Multi Response Optimization of Turning Parameters using Grey Relational Analysis in The Taguchi Methodology

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Abstract— Now days, the role of surface quality and material rate in metal machining is most important. There are many machining process such as drilling, shaping, turning, slotting, grinding etc. Among the all machining process, turning is the machining process commonly used in industries to produce cylindrical workpieces. Turning parameters play a crucial role in turning the given work piece to the required shape. In the present work, turning process has been taken up for the surface roughness and material removal rate optimization. An attempt was also made to optimize the turning parameters for minimum surface roughness and maximum metal removal rate using Taguchi methodology. Also, grey relation analysis with Taguchi methodology was also used for the optimization of machining parameters for multi response optimization.

Key words: Taguchi methodology, grey relation analysis, multi response optimization

I. Introduction

Turning is the removal of metal from the outer diameter of a rotating cylindrical work piece. Turning is used to reduce the diameter of the work piece, usually to a specified dimension, and to produce a smooth finish on the metal. Often the work piece will be turned so that adjacent sections have different diameters. It is the most common process for the production of cylindrical shapes because of its simplicity, rapidity and economy. The purpose of the metal cutting process is not only to shape machine components but also to manufacture them so that they can achieve their functions according to geometric, dimensional and surface considerations. Here, through turning process has been selected for the study to determine the impact of process parameters on the surface roughness and material removal rate.

II. Literature review

Turning is an important operation in several manufacturing processes in some industries, which gives more importance to variety and accuracy to the machining. So, therefore many researchers investigated and formulated the effect of cutting variables for the optimization of the surface roughness and material removal rate. Rech et. al. (2003) experimentally investigated the effect of turning parameters on surface integrity in finish hard turning of case hardened steel. They investigate the effect of feed and speed on surface roughness, residual stresses and white layers. Results revealed that Tin coating substantially improves the surface integrity of hard turned surfaces. Noordin et. al. (2004) studied the performance of a multilayer tungsten carbide tool during turning of AISI 1045 steel using response surface methodology. The turning parameters for investigation were consider as cutting speed, feed and the side cutting edge angle (SCEA) of the cutting tool. Tangential force and surface roughness were considered as the response variables. All the turning experiments were performed at constant depth of cut and under dry cutting conditions. The feed was found most significant factor that influences the surface roughness and the tangential cutting force. Grzesik et.al (2005) investigated the effect of turning parameter on surface roughness produced during hard turning of hardened construction steel using mixed alumina cutting tools using 2D and 3D analysis. Davim et. al. (2007) used L27 orthogonal array based Taguchi methodology and artificial neutral network to develop surface roughness prediction model during turning of free machining steel. An attempt was also carried out to investigate the effect of turning parameters on surface roughness. The results revealed that cutting speed and feed rate had more effect in reducing the surface roughness, while the depth of cut had the least effect. Tzeng et. al (2008) used L9 orthogonal based Taguchi methodology with grey relation grade to optimized turning parameters for multi-response optimization during the turning of SKD 11 on computer numerical control machine. Nine experimental runs based on orthogonal array of Taguchi method were performed. The average surface roughness, maximum value of surface roughness and roundness were selected as quality targets. The results revealed that average surface roughness was most influenced by depth of cut and maximum value of surface roughness and the roundness was influenced by cutting speed. Suresh et. al (2012) used L27 orthogonal array based Taguchi methodology to investigate the effect of cutting speed, feed rate and depth of cut on surface roughness, machining force and tool wear during the turning of AISI 4340 steel. An attempt was also made to optimize the turning parameters for minimum surface roughness, minimum cutting force and minimum tool wear. Selvaraj et. al (2013) employed Taguchi methodology to optimize the turning parameters for minimum surface roughness, minimum cutting force and minimum tool wear during the dry turning of nitrogen alloyed duplex stainless steel. The cutting speed and feed rate were considered as turning parameters. Johnsan et. al. (2014) employed Taguchi methodology for the optimization of cutting parameters and minimal use of cutting fluid during turning of oil hardened non shrinkable steel (OHNS). An attempt was also made to compare result that was obtained with dry turning and conventional wet turning with same machining conditions. The results indicated that the use of minimum cutting fluid increased the cutting performance and produced good surface finish.

