International Journal of Applied Engineering Research ISSN 0973-4562 Volume 10, Number 23 (2015) pp 43912-43918

Taguchi-Fuzzy Multi Output Optimization (MOO) in Turning of AA6351

P. Jayaraman*

Research Scholar, St. Peter's University, Associate Professor, Prathyusha Institute of Technology and Management, Chennai-602025, India, Mobile: +91 9840397361. jayaramansharmila@gmail.com

L. Mahesh Kumar

Department of Mechanical Engineering, Professor, St. Peter's University, Chennai-600054, India, Mobile: +91 98400 24189

V.S. Senthil kumar

Department of Mechanical Engineering, Associate Professor, Anna University, Chennai-600025, India, Mobile: +91 9444952438 vsskumar@annauniv.edu

Abstract

This paper presents the application of Taguchi method with logical fuzzy reasoning for multiple output optimization of turning of AA6351 aluminium alloy using uncoated tungsten carbide tool. The machining parameters (cutting speed, feed rate and depth of cut) are optimized with the considerations of the multiple performance characteristics namely surface roughness (R_a), material removal rate (MRR), machining force (F_m) and cutting power (P_c). Taguchi's concepts of orthogonal arrays, signal to noise (S/N) ratio, ANOVA have been fuzzified to optimize the turning process parameters through a single comprehensive output measure (COM). The result analysis shows that cutting speed of 75.39 m/min, feed rate of 0.05 mm/rev, depth of cut of 1 mm are the most preferable machining parameters for dry turning of AA6351, while considering all the above mentioned output characteristics together.

Keywords: Turning, Orthogonal array, Taguchi-Fuzzy hybrid approach, ANOVA, Multi output optimization (MOO), Comprehensive output measure (COM)

Introduction

Today's rapid changing manufacturing environment requires the application of optimization techniques in metal cutting processes to effectively respond to extreme competitiveness and to meet the increasing demand of customizable quality product (lesser cost, quickly deliverable, superior quality) in the market. Taguchi's method is one of the most effective and robust systems of off-line quality control where the quality is in-built at the product design stage instead of controlling it at the production stage or through the inspection of final finished products. Aggarwal et. al. [1] comparatively used response surface methodology and Taguchi method to conclude that the low temperature cutting conditions significantly reduces the power consumption as compared to dry and wet cutting conditions.

Most of the engineering processes comprise of multiple responses. Generally, single response optimization can be used to model only the simplest systems and bulk of the processes are too intricate to be classified into individual responses. However analyzing and solving a multiple performance characteristics is a demanding research problem as against the most analyzed Taguchi applications in the area of optimization of a single performance characteristic which is time consuming and exorbitant in cost. Statistical design of experiments (DOE) refers to the effective process of planning the experiment in such a manner so that the proper data can be analyzed by statistical methods, resulting in valid and objective conclusions [2]. Zadeh [3] instigated the theory of fuzzy logics to deal with uncertain and unclear information. His definition of performance characteristics such as smaller-the-better (SB), larger-the-better (LB), and nominal-the-best (NB) contains a certain degree of uncertainty and vagueness. Therefore, optimization of the complicated multiple performance characteristics with fuzzy logic have been considered in this study by transforming it into the optimization of a single comprehensive output measure (COM) for a turning process.

