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Experimental and statistical investigations of surface roughness, vibration, and energy consumption values of titanium alloy during machining using response surface method and grey relational analysis

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Abstract. This study aims to investigate the consistency between the results obtained from the turning operation. To this end, Ti 6Al-4V alloy workpiece was machined using CNC lathe. In addition, surface roughness (Ra), vibration, and energy consumption values were determined through turning. Experimental results were then analyzed statistically. Response Surface Method (RSM) and grey relational analysis were employed for statistical analysis. According to RSM analysis, grey relational analysis, and ANOVA and regression analysis, the feed rate was found the most effective parameter that negatively affects surface roughness, energy consumption, and vibration. Finally, the steps involved in conducting grey relational analysis and the process of obtaining the results were examined.

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1. Introduction

Turning is the process of removing chips from a cylindrical material using a suitable cutting tool [1]. Turning is nowadays one of the most preferred methods in manufacturing [2]. A number of studies have been conducted on turning, hence new developments related to turning [3]. In this regard, turning still remains popular in both academic and industrial applications.

There are many cutting parameters that affect the surface quality, vibration, energy consumption, material removal rate, wear, temperature, acoustic emission, sound intensity, and cutting forces to be obtained during the turning process. The most important of all these cutting parameters are the primary motion cutting speed and secondary motion feed rate. Other important cutting parameters include depth of cut, workpiece material, material hardness, cutting tool geometry, cutting tool tip angle, cutting tool coating, workpiece length, cooling type, etc. [4–7].

Surface roughness, indicating the quality, is a quality criterion that becomes effective in the combination of two parts [8,9]. Surface roughness measurement is an important parameter in many engineering applications [10,11]. While determining the optimum surface roughness, it is likely to witness time and material loss.

Observed in almost all machining processes, vibration is one of the most important factors affecting the product quality [12,13]. Excessive vibration between the tool and workpiece results in poor surface quality, rapid tool wear, and work accidents [14]. It is caused by the cutting parameters not being selected appropriately. Appropriate cutting parameters must be selected to obtain optimum vibration values [15].

In line with the development of technology, energy consumption follows an ever-increasing trend. In this

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regard, the need for providing energy economically becomes more important than ever [16]. In addition, attempts were made to increase the efficiency of the consumed energy. As in every field, ways to reduce energy consumption in machining and optimizing the effective parameters have been explored in numerous researches [17].

Correct evaluation of the obtained test results is of significance. Artificial intelligence methods, statistical methods, and optimization methods are generally used for evaluation [18]. In addition, Response Surface Method (RSM) is another statistical method used in machining in recent years. Correct experiment design can provide accurate data for optimum results [19]. It determines the optimum values among multiple parameters. Therefore, the experience required for similar operations is realized in the form of computer learning. RSM is also used in academic studies due to its ability to reduce the number of experiments. Furthermore, it is regarded as a method that saves time and cost for both researchers and industrial managers. Minitab and Design Expert are programs used for RSM analysis [20].

Grey relational analysis is a statistical approach to eliminating uncertainty and obtaining the most appropriate results when there are many results in one. Grey relational analysis is widely applied in machining [21,22]. Here, the term “grey” refers to deficiency and/or uncertainty, but it is often used in relation to the concept of knowledge. While the information is fully known in the white system, it is unknown in the black system. The grey system is somewhere between these two systems [23]. Table 1 presents a comparison among white, black, and grey systems.

Titanium is an engineering material with a wide range of applications due to its superior properties. Titanium is used in many fields, especially in the space, aviation, automobile, medical, chemical, and defense industries. Titanium material machinability is difficult compared to other materials. Titanium material is processed with special tools or cutting fluids [24]. Given that the production volume of this material, called the space age metal, costs hundreds of millions of dollars per year, it is used in many studies and industries as well. Titanium has recently been the subject of many studies in the field of machinability (turning, milling, drilling, grinding, honing, etc.) [25,26].