III. Analysis methodology and experimentation

A. *Design of Experiment:*

Design of Experiment is a powerful approach to improve product design or improve process performance where it can be used to reduce cycle time required to develop new product or processes. Design experiment is a test or series of test that the input variable (parameter) of a process is change so that observation and identifying corresponding changes in the output response can be verify. The result of the process is analysed to find the optimum value or parameters that have a most significant effect to the process. The objectives of the experiment may include (Montgomery, 2005)

- Determining variables that are most influential on the response, y.
- To set the influential x's so that y is near the nominal requirement.
- To set the influential x's so that variability in y is small.

To set the influential x's so that the effects of the uncontrollable variables are minimized.

B. *Taguchi's Philosophy:*

The entire of the technology and techniques arise entirely out of these three ideas. These concepts are:

- Quality should be designed into the product and not examined into it.
- Quality is best achieved by minimizing the deviations from the objective. The product or process should be so designed that it is protected to uncontrollable environmental variables.
- The cost of quality should be sedate as a function of deviation from the average and the losses should be sedate system-wide.

C. *Signal to Noise Ratio:*

The signal to noise ratio is a simultaneous statistic. A simultaneous statistic is able to look at two characteristics of a delivery and roll these characteristics into a single number or figure of merit. The signal to noise ratio combines both the parameters into a single metric. A high value of signal to noise ratio implies that is much higher than the random effects of noise factors. Process operation consistent with higher signal to noise ratio always yields best quality with minimum variation.

1) *Nominal the Best:*

It is expressed by the equation,

$$(S/N)_{NB} = 10 \log (MSD_{NB}) \quad = \quad 10 \log \left[\frac{y^2}{s^2} - \left(\frac{1}{n}\right)\right] \tag{3.1}$$

Where y = signal factors
s = noise factors

It is used whenever there is a nominal or target value and a variation about the value, such as dimensions, voltage, weight and so forth. The target is limited but not zero. For robust design, the S/N ratio should be maximized. It is maximum when the average is large and the difference is small.

2) *Smaller the Better:*

The S/N ratio for smaller the better is used for situation where the target value is zero, such as computer response time, automotive emission, corrosion. The equation for smaller the better ratio is

$$(S/N)_{LB} = -10 \log (MSD_{LB}) \quad = \quad -10 \log \left[{(\Sigma\, y^2)}/{N}\right] \tag{3.2}$$

The negative sign is used to ensure that the target value gives the best value for the response variable and therefore robust design. Mean standard deviation is given to display the relationship to the loss function.

3) *Larger the Better:*

It is used where value is desired, such as weld strength; material removal rate etc. for the mathematical view point, the objective value is zero. It is the reciprocal of the smaller the better. The equation is

$$(S/N)_{HB} = -10 \log (MSD_{HB}) \quad = \quad -10 \log \left[{\Sigma(1/y)^2}/{N}\right] \tag{3.3}$$

D. *Grey Relational Analysis:*

Grey relational analysis is a method of measuring the degree of approximation between sequences according to the grey relational grade. The theories of grey relational analysis have already attracted the interest of researchers. In the grey relational analysis, the measured values of the experimental results were first normalized in the range between zero and one, which is also called grey relational generation. With the grey relational analysis, the optimal combination of the process parameters can be predicted.