In turning of aluminium alloy, machining parameter selection for achieving optimal performance like a good surface finish, high material removal rate, close tolerance-dimensional accuracy, high strength and lesser cutting force are important and essential. Most of the optimization techniques do have certain constraints, assumptions and limitations for implementation in real life machining process problems. The optimum setting of parameters for various responses is usually a conflicting task and the weightage of responses is a matter of researcher's decision. Still the researchers continually struggle to find still better optimized cutting conditions in order to economize the machining problem at hand. Lin et al. [4] optimized the electrode wear rate and material removal rate of an electrical discharge machine by determining the optimum machine parameter setting of work-piece polarity, pulse on time, duty factor, voltage, current and dielectric fluid using Taguchi method with fuzzy logics. Hasan Gokkaya et al. [5] have put their effort to study the effect of cutting speed and feed rate on BUE-BUL formation, cutting forces and surface roughness when machining AA6351 alloy. They came out with a conclusion that the only significant factor for the cutting force Fc, is feed rate. They have also found out that cutting force is lesser at higher cutting speed and higher feed rates are root cause for higher cutting forces. The surface roughness increases with increase in cutting speed and feed rate is the dominant factor in determining the surface roughness. Our experimental results agree with these results. Mahamani [6] has studied the influence of process parameters on cutting force and surface roughness during turning of AA2219-TiB2/ZrB2 MMC and came out with the conclusion that lower cutting force and surface finish are obtained at higher cutting speed, lower feed rate and lower depth of cut. Response graphs show that feed rate offers greater influence on cutting force and surface roughness. Generally, higher feed rate will increase the area of cut, which increases the frictional force between the cutting edge and work piece material. This effect increases the cutting force when increasing the feed rate. Increase in feed rate also increases the chip load, which cause excessive cutting force. At lower cutting speed, built up formation will be more. Built up edge formation will increase the contact area of the cutting edge, which increases the cutting force. Higher cutting speed breaks the built up edge formation. Therefore cutting force is minimized when operating with higher cutting velocity. Increase in depth of cut increases the cutting force. Contact area and radial force is increased when increasing the depth of cut, which increases the cutting force.

Surendra kumar saini et al. [7] have made an attempt to optimize multi-objective response during CNC turning using Taguchi-fuzzy application and it was determined that feed rate is the most significant parameter on comprehensive output measure of surface roughness and MRR, followed by depth of cut and spindle speed. Anil gupta et al. [8] have performed Taguchi-fuzzy multi-output optimization in high speed CNC turning of AISI P-20 tool steel. They have considered combined value of surface roughness, tool life, cutting force and power consumption as single comprehensive output measure (COM). The result analysis shows that cutting speed of 160 m/min, nose radius of 0.8 mm, feed rate of 0.1 mm/rev, depth of cut of 0.2 mm and the cryogenic environment are the most favorable cutting parameters for high speed CNC turning of AISI P-20 tool steel. Ashok kumar sahoo et al. [9] have used grey relational analysis to perform multi-objective optimization of surface roughness and MRR in turning of AISI 1040 steel and determined that cutting speed is the most influencing parameter affecting combined grey relational grade followed by depth of cut and feed rate. Chorng-Jyh Tzeng et al. [10] have used Grey relational analysis to perform optimization of turning operations with multiple performance characteristics such as average surface roughness, maximum surface roughness, and roundness. The depth of cut was identified to be the most dominating parameter affecting the grey relational grade followed by cutting speed and feed rate. For simultaneous optimization of multi-responses, Taguchi's normalized quality loss function [11] and grey based Taguchi method have been popularly used in drilling [12], arc welding process [13] and turning [14] and greatly improved through this approach.

In the present study, the Taguchi method with fuzzy logic is used as an efficient approach to determine the optimal machining parameters for turned parts for optimization of surface roughness, material removal rate, machining force and cutting power. The experimental design used orthogonal array L_{27} for the three controllable factors, i.e., cutting speed, feed rate and depth of cut, each at three levels to find the optimum combination of factors and levels in turning of AA6351. The single-response optimization was conducted using Taguchi method. For a multi-response case, fuzzy logic unit (FLU) was employed to transform the four correlated responses to a single response called comprehensive output measure (COM). Finally, the analysis of variance (ANOVA) was used to find out the most influential turning parameter for problems of single and multiple responses.

