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Empirical modelling of machining parameters for turning operations using multi-objective Taguchi method

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ABSTRACT

This paper presents an effective approach for the optimisation of process parameters in the turning operation for machining ASTM A36 Mild Steel bar with multi-performance characteristics using multi-objective Taguchi method. Based on Taguchi orthogonal array, 27 experimental runs were performed to identify the optimal level of process parameters. The multiple performance characteristics including power consumption, surface roughness and frequency of tool vibration were the quality variables considered for the optimisation. An input-output inprocess parameter relationship model was developed using regression analysis for the power consumption, surface roughness and frequency of tool vibration. The optimum combination of machining parameters and their levels for the optimum multi-performance characteristics of the turning process was $A_1B_1C_1$ (i.e. speed: 160 r.p.m, feed rate: 0.08 mm/rev and depth-of-cut: 0.1 mm). This study will be very useful to shop floor engineers in deciding the levels of the turning parameters for optimal performance characteristics.

Keywords: ANOVA; Taguchi method; optimisation; regression analysis; Turning.

INTRODUCTION

Turning is one of the most basic machining processes in industrial production systems. It is carried out on a lathe that provides the power to turn the workpiece at a given rotational speed and feed the cutting tool at a specified rate and depth of cut. Researchers have attempted several approaches to identify multiple process parameter settings that can increase quality at higher productivity levels, requiring the turning process to be executed more efficiently [1-4]. Thus, it is of utmost important to identify the optimal parameter settings to increase tool life, improve surface accuracy, and reduce cutting force and chip thickness in turning operations. Cutting speed, feed rate, depth of cut, tool-workpiece material, tool geometry, and coolant conditions are the turning parameters that highly affect the performance [5-8]. Turning produces three cutting force components: the main cutting force i.e. thrust force, (F_Z), which is produced in the cutting speed direction; feed force, (F_X), which is produced in the feed rate direction; and radial force, (F_Y), which is produced in radial direction and normal to the cutting speed). Out of the three force components, the cutting force (main force) constitutes about 70% to 80% of the total force 'F' and is used to calculate the power 'P' required to perform the machining operation. Power is the product of main cutting force and the cutting velocity and is a better criterion for design and selection of any machine tools. Power consumption may be used for monitoring the tool conditions [9-12]. Many researchers and practitioners have studied the effects of optimal selection of machining parameters in turning.

Anthony [13] has demonstrated the Taguchi quality loss function based on multi-objective optimisation technique for manufacturing processes with an example of the electronic assembly process and found considerable improvement in multiple quality characteristics in comparison to single quality characteristics. Multi-objective Taguchi method (MTM) approach has been used for the optimisation of the laser beam cutting process by Dubey and Yadava [14]. The authors found that quality characteristics were improved considerably. Sometimes, scientific methods based on Taguchi orthogonal array were used [15]. This method can analyse and provide optimum parameters for a given set of independent parameters and a response variable. Fong and Chen [16] presented an approach to optimise the process parameters in the turning of tool steels. They performed Taguchi experiments with eight independent parameters that included cutting speed, feed, and depth of cut, coating type, type of insert, chip breaker geometry, coolant, and band nose radius. The optimum turning parameters were determined based on grey relational grade that maximised the accuracy and minimised the surface roughness and dimensional precision. Several researchers and practitioners have applied grey relational analysis (GRA) to different machining processes that included electric discharge machining [17], determining tool condition in turning [18], chemical mechanical polishing [19], side milling [19, 20], and flank milling [21] to compare the performance of diamond tool carbide inserts in dry turning [22], and optimisation of drilling parameters to minimise surface roughness and burr height [23]. Lin [24] used grey relational analysis to optimise turning operations with multiple performance characteristics and analysed the tool life, cutting force, and surface roughness in turning operations. Al-Refaie et al. [25] applied the Taguchi method grey analysis (TMGA) to determine the optimal combination of control parameters in milling and measuring the machining performance such as the material removal rate and surface roughness. Based on the ANOVA, it was found that the feed rate was significant to the control parameters for responses. The machining parameters are usually selected based on either the experience or the proposed guidelines of the manufacturers. This selection procedure does not lead to the optimal and economically effective use of the machines and the quality of the surface generated. Hence, there is a necessity for a simple and effective experimental method for a multi-objective optimisation problem [11, 26-30].

