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Optimization of Cutting Parameters for Hard Boring of AISI 4340 Steel Using Signal-to-Noise Ratio, Grey Relation Analysis and Analysis of Variance

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Abstract
Tool vibration in the boring process is the main concern because of the tool overhanging which leads to high tool wear, cutting force and cutting temperature. Interaction between machine dynamics and the metal cutting operation tool also results in tool vibration. The optimized cutting parameters will able to decrease tool vibration and in turn, increase the productivity in the manufacturing sector. In this study, statistical mathematical approaches to develop models for determining the impact of individual cutting parameters on cutting temperature, tool wear, cutting force, and tool vibration when hard boring AISI 4340 steels. During hard boring of AISI 4340 steel, the current investigation consisted of 27 run trials with three varying levels of cutting velocity, feed rate, and depth of cut and each of these variables was tested at three different levels. This work intends to simultaneous optimize statistical analysis such as Signal-to-Noise (S/N) ratio, Analysis of Variance (ANOVA) and Grey Relational Analysis (GRA). ANOVA and S/N ratio is used to identify the important cutting parameters on the single response optimization and GRA is used to optimize the multi-response optimization technique on cutting parameters. The results shows that both single and multi-response optimization technique shows the same optimized cutting parameter.

Keywords
hard boring, tool vibration, cutting temperature, cutting force, Taguchi, ANOVA, GRA

1 Introduction

Boring operation is used to enlarge holes in a casting or that are pre-drilled on a structure. The operation is tedious when compared with external turning process due to the variables impacting the cutting parameters. Tool wear, greater cutting force, and elevated temperatures are all brought on by the considerable length of boring bar, which in turn causes vibrations. Among most common uses of boring are the expanding and smoothing of previously drilled, cored, or pierced holes and internal surfaces. According to Quintana and Ciurana [1] unstable cutting conditions might improve productivity and quality of work by dampening the tool vibration that reduces them. Because of the dynamic contact between the cutting tool and the workpiece, a boring bar's tool vibration develops, leading to the production of wavy surfaces [2–4]. The irregular surface and the vibration in tool post and the machine, resulting in a wide range of cutting forces. Vibration in tools causes premature tool failure and unpleasant noise [5–7]. In their discussion of vibrations in machining, Huang and Chen [8] acknowledged three types of vibrations such as free vibrations, forced vibrations, and self-excited vibrations. Misalignment causes free and forced vibration, which may be the results of machine tool components a faulty gear drives, motors, etc. Disorders in the cutting zone, or "chatter", are brought on by the design of the machine tool and the interplay of the chip removal process. Tool vibration is also significantly affected by the length-to-diameter ratio (L/D) of the boring bar [9].

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Cutting temperature is the average integral temperature at the tool-chip and tool-workpiece interfaces, which is used to connect the tribological conditions at those locations to tool wear [10]. Due to the need to optimize the cutting parameter in order to raise both output quality and production speed, Salgado et al. [11] chose feed rate, spindle speed, and depth of cut as the input information for the evaluation of vibration and tool life [12].

Using RSM on AISI 4340 with coated carbide tool inserts, Suresh et al. [13] conducted experiments to determine the influence of machining settings on observable properties. The criticality of the setup is amplified by the emergence of chatter between the workpiece and the cutting tool as a result of the overhang of the workpiece and the internal cutting. Korkut and Kucuk [14] conducted experiments and studies to determine that the best L/D ratio for least vibration amplitude in boring operation 3 is better for reducing chatter, which leads to non-continuous cutting contact and, in turn, increases surface finish and flank wear with intermittent cutting and thrust forces. The L/D ratio used in this analysis is 3. Surface roughness, flank wear, and cutting forces are typically caused by vibrations in the workpiece. According to Teti et al. [15], there are two distinct types of vibrations that occur during metal cutting: those caused by the rotation of the cutting tool and those caused by the metal itself. Since it is difficult to physically isolate the vibrations from the machinery, the vibrations caused by spinning parts have been treated as constant throughout the experiment by using the same equipment to process workpieces with the same L/D ratio. To reduce the tremors that come from the actual cutting process, researchers have experimented with different frequency modulation schemes and evaluated the effects on vibration amplitude. Cutting force, feed rate, and depth of cut are three of many cutting parameters that can be adjusted experimentally to optimize cutting conditions and reduce vibration amplitude. Recent Grey Relational Analysis (GRA) and Taguchi approaches are utilized for multi-objective response optimization, which helps to shed light on the challenges inherent in the experimental approach by optimizing a set of cutting parameters that have a mutual impact on the response characteristics to be minimized. Through the application of GRA, Sivasakthivel et al. [16] reduced the vibration amplitude in their end milling experiments by optimizing the cutting parameters. GRA was used by Tosun and Pihtili [17] to improve the face milling of 7075 Al alloy based on observable metrics like surface quality and material removal rate (MRR). Optimization of machining parameters on hardened steel was first observed by Gopalsamy et al. [18], used Taguchi method to find optimum process parameters in end milling with hardened steel. Signal-to-Noise ratio (S/N) and Analysis of Variance (ANOVA) are used to study the performance characteristics of machining parameters with consideration of surface finish and tool life. Özel et al. [19] investigated the relationship between surface roughness and machining parameters such cutting speed, cutting tool shape, and feed in the hard turning of AISI H13 steel. Using ANOVA, Adarsha et al. [20] determined the significant machining parameters and projected response of GRG values from experiments on modelling and optimizing boring of AISI 4340. The literature review shows that there is a dearth of information on the use of single and multi-objective response optimization techniques to improve machining outcomes including cutting temperature, tool wear, cutting forces, and tool vibration when dealing with multi-layered cutting tools. In this study, cutting velocity, feed rate and depth of cut were investigated to determine their effect on cutting temperature, tool wear, cutting force, and tool vibration. An ANOVA is used to determine which factors have the greatest effect on the values used for cutting [21]. The GRA was also used to aggregate the responses into a single numerical score, rank the scores, and finally establish the best settings for the cutting parameters [22]. The cutting velocity, feed rate, and depth of cut were enhanced for hard boring 45 HRC AISI 4340 steel using S/N ratio, ANOVA and GRA.