Optimization of multiple performance characteristics with fuzzy logic

Originally developed by Fisher [15] the conventional experimental design methods [16] are complex in application due to increase in the number of experiments to be performed with the increase in the number of process parameters. Basically, the Taguchi method is designed to handle the optimization of a single performance characteristic. The normal recommendation for the optimization of a process with multiple performance characteristics is a matter of engineering judgment, as it involves achieving a tradeoff between several multiple conflicting problems and variables. The application of the Taguchi method in a process with multiple performance characteristics cannot be straightforward. In this paper, the use of fuzzy logic to deal with the optimization of a process with multiple performance characteristics is presented. First, several fuzzy rules are derived based on the performance requirement of the process. The loss function corresponding to each performance characteristic is fuzzified and then a single COM is obtained through fuzzy reasoning on the fuzzy rules. The COM can be used to optimize the process based on the Taguchi approach.

Turning Process Parameters and Material Selection

The turning process parameters and material selection are explained in detail in the following chapters.

A. Process parameters

The process parameters selected for the present work are shown in Table 1.

TABLE. 1. Machining Parameters and their Levels.

Sl.No	Factors	Unit	Symbols	Level 1	Level 2	Level 3
1	Cutting speed	m/min	v	75.39	113.09	150.79
2	Feed rate	mm/rev	f	0.05	0.10	0.15
3	Depth of cut	mm	d	1	1.5	2

B. Work material

The work material selected for the study was AA6351 Aluminium alloy, which is used extensively in the aviation industry. AA6351 alloy, whose main alloy elements are Mg and Si, is one of the most important alloy among 6XXX series and has a natural aging capability. Strength and hardness of AA6351 alloy can be increased by heat treatment. Test specimens used for the experiments were AA6351 aluminium alloy having 48 mm diameter and 300 mm length. Chemical composition of the test specimen is shown in Table. 2.

TABLE. 2. Chemical Composition of AA6351 alloy (% weight)

Si	Fe	Cu	Mn	Mg	Ti	Cr	Zn	Al
0.978	0.215	0.047	0.792	0.744	0.020	0.006	0.018	97.180

C. Tool material

The cutting tool selected for machining AA6351 was uncoated tungsten carbide inserts of Sandvik make. The tungsten carbide inserts used were of ISO coding DCGX 11 T3 04 Al H10 and tool holder of ISO coding SDJCR 2525. The selection of parameters of interest and their ranges was based on the literature reviewed and results of some preliminary experiments.

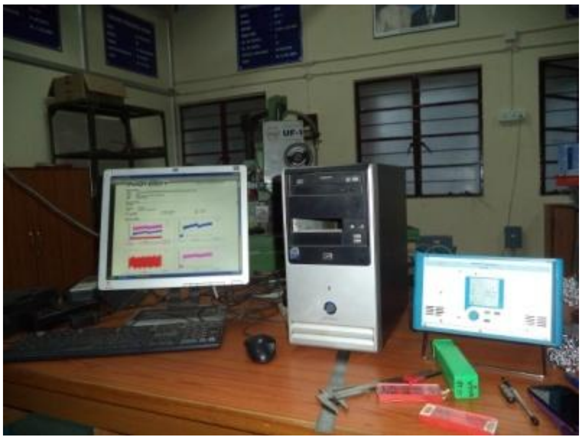
D. Experimental set up

The experiment for turning forces were carried out on a centre lathe with variable speed and feed drive (2.2 KW spindle power, 1400 rpm maximum rotational speed, manufactured by Kirloskar). Three different components of forces, namely cutting force (F_z), feed force (F_x) and thrust force (F_y) were measured through a Kistler 3-component piezoelectric dynamometer (Model 9257B) as shown in Fig.1.a. The charge generated at the dynamometer was amplified using three multi channel charge amplifier (Fig. 1 b.) (manufactured by kistler, Type 5070A). The amplified signal was acquired and sampled using data acquisition system and stored in computer using KISTLER Dynoware software. The surface roughness (Ra) was measured using Mitutoyo SJ-210 surface roughness tester. The machining force (F_m) and cutting power (P_c) were calculated from the following formulae.

$$F_m = \sqrt{F_x^2 + F_y^2 + F_z^2} \qquad (1)$$

$$P_c = F_c . v \qquad (2)$$

(a)



(b)

Fig. 1.Experimetal set up. a. piezoelectric dynamometer, b. Charge amplifier

Optimization of Turning Parameters

In this section, the use of the Taguchi method with fuzzy logic to determine the machining parameters with optimal machining performance in the turning process is illustrated.

