approach. Taguchi's shortcoming is made for a single response and doesn't do good for multi-response Optimization. The requirement to solve the multi-response problem is highly sought because it is gauged on various responses and quality characteristics after production. To overcome the shortcoming, the Taguchi grey relational analysis (GRA) is employed to do away with the non-optimal values for the responses remaining. AISI 202 austenitic stainless steel uses various manufacturing industries: automotive, process industry, electrical, etc. It is identified that there is no work on AISI 202 austenitic stainless steel in optimizing the multi-response characteristics of Ra and MRR in milling operation. In this investigation, an optimization model to solve two objectives on Taguchi based grey method has been utilized to identify an optimal control parameters' combination of milling operation say Feed, speed & depth of cut to achieve a high MRR and minimum SR.

II EXPERIMENTAL DESIGN

A. Material used – Workpiece

The material chosen for the experiment was AISI stainless steel 202. The most prevalently used series of steel is the 300 series. The 200 series is considered the best alternative to the 300 series in the hike aspect in the Nickel prices, and it is hard to differentiate the 200 series from the usually used 300 series. Considering the cost viability and technical validity, the 200 series was chosen. AISI 202 steel's chemical composition is as follows: Cr - 17%, Ni - 4%, Mn – 7.5%, N – 0.25 %.

B. Cutting inserts

The cemented carbide tool has strong metallic characteristics showcasing great electrical conductivity as well as thermal conductivity. The P30 grade cemented carbide provides a good mix of benefits like good resistance against wear, hardness, and toughness.

Therefore, the chosen cutting tool and insert for this experiment are the HSS tool with a Cemented carbide insert, ISO Grade, and specification P 30 CNMG-120404-HK-1500 of the following composition WCCo+ TiC+ TaC was used to experiment.

III. MEASUREMENTS

After carrying out the machining on the work material, the machined surface's Ra (surface roughness) measurement was done along the direction of Feed using Mitutoyo Surf Test 301 profilometer. Before the measurement is done, calibration using a standard calibration block was done on the equipment. The average of 5 readings of the Ra was taken and used for the analysis. The Setup for Ra measurement is shown below in Fig. 1

. **Fig. 1**. Setup for roughness measurement

MRR (g/min) is calculated as follows.

$$MRR == (W_i - W_f) / t.$$

Where,

W_i – weight (initial)

W_f – weight (final)

t –time for one experiment.

IV. EXPERIMENTAL SETUP

The experiment was done using LMILL 55 Milling machine. AISI 202 bars (50mm *45mm* 15mm) was the material block. Machining was done on a canned cycle and in absolute mode. Data about the MRR are noted. The Setup of the experiment is displayed below in Fig.2

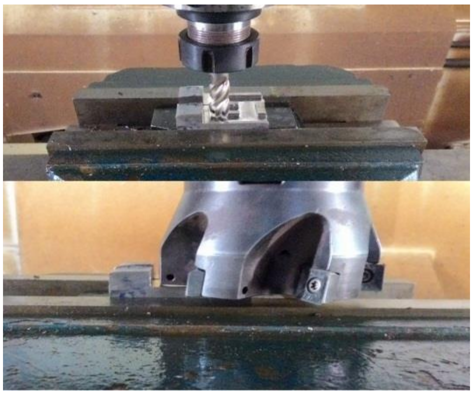

Fig 2. Setup of the experiment

A. Taguchi's experimental plan – L27 OA

Taguchi framework uses an orthogonal array, which reduces the total number of experiments carried out. Thus reducing the cost of experimentation, time, and effort involved. Taguchi's L27 orthogonal array was utilized towards the design of experimentation to determine the relation of how the output factors are being affected by the controlled parameters [1-3]. Controlled parameters used here are Speed(v), Depth of cut(d), Feed(f). The selected factors to be observed are MRR & Ra. The respective level values taken for each control variable is as shown in Table.1. The experiment plan on the 3 milling parameters mentioned above using 3 levels (3*3) is done by the Taguchi L27 orthogonal array. The values recorded for each of these trials are as shown below in Table 2.