The purpose of this paper is to present the application of multi-objective Taguchi method in selecting optimum turning conditions on multi-performance characteristics, namely the power consumption, surface roughness and frequency of tool vibration. In addition, significant controllable process parameters which affect the multi-performance characteristics in the turning process were determined. Further mathematical models were developed from the experimental results which were used in the quantification of power consumption, surface roughness and frequency of tool vibration. Thus, the results can be used by engineers willing to identify an optimal solution of the turning operation of ASTM A36 Mild Steel bar.

METHODS AND MATERIALS

Experimental Setup

The experiments were carried out on an experimental lathe setup. The workpiece material was ASTM A36 Mild Steel bar of 24 mm in diameter. The cutting tool was HSS MIRANDA S-400 (AISI T – 42). The composition percentage of the workpiece material is listed in Table 1. In the present experimental study, spindle speed, feed and depth of cut were considered as machining parameters. The machining parameters with their units and their levels as considered for experimentation are listed in Table 2. Flowchart of the methodology used is shown in Figure 1.

Table 1. Chemical composition of Mild Steel (ASTM A36) [31].

Material Composition	C	Mn	Si	S	P
Weight Percentage (%)	0.15	0.79	0.22	0.022	0.030

Table 2. Machining parameters and their limits.

Symbol	Machining Parameter	Unit	Level 1	Level 2	Level 3
A	Spindle Speed	RPM	160	240	400
B	Feed	mm/rev	0.08	0.16	0.32
C	Depth of cut	mm	0.1	0.15	0.2

Table 3 shows the specifications of the Panther Lathe machine. This machine has been manufactured with a view to obtain the highest degree of working accuracy and it has been thoroughly tested for its performance to confirm IS 11118-1984, IS 1878(part - I)-1971.

Table 3. Specifications of Panther Lathe [Model-2050/4].

Parameters	Value	Unit
Length of bed	3030	mm
Height of centre	270	mm
Width of bed	325	mm
Swing over cross slide	325	mm
Swing in gap	830	mm
Motor capacity	3	HP
No. of spindle speed / range	8	-
Spindle speed range	30 - 1235	rpm
Spindle bore	52	mm
Spindle nose	A2 Size 6	-
Taper in centre sleeve	4	MT
Tail stock spindle diameter	63	mm
Feed range	40	mm/Rev.
Range of longitudinal speed per rev.	0.064 to 1.98	mm/Rev.
Transverse feeds per revolution	0.016 to 0.48	mm/Rev.
Threads no. range	40/2 to 60	TPI

Measurement of Quality Responses

After cutting all the specimens, the roughness of the cut surface was measured by utilising the Mar Surf PS1 surface roughness tester. Arithmetic mean roughness (R_a) was utilised as the surface finish parameter to demonstrate the surface quality of the machined specimens. Cutting forces were measured using the Lathe tool dynamometer and cutting tool vibration was measured using the PicoScope 2202.