A. Orthogonal array experiment

To select an appropriate orthogonal array for the experiments, the total degrees of freedom need to be computed. The degrees of freedom are defined as the number of comparisons between process parameters that need to be made to determine which level is better and specifically how much better it is. In the present study, the interaction between the machining parameters is neglected. Therefore, there are 6 degrees of freedom due to three, three-level machining parameters in turning process. Design of experiment (DOE) and Taguchi's techniques have been used to accomplish the objective of the experimental study. L27 orthogonal has been used for conducting the experiments and is shown in Table 3.

TABLE. 3. Experimental layout using an L_{27} Orthogonal array

Trial No	Cutting speed, v (m/min)	Feed rate, f (mm)	Depth of cut, d (mm)
1	75.39	0.05	1
2	75.39	0.05	1.5
3	75.39	0.05	2
4	75.39	0.1	1
5	75.39	0.1	1.5
6	75.39	0.1	2
7	75.39	0.15	1
8	75.39	0.15	1.5
9	75.39	0.15	2
10	113.09	0.05	1
11	113.09	0.05	1.5
12	113.09	0.05	2
13	113.09	0.1	1
14	113.09	0.1	1.5
15	113.09	0.1	2

16	113.09	0.15	1
17	113.09	0.15	1.5
18	113.09	0.15	2
19	150.79	0.05	1
20	150.79	0.05	1.5
21	150.79	0.05	2
22	150.79	0.1	1
23	150.79	0.1	1.5
24	150.79	0.1	2
25	150.79	0.15	1
26	150.79	0.15	1.5
27	150.79	0.15	2

B. Signal-to-noise ratio

Taguchi's loss function estimates the deviation between experimental value and desired value. Usually, there are three categories of the performance characteristics in the analysis of the signal-to-noise ratio, i.e., the smaller-the-better, the larger-the-better, and the nominal-the-best. To obtain optimal machining performance, the minimum R_a, F_m, P_c are desired therefore smaller-the-better characteristic is chosen for these three, where as maximum MRR is desired and therefore larger the better characteristics is chosen for MRR.

For 'smaller the better' type of machining quality characteristics, the S/N ratio is given by

$$S/N_{SB} = -10 \log_{10}\left(\frac{1}{n}\sum_{i=1}^{n} {y_i}^2\right) \quad (3)$$

where y_i is the value of surface roughness, machining force and cutting power for the i^{th} test in that trial.

For 'larger the better' type of machining quality characteristic, the S/N ratio is given by

$$S/N_{LB} = -10 \log_{10}\left(\frac{1}{n}\sum_{i=1}^{n} \frac{1}{{y_i}^2}\right) \quad (4)$$

where y_i is the value of MRR for the i^{th} test in that trial.

Table. 4 shows the experimental results for surface roughness, MRR, machining force and cutting power and their S/N ratio based on the experimental parameter combinations (Table 1). The table also shows that the engineering units for all the four measured outputs are different. To consider these four different performance characteristics in the Taguchi method, the S/N ratios corresponding to the surface roughness, MRR, machining force and cutting power are processed by the fuzzy logic unit.