TABLE. 1

CONTROL VARIABLES & LEVELS

Control parameter	**Level 1**	**Level 2**	**Level 3**
Speed(V) (rpm)	250	275	300
Feed(f) (feed/rev)	0.05	0.10	0.15
Depth of cut (d) (mm)	1	1.5	2

TABLE 2

Taguchi's L27 orthogonal array is shown below

Exp #	**Speed (v)**	**Feed (f)**	**Depth of cut (d)**	**Ra**	**MRR**
1	1	1	1	0.2520	0.018994
2	1	1	2	0.2908	0.028037
3	1	1	3	0.3354	0.038255
4	1	2	1	0.2832	0.035321
5	1	2	2	0.3320	0.057561
6	1	2	3	0.3816	0.074091
7	1	3	1	0.3564	0.054445
8	1	3	2	0.4156	0.080700
9	1	3	3	0.4774	0.117786
10	2	1	1	0.3232	0.020989
11	2	1	2	0.3644	0.034243
12	2	1	3	0.4032	0.042049
13	2	2	1	0.2478	0.038173
14	2	2	2	0.2998	0.063161

15	2	2	3	0.3506	0.081691
16	2	3	1	0.2800	0.052665
17	2	3	2	0.3652	0.096263
18	2	3	3	0.4454	0.118743
19	3	1	1	0.2656	0.021505
20	3	1	2	0.3156	0.031748
21	3	1	3	0.3572	0.040791
22	3	2	1	0.2362	0.033539
23	3	2	2	0.2704	0.051551
24	3	2	3	0.3596	0.080087
25	3	3	1	0.2298	0.052539
26	3	3	2	0.2782	0.089952
27	3	3	3	0.3506	0.160837

V. ANALYSIS AND DISCUSSION

Both single response and multi-objective Optimization can be obtained using ANOVA, regression analysis.

A. Single Response optimization

***a) Analysis of variance*:** Determination of the statistically significant control parameter influencing the output factor MRR and the Ra in machining the work material AISI 202 Stainless steel is done using ANOVA. And also to find the % of the share of the control factors on the responses. [4,5]. Results of Analysis of variancei(ANOVA) are shown in Table (3–4). A 95% confidence level was chosen. The result delineates that the most significant process parameter is Feed. The second most significant factor after Feed is the depth of cut for Ra (Table 3). Results show that the control parameters depth of cut & Feed has P-value < 0.05, signifying that these two possess higher physical significance & statistical significance over both the MRR and Ra.

TABLE 3

ANOVA FOR Ra, USING ADJUSTEDiSSiFOR TEST

Source	DF	Seq SS	Adj SS	Adj MS	F	P	R^2
Speed(v)	2	0.001342	0.001342	0.000671	0.99	0.412	91.77%
Feed(f)	2	0.020644	0.020644	0.010322	15.29	0.002*	
DOC(d)	2	0.016487	0.016487	0.008243	12.21	0.004*	
(v)*(f)	4	0.065188	0.065188	0.016297	24.15	0	
(f)*(d)	4	0.077437	0.077437	0.019359	28.68	0	
(v)*(d)	4	0.026813	0.026813	0.006703	9.93	0.003	
Error	8	0.0054	0.0054	0.000675			
Total	26	0.21331					