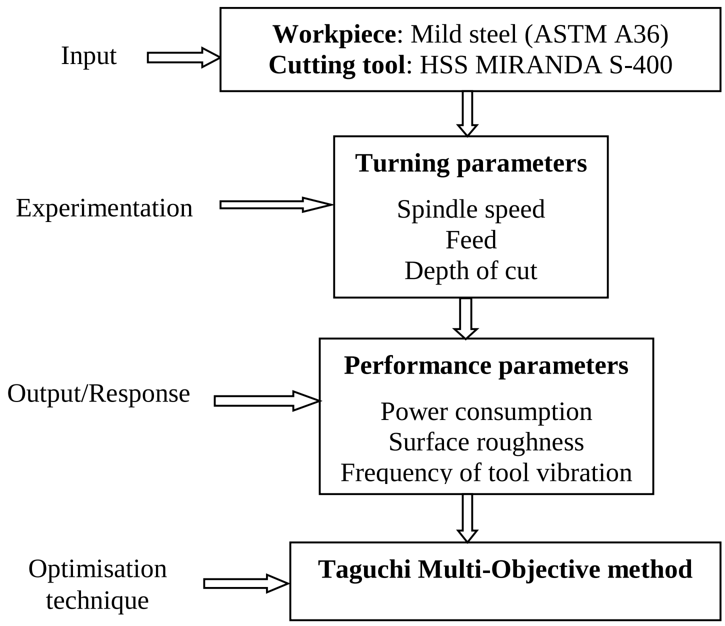

Figure 1. Flowchart of the methodology used.

The power to perform machining can be computed from $P = F_c \times V$, where, P = cutting power, F_c = cutting or tangential force [this force is in the direction of primary motion. It constitutes about 70~80 % of the total force] and V = cutting speed. Dynamometer is a cutting force measuring instrument used to measure the cutting forces coming on the tool tip on the Lathe Machine. The sensor is designed in such a way that it can be rigidly mounted on the tool post and the cutting tool can be fixed to the sensor directly. This feature will help to measure the forces accurately without loss of the force. The sensor is made of a single element with three different wheat stones strain gauge bridge. Provision was made to fix 1/2" size tool bit at the front side of the sensor.

Capacity	:X,Y,Z-Force500kg
Excitation	10Vdc
Linearity	:2%
Accuracy	2%
Cross-Sensitivity	5%
Max. Over Load	: 150

Taguchi and Multi-objective Taguchi Method

Taguchi's robust design is a simple, systematic and more efficient technique for optimising the process parameters [32]. In this method, the main parameters which are assumed to have influence on the process results are located at different rows in a designed orthogonal array (OA). With such arrangement, completely randomised experiments can be conducted. An advantage of the Taguchi method is that it emphasises a mean performance characteristic value close to the target value rather than a value within certain specification limits, thus improving the product quality. Experimental conditions, cutting force and calculated power is presented in Table 4.In this present work, optimisation of welding operations using Taguchi's robust design methodology with multiple performance characteristics is proposed. In order to optimise the multiple performance characteristics, the Taguchi parametric design approach was not applied directly, since each performance characteristic may not have the same measurement unit and of the same category in the S/N ratio analysis. Therefore, to solve problems of this kind, steps 1– 3 were followed first, and then the traditional Taguchi technique for single response optimisation was performed.

Table 4. Experimental conditions, cutting force and calculated power.

Exp. No	Spindle Speed (RPM)	Feed rate (mm/rev)	Depth of cut (mm)	Force, F_c (N)	Cutting speed, V (m min^{-1})	Power, P (W)
1	160	0.08	0.15	48	12.06	9.65
2	160	0.08	0.2	64	12.06	12.86
3	160	0.32	0.15	192	12.06	38.6
4	160	0.32	0.1	87.04	12.06	17.5
5	160	0.16	0.1	43.68	12.06	8.8
6	400	0.32	0.15	130.56	30.16	65.63
7	240	0.16	0.1	50.68	18.09	15.28
8	400	0.16	0.15	70.52	30.16	35.5
9	160	0.16	0.2	107.36	12.06	21.6
10	400	0.16	0.1	54.68	30.16	27.5
11	240	0.16	0.15	80.52	18.09	24.28
12	400	0.08	0.2	64	30.16	32.17
13	240	0.32	0.1	100.04	18.09	30.16
14	240	0.08	0.1	25	18.09	7.54
15	240	0.08	0.15	48	18.09	14.47
16	160	0.08	0.1	33	12.06	6.63
17	240	0.08	0.2	64	18.09	19.3
18	160	0.32	0.2	174.08	12.06	35
19	400	0.08	0.15	38	30.16	19.1
20	160	0.16	0.15	80.52	12.06	16.2
21	400	0.16	0.2	127.36	30.16	64.02
22	240	0.32	0.15	192	18.09	57.9
23	400	0.32	0.1	109.36	30.16	56
24	240	0.32	0.2	194.08	18.09	58.5
25	400	0.32	0.2	174.08	30.16	87.5
26	240	0.16	0.2	127.36	18.09	38.4
27	400	0.08	0.1	27.34	30.16	13.74