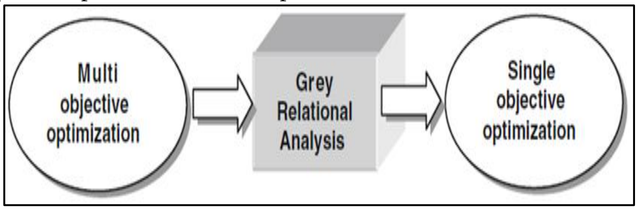

Fig. 1:

E. *Analysis of Variance (Anova):*

The main purpose of the analysis of variance (ANOVA) is the application of a statistical method to identify the effect of individual factors. Results from ANOVA can determine very clearly the impact of ach factor on the process results. The taguchi experimental method cannot judge the effect of individual parameters on the entire process; thus, the percentage of contribution using ANOVA is used to compensate for this effect. The total sum of the squared deviations SST is disintegrated into two sources: the sum of the squared deviations due to each process parameter and the sum of the squared error. The percentage contribution by each of the process parameter in the total sum of the squared deviations SST can be used to calculate the importance of the process-parameter change on the performance characteristics.

F. *Research Work:*

In the present research work, feed, cutting speed and depth of cut were considered as turning parameters while surface roughness and MRR were considered as response. The minimum and maximum values of process parameters is selected according to review of past literature and based on machine specification. The levels of process parameters are decided according to L27 orthogonal array (3 factor 3 level) based Taguchi methodology as shown in table 3.1. Table 3.2 shows design matrix in actual form of parameters according to L27 orthogonal array based Taguchi methodology.

Parameters	Unit	Type	Levels		
			1	2	3
Cutting Speed	m/min	Numeric	100	200	300
Feed rate	mm/rev	numeric	0.1	0.15	0.2
Depth of cut	mm	numeric	0.2	0.5	0.8

Table 3.1: Parameters and levels of parameters according to Taguchi design

Sr. no.	Cutting speed (m/min)	Feed (mm/rev.)	Depth of cut (mm)
1	100	0.1	0.2
2	100	0.1	0.5
3	100	0.1	0.8
4	100	0.15	0.2
5	100	0.15	0.5
6	100	0.15	0.8
7	100	0.2	0.2
8	100	0.2	0.5
9	100	0.2	0.8
10	200	0.1	0.2
11	200	0.1	0.5
12	200	0.1	0.8
13	200	0.15	0.2
14	200	0.15	0.5
15	200	0.15	0.8
16	200	0.2	0.2
17	200	0.2	0.5
18	200	0.2	0.8
19	300	0.1	0.2
20	300	0.1	0.5
21	300	0.1	0.8
22	300	0.15	0.2
23	300	0.15	0.5
24	300	0.15	0.8
25	300	0.2	0.2
26	300	0.2	0.5
27	300	0.2	0.8

Table 3.3: design matrix in actual form of parameters

IV. RESULTS AND DISCUSSIONS

The analysis of variance (ANOVA) is based on three assumptions. (1) The variables are normally distributed (2) Homogeneity of variance (3) Independence.

A. *Anova for Mean For Surface Roughness:*

The population normality can be checked with a normal probability plot of residuals. If the distribution of residuals is normal, the plot will resemble a straight line. The normal probability plot of the residuals for surface roughness is shown in figure.4.1. The normal probability plot indicates whether the residuals follow a normal distribution or not, if the residuals follow a normal distribution majority of points will follow a straight line except some moderate scatter even with normal data. The figure displays that the residuals generally fall on a straight line implying that the errors are distributed normally.

The constant variance assumption can be checked with Residuals versus Fits plot. The figure.4.2 represents residuals versus the predicted surface roughness plot. This plot should show a random pattern of residuals on both sides of 0, and should not show any recognizable patterns. A common pattern is that the residuals increase as the fitted values increase. The figure shows that there is no obvious pattern and it shows unusual structure. This implies that there is no reason to suspect any violation of the independence or constant variance assumption.