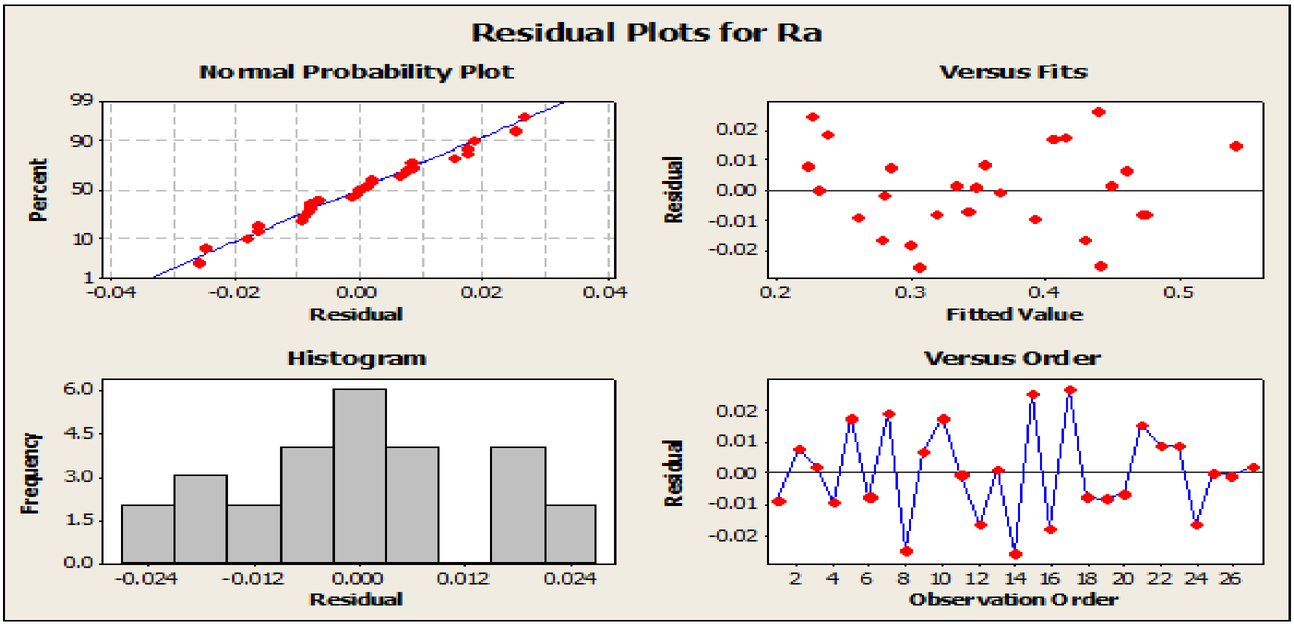

Fig. 3 Residual Plot for Ra

The residual plot for Ra is displayed in Fig.4. In the figure, the plot of the normal probability of the same is shown. Interpretation of the plot uncovers that the residuals are all along a straight line, suggesting a normal distribution of the errors & no blatant pattern is observed. This denotes the model, which is developed, turns out to be sufficient.

Ra's top significant factors were the Feed & depth of cut as it has P-value < 0.05, signifying that these two possess higher physical significance & statistical significance. As displayed in Table .3

TABLE 4

ANOVA FOR MRR, BY USING ADJ. SS FOR TESTS

Source	DF	Seq SS	Adj SS	Adj MS	F	P	R^2
Speed (v)	2	0.0001975	0.0001975	0.0000988	1.54	0.272	94.63%
Feed (f)	2	0.0167332	0.0167332	0.0083666	130.57	0*	
DOC (d)	2	0.0100942	0.0100942	0.0050471	78.77	0*	
(v)*(f)	4	0.0003401	0.0003401	0.000085	1.33	0.339	
(f)*(d)	4	0.0027142	0.0027142	0.0006785	10.59	0.003	
(v)*(d)	4	0.0004242	0.0004242	0.0001061	1.66	0.252	
Error	8	0.0005126	0.0005126	0.0000641			
Total	26	0.0310161					

The residual plot (Ra) is displayed in Fig.4. In the figure, the plot of the normal probability of the same is shown. Interpretation of the plot uncovers that the residuals are all along a straight line, suggesting a normal distribution of the errors & no blatant pattern is observed.

This denotes the model, which is developed, turns out to be sufficient. In the case of MRR, the top significant factors were the Feed & depth of cut as it has P-value < 0.05, signifying that these two possess higher physical significance & statistical significance. As displayed in Table .4