Step 1: The loss function was normalised corresponding to each performance characteristic as follows-

$$y_{ij} = \frac{L_{ij}}{L_i^*} \tag{1}$$

where, y_{ij} is the normalised quality loss associated with the ith quality characteristic at the jth trial condition, and it varies from a minimum of zero to a maximum of 1. L_{ij} is the quality loss or MSD for the ith quality characteristic at the jth trial, and L_i* is the maximum quality loss for the ith quality characteristic among all the experimental runs.

Step 2: A weighting method was applied to determine the importance of each normalised loss function. The total normalised quality loss function Y_j in the jth experiment is given under:

$$Y_j = \sum_{i=1}^{k} W_i y_{ij} \tag{2}$$

where, W_i represents the weighting factor for the ith quality characteristic and k is the total number of quality characteristics.

Step 3: In multi-objective optimisation, a single overall S/N ratio for all quality characteristics is computed in place of separate S/N ratios for each of the quality characteristic. This overall S/N ratio is known as multiple S/N ratio (MSNR). The total loss function was transformed into a multiple S/N ratio (MSNR) as follows:

$$MSNR = -10\log_{10}(Y_j) \tag{3}$$

Based on the multiple S/N ratio (MSNR), the optimal factors or level combination were determined like the traditional Taguchi technique. Finally, the optimal process parameters were verified through the confirmation experiment. Usually, there are three categories of quality characteristics in the analysis of S/N ratio: nominal the better, the lower the better and the higher the better. The summary statistics η (dB) of the HB performance characteristics is expressed as follows:

$$\eta = -10\log_{10}\left[\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_i^2}\right] \tag{4}$$

where i=1, 2 ….n

The summary statistics η (dB) of the LB performance characteristics is expressed as follows:

$$\eta = -10\log_{10}\left[\frac{1}{n}\sum_{i=1}^{n} y_i^2\right] \tag{5}$$

where i=1, 2 ….n

RESULTS AND DISCUSSION

Multi-objective optimisation

From Table 5, quality loss values for different quality characteristics (smaller-is-better for power consumption, frequency of tool vibration and also for surface roughness) in each experimental run were calculated using Eqs. (4). These quality loss values are shown in Table 6. The normalised quality loss values for all the quality characteristics in each experimental run have been calculated using Eq. (1) as shown in Table 7. The total normalised quality loss values (TNQL) and MSNR for multiple quality characteristics for power consumption, frequency of tool vibration and also for surface roughness have been calculated using Eqs. (2) and (3), respectively [11]. These results are shown in Table 8. In calculating the total normalised quality loss values, three unequal weights, w_1= 0.4 for power consumption, w_2= 0.4 for surface roughness, and w_3=0.2 for frequency of tool vibration were used. Higher weighting factor was assigned to the power consumption and also for surface roughness because it is more important compared to the frequency of tool vibration in order to achieve good quality in the turning process. The effect of different control factors on MSNR is shown in Table 9. The optimum set of parameters was A in the first level, B in the first level, and C in the first level respectively (A1B1C1).

Table 5. Experimental design and collected response data.