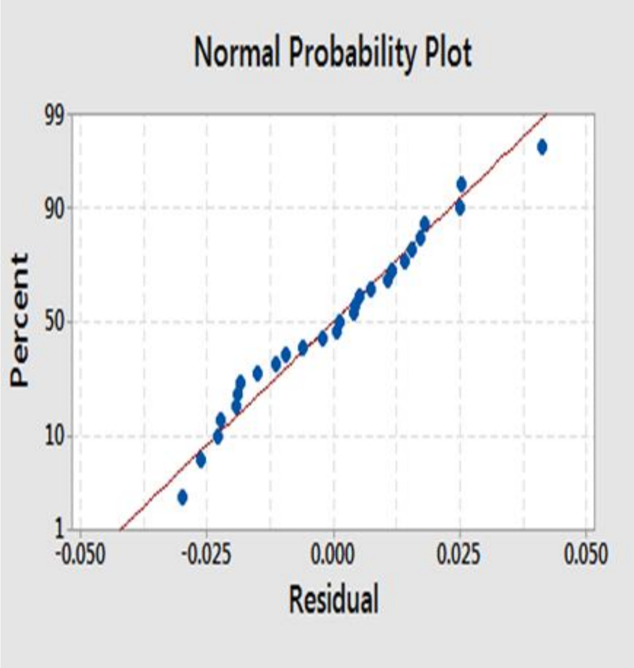

Fig. 4.1: Normal Probability Plot of Residuals for Surface Roughness

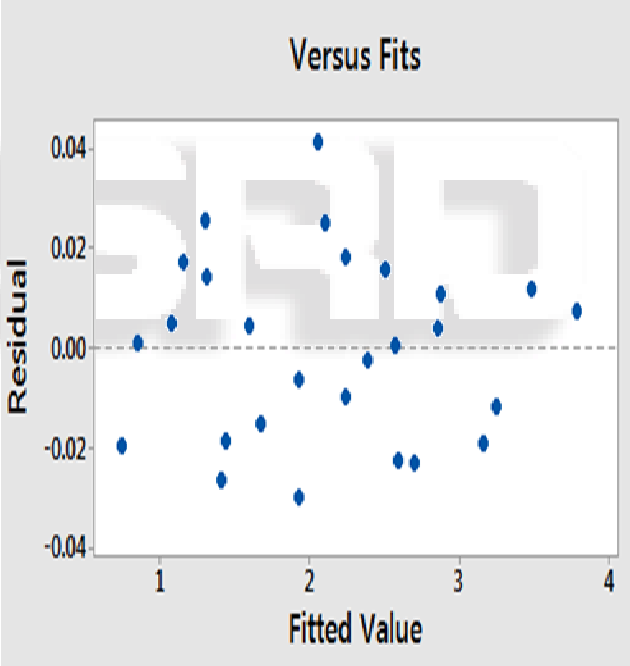

Fig. 4 .2: Plot of residuals v/s predicted surface roughness

The assumption of independence can be checked with Residuals versus Order plot. The figure.4.3 represents Residuals versus Order plot for surface roughness. The independence, especially of time related effects, can be checked with the Residuals versus Order (time order of data collection) plot. A positive correlation or a negative correlation means the assumption is violated. If the plot does not reveal any pattern, the independence assumption is satisfied. The figure 4.3 shows that plot have no obvious pattern. Thus, independence assumptions are satisfied.

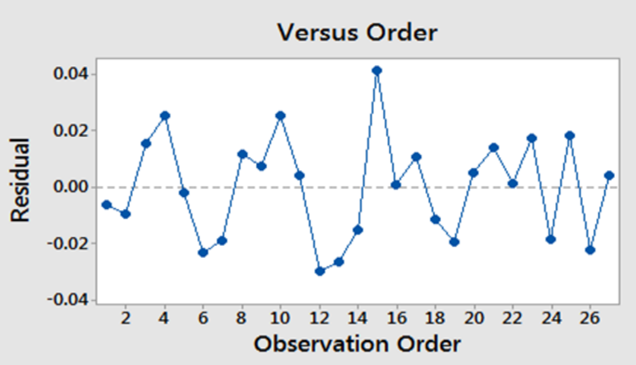

Fig. 4.3: Plot of residuals v/s order

As mention above, in this work the ANOVA was carried out for a significance level of α = 0.05, i.e. for a confidence level of 95%. The ANOVA for mean for surface roughness is summarized in Table 4.1.