The objective of this study is to investigate the effect of cutting parameters on the surface roughness, energy consumption, and vibration in the cutting tool while machining titanium 6Al-4V ELI (grade 5) alloy. To this end, RSM method was employed to reduce the number of experiments and optimize the results. The obtained results were evaluated through the grey relational analysis. In addition, RSM and grey relational analysis were used together to contribute to the literature so as to the originality and comparativeness of the results.

2. Experimentation

This section elaborates the experimental design, experimental method, and devices used in the experiments, Finally, acquisition of data at the end of the experiment is given. Figure 1 shows the flowchart of this study.

Ti-6Al-4V (grade 5) alloy, also called TC4 or Ti64, was chosen as the workpiece. Titanium alloy consists of approximately 90% titanium, 6% aluminum, 4% vanadium, 0.25% (max) iron, and 0.2% (max) oxygen. The dimensions of the workpiece are Ø80 × 200 mm. Workpiece hardness was calculated as 290 HB using Proceq equotip 3 hardness device. Turning operation was carried out using CNC Lathe LT-20C under dry cutting conditions. In this study, Sangeo DNMG 150608R and SMOXH TDJNR 2525 M15 were used as the cutting tool and tool holder, respectively. The machining length was determined to be 120 mm. In addition, RSM was used for the experimental design. Design Expert program was employed to conduct RSM. Table 2 shows the parameters used in the experimental design. Low cutting speeds or cutting fluid should be used when turning titanium material; otherwise, high tool wear occurs.

Ra, vibration, and energy consumption are referred to as the result of the experiment. Ra and vibration were measured by Mitutoyo SJ-210 and UT312 pocketable vibrometer, respectively. The value of the

Table 1. Comparison of white, black, and grey systems [23].

	Black system	**Grey system**	**White system**
Information	The exact unknown	Missing	Certainly known
View	Dark	Grey	Clear
Process	New	Exchange of the old with the new	Old
Feature	Chaos	Difficulty (complexity)	Tidy
Methodology	Negative	Change	Positive
Behaviour	Tolerant	Tolerant	Seriously
Conclusion (decision)	No solution	Many solutions	One solution

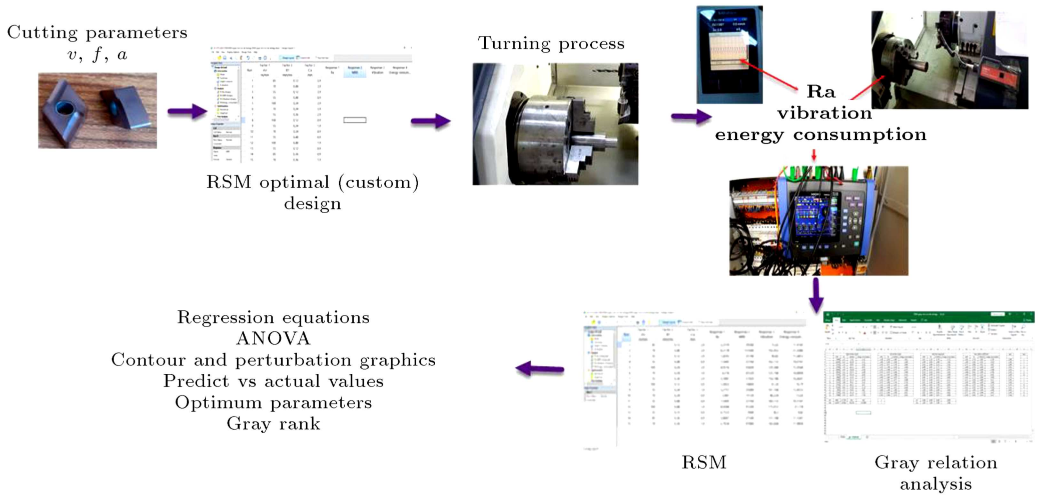

Figure 1. Flowchart for the study.

Table 2. Response Surface Method (RSM) factors.