Exp. No.	Input Parameters			Responses		
	Spindle Speed (RPM)	Feed (mm/rev)	Depth of cut (mm)	Power consumption P(W)	Surface roughness R_a (μm)	Frequency of tool vibration f (Hz)
1	160	0.08	0.15	9.65	1.97	270.7
2	160	0.08	0.2	12.86	2.01	281
3	160	0.32	0.15	38.6	6.84	335
4	160	0.32	0.1	17.5	6.16	322.9
5	160	0.16	0.1	8.8	2.58	295
6	400	0.32	0.15	65.63	5.46	395
7	240	0.16	0.1	15.28	2.38	326.5
8	400	0.16	0.15	35.5	1.68	362
9	160	0.16	0.2	21.6	3.02	310
10	400	0.16	0.1	27.5	2.29	347
11	240	0.16	0.15	24.28	2.20	337.7
12	400	0.08	0.2	32.17	1.66	355
13	240	0.32	0.1	30.16	6.01	350
14	240	0.08	0.1	7.54	1.59	297
15	240	0.08	0.15	14.47	1.80	321
16	160	0.08	0.1	6.63	1.88	260
17	240	0.08	0.2	19.3	1.82	327
18	160	0.32	0.2	35	6.72	347
19	400	0.08	0.15	19.1	1.54	340
20	160	0.16	0.15	16.2	3.42	302.7
21	400	0.16	0.2	64.02	2.60	384
22	240	0.32	0.15	57.9	5.84	370
23	400	0.32	0.1	56	5.82	376
24	240	0.32	0.2	58.5	6.28	375.7
25	400	0.32	0.2	87.5	5.89	420
26	240	0.16	0.2	38.4	2.84	357
27	400	0.08	0.1	13.74	1.38	322

Confirmation test

After obtaining the optimal level of the machining parameters, the next step was to verify the improvement of the performance characteristics using this optimal combination. The confirmation experiment was performed by conducting a test with a specific combination of the factors and levels previously evaluated. Then, the predicted value of MSNR ($\hat{\gamma}$) at the optimum parameter levels was evaluated by using the following equation:

$$\hat{\gamma} = \gamma_m + \sum_{i=0}^{o}(\overline{\gamma_J} - \gamma_m) \tag{6}$$

where $\gamma_m$is the mean MSNR of all experimental runs, $\overline{\gamma_J}$ is the average MSNR at the optimum level and o is the number of machining parameters that significantly affects the multiple performance characteristics.

Finally, experiments were conducted by using the best process parameters for optimum performance characteristics, and the mean results are presented in Table 10. Hence, using the present approach, turning of ASTM A36 Mild Steel was successfully optimised for power consumption, frequency of tool vibration and also for surface roughness.

Table 6. Quality loss values for weld bead width and weld bead hardness.

Expt. No	Power consumption	Surface roughness	Frequency of tool vibration	Expt. No	Power consumption	Surface roughness	Frequency of tool vibration
1	-19.691	-5.889	-48.650	15	-23.209	-5.105	-50.130
2	-22.185	-6.064	-48.974	16	-16.430	-5.483	-48.300
3	-31.732	-16.701	-50.501	17	-25.711	-5.201	-50.291
4	-24.861	-15.792	-50.181	18	-30.881	-16.547	-50.807
5	-18.890	-8.232	-49.396	19	-25.621	-3.750	-50.630
6	-36.342	-14.744	-51.932	20	-24.190	-10.681	-49.620
7	-23.682	-7.532	-50.278	21	-36.126	-8.299	-51.687
8	-31.005	-4.506	-51.174	22	-35.254	-15.328	-51.364
9	-26.689	-9.600	-49.827	23	-34.964	-15.299	-51.504
10	-28.787	-7.197	-50.807	24	-35.343	-15.959	-51.497
11	-27.705	-6.848	-50.571	25	-38.840	-15.402	-52.465
12	-30.149	-4.402	-51.005	26	-31.687	-9.066	-51.053
13	-29.589	-15.578	-50.881	27	-22.760	-2.798	-50.157
14	-17.547	-4.028	-49.455				

Table 7. Normalised quality loss values.