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Cutting speed	2	5.6021	5.6021	2.80103	2614.96	0.000
Feed	2	10.0622	10.0622	5.03108	4696.87	0.000
Depth of cut	2	1.6901	1.6901	0.84504	788.90	0.000
Cutting speed *Feed	4	0.1017	0.1017	0.02542	23.73	0.000
Cutting speed * Depth of cut	4	0.0089	0.0089	0.00222	2.07	0.177
Feed *Depth of cut	4	0.0032	0.0032	0.00081	0.76	0.581
Residual Error	8	0.0086	0.0086	0.00107		
Total	26	17.4766				

Table 4.1: Resulting ANOVA table for mean of surface roughness

In the table 4.1, the value of "Prob. > F" for speed is less than 0.0001 which is less than 0.05, that indicates the cutting speed has significant effect on surface roughness. In the same manner, the value of "Prob. > F" for main effect of feed, depth of cut and two-level interaction of speed and feed are less than 0.05 so these terms have significant effect on surface roughness. Other terms are said to be insignificant terms.

B. Minimization of Surface Roughness

The difference between the maximum and the minimum value of the turning parameters for surface roughness values is shown in table 4.2. The most effective factor affecting performance characteristics is obtained by comparing these values. This comparison gives the level of importance of controllable factors over the minimum surface roughness. The most effective controllable factor corresponds to the maximum of these values. Thus the feed has been found most significant parameter that affects the surface roughness followed by speed and depth of cut.

Level	Cutting speed	Feed	Depth of cut
1	2.700	1.627	1.814
2	2.076	1.754	2.122
3	1.587	2.981	2.427
Delta (Max.-Min.)	1.113	1.354	0.613
Rank	2	1	3

Table 4.2: Response table for surface roughness

C. Anova for Mean for Metal Removal Rate (MRR):

In the present work, for the analysis of MRR, the ANOVA test was carried out at significance level of α = 0.05, i.e. for a confidence level of 95%. The normal probability plot of the residuals for MRR is shown in figure.4.7. The figure displays that the residuals generally fall on a straight line implying that the errors are distributed normally. The figure.4.8 represents residuals versus the predicted MRR plot. The figure shows that there is no obvious pattern and it shows unusual structure. This implies that there is no reason to suspect any violation of the independence or constant variance assumption. The figure.4.9 represents Residuals versus Order plot for MRR. The figure shows that plot have no obvious pattern. Thus, independence assumptions are satisfied.