The application of statistical and mathematical approaches, more specifically the S/N ratio, ANOVA and GRA, was used in this article to address the problem of tool vibration during the boring process and its influence on cutting temperature, tool wear, cutting force, and overall productivity in the manufacturing industry. The novelty of this article lies in the application of these statistical and mathematical approaches. The hard boring of AISI 4340 steels is the primary subject of this research, which includes 27 separate run experiments with variable levels of cutting velocity, feed rate, and depth of cut. ANOVA and the S/N ratio are the tools that are used to zero down on the essential cutting parameters for single response optimization. In addition to this, GRA is utilized in order to maximize the effectiveness of the multi-response optimization method for the cutting parameters. According to the findings of the research, utilizing either a single or multi-response optimization technique ultimately results in the same set of cutting parameters that are optimized.

This leads one to believe that the statistical analysis methods that were utilized in the study efficiently identified and optimized the cutting parameters to reduce tool vibration, which ultimately led to an increase in productivity. In general, the novelty of the work, consists in the integration of statistical analytic techniques and their application to address tool vibration, optimize cutting parameters, and boost productivity in hard boring of AISI 4340 steels.

2 Experimental setup

The cutting experiments were conducted using a Kirloskar lathe, and the input/output parameter diagram is depicted in Fig. 1. The cutting force is measured by a Kistler dynamometer, the tool wear is detected by a Metzer 0.005 mm count toolmakers microscope, and the cutting temperature is monitored by a non-contact type pyrometer. The piezoelectric type of accelerometer positioned on the top surface of the tool holder was utilized for monitoring the displacement of the tool vibration. Both replicates of the experiments were run for 60 seconds while the boring was in a dry state. S/N ratio, ANOVA, and GRA were performed to determine the impact and role of cutting parameters from experimental data.

2.1 Material selection

Due to its hardenability, AISI 4340 steel finds widespread use across the automotive and adjacent sectors. The dimensions of the piece were 100 mm in outer diameter, 50 mm in inner diameter, and 100 mm in length [23]. Specifications for the tool holder used in this study were S25T PCLNR 12F3. A tool holder with description S25T PCLNR 12F3 and insert having a description of CNMG 120408 MT TT5100 from m/s. Taegu Tec was used [24].

2.2 Design of experiments

The cutting parameters can be analyzed and optimized by using the Taguchi approach, which can be broken down into three stages: system design, parameter design, and tolerance design [25–27]. The steps of Taguchi parameter design are as follows:

1. choosing an orthogonal array (OA);
2. conducting experiments using the OA;
3. assessing the data;
4. determining the best condition;
5. performing confirmation runs [28].

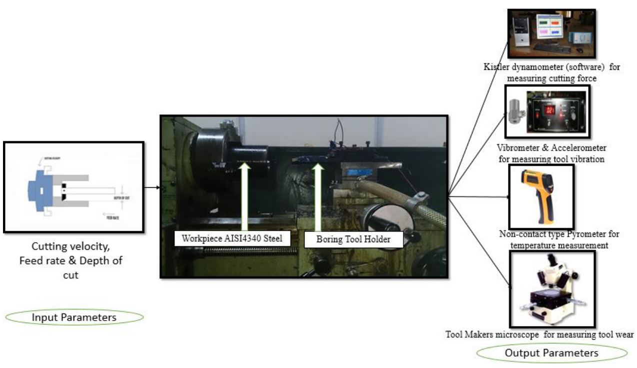

Fig. 1 Detail representations of input and output parameters

In the present experimental studies, the time-saving Taguchi orthogonal array was used to examine the impacts of machining parameters. On the basis of these early tests, we used the Taguchi method to create a 27-run experiment with three levels of input variables. Table 1 [1–3] displays three levels of cutting parameters from cutting velocity, feed rate and depth of cut. The practicable range for the cutting parameters was based on liteture survey, i.e., cutting velocity in the range of 60-100 m/min, feed rate in the range 0.06–0.1 mm/rev and the depth of cut in the range 0.5–0.7 mm [2]. Parameters such as cutting force, cutting temperature, tool wear, and tool vibration were recorded during each run.