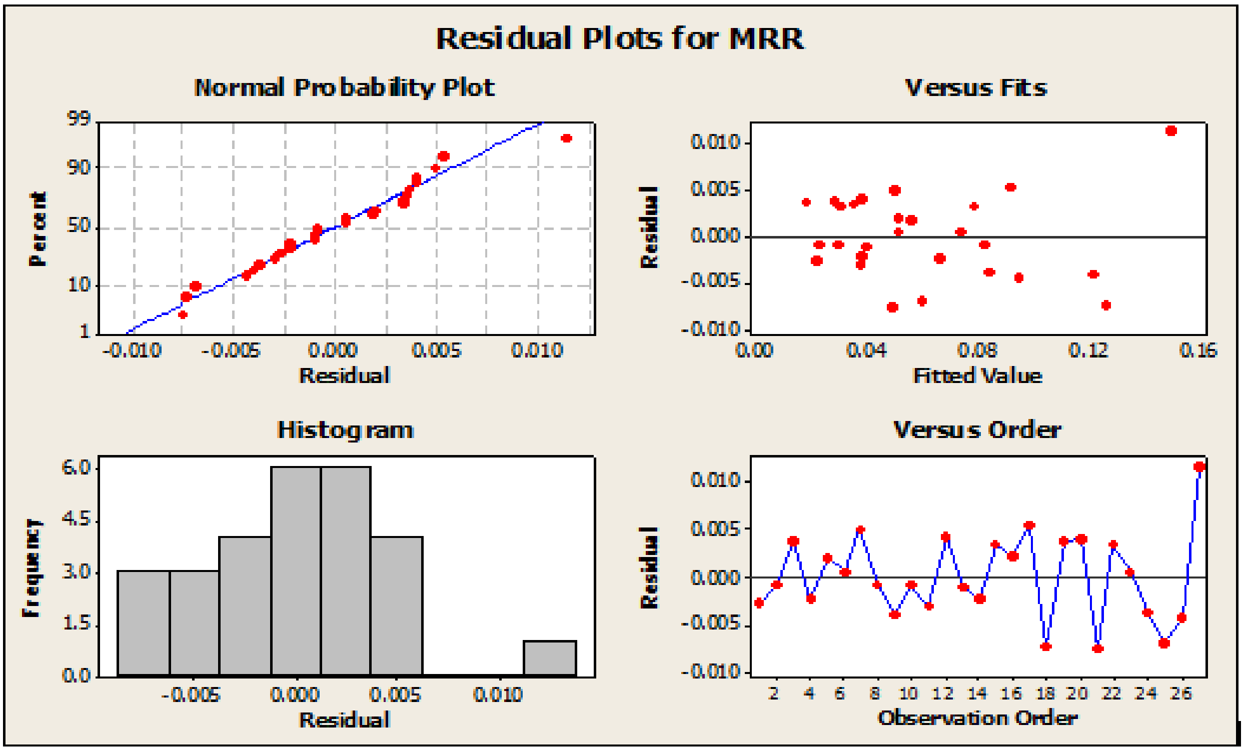

Fig. 4 Residual Plot for MRR

b) Regression analysis:

Regression analysis forms a relationship between the two that are dependant variables & independent variables. It is used for predicting the dependent variable for any change in the independent variable. Here the dependant variable is a function of various independent variables. The regression model is first-order, consisting of first-order predictors, and the interaction between them is as follows, which is shown in equation (1). Here Y is the dependant variable, β is the least square estimate, and X is independent.

Y = β0+ β2X2+ β3X3 + β 1X1+ β 4X12 +β5X22+ β 6X32 + β 7X1X2 +
β 8X1X3 + β 9X2X3 (1)

The surface roughness(Ra) shown as a quadratic response surface model is denoted as a function of control parameters such as V, f, d.

Ra= -2.58972+0.0198189*V+5.23711*f-0.0490556*d-3.30311e*V2*10-005+12.9689*f2+0.0158222*d2
-0.0300667*f *V ++0.00022*d*V +0.507333*d*V

A similar response surface model for MRR is shown below MRR,

MRR= -0.0786889+0.000859298*V+0.471566*f-0.0787686*d-2.50789*V2*10-006
–0.348718*f2+0.00357049*d2+
0.000217983*f*V+0.000351743*d*V+0.033961*
d*f

B. Optimization- Multi-objective

a) Grey relational analysis(GRA): Primary activity that has to be performed in GRA is data pre-processing, which aids raw data normalization to analyze further ahead. Here, a linear normalization of the experiments' output is done between the values 0 - 1 [4]. The analysis usually comprises of three different categories of performance characteristics in which, For Ra, smal1er the better is desired & higher, the better for MRR is desired. The following equation shows the Expression for the category "smaller the better" as [4].

$$xi(k) = \frac{\max \eta i(k) - \eta i(k)}{\max \eta i(k) - \min \eta i(k)}$$

The Expression for "higher the better is as shown below,"

$$xi(k) = \frac{\eta i(k) - \min \eta i(k)}{\max \eta i(k) - \min \eta i(k)}$$

Where,

$x_i(k)$ – In the i^th^ experiment, the k^th^ performance characteristic's normalized value