Expt. No	Power consumption	Surface roughness	Frequency of tool vibration	Expt. No	Power consumption	Surface roughness	Frequency of tool vibration
1	0.507	0.353	0.937	15	0.598	0.306	0.965
2	0.571	0.363	0.943	16	0.423	0.328	0.930
3	0.817	1.000	0.972	17	0.662	0.311	0.968
4	0.640	0.946	0.966	18	0.795	0.991	0.978
5	0.486	0.493	0.951	19	0.660	0.225	0.975
6	0.936	0.883	1.000	20	0.623	0.640	0.955
7	0.610	0.451	0.968	21	0.930	0.497	0.995
8	0.798	0.270	0.985	22	0.908	0.918	0.989
9	0.687	0.575	0.959	23	0.900	0.916	0.992
10	0.741	0.431	0.978	24	0.910	0.956	0.992
11	0.713	0.410	0.974	25	1.000	0.922	1.010
12	0.776	0.264	0.982	26	0.816	0.543	0.983
13	0.762	0.933	0.980	27	0.586	0.168	0.966
14	0.452	0.241	0.952				

Table 8. Total normalised quality loss values (TNQL) and Multiple S/N ratios (MSNR).

Expt. No	TNQL	MSNR (dB)	Expt. No	TNQL	MSNR (dB)
1	0.531	2.747	15	0.554	2.562
2	0.562	2.500	16	0.487	3.129
3	0.921	0.356	17	0.583	2.343
4	0.828	0.822	18	0.910	0.409
5	0.582	2.351	19	0.549	2.607
6	0.927	0.327	20	0.696	1.574
7	0.618	2.091	21	0.770	1.136
8	0.624	2.046	22	0.928	0.325
9	0.697	1.570	23	0.925	0.339
10	0.664	1.775	24	0.945	0.248
11	0.644	1.910	25	0.971	0.128
12	0.612	2.130	26	0.740	1.307
13	0.874	0.586	27	0.495	3.058
14	0.468	3.301			

Table 9. Multiple S/N responses (average factor effect at different levels).

Symbol	Factors	Mean of multiple S/N ratio (dB)			
		Level I	Level II	Level II	Max- Min
A	Spindle Speed	1.718*	1.630	1.505	0.213
B	Feed	2.708*	1.751	0.393	2.315
C	Depth of cut	1.939*	1.606	1.308	0.631

[* Shows optimal turning parameters]

Table 10. Results of the confirmation experiment.

	Initial machining parameters	Optimal machining parameters	
		Prediction	Experiment
Setting Level	$A_1B_1C_2$	$A_1B_1C_1$	$A_1B_1C_1$
Power consumption P(W)	9.65		6.63
Surface roughness R_a(μm)	1.97		1.88
Frequency of tool vibration f(Hz)	270.7		260
Multiple S/N ratio (dB)	2.747439	3.12962	3.128776

Improvement in multiple S/N ratio = 0.381337 dB

Table 11. Log transformed for process parameters.

N	ln (N)	f	ln (f)	d_{cut}	ln (d_{cut})	N	ln (N)	f	ln (f)	d_{cut}	ln (d_{cut})
160	5.075	0.08	-2.526	0.15	-1.897	240	5.481	0.08	-2.526	0.15	-1.897
160	5.075	0.08	-2.526	0.2	-1.609	160	5.075	0.08	-2.526	0.1	-2.303
160	5.075	0.32	-1.139	0.15	-1.897	240	5.481	0.08	-2.526	0.2	-1.609
160	5.075	0.32	-1.139	0.1	-2.303	160	5.075	0.32	-1.139	0.2	-1.609
160	5.075	0.16	-1.833	0.1	-2.303	400	5.991	0.08	-2.526	0.15	-1.897
400	5.991	0.32	-1.139	0.15	-1.897	160	5.075	0.16	-1.833	0.15	-1.897
240	5.481	0.16	-1.833	0.1	-2.303	400	5.991	0.16	-1.833	0.2	-1.609
400	5.991	0.16	-1.833	0.15	-1.897	240	5.481	0.32	-1.139	0.15	-1.897
160	5.075	0.16	-1.833	0.2	-1.609	400	5.991	0.32	-1.139	0.1	-2.303
400	5.991	0.16	-1.833	0.1	-2.303	240	5.481	0.32	-1.139	0.2	-1.609
240	5.481	0.16	-1.833	0.15	-1.897	400	5.991	0.32	-1.139	0.2	-1.609
400	5.991	0.08	-2.526	0.2	-1.609	240	5.481	0.16	-1.833	0.2	-1.609
240	5.481	0.32	-1.139	0.1	-2.303	400	5.991	0.08	-2.526	0.1	-2.303

