Optimal Setting of Process Parameters While Turning of AISI 1040 Steel

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Abstract

In the present work, Taguchi based Utility technique has been employed to find the optimal combination of cutting parameters in dry turning of AISI 1040 using a tungsten carbide tool. The experiments are planned as per the Taguchi's standard L27 (3^3) Orthogonal Array. Cutting speed, feed and depth of cut are selected as the three controllable variables at three different levels, whereas Material Removal Rate (MRR) and Surface Roughness (R_a) are considered as the experimental responses. The results of multi-response optimization based on utility analysis showed that the optimal combination of process parameters would be at 760 RPM of speed, 0.3 mm/rev of feed and 1.5 mm of depth of cut respectively. ANOVA results showed that depth of cut is the major contributing factor and followed be cutting speed and feed respectively.

Keywords: Material Removal Rate (MRR), Surface Roughness (R_a), AISI 1040, Taguchi Utility method and ANOVA.

1. Introduction

In manufacturing industries the engineers are facing challenges in setting of optimal combination of cutting parameters for achieving the desired characteristics like material removal rate, surface finish and dimensional deviations, etc. In general, there are many factors which influence the machining performance characteristics. The surface roughness mainly depends on the factors like nature of material, work piece dimensions, cutting parameters (speed, feed and depth of cut), coolant used, machining process, rigidity of the system consisting of machine tool, fixture cutting tool and work and cutting tool nomenclature, etc. Surface finish plays a major role in the selection of material since it influences the appearance, corrosion resistance, wear resistance, fatigue resistance, lubrication holding capacity, load carrying capacity, noise generation in case of gears, etc.

The performance/quality of the any machining products can be evaluated by the multiple quality characteristics/responses. In general, the optimal setting of cutting parameters for one response gives detrimental results for other responses. To solve this problem, there is a need to obtain optimal setting of cutting parameters which satisfy multiple quality characteristics that are required by the customer. Many researchers employed different methods to optimize the multi-responses. Maheswara Rao et al. (2016) investigated the influence of cutting parameters on multiple responses using grey analysis and regression method in dry turning of AA7075 alloy. The experiments are conducted as per Taguchi's L9 OA. From the results they found that high values of cutting speed, depth of cut and low value of feed are the optimal conditions for achieving a high material removal rate and low surface roughness simultaneously. The regression models prepared are found more accurate and adequate. Upinder Kumar et al. (2013) conducted an experiment to optimize the surface roughness and material removal rate simultaneously using grey relational analysis. The L9 OA is used for machining of AISI 1045 steel. The optimal combination of the combined response is found at cutting speed of 188 m/min, feed rate of 0.2 rev/min and depth of cut of 1.5 mm. Prasad Karande et al. (2016) conducted a study on the ranking performance of some MCDM methods for industrial robot selection problems. They used a weighted sum method

(WSM), weighted product method (WPM), weighted aggregated sum product assessment method (WASPAS), multi-objective optimization on the basis of ratio analysis and reference point approach (MOORA) method, and a multiplicative form of MOORA (MULTMOORA) methods. From the study, they concluded that among all the method multiplicative form of MOORA is the most robust method being least affected by the changing weights of the important and critical criteria's. Ch. Maheswara Rao et al. (2016) employed various MCDM methods of WSM, WPM and TOPSIS methods for the optimization of multiple responses. From the results, they found that the feed is the most influencing parameters in effecting the multiple responses. From the above survey, it is observed that there are many methods to optimize the multi responses effectively. But in the present work Taguchi based Utility concept is adopted because of its relative ease and simple calculations compared to the other methods and the results obtained are similar to that of other methods.

2. Experimental Details

2.1. Selection of Material

Medium carbon steel AISI 1040 is used as the work material for the present investigation, which has a wide range of applications in manufacturing industries. It is commonly used for general purpose axles, shafts, gears, bolts & studes, spindles, automotive and general engineering components etc. The work specimens are taken in the form of cylindrical shape and machining was carried on conventional lathe. The chemical composition and mechanical properties of AISI 1040 steel are given in the tables 1 and 2.