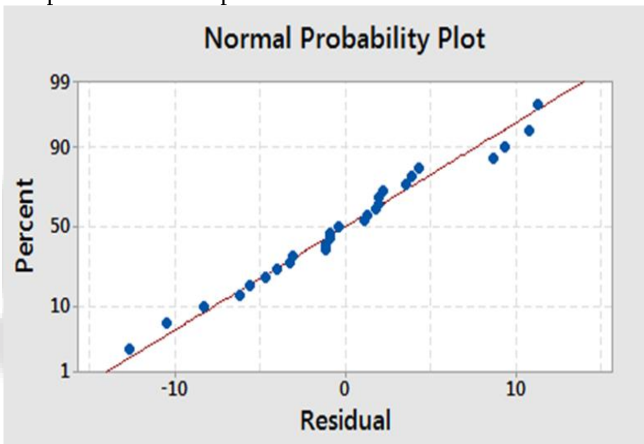

Fig. 4.7: Normal probability plot of residuals for MRR

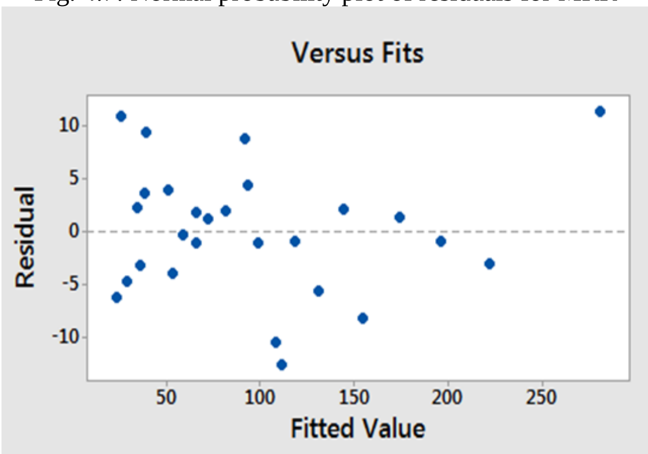

Fig. 4.8: Plot of residuals v/s predicted MRR

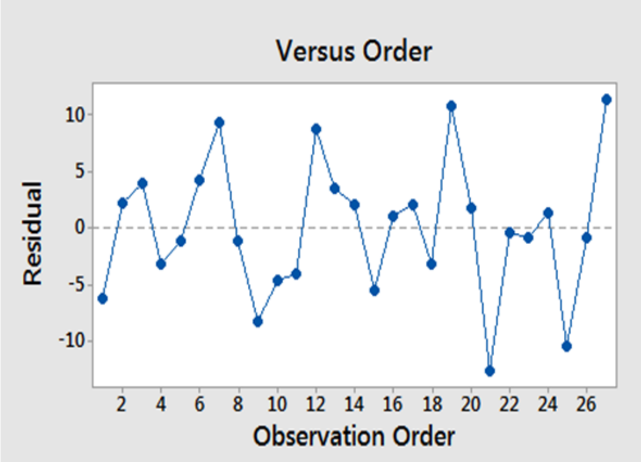

Fig. 4.9: Plot of residuals v/s order

1) Anova Table for Mean for MRR:

The ANOVA was carried out for a significance level of $\alpha = 0.05$, i.e. for a confidence level of 95%. The ANOVA for mean for surface roughness is summarized in Table 4.5.

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Cutting speed	2	16477	16477.4	8238.7	69.69	0.000
Feed	2	39317	39317.1	19658.5	166.29	0.000
Depth of cut	2	42790	42790.3	21395.1	180.98	0.000
Cutting speed *Feed	4	3632	3631.7	907.9	7.68	0.008
Cutting speed* Depth of cut	4	2568	2568.3	642.1	5.43	0.021
Feed *Depth of cut	4	5956	5956.1	1489.0	12.60	0.002
Residual Error	8	946	945.7	118.2		
Total	26	111687				

Table 4.5: Resulting ANOVA table for mean of MRR

In the table 4.5, the value of "Prob. > F" for speed is less than 0.0001 which is less than 0.05, that indicates the cutting speed has significant effect on MRR. In the same manner, the value of "Prob. > F" for main effect of feed, depth of cut and two-level interaction of speed and feed; feed and depth of cut ; cutting speed and depth of cut are less than 0.05 so these terms have significant effect on MRR. Other terms are said to be insignificant terms.

D. Maximization of MRR Using Mean:

The difference between the maximum and the minimum value of the turning parameters for MRR values is shown in table 4.6. The most effective factor affecting MRR is obtained by comparing these values. The most effective controllable factor corresponds to the maximum of these values. Thus the depth of cut has been found most significant parameter that affects the MRR followed by feed and speed.

Level	Cutting speed	Feed	Depth of cut
1	66.43	54.18	48.25
2	96.27	88.78	95.63
3	126.94	146.68	145.76
Delta (Max.-Min.)	60.51	92.50	97.50
Rank	3	2	1

Table 4.6: Response table for MRR based on mean

V. CONCLUSION AND FUTURE SCOPE

The objective of the present work is to optimize EDM parameters for maximum MRR. An attempt has also been made to investigate the effects of the EDM parameters on surface roughness and MRR. Design of experiment using 2 level full factorial designs has been used to develop relationship for MRR. The maximum MRR 78.3656 mm3/min has been obtained at voltage 30 V, current 25 A, pulse on time 200 microseconds pulse off time 12 microseconds and with kerosene +Si-C powder.

All the five independent parameters (Current, Voltage, Pulse on time Pulse off time and type of dielectric medium) seem to be the influential EDM parameters that affect the MRR

The MRR prediction model clearly shows that the pulse on seems to be the most significant factor that affect the MRR.MRR increases as increase in pulse on time, increase in current but decreases as increase in pulse off time and increase in voltage

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