	Factor	Unit	Lowest	Highest	Level 1	Level 2	Level 3	Level 4
A	Cutting speed	m/min	55	100	55	70	85	100
B	Feed rate	mm/rev	0.12	0.48	0.12	0.24	0.36	0.48
C	Depth of cut	mm	0.9	3.9	0.9	1.9	2.9	3.9

vibration acceleration (O-P) of this device is 0.1 $\sim$ 199.9 m/s^2'dir (Frequency response: 10 $\sim$ 1500 Hz; Amplitude error of $\leq \pm 5\%$). Energy consumption was determined using Hioki Power Quality Analyzer PW3198. Ra was performed after the end of the procedure, and vibration and energy consumption were measured while the machine was running. While the vibrometer was fixed to the tool holder, the energy consumption meter was connected to the spindle power cable.

Experiment list was created with RSM optimal (custom) design. A total of 15 experiments were carried out. Table 3 presents the experiment list as well as the obtained results.

3. Experimental results

Experiments on the Ra, vibration, and energy consumption were carried out in three replications, and their average values were calculated. Table 3 shows the values of the Ra, vibration, and energy consumption.

Table 3. Experimental design and results.

No	*V* (m/min)	*f* (mm)	*a* (mm/rev)	Ra (μm)	Vibration (m/s^2)	Energy consumption (kWh)
1	85	0.12	2.9	2.23	72.62	11.91
2	70	0.48	3.9	8.52	192.95	21.51
3	55	0.12	3.9	1.43	90.82	11.05
4	55	0.48	0.9	7.54	162.11	19.07
5	100	0.24	3.9	4.95	129.38	15.96
6	70	0.24	3.9	4.22	125.74	14.89
7	55	0.36	2.9	5.60	154.19	16.66
8	100	0.12	0.9	1.95	61.26	10.79
9	55	0.24	1.9	3.28	101.74	13.46
10	70	0.24	0.9	3.98	98.22	13.02
11	55	0.48	0.9	7.54	160.11	19.57
12	100	0.48	1.9	8.93	175.91	21.18
13	55	0.12	0.9	0.75	58.30	9.82
14	85	0.36	0.9	5.81	131.15	17.33
15	70	0.36	1.9	5.70	142.67	17.99

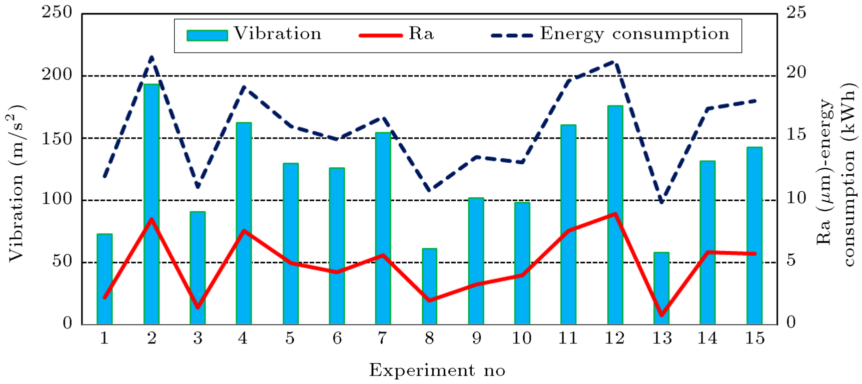

Figure 2. Combined graphics for vibration, surface roughness, and energy consumption.

Table 4. Regression equations for Ra, vibration, and energy consumption.

Equations	R^2
$\text{Ra} = 5.14 + 0.61 * A + 3.28 * B + 0.33 * C - 0.003 * A * B + 0.09 * A * C - 0.02 * B * C - 0.12 * A^2 + 0.02 * B^2 + 0.02 * C^2$	0.9961
$\text{Vibration} = 127.49 - 1.07 * A + 53.48 * B + 15.14 * C + 0.91 * A * B - 1.61 * A * C + 0.77 * B * C + 3.06 * A^2 - 5.82 * B^2 + 2.56 * C^2$	0.9981
$\text{Energy consumption} = 16.35 + 0.75 * A + 4.83 * B + 0.77 * C + 0.05 * A * B + 0.19 * A * C - 0.04 * B * C - 0.41 * A^2 + 0.11 * B^2 - 0.19 * C^2$	0.9953

Figure 2 illustrates a combined graph for Ra, vibration, and energy consumption. As observed in this figure, the three values affected each other. In other words, Ra, vibration, and energy consumption were linearly proportional.