2.2.1 S/N ratio characteristics

S/N ratio is a quality metric that compares the mean to the standard deviation to determine the deviation of an attribute from its ideal value. S/N ratio (η) was calculated using Eq. (1) by Yang and Tarng [21]:

$$\eta = -10\log\left(\mathrm{MSD}\right). \tag{1}$$

Equation (2) was developed by Yang and Tarng [21] to find the Mean Square Deviation (MSD) of cutting force, vibration, temperature, and tool wear, where a smaller value indicates a higher quality cut (MSD):

$$\mathrm{MSD} = \frac{1}{M}\sum_{i=1}^{m} S_i^2. \tag{2}$$

In this expression, m represents the total number of trials, and S_i represents the cutting characteristics (including force, vibration, temperature, and wear) measured during the i^{th} trial. By calculating the S/N ratio ($\acute{\eta}$), we were able to forecast and verify that the quality characteristic was

Table 1 Varying input parameters for boring process

Source number	Variable	Level 1	Level 2	Level 3
[1]	Cutting velocity (m/min)	60	80	100
[2]	Feed rate (mm/rev)	0.06	0.08	0.1
[3]	Depth of cut (mm)	0.5	0.6	0.7

at its highest possible level. In order to get the optimum value of the estimated S/N ratio, Yang and Tarng [21] implemented Eq. (3):

$$\acute{\eta} = \eta_m + \sum_{i=1}^{0} \left(\eta_i - \eta_m\right). \tag{3}$$

2.2.2 ANOVA

By implementing ANOVA, we can pinpoint which of our design parameters had the biggest impact on our outcome. The following equation was developed by Yang and Tarng [21] to get the total sum of squared deviations (SS_T):

$$SS_T = \sum_{i=1}^{n} \left(\eta_i - \eta_m\right)^2 . \tag{4}$$

The SS_T is generated from the total of the squared deviations (SS_d) attributable to each design parameter and the sum of the squared error (SS_e). In this formula, n represents the number of experiments, η_m represents the overall mean S/N ratio, and η_i represents the individual mean S/N ratio for the i^{th} experiment.

2.2.3 GRA

When the GRA was applied to several responses, its established causal relationships between those responses, allowing for the extraction of optimal parameters that would boost productivity while maintaining or improving product quality [22]. In GRA, several output answers are combined into a single response, and the best possible set of slicing parameters were derived from a combination of control elements. The following is a detailed account of each stage of the GRA approach:

- Step I: Using Eq. (2), determine the S/N ratio of the responses at the output; lesser values are preferable for the reducing criterion.
- Step II: Adjusting the range of the S/N ratio to be uniformly between 0 and 1 in order to reduce data inconsistencies. Pre-processing formulas for cutting parameters are based on the principle that smaller values are preferable. A pre-processing formula for the smaller-the-better criterion is as follows:

$$x_i^*\left(k\right) = \frac{a_i\left(k\right) - \min a_i\left(k\right)}{\max a_i\left(k\right) - \min a_i\left(k\right)}. \tag{5}$$

If $a_i(k)$ is the acquired output response and i and k are the experimental number and sequence of comparability, respectively, and the terminology stands for normalized values. The maximum and minimum values of the output answers a_i at step k, respectively, are denoted by max $a_i(k)$ and min $a_i(k)$, respectively (k).

- Step III: Use the reference sequence (taken to be 1) and the comparability sequence (Eq. (6)) to get the deviation sequence ($\Delta_{oi}(k)$):

$$\Delta_{oi}\left(k\right) = x_o^*\left(k\right) - x_i^*\left(k\right). \tag{6}$$

- Step IV: Grey Relational Coefficients (GRC) value is determined using the obtained deviation sequence ($\Delta_{oi}(k)$) and Eq. (7).

$$\xi_i\left(k\right) = \frac{\Delta_{\min} + \zeta\Delta_{\max}}{\Delta_{oi}\left(k\right) + \zeta\Delta_{\max}}. \tag{7}$$

Maximum ($\Delta_{\max}$) and minimum ($\Delta_{\min}$) values of the obtained deviation sequence, with the value of the identification coefficient (ζ) typically set at 0.5.

- Step V: Calculate the GRG by averaging the GRC values for each output response; the formula for this is given in Eq. (8):

$$\gamma_i = \frac{1}{n}\sum_{k=1}^{n} \xi_i\left(k\right), \tag{8}$$

where γ_i denotes the i^{th} GRG and n is the total number of trials [22].