TABLE. 4. Experimental results for output variables and their S/N ratio

Trial No	R_a		MRR		F_m		P_c	
	μ_m	S/N	mm^3/min	S/N	N	S/N	Watts	S/N
1	0.736	2.662	3691.371	71.344	113.13	-41.071	121.82	-41.714
2	0.76	2.384	5478.152	74.773	169.82	-44.600	183.57	-45.276
3	0.948	0.464	7225.663	77.178	199.85	-46.014	211.47	-46.505
4	1.051	-0.432	7382.743	77.364	221.28	-46.899	234.84	-47.415
5	1.07	-0.588	10956.3	80.793	289.76	-49.241	301.69	-49.591
6	1.251	-1.945	14451.33	83.198	347.84	-50.827	369.41	-51.350
7	2.018	-6.098	11074.11	80.886	342.80	-50.701	354.58	-50.994
8	2.162	-6.697	16434.46	84.315	481.96	-53.660	498.08	-53.946
9	2.242	-7.013	21676.99	86.720	502.86	-54.029	542.18	-54.683
10	1.06	-0.506	5537.057	74.866	119.51	-41.548	197.72	-45.921
11	1.103	-0.852	8217.228	78.295	144.12	-43.175	233.15	-47.353
12	1.109	-0.899	10838.49	80.699	138.36	-42.820	232.21	-47.318
13	1.228	-1.784	11074.11	80.886	207.37	-46.335	333.43	-50.460
14	1.295	-2.245	16434.46	84.315	215.56	-46.671	351.52	-50.919
15	1.449	-3.221	21676.99	86.720	266.39	-48.510	451.23	-53.088
16	2.091	-6.407	16611.17	84.408	278.88	-48.908	440.30	-52.875
17	2.251	-7.048	24651.68	87.837	361.09	-51.152	595.42	-55.496
18	2.259	-7.078	32515.48	90.242	372.60	-51.425	615.96	-55.791
19	0.971	0.256	7382.743	77.364	101.30	-40.113	220.30	-46.860
20	0.993	0.061	10956.3	80.793	131.87	-42.403	290.02	-49.249
21	1.099	-0.820	14451.33	83.198	149.65	-43.502	319.42	-50.087
22	1.368	-2.722	14765.49	83.385	177.44	-44.981	380.49	-51.607
23	1.46	-3.287	21912.61	86.814	227.97	-47.158	489.82	-53.801
24	1.375	-2.766	28902.65	89.219	270.59	-48.646	596.37	-55.510
25	2.102	-6.453	22148.23	86.907	209.72	-46.433	460.16	-53.258
26	2.142	-6.616	32868.91	90.336	298.50	-49.499	628.04	-55.960
27	2.257	-7.071	43353.98	92.741	363.56	-51.211	794.91	-58.006

C. Single characteristic optimization

When a single-response problem is considered, Taguchi method can be utilized to obtain the optimal level/factor combination of turning process. A smaller value of surface roughness, machining force and cutting power is normally required in metal machining. Therefore, the smaller-the-better methodology of S/N ratio was employed for the aforesaid responses. On the other hand for MRR, higher the better methodology of S/N ratio is employed, as higher value of the same is desired in metal machining. The S/N ratios of four responses of the 27 experimental runs are listed in Table. 4. along with their experimentally measured values.

The response table of S/N ratios of R_a was calculated, as shown in Table 5. The S/N ratio of factors v-f-d is maximum at v1, f1 and d1 respectively. As a result, the factor/level combination v1f1d1 was recommended. It can be seen that the contribution of factor feed rate to the R_a was the largest (94.51%) followed by factor cutting speed (2.49%) and depth of cut (1.41%). Thus, feed rate was most important factor followed by cutting speed as far as R_a is concerned.

The same analysis procedure was applied to optimize the turning conditions for the MRR, machining force and cutting power also. The levels that gave the better average response were v3f3d3 for MRR, v3f1d1 for the machining force, and v1f1d1 for the cutting power. A combined analysis of all the four ANOVAs showed that the optimal factor/level combination, or the most important factor, for one quality was usually different from that for another quality. In such a case, an engineering judgment that refers to past experience is the only real guarantee of correct decision-making in the turning process.