Table 1.Chemical composition of AISI 1040 Steel

C	Si	Mn	Ni	Cr	Mo	S	P
0.35-0.45	0.05-0.35	0.6-1	-	-	-	0.06 max	0.06 max

Table 2.Mechanical properties of AISI 1040 Steel

Maximum Stress (N/mm2)	Yield Stress (N/mm2)	% Elongation	Impact (J)	Hardness (BHN)
700-850	465	16	28	201-255

2.2 Selection of Cutting Parameters and Their Levels

The cutting parameters speed, feed and depth of cut are considered as the controllable input variables in the present study. A series of experiments are conducted as per the Taguchi's standard L27 Orthogonal Array. The selected cutting parameters with their levels and Standard L27 OA in the coded form are given in the tables 3 and 4.

Table 3. Cutting Parameters and Their Levels

Cutting parameters			
Levels in coded form	Spindle speed (N) (RPM)	Feed (f) (mm/rev)	Depth of cut (d) (mm)
-1	360	560	760
0	0.1	0.2	0.3
1	0.5	1	1.5

Table 4. Taguchi's L27 OA With Actual Experimental Values

S.No.	Factorial combination		
	(N)	(f)	(d)
1	360	0.1	0.5
2	360	0.1	1
3	360	0.1	1.5
4	360	0.2	0.5
5	360	0.2	1
6	360	0.2	1.5
7	360	0.3	0.5
8	360	0.3	1
9	360	0.3	1.5
10	560	0.1	0.5
11	560	0.1	1
12	560	0.1	1.5
13	560	0.2	0.5
14	560	0.2	1
15	560	0.2	1.5
16	560	0.3	0.5
17	560	0.3	1
18	560	0.3	1.5
19	760	0.1	0.5
20	760	0.1	1
21	760	0.1	1.5
22	760	0.2	0.5
23	760	0.2	1
24	760	0.2	1.5
25	760	0.3	0.5
26	760	0.3	1
27	760	0.3	1.5

3. Methodology

The performance of any machining process is measured based on the number of output characteristics. Therefore, a combined measure is necessary to measure its overall performance, which must take into account the relative importance of all the quality characteristics. Such a composite index represents the overall utility of a product/process. Utility refers to the satisfaction that each attributes provides to the decision maker. Thus, utility theory assumes that any decision is made on the basis of the utility maximization principle, according to which the best choice is the one that provides the highest satisfaction to the decision maker. According to the utility theory, if x_i is the measure of effectiveness of an attribute (or quality characteristics) 'i' and there are *'n'* attributes evaluating the outcome space, then the joint utility function can be expressed as

$U\ (x_1, x_2 \ldots \ldots \ldots \ldots \ldots, x_n) = f\big(U_1(x_1), U_2(x_2) \ldots \ldots \ldots \ldots \ldots, U_n(x_n)\big)$...............Eq. (1)

Where, $U_i(x_i)$is the utility of the i^{th} attribute

The overall utility function is the sum of individual utilities. If the attributes are independent then

$U(x_1, x_2, \ldots \ldots \ldots \ldots, x_n) = \sum_{i=1}^{n} U_i(x_i)$...........................Eq. (2)

The attributes may be assigned weights depending upon the relative importance or priorities of the characteristics. The overall utility function after assigning weights to the attributes can be expressed as

$U(x_1, x_2, \ldots \ldots \ldots \ldots, x_n) = \sum_{i=1}^{n} W_i U_i(x_i)$........................Eq. (3)

Where, W_i is the weight assigned to the attribute i. The sum of the weights for all the attributes must be equal to 1. The overall utility computed is treated as a single objective function and it is optimized using Higher-the-Better (HB) characteristic.

4. Results and Discussions

The experimental results of both material removal rate and surface roughness obtained are given in table 5. The individual utility values for the responses are calculated using the Higher-the-Better (HB) and Lower-the-Better (LB) characteristics given in the Eqs. (4) and (5) for the responses respectively and the values are depicted in the table 6.

Higher-the-Better (HB): $-10\log_{10}\left(\frac{1}{MRR^2}\right)$......................Eq. (4)

Lower-the-Better (LB): $-10\log_{10}(R_a^2)$...........................Eq. (5)

Table 5. Experimental Results

S.No.	MRR, Cm^3/min	R_a, µm
1	11.38	5.0
2	21.75	5.7
3	31.39	4.7
4	20.74	5.6
5	38.66	6.2
6	53.01	7.2
7	39.38	9.4
8	69.72	8.9
9	100.02	5.5
10	13.70	5.0
11	24.30	5.3
12	34.71	3.8
13	13.98	5.3
14	25.80	4.4
15	36.25	6.9
16	46.12	9.2
17	78.50	7.0
18	92.03	4.4
19	25.52	2.5
20	46.32	3.7
21	66.26	7.4
22	42.86	5.1
23	78.53	4.0
24	102.46	6.7
25	63.72	8.0
26	117.80	6.9
27	119.60	3.5