3 Results and discussion

3.1 Analysis of the S/N ratio

Tabulated in Table 2 are S/N ratio values which was determined by using the Taguchi method conversion of empirically acquired values of tool vibration, cutting force, cutting temperature, and tool wear. For the purpose of this investigation, the S/N ratio was determined for cutting tool vibration, cutting force, cutting temperature, and cutting tool wear, with the smaller the value, the better. Figs. 2 to 5 were used to find the best machining settings to minimize vibration, force, temperature, and wear. Table 3 lists the S/N ratios for cutting parameters. The best results were obtained with a cutting velocity of 100 m/s, a feed of 0.06 mm/rev, and a depth of cut of 0.5 mm, as can be seen in Fig. 2. Cutting force were similarly with a cutting velocity of 100 m/s (S/N = −54.3678), a feed rate of 0.06 mm/rev (S/N = −54.3074), and a depth of cut of 0.5 mm (S/N = −54.3798) as can be seen in Fig. 3. With a cutting velocity of (S/N = −32.8177) 100 m/s, a feed of (S/N = −32.7722) 0.06 mm/rev, and a depth of cut (S/N = −33.5678) of 0.5 mm, the optimal values for cutting temperature is shown in Fig. 4. For tool wear, a cutting velocity of (S/N = 19.0738) 100 m/s, a feed

Table 2 S/N ratios of experimental results for cutting parameters

	Control factors			Responses				S/N ratio			
Runs	Cutting velocity (m/s)	Feed rate (mm/rev)	Depth of cut (mm)	Tool vibration (mm)	Cutting temperature (°C)	Cutting force (N)	Tool wear (mm)	Vibration (dB)	Temperature (dB)	Force (dB)	Tool wear (dB)
1	60	0.06	0.5	0.913	61.02	523.42	0.05	0.7906	−35.7094	−54.3770	26.0206
2	60	0.06	0.6	1.282	81.58	590.84	0.075	−2.1578	−38.2317	−55.4294	22.4988
3	60	0.06	0.7	1.84	88.65	638.26	0.0827	−5.2964	−38.9536	−56.1000	21.6499
4	60	0.08	0.5	1.352	82.02	595.1	0.08	−2.6195	−38.2784	−55.4918	21.9382
5	60	0.08	0.6	1.872	109.05	663.14	0.0885	−5.4461	−40.7525	−56.4321	21.0611
6	60	0.08	0.7	2.29	114.12	711.18	0.1	−7.1967	−41.1472	−57.0396	20.0000
7	60	0.1	0.5	2.086	103.03	655.42	0.1034	−6.3863	−40.2593	−56.3304	19.7096
8	60	0.1	0.6	2.362	123.2	723.96	0.115	−7.4656	−41.8122	−57.1943	18.7860
9	60	0.1	0.7	2.694	152.25	772.5	0.1376	−8.6080	−43.6511	−57.7580	17.2276
10	80	0.06	0.5	0.73	33.25	462.08	0.0347	2.7335	−29.8970	−53.2943	29.1934
11	80	0.06	0.6	0.802	57.9	527.5	0.0585	1.9165	−35.2536	−54.4444	24.6569
12	80	0.06	0.7	1.098	58.97	572.94	0.0667	−0.8120	−35.4126	−55.1622	23.5175
13	80	0.08	0.5	1.018	54.59	528.68	0.0585	−0.1550	−34.7423	−54.4639	24.6569
14	80	0.08	0.6	1.492	87.03	594.64	0.0772	−3.4754	−38.7934	−55.4851	22.2477
15	80	0.08	0.7	1.696	87.57	640.58	0.0931	−4.5885	−38.8471	−56.1315	20.6210
16	80	0.1	0.5	1.726	97.1	584.96	0.0785	−4.7408	−39.7444	−55.3425	22.1026
17	80	0.1	0.6	1.942	105.03	651.34	0.0985	−5.7650	−40.4263	−56.2762	20.1313
18	80	0.1	0.7	2.249	132.65	697.7	0.1183	−7.0398	−42.4541	−56.8734	18.5403
19	100	0.06	0.5	0.36	29.9	407.74	0.022	8.8739	−18.9878	−52.2077	33.1515
20	100	0.06	0.6	0.211	31.35	472.3	0.032	13.5144	−27.3657	−53.4844	29.8970
21	100	0.06	0.7	0.63	57.14	516.86	0.052	4.0132	−35.1388	−54.2675	25.6799
22	100	0.08	0.5	0.46	31.21	472.12	0.052	6.7448	−29.3106	−53.4810	25.6799
23	100	0.08	0.6	0.978	51.75	537.16	0.0549	0.1932	−34.2782	−54.6021	25.2086
24	100	0.08	0.7	0.894	70.43	582.2	0.0794	0.9732	−36.9552	−55.3014	22.0036
25	100	0.1	0.5	1.1045	57.42	526.62	0.072	−0.8633	−35.1813	−54.4299	22.8534
26	100	0.1	0.6	1.388	79.68	592.06	0.0883	−2.8478	−38.0270	−55.4473	21.0808
27	100	0.1	0.7	1.922	101.33	637.48	0.0979	−5.6751	−40.1148	−56.0893	20.1843