TABLE. 5. Response Table for S/N ratio of R_a

Level	Cutting speed(v)	Feed(f)	Depth of cut(d)
1	-1.9181	0.3056	-2.3871
2	-3.3378	-2.1100	-2.7653
3	-3.2686	-6.7201	-3.3721
Delta	1.4196	7.0257	0.9850
Rank	2	1	3

International Journal of Applied Engineering Research ISSN 0973-4562 Volume 10, Number 23 (2015) pp 43912-43918
© Research India Publications. http://www.ripublication.com

D. Fuzzy logic implementation and results for multiple responses in turning

A fuzzy logic unit (FLU) comprises a fuzzifier, membership functions, a fuzzy rule base, an inference system, and a defuzzifier. First, the fuzzifier uses membership functions to fuzzify the S/N ratios. Next, the inference system performs a fuzzy reasoning on fuzzy rules to produce a fuzzy value. Finally, the defuzzifier translates the fuzzy value into a COM. In the present work, fuzzy reasoning is based on the four-input-one-output fuzzy logic unit. The fuzzy rule base consists of a group of if-then control rules with the four inputs, x_1 and x_2, and one output y, i.e.,

- Rule 1: if x_1 is A_1 and x_2 is B_1 and x_3 is C_1 and x_4 is D_1 then y is E_1 else
- Rule 2: if x_1 is A_2 and x_2 is B_2 and x_3 is C_2 and x_4 is D_2 then y is E_2 else
- …
- Rule n: if x_1 is A_n and x_2 is B_n and x_3 is C_n and x_4 is D_n then y is E_n else.

A_i, B_i, C_i, D_i and E_i are fuzzy subsets defined by the corresponding membership functions, i.e., μA_i, μB_i, μC_i, μD_i, μE_i. In this paper, two fuzzy subsets (low and high) are assigned to the four inputs. Five fuzzy subsets are assigned to the only output COM. Various degree of membership to the fuzzy sets is calculated based on the values of x_1, x_2, x_3, x_4 and y. Sixteen fuzzy rules as given in Table 6. are derived directly based on the fact that larger is the S/N ratio, the better is the performance characteristic. By taking the max-min compositional operation the fuzzy reasoning of these rules yields a fuzzy output. Supposing that x_1, x_2, x_3 and x_4 are the four input values of the fuzzy logic unit, the membership function of the output of fuzzy reasoning can be expressed as

$$\mu C_0(y) = (\mu A_1(x_1)\ \Lambda\ \mu B_1(x_2)\ \Lambda\ \mu C_1(x_3)\ \Lambda\ \mu D_1(x_4)\ \mu E_1(y))$$

$$V \ldots (\mu A_n(x_1)\ \Lambda\ \mu B_n(x_2)\ \Lambda\ \mu C_n(x_3)\ \Lambda\ \mu D_n(x_4)\ \mu E_n(y)), \qquad (5)$$

Where Λ is the minimum operation and V is the maximum operation.

Finally, a defuzzification method, called the centroid method, is adopted here to transform the fuzzy inference output μC_0 into a non-fuzzy value yo, i.e.,

$$y_o = \frac{\Sigma y \mu C_0(y)}{\Sigma \mu C_0(y)} \qquad (6)$$

In this paper, the non-fuzzy value yo is called COM. Based on the above discussion, the larger is the COM, the better is the performance characteristic. Table. 7. shows the MATLAB generated fuzzy logic unit results for the COM using the experimental combinations of Table 3.