Table 6. Individual Utility Values of Responses

S.No.	S/N of MRR (η_1)	S/N of R_a (η_2)
1	21.1228	-13.9794
2	26.7492	-15.1175

3	29.9358	-13.4420
4	26.3362	-14.9638
5	31.7452	-15.8478
6	34.4872	-17.1466
7	31.9055	-19.4626
8	36.8671	-18.9878
9	40.0017	-14.8073
10	22.7344	-13.9794
11	27.7121	-14.4855
12	30.8091	-11.5957
13	22.9101	-14.4855
14	28.2324	-12.8691
15	31.1862	-16.7770
16	33.2778	-19.2758
17	37.8974	-16.9020
18	39.2786	-12.8691
19	28.1376	-7.9588
20	33.3154	-11.3640
21	36.4250	-17.3846
22	32.6410	-14.1514
23	37.9007	-12.0412
24	40.2111	-16.5215
25	36.0855	-18.0618
26	41.4229	-16.7770
27	41.5546	-10.8814

The overall utility function based on Signal-to-Noise ratios can be calculated using the Eq. (6) and the values are given in the table 7.
Overall utility (η_{obs}) = $W_1\eta_1 + W_2\eta_2$........................Eq. (6)

Where, W_1 and W_2 are the weights assigned for the responses and η_1, η_2 are the Signal-to-Noise ratios for the responses. In the present work, equal importance is given for both material removal rate and surface roughness, so $W_1 = W_2 = 0.5$, such that $W_1 + W_2 = 1$.

Table 7. Overall Utility Value of Multi-Response and S/N Ratios

S.No.	η_{obs}	S/N of η_{obs}
1	3.5717	11.0575
2	5.8158	15.2922
3	8.2469	18.3258
4	5.6862	15.0964
5	7.9487	18.0059
6	8.6703	18.7607
7	6.2214	15.8778
8	8.9396	19.0264
9	12.5972	22.0055
10	4.3775	12.8245
11	6.6133	16.4084
12	9.6067	19.6515
13	4.2123	12.4904

14	7.6816	17.7090
15	7.2046	17.1522
16	7.001	16.9032
17	10.4977	20.4219
18	13.2047	22.4146
19	10.0894	20.0773
20	10.9757	20.8086
21	9.5202	19.5729
22	9.2448	19.3180
23	12.9297	22.2318
24	11.8448	21.4706
25	9.0118	19.0962
26	12.3229	21.8143
27	15.3366	23.7146

The overall utility obtained is analysed by using Taguchi method and the results are given in the table 8. The Main effect plot is drawn for the mean values and shown in the figure 1. From the plot, the main effect is observed due to depth of cut and followed by the speed and feed for the multi-response. The optimal combination of cutting parameters is found at the levels showing high mean values i.e. N3-f3-d3.
Cutting speed: level 3, 760 RPM
Feed: level 3, 0.3 mm/rev
Depth of cut: level 3, 1.5 mm

Table 8. Response Table for Means of η_{obs}

Level	Speed (N)	Feed (f)	Depth of cut (d)
1	7.522	7.646	6.602
2	7.822	8.380	9.303
3	11.253	10.570	10.692
Delta (Max-Min)	3.731	2.924	4.091
Rank	2	3	1

Figure 1. Main Effect Plots For Means of Overall Utility (η_{obs})

The ANOVA is used to find the influence of the cutting parameters at α = 0.05 (95% of confidence level) on the multi-response. Table 9 shows the ANOVA results of multi-responses and from the results it is found that the depth of cut is the most influencing parameter (33.5790%) and followed by the cutting speed (33.3462 %) and feed (17.9580 %) respectively. The residual plots for η_{obs} are drawn and from the figure 2, it is clear that the residuals are distributed normally and does not following any regular pattern hence the model prepared is accurate and adequate.