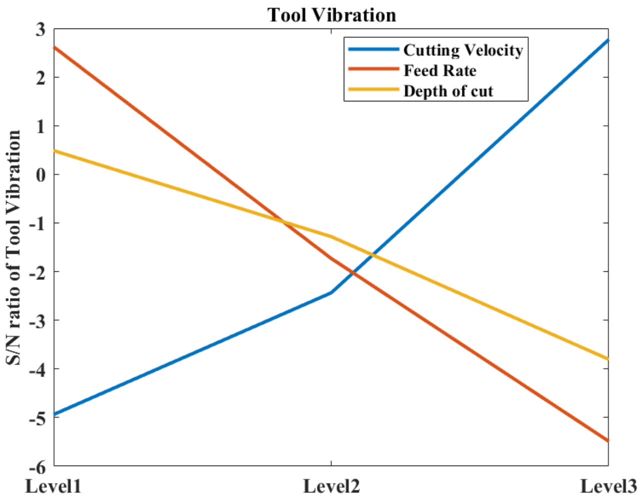

Fig. 2 S/N ratio interaction of cutting velocity, feed rate and depth of cut on tool vibration

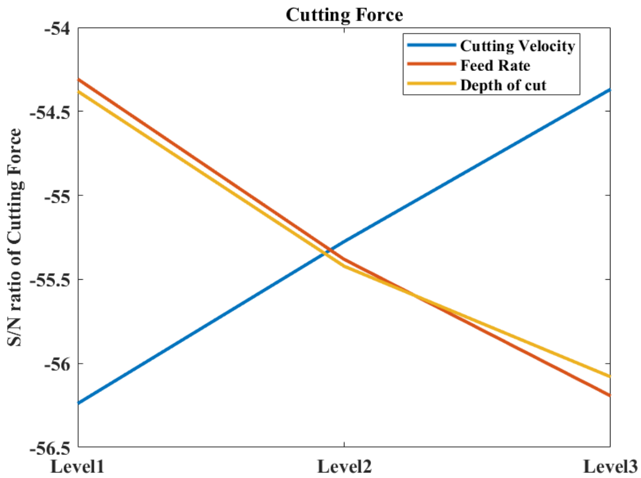

Fig. 3 S/N ratio interaction of cutting velocity, feed rate and depth of cut on cutting force

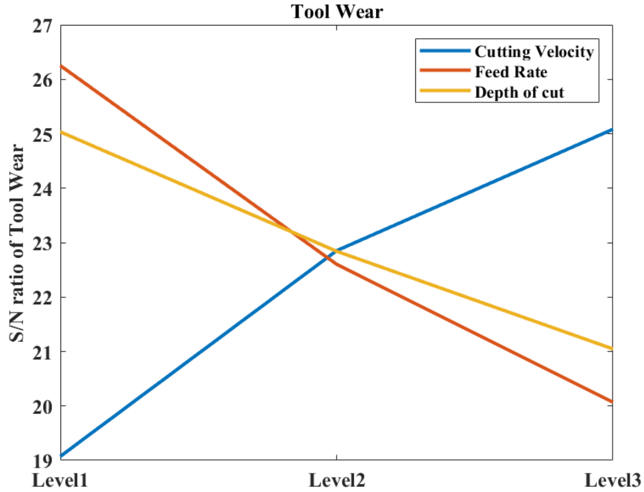

Fig. 4 S/N ratio interaction of cutting velocity, feed rate and depth of cut on tool wear

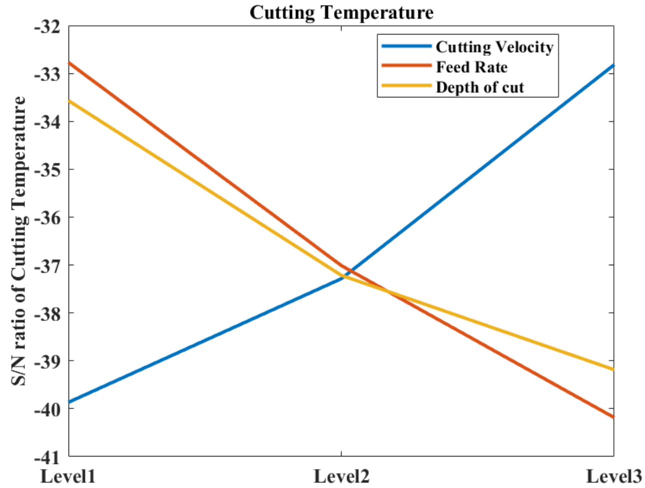

Fig. 5 S/N ratio interaction of cutting velocity, feed rate and depth of cut on cutting temperature