Regression Analysis of Performance Characteristics

Regression analysis [22] for power consumption (P_c), surface roughness (R_a) and frequency of tool vibration (fv) of the materials was obtained by using the statistical software MINITAB 13. The correlations were formed for process parameters by assuming a log transformed response variable and are listed in Tables 11 and 12. The following model was assumed for the best curve fitting:

$$\ln (Y) = \beta_0 + \beta_1 \ln(N) + \beta_2 \ln (f) + \beta_3 \ln (doc)$$

where, Y is the performance characteristics and β_0, β_1, β_2, β_3 are regression coefficients.

Table 12. Log transformed for performance characteristics.

P_c	ln (P_c)	R_a	ln (R_a)	f.v	ln (f.v)	P_c	ln (P_c)	R_a	ln (R_a)	f.v	ln (f.v)
9.65	2.267	1.97	0.678	270.7	5.601	14.47	2.672	1.8	0.588	321	5.771
12.86	2.554	2.01	0.698	281	5.638	6.63	1.892	1.88	0.631	260	5.561
38.6	3.653	6.84	1.923	335	5.814	19.3	2.960	1.82	0.599	327	5.790
17.5	2.862	6.16	1.818	322.9	5.777	35	3.555	6.72	1.905	347	5.849
8.8	2.175	2.58	0.948	295	5.687	19.1	2.950	1.54	0.432	340	5.829
65.63	4.184	5.46	1.697	395	5.979	16.2	2.785	3.42	1.230	302.7	5.713
15.28	2.727	2.38	0.867	326.5	5.788	64.02	4.159	2.6	0.956	384	5.951
35.5	3.570	1.68	0.519	362	5.892	57.9	4.059	5.84	1.765	370	5.914
21.6	3.073	3.02	1.105	310	5.737	56	4.025	5.82	1.761	376	5.930
27.5	3.314	2.29	0.829	347	5.849	58.5	4.069	6.28	1.837	375.7	5.929
24.28	3.190	2.2	0.788	337.7	5.822	87.5	4.472	5.89	1.773	420	6.040
32.17	3.471	1.66	0.507	355	5.872	38.4	3.648	2.84	1.044	357	5.878
30.16	3.407	6.01	1.793	350	5.858	13.74	2.620	1.38	0.322	322	5.775

Quantification of power consumption

The regression analysis results for power consumption are presented in Table 13, which yielded the correlation between the power consumption and process parameters.

$$\ln (Pc) = 1.66 + 0.960 \ln(N) + 0.872 \ln (f) + 1.11 \ln (doc) \tag{7}$$

The above equation can also be expressed in exponential form as follows:

$$P_C=5.259 (N)^{0.960}(f)^{0.872}(d.o.c)^{1.11} \tag{8}$$

Table 13. Coefficients and intercepts for power consumption.

Predictor	Coef	SE Coef	T	P
Constant	1.6653	0.4210	3.93	0.001
ln(N)	0.96005	0.06779	14.16	0.000
ln(f)	0.87202	0.04491	19.42	0.000
ln(doc)	1.11350	0.08939	12.46	0.000

S = 0.1321 R-Sq = 97.0% R-Sq (adj) = 96.6%

Quantification of surface roughness

Similarly, the regression analysis results for surface roughness are presented in Table 14 which yielded the correlation between the surface roughness and process parameters.

$$\ln (Ra) = 4.47 - 0.257 \ln(N) + 0.910 \ln (f) + 0.152 \ln (doc) \tag{9}$$

The above equation can also be expressed in exponential form as follows:

$$R_a=87.36(N)^{-0.257}(f)^{0.910}(d.o.c)^{0.152} \tag{10}$$

Table 14. Coefficients and intercepts for surface roughness.