Table 9. ANOVA Results for η_{obs}

Source	DF	Seq SS	Adj MS	F	P	% Contribution
Speed (N)	2	77.34	38.669	22.06	0.000	33.3462
Feed (f)	2	41.65	20.827	11.88	0.000	17.9580
Depth of cut (d)	2	77.88	38.940	22.21	0.000	33.5790
Error	20	35.06	1.753			15.1166
Total	26	231.93				100.0000

S = 1.32397, R^2 = 84.88%, R^2(adj) = 80.35%

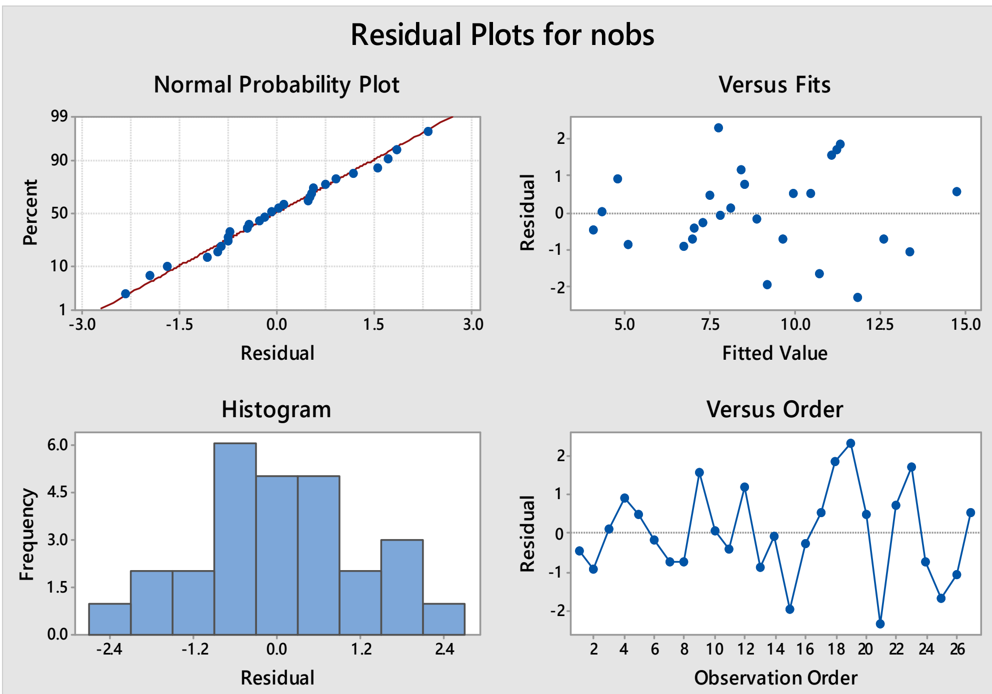

Figure 2. Residual Plots for η_{obs}

Optimal design for η_{obs}

For the overall Utility value (η_{obs}), depth of cut and speed are the most significant factors at d3 and N3 levels.

μ_{A3B3} = A3 + B3 – T

Where, A3 = 10.692, B3 = 11.253

T = 8.8656

μ_{A3B3} = A3 + B3 – T

= 10.692 + 11.2530 – 8.86 56 = 13.0794

$$CI = \sqrt{\frac{(F_{95\%,1,doferror} \times V_{error})}{(n_{eff})}}$$

Where, $\eta_{eff} = \frac{N}{(1+dof)}$; where, N is total number of experiments, dof is degree of freedom.

$\eta_{eff} = \frac{27}{(1+2+2)} = 5.4$
$V_{error} = 1.753$
$F_{95\%,1,20} = 4.3512$ (From standard F-table at $\alpha = 0.05$)
$CI = \sqrt{\frac{(4.3512 * 1.753)}{5.4}} = 1.1884$
The predicted optimal range = $\mu_{A1B3} - CI \leq \mu_{A1B3} \leq \mu_{A1B3} + CI$
$= 13.0794 - 1.1884 \leq \mu_{A3B3} \leq 13.0794 + 1.1884$
$= 11.891 \leq \mu_{A3B3} \leq 14.2678$

5. Conclusions

From the experimental, Taguchi based Utility method and ANOVA the following conclusions are made

- Taguchi based Utility results concluded that, the maximum Material Removal Rate and minimum Surface Roughness simultaneously is obtained at N3-f3-d3.
  Cutting speed: level 3, 760 RPM
  Feed: level 3, 0.3 mm/rev
  Depth of cut: level 3, 1.5 mm
- ANOVA results showed that the depth of cut is the most dominant factor followed by speed and feed on the multiple responses.
- The residual plots for overall utility showed that the residuals are lying nearer to the straight line hence following the normal distribution.

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