Table 3 Taguchi analysis of cutting parameters

	Control factors											
Levels	Tool vibration (dB)			Cutting force (dB)			Temperature (dB)			Tool wear (dB)		
	A	B	C	A	B	C	A	B	C	A	B	C
Level 1	−4.93	2.61	0.48	−56.2	−54.3	−54.3	−39.8	−32.7	−33.5	19.07	26.25	25.03
Level 2	−2.43	−1.72	−1.28	−55.2	−55.3	−55.4	−37.2	−37.0	−37.2	22.85	22.60	22.84
Level 3	2.76	−5.48	−3.80	−54.3	−56.1	−56.0	−32.8	−40.1	−39.1	25.08	20.06	21.04

(S/N = −20.0684) of 0.06 mm/rev, and a depth of cut of (S/N = 21.0471) 0.5 mm, as depicted in Fig. 5. S/N ratio is S/N ratio, and its unit of expression is decibels (dB).

3.2 ANOVA

To find out how each variable in the experimental design affects the results, an ANOVA is performed. Tables 4 to 7 display the analysis of variance results from the experimental data for the process parameters of tool vibration, cutting force, tool wear and cutting temperature, respectively. A statistical analysis of of process parameters that affects tool vibration, cutting force, tool wear and cutting temperature is calculated [23]. Table 4 [1–5] displays the results of an analysis showing that feed rate is the most influential component in determining tool vibration, with a 44.63% share, followed by cutting velocity and depth of cut, each accounting for 36.88% and 14.91%. Table 5 [1–5] displays the results of a statistical analysis that determined the following: cutting velocity, feed rate, and depth of cut each contributed 35.51%, 35.56%, and 28.83%, respectively, to the total cutting force. The feed rate was the most important component that affected the efficiency of the cutting force. Table 6 [1–5] shows that feed rate is similarly the most influential factor in determining how quickly tools wear. It was determined that 22.47%, 53.78%, and 21.64% of tool wear may be attributed to the parameters of cutting velocity, feed rate, and depth of cut, respectively. Table 7 [1–5] shows that 34.15%, 42.03%, and 20.73% of total temperature may be attributed to cutting velocity, feed rate, and depth of cut, respectively. Table 7 [1–5] demonstrates that feed rate was the most influential element in determining the cutting temperature, followed by cutting velocity and depth of cut. The summary of ANOVA findings shows that for the cutting parameters error percentage (%) was quite low and is less than 5%.

In this part, ANOVA was utilized to analyze the significant effect of cutting parameters on tool vibration. Using ANOVA, we identified both the independent and interactive effects of the cutting parameters on the tool vibration. Table 4 [1–5] indicates that the feed rate has the greatest impact on tool vibration, followed by the depth of cut and the cutting velocity. The optimum cutting condition was obtained when the depth of cut and feed rate decreases along with the increasing of cutting velocity, as shown in Fig. 2. Increases in feed rate result in greater material removal from the workpiece, which then drifts over the cutting tool as chips. As a result, cutting tool damage and surface quality are impacted by crack development and

Table 4 ANOVA for vibration

Source number	Parameter	Degree of freedom	Sequential sum of square	Adjusted sum of square	Adjusted mean square	Statistic value	Probability value	Contribution (%)
[1]	Cutting velocity	2	4.2611	4.2611	2.1305	103.26	0.000	36.88
[2]	Feed rate	2	5.1563	5.1563	2.5781	124.96	0.000	44.63
[3]	Depth of cut	2	1.7226	5.1563	0.8613	41.75	0.000	14.91
[4]	Error	20	0.4126	0.4126	0.0206			3.57
[5]	Total	26	11.5526					

Table 5 ANOVA for cutting force

Source number	Parameters	Degree of freedom	Sequential sum of square	Adjusted sum of square	Adjusted mean square	Statistic value	Probability value	Contribution (%)
[1]	Cutting velocity	2	71025	7025	35512	4116.76	0.000	35.51
[2]	Feed rate	2	71121	71121	35560	4122.33	0.000	35.56
[3]	Depth of cut	2	57673	57673	28836	3342.85	0.000	28.83
[4]	Error	20	173	173	9			0.086
[5]	Total	26	199991					

Table 6 ANOVA for tool wear

Source number	Parameters	Degree of freedom	Sequential sum of square	Adjusted sum of square	Adjusted mean square	Statistic value	Probability value	Contribution (%)
[1]	Cutting velocity	2	0.0044126	0.0196364	0.0022063	106.97	0.000	22.47
[2]	Feed rate	2	0.0105607	0.0105607	0.0052804	256.00	0.000	53.78
[3]	Depth of cut	2	0.0042506	0.0042506	0.0021253	103.04	0.000	21.64
[4]	Error	20	0.0004125	0.0004125	0.0000206			2.10
[5]	Total	26	0.0196364					