TABLE. 6. Fuzzy rules used

S/N for R_a	S/N for MRR	S/N for F_m	S/N for P_c	COM
Low	Low	Low	Low	Lowest
			High	Low
		High	Low	Low
			High	Medium
	High	Low	Low	Low
			High	Medium
		High	Low	Medium
			High	High
High	Low	Low	Low	Low
			High	Medium
		High	Low	Medium
			High	High
	High	Low	Low	Medium
			High	High
		High	Low	High
			High	Highest

TABLE. 7. Results for the COM

Run No.	Comprehensive output measure (COM)
1	0.726
2	0.588
3	0.55
4	0.522
5	0.495
6	0.471
7	0.414
8	0.325
9	0.305
10	0.575
11	0.553
12	0.559
13	0.501
14	0.508
15	0.472
16	0.429
17	0.368
18	0.363
19	0.589
20	0.57
21	0.549
22	0.506
23	0.481
24	0.473
25	0.459
26	0.386
27	0.311

E. Analysis of variance (ANOVA) of COM

The ANOVA investigates those process parameters which significantly affect the performance characteristics. This is accomplished by separating the total variability of the multi-response performance indexes, which is measured by the sum of the squared deviations from the total mean of the COM, into contributions by each of the process parameter and the error.

The response for COM is shown in Table.8. The results of ANOVA for COM shown in Table 9. indicates that feed rate is the most significant machining parameters in affecting the multiple performance characteristics (COM) followed by depth of cut and cutting speed. Based on the above discussion, the optimal machining parameters are the cutting speed at level 1 (v = 75.39 m/min), feed rate at level 1 (f = 0.05 mm/rev) and depth of cut at level 1 (d = 1 mm) or $v_1f_1d_1$ in short.

TABLE. 8. Response Table for COM

Level	Cutting speed(v)	Feed(f)	Depth of cut(d)
1	0.4884	0.5843	0.5246
2	0.4809	0.4921	0.4749
3	0.4804	0.3733	0.4503
Delta	0.0080	0.2110	0.0742
Rank	3	1	2

TABLE. 9. Analysis of Variance for COM, using Adjusted SS for Tests

Source	DF	Seq SS	Adj SS	Adj MS	F	P	% contribution
Cutting Speed (m/min)	2	0.000364	0.000364	0.000182	0.15	0.862	0.14%
Feed (mm)	2	0.201402	0.201402	0.100701	82.57	0.000	79.95%
Depth of cut (mm)	2	0.025736	0.025736	0.012868	10.55	0.001	10.21%
Error	20	0.024391	0.024391	0.001220			9.68%
Total	26	0.251893					

Conclusions

The hybrid Taguchi-fuzzy approach is used in this study to optimize the turning conditions of AA6351. The cutting parameters optimization is carried out through experiments with full factorial design. The fuzzification process takes care of the vagueness in the information and produces the best suitable cutting conditions in the present study. The results are summarized as follows:

(1) The factor/level combination v1f1d1 for surface roughness, v3f3d3 for MRR, v3f1d1 for machining power and v1f1d1 for cutting power are the recommended optimum parameters, for turning when all four responses are considered independently.

(2) It can be seen that the contribution of factor feed rate to the R_a was the largest (94.51%) followed by factor cutting speed (2.49%) and depth of cut (1.41%). It can be seen that the contribution of factor feed rate to the MRR was the largest (48.95%) followed by factor cutting speed (21.75%) and depth of cut(20.47%).

(3) It can be seen that the contribution of factor feed rate to the F_m was the largest (68.35%) followed by factor depth of cut (13.16%) and cutting speed (10.79%). It can be seen that the contribution of factor feed rate to the P_c was the largest (65.15%) followed by depth of cut (14.93%) and cutting speed (14.19%).

(4) In the multi-response problem, all the four responses surface roughness, material removal rate, machining force and cutting power were simultaneously considered, and v1f1d1 was the recommended optimum condition as per the hybrid Taguchi-fuzzy approach.

(5) It can be concluded that lower level of cutting speed (75.39 m/min), lower level of feed rate (0.05 mm/rev) and lower level of depth of cut (1 mm) yield the optimal result. It can be seen that the contribution of factor feed rate to the COM was the largest (79.95%) followed by depth of cut (10.21%) and cutting speed (0.14%).