$\eta_i(k)$- In with experiment, the k^th^ experimental result value.

max ηi(k) – maximum of ηi(k),

min ηi(k) – a minimum of ηi(k)

The Expression of grey relational coefficient,

$$\xi i(k) = \frac{\Delta \min + \zeta \Delta \max}{\Delta oi(k) + \zeta \Delta \max}$$

The (xo) is reference sequence & (xi) is comparability sequence, whee in the above equation. The Δoi is the different sequence of both. ζ is the discriminating co-efficient, which is taken as ζ=0.5 (varies between 0-1). The GRG - ξ(xo, xi) determination is through averaging of the ζ (k) values, which corresponds to the respective output characteristic. Here, GRG expression is denoted as,

$$\xi(xo, xi) = \frac{1}{n} \sum_{k=}^{n} \xi i(k)$$

Here, n = the number 0f performance characteristics. GRG depicts any correlation between (xo) and (xi) [2]. The GRG found out varies between 0 to 1. Where 1 denotes that (xo) and (xi) are similarly coincident. GRG, along with the ranks, are displayed in Table 5.

TABLE 5
GREY RELATION GRADE AND THE RANK

Experiment #	Grey Relational Grade	Rank
1	0.80035329	3
2	0.77833996	5
3	0.82080581	1
4	0.69849301	12
5	0.72710144	10
6	0.77046461	6
7	0.65905093	16
8	0.61282464	20
9	0.38368469	25
10	0.76572709	8
11	0.80966212	2
12	0.68116328	14
13	0.67887519	15
14	0.71338018	11
15	0.62713978	19
16	0.554674	23
17	0.64099687	17
18	0.36459739	27
19	0.76641401	7
20	0.7936959	4
21	0.68400651	13
22	0.75465078	9
23	0.60096972	21
24	0.55840412	22
25	0.63832784	18
26	0.51349763	24
27	0.36795513	26

From Table.5, we see that the run, i.e., experiment number 3, has the optimal machining parameters' settings among the 27experiments done [5,6].

Additionally, the determination of optimum control parameters to achieve the desired Ra & MRR, the Taguchi's response table was utilized for the GRG average calculation for all the 3 levels of the milling parameters under consideration. The highest GRG value signifies that (xi) & (xo) has a greater correlation [7-9]. It can also be interpreted as without focusing on the category of the performance characteristics. A bigger GRG is nothing but an indication of better performance [10]. To segregate the control variables' impact on the GRG at various levels, the GRG response table is framed using the Taguchi framework. Thus the optimal control parameters of Milling are the ones with higher GRG. The optimal milling control parameter levels are V1, f2, and d2. The response table for GRG value is displayed below in Table. 6

TABLE 6
GRG RESPONSE TABLE

Milling Parameter	Average Grey Relational Grade by factor level		
	Level 1	**Level 2**	**Level 3**
Speed (V)	0.651937*	0.650589	0.630507
Feed rate (f)	0.606942	0.706605*	0.619487
Depth of cut (d)	0.632291	0.701841*	0.68783

VI. RESULTS AND DISCUSSION

- Employing the Taguchi method, individually, the process parameters (MRR & SR) are optimized.
- Optimal control parameters for a better output characteristic by GRA is found to be V1-f2-d2
- By ANOVA, the control parameters, Feed is highly significantly affecting the MRR and SR and then follows the depth of cut.

VII. CONCLUSION

Based on results & discussions done after carrying out GRA together with the Taguchi method to optimize the MRR and Ra simultaneously, the conclusions are observed as follows:

- On employing ANOVA, the process parameters say. A feed is a factor that high significance and then the depth of cut influencing the MRR & SR with a confidence level of 95%.
- On doing GRA, GRG value was considered a metric to identify control parameters' combination, which was optimal for multiple machining characteristics. For calculating the GRG values, both the machining characteristics were given equal weights.
- The recommended parameters for milling operation of A1S1 202 stainless-steel are 1.5 mm depth of cut, 275 rpm Speed, and feed rate - 0.10 feed/rev.

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