Table 7 ANOVA for cutting temperature

Source number	Parameters	Degree of freedom	Sequential sum of square	Adjusted sum of square	Adjusted mean square	Statistic value	Probability value	Contribution (%)
[1]	Cutting velocity	2	10563.6	10563.6	5281.8	110.87	0.000	34.15
[2]	Feed rate	2	13001.0	13001.0	6500.5	136.46	0.000	42.03
[3]	Depth of cut	2	6413.7	6413.7	3206.8	67.32	0.000	20.73
[4]	Error	20	952.8	952.8	47.6			3.08
[5]	Total	26	30931.1					

thermal softening, diffusion, as well as the heat generated between the tool and the chip. When reducing the feed rate and depth of cut and increase in cutting velocity, as shown in Fig. 2, tool vibrations lessens. According to the findings, feed rate is the most significant factor in determining the amplitudes of tool vibrations. Cutting forces, tool wear and cutting temperature will all be affected by an increase in acceleration of the cutting tool and also the amplitude of the tool vibrations caused by overhanging.

The significant effect of machining parameters on the cutting force, ANOVA was employed in Section 3.2 and findings were shown in Table 5 [1–5]. The data demonstrate that the feed rate is the most influential parameter in determining the cutting force, whereas the depth of cut and the cutting velocity play a minor role. Interactions among cutting velocity, feed rate, and depth of cut are plotted graphically in Fig. 3. Greater machining forces are induced in the machining process as feed rates and depth of cuts are increased, resulting in a greater rate of material removal from the work piece. It's possible that this is due to bonding happening frequently at the borders of the chip-cutting tool interplay, which causes material from the workpiece to stick to the cutting tool. During the machining process, high shear stress and temperatures are generated.

Increasing the depth of cut increases the contact area between the tool and the chip, which is a sign of high cutting forces and eventually leading to tool failure. When the cutting velocity is increased slightly, the feed rate and depth of cut can be reduced, as shown in Fig. 3. This results in reduced cutting forces.

ANOVA was utilized to examine the significant impact of machining factors on tool wear. Table 6 [1–5] demonstrates that the feed rate is the most important factor in the machining process, followed by the depth of cut and the cutting velocity. Fig. 4 shows the impacts of cutting velocity, feed rate, and depth of cut on tool wear as illustrated by the interactions plots. Due to the lack of more amount of material, the cutting-edge experiences significant amount of force when machining hard materials with low machining parameters, which results in tool damage or diffusion. The effect of tool being pushed deeper into the workpiece at greater depths of cut, more tool wear is being seen at these settings. Fig. 4, demonstrates that the tool wear increases as cutting velocity decreases because of reduced exposure of material to strain. Fig. 4 demonstrates that the least amount of tool wear was achieved by slightly increasing cutting velocity and decreasing feed rate and depth of cut. It was determined that excessive feed rates and depths of cut lead to increased tool wear, with the feed rate having a greater impact on tool life than either cutting velocity or depth of cut [17].

Table 7 [1–5] displays the results of an analysis of variance performed to determine the impact of various machining settings on the cutting temperature. The cutting temperature is found to be affected most by the feed rate, with less of an impact coming from the depth of cut and the cutting velocity. Interaction effects, including cutting velocity, feed rate, and depth of cut, on cutting temperature are shown in Fig. 5. As seen in Fig. 5, this causes the cutting temperature to drop, allowing for a slightly reduced feed rate and depth of cut. When machining process is performed under ideal cutting condition, feed rate has a far greater impact on cutting temperature than either depth of cut or cutting velocity [17].

3.3 GRA

The better the numerous performance characteristics, the higher the Grey Relational Grade (GRG), which is a statistical method used to convert the many objective optimization issues to a single equivalent objective function optimization problem [29, 30]. GRA was performed on experimental data using the aforementioned methods, and the resulting normalization information, coefficients, and grades are displayed in Table 8. Among the 27 trials, the results suggest that the ideal machining parameters for attaining many performances simultaneously were those of test number 19 (maximum GRG = 1.000, cutting velocity = 100 m/min, feed rate = 0.06 mm/rev, and depth of cut = 0.5 mm). Table 9 [1–3] shows the results of a GRA study, which concluded that the best cutting performance could be achieved by keeping the cutting velocity at Level 3 (100 m/min), the feed rate at Level 1 (0.06 mm/rev), and the depth of cut at Level 1 (0.5 mm). The findings demonstrate that as cutting depth, feed rate, and cutting velocity are increased, tool vibration, cutting force, tool wear, and cutting temperature also increases.

Table 9 [1-3] displays the GRG response table for various cutting parameters. In GRA, a higher GRG is required to achieve better performance, which is why the GRG value corresponding to the greatest possible cutting parameters is considered to be optimal. Based on the results shown in Table 9 [1-3], it would appear that the feed rate is the most influential element in cutting performance, followed by cutting velocity and depth of cut, with respective GRG of 0.5607, 0.5519 and 0.5294.