It can be concluded that the optimization methodology developed in this study is useful in improving multiple performance characteristics in turning.

References

[1] A. Aggarwal, H. Singh, P. Kumar, & M. Singh, “Optimizing power consumption for CNC turned parts using response surface methodology and Taguchi's technique-A comparative analysis,” Journal of Materials Processing Technology, 200, pp. 373-384, 2008.

[2] E. A. Elsayed, A. Chen, “Optimal levels of process parameters for products with multiple characteristics,” International journal of Production Research, 31(5), pp. 1117-1132, 1993.

[3] L. Zadeh, “Fuzzy sets,” Information and Control, 8, pp. 338-353, 1965.

[4] J. L. Lin, K. S. Wang, B. H. Yan, Y. S. Tarng, Y. S., “Optimization of the electrical discharge machining process based on the Taguchi method with fuzzy logics,” Journal of Material processing technology, 102, pp. 48-55, 2000.

[5] Hasan Gokkaya, Ahmet Taskesen, “The effects of cutting speed and feed rate on BUE-BUL formation, cutting forces and surface roughness when machining AA6351 (T6) Alloy,” Journal of Mechanical Engineering, 54, 7-8, pp. 521-530, 2008.

[6] A. Mahamani, “Influence of process parameters on cutting force and surface roughness during turning of AA2219-TiB2/ZrB2 In-situ metal matrix composites,” Procedia material science, 6, pp. 1178-1186, 2014.

[7] Surendra kumar saini, Sharad kumar pradhan, “Optimization of multi-objective response during CNC turning using Taguchi-Fuzzy application, Procedia Engineering, 97, pp. 141-149, 2014.

[8] Anil Gupta, Hari singh, Aman Aggarwal, “Taguchi-fuzzy multi output optimization (MOO) in high speed CNC turning of AISI P-20 tool steel,” Expert systems with applications, 38, pp. 6822-6828, 2011.

[9] Ashok Kumar Sahoo, Achyuta Nanda Baral, Arun Kumar Rout, B. C. Routra, “Multi-objective optimization and predictive modeling of surface roughness and material removal rate in turning using Grey Relational and Regression Analysis,” Procedia Engineering, 38, pp. 1606-1627, 2012.

[10] Chorng-Jyh Tzeng, Yu-Hsin Lin, Yung-Kuang Yang, Ming-Chang Jeng, “Optimization of turning

operations with multiple performance characteristics using the Taguchi method and Grey relational analysis," Journal of Materials Processing Technology, 209, pp. 2753-2759, 2009.

[11] C. Y. Nian, W. H. Yang, Y. S. Tarng, "Optimization of turning operations with multiple performance characteristics," Journal of Materials Processing Technology, 95, pp. 90-96, 1999.

[12] A. Noorul Haq, P. Marimuthu, R. Jeyapaul, "Multi response optimization of Machining parameters of drilling Al/SiC Metal matrix composite using grey relational analysis in the Taguchi method," International Journal of Advanced Manufacturing Technology, 37, pp. 250-255, 2008.

[13] S. Datta, A. Bandyopadhyay, P. K. Pal, "Modeling and optimization of features of bead geometry including percentage dilution in submerged arc welding using mixture of fresh flux and fused slag," International Journal of Advanced Manufacturing Technology, 36, pp. 1080-1090, 2008.

[14] C. L. Lin, "Use of Taguchi method and grey relational analysis to optimize turning operations with multiple performance characteristics," Materials & Manufacturing Processes, 19/2, pp. 209-220, 2004.

[15] R. A., Fisher, Statistical methods for research worker, London: Oliver & Boyd, 1925.

[16] D. C. Montgomery, Design and analysis of experiments (4^{th} ed.), New York; Wiley, 1997.