Predictor	Coef	SE Coef	T	P
Constant	4.4726	0.5132	8.71	0.000
ln(N)	-0.25731	0.08265	-3.11	0.005
ln(f)	0.91010	0.05475	16.62	0.00
ln(doc)	0.1517	0..1090	1.39	0.177

S = 0.1610 R-Sq = 92.6% R-Sq (adj) = 91.6%

Quantification of Frequency of Tool Vibration

The regression analysis results for frequency of tool vibration are presented in Table 15 which yielded the correlation between the frequency of tool vibration and process parameters.

$$\ln(f.v) = 5.13 + 0.208 \ln(N) + 0.125 \ln(f) + 0.122 \ln(doc) \tag{11}$$

The above equation can also be expressed in the exponential form as follows:

$$f.v = 169.01\,(N)^{0.208}(f)^{0.125}(d.o.c)^{0.122} \tag{12}$$

Table 15. Coefficients and intercepts for frequency of tool vibration.

Predictor	Coef	SE Coef	T	P
Constant	5.13002	0.07546	67.99	0.000
ln(N)	0.20810	0.01215	17.13	0.000
ln(f)	0.124950	0.008050	15.52	0.000
ln(doc)	0.12209	0.01602	7.62	0.000
S = 0.02367	R-Sq = 96.3%	R-Sq (adj) = 95.8%		

The regression analysis Eqs. (8), (10) and (12) determined the value of power consumption, surface roughness and frequency of tool vibration respectively for the turning of ASTM A36 Mild Steel. This would serve as a useful guide for selecting the proper values of process parameters to obtain the desired power consumption, surface roughness, and frequency of tool vibration of the turned product. It can be seen from Table 16 that p-values for the response power consumption, surface roughness and frequency of tool vibration were less than 0.05, which showed that they were significant. Also, the values of R-sq (adj) were more than 90%, which indicated a good fit. It confirmed that the model has adequately described the observed data.

Table 16. ANOVA for power consumption, surface roughness and frequency of tool vibration.

Source	DF	SS	MS	F	P
Power consumption					
Regression	3	12.7805	4.2602	244.25	0.000
Residual Error	23	0.4012	0.0174		
Total	26	13.1816			
Surface roughness					
Regression	3	7.4646	2.4882	95.98	0.000
Residual Error	23	0.5962	0.0259		
Total	26	8.0609			
Frequency of tool vibration					
Regression	3	0.33190	0.11063	197.43	0.000
Residual Error	23	0.01289	0.00056		
Total	26	0.34479			

CONCLUSIONS

In this paper, an attempt has been made for the optimisation of the turning process of mild steel with multi-performance characteristics based on the combined full factorial design of experiments and Grey relational analysis. Based on the results of the present study, the following conclusions are drawn:

- The optimum combination of turning parameters and their levels for the optimum multi-performance characteristics of turning process was $A_1B_1C_1$ (i.e. speed—160 r.p.m., feed rate—0.08 mm/rev and depth-of-cut—0.1 mm).
- Among the tested parameters, the feed rate showed the strongest correlation to power consumption and surface roughness.
- Confirmation test results proved that the determined optimum condition of turning parameters satisfied the real requirements.

Regression models correlating power consumption, surface roughness and frequency of tool vibration with process parameters have also been obtained. These equations provide a useful guide for setting proper values of turning parameters as to obtain the desired power consumption, surface roughness and frequency of tool vibration. Further into the future, researchers might attempt to consider the other performance criteria, such as tool wear, surface morphology of machined surface, MRR etc. as output parameters.

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