4 Conclusions

Cutting tests were conducted on hardened AISI 4340 steel during boring process and following were made:

- Through the use of S/N ratio, Analysis of Variance, and Grey Relation Analysis, the optimal set of AISI 4340 steel for boring process is cutting velocity is 100 m/s, feed rate is 0.06 mm/rev and depth of cut is 0.5 mm was determined.
- When it comes to reducing vibration, cutting force, cutting temperature, and tool wear, feed rate is the most important cutting parameter, followed by cutting velocity and depth of cut.
- The present study used the (Taguchi) S/N ratio and ANOVA to evaluate a single performance criterion. The grey relational theory was then used for a multi-performance analysis. The influence of cutting parameters, including cutting velocity, feed rate, and depth of cut, is the same when a single or multi performance analyses are conducted.

Table 8 Normalized GRC, GRG, rank

Runs	Normalized values				GRC				GRG	Rank
	Vibration	Temperature	Force	Tool wear	Vibration	Temperature	Force	Tool wear		
1	0.424844393	0.32200424	0.609149313	0.552186353	0.465048963	0.424449745	0.561261284	0.52752986	0.494572463	6
2	0.291569617	0.219737907	0.419539583	0.331020568	0.413759871	0.390545032	0.462765681	0.427723522	0.423698527	13
3	0.149694876	0.190467719	0.298725509	0.277711761	0.370286679	0.381815712	0.416224605	0.409068814	0.394348952	18
4	0.270695961	0.217843546	0.408296736	0.295817261	0.406734204	0.389968009	0.457999913	0.415219371	0.417480374	14
5	0.142925218	0.117527956	0.238881584	0.240738741	0.368439534	0.361670966	0.396473474	0.397058193	0.380910542	21
6	0.063792734	0.101523564	0.129430594	0.174100946	0.348139166	0.357531945	0.364811879	0.377102615	0.361896401	24
7	0.100426514	0.13752684	0.257206835	0.155863548	0.357251695	0.366979706	0.402319561	0.371986043	0.374634251	23
8	0.051638113	0.07456133	0.101558112	0.097866126	0.34521759	0.350769213	0.357540778	0.35659933	0.352531728	26
9	0	0	0	0	0.333333333	0.333333333	0.333333333	0.333333333	0.333333333	27
10	0.512672427	0.557675575	0.804213034	0.751434502	0.506417539	0.530602823	0.71861076	0.667944223	0.605893836	3
11	0.475740007	0.340488058	0.596998083	0.466546784	0.488157307	0.431215912	0.55370868	0.483814838	0.489224184	7
12	0.352400251	0.334039165	0.467683783	0.394994069	0.435691974	0.428830871	0.484347714	0.452486259	0.450339204	11
13	0.382102911	0.361219608	0.593501274	0.466546784	0.447268362	0.439066218	0.551572756	0.483814838	0.480430543	9
14	0.232009092	0.19696299	0.409506869	0.315250531	0.394324594	0.383718955	0.458508161	0.422030153	0.414645466	15
15	0.181691523	0.194784562	0.293047451	0.213099294	0.379273902	0.383078521	0.414266493	0.388530364	0.39128732	19
16	0.174807119	0.158403545	0.435191772	0.30614177	0.377303566	0.372690311	0.469568122	0.418810197	0.409593049	17
17	0.128511365	0.130755929	0.266979057	0.18234486	0.364567367	0.365164992	0.405508116	0.379461959	0.378675608	22
18	0.070886053	0.048533599	0.159377829	0.082434111	0.349867133	0.344479211	0.37296116	0.352717291	0.355006199	25
19	0.790238794	1	1	1	0.704462283	1	1	1	0.926115571	1
20	1	0.660308151	0.769977882	0.795618983	1	0.595456536	0.684910755	0.709843094	0.747552596	2
21	0.570516596	0.345141383	0.628886576	0.530792947	0.537933219	0.43295343	0.573978068	0.515885639	0.515187589	5
22	0.693996253	0.581450503	0.770574416	0.530792947	0.620344511	0.54433648	0.685470884	0.515885639	0.591509379	4
23	0.397841709	0.380035174	0.56859891	0.501190929	0.453655345	0.446442592	0.536825655	0.500596175	0.484379942	8
24	0.433101453	0.271495696	0.442593056	0.299923644	0.468648122	0.406998981	0.472854848	0.416640156	0.441285527	12
25	0.350082788	0.343419838	0.599610968	0.353287413	0.434813911	0.432308989	0.555315516	0.43602905	0.464616866	10
26	0.260378071	0.228037167	0.416311539	0.241972818	0.403348786	0.393093247	0.461387214	0.397447692	0.413819235	16
27	0.132575899	0.14338627	0.300639148	0.185677632	0.616588	0.584649	0.574606	0.592821	0.38288216	20

Table 9 Response table for GRG

Source number	Control factors	Level 1	Level 2	Level 3	Delta	Rank
[1]	Cutting velocity	0.39260073	0.441677268	0.551927652	0.159326	2
[2]	Feed rate	0.560770325	0.440425055	0.38501027	0.175760	1
[3]	Depth of cut	0.52942737	0.453937536	0.402840743	0.120586	3

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