According to Figure 2, the values of vibration and energy consumption measured on-line affect the surface roughness. This result shows the importance of real-time manufacturing. Thus, manufacturing can be achieved both with the best surface quality and at the lowest cost.

Azizi et al. concluded in their study that the surface roughness increased upon increasing the feed rate [27]. They also pointed out that both surface roughness and tool vibration were linearly proportional [25], which in turn caused an increase in the vibration of the cutting tool and negatively affected the surface roughness. Camposeco-Negrete stated that the most effective parameter in energy consumption per machining cycle was feed rate [28].

4. Applied statistical analysis

Statistical analysis was employed to determine the interactions among the parameters, effective parameters, and optimum parameters. In case of obtaining multiple results, it is important to determine the optimum values. In this regard, RSM and grey relational analyses were used to examine the results.

4.1. RSM model

A careful review of the literature revealed that the minimum values for Ra, vibration, and energy consumption were desired in the analysis [29,30].

RSM analysis of the Ra, vibration, and energy consumption was performed using design expert program. The quadratic regression model was created for Ra, vibration, and energy consumption. Table 4 shows the obtained equations and coefficient of determination (R^2) whose value is between 0 and 1 [31]. In case the R^2 value is greater than 0.8, it is indicative of a good relationship among the variables. While calculating the R^2 values in Table 4, it was observed that there was good agreement among the cutting parameters of the Ra, vibration, and energy consumption.

B factor was found to be the most effective factor while examining the equations for surface roughness, vibration, and energy consumption. In addition, according to the findings, the most effective parameter of surface roughness, vibration, and energy consumption was feed rate.

Tables 5–7 present the ANOVA results. The created quadratic regression model is meaningful since $P < 0.05$ [31,32]. Based on Tables 5–7, the most

Table 5. Analysis of Variance (ANOVA) results for Ra.

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-value	P-value
Regression	9	94	99.61%	93.8613	10.429	141.72	0
$A-v$	1	1	0.81%	0.0834	0.0834	1.13	0.336
$B-f$	1	92	97.63%	1.4747	1.4747	20.04	0.007
$C-a$	1	1	1.08%	0.0004	0.0004	0	0.948
A^2	1	0	0.02%	0.0337	0.0337	0.46	0.528
B^2	1	0	0.00%	0.002	0.002	0.03	0.876
C^2	1	0	0.01%	0.0016	0.0016	0.02	0.887
AB	1	0	0.00%	0.0001	0.0001	0	0.975
AC	1	0	0.05%	0.0469	0.0469	0.64	0.461
BC	1	0	0.00%	0.0028	0.0028	0.04	0.853
Error	5	0	0.39%	0.3679	0.0736		
Total	14	94	100.00%				

Table 6. Analysis of Variance (ANOVA) results for vibration.

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-value	P-value
Regression	9	24653.5	99.81%	24653.5	2739.28	284.91	0
$A-v$	1	73.3	0.30%	17.8	17.75	1.85	0.232
$B-f$	1	22070.5	89.35%	662	661.97	68.85	0
$C-a$	1	2409.1	9.75%	19.5	19.51	2.03	0.214
A^2	1	1.1	0.00%	21.3	21.31	2.22	0.197
B^2	1	64.5	0.26%	82.2	82.19	8.55	0.033
C^2	1	9.4	0.04%	15.4	15.43	1.6	0.261
AB	1	7.5	0.03%	4.6	4.6	0.48	0.52
AC	1	14.8	0.06%	13	13.04	1.36	0.297
BC	1	3.4	0.01%	3.4	3.39	0.35	0.578
Error	5	48.1	0.19%	48.1	9.61		
Total	14	24701.6	100.00%				

Table 7. Analysis of Variance (ANOVA) results for energy consumption.

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-value	P-value
Regression	9	205.546	99.53%	205.546	22.8385	118.86	0
$A-v$	1	0.91	0.44%	0.514	0.5142	2.68	0.163
$B-f$	1	197.984	95.87%	2.662	2.6617	13.85	0.014
$C-a$	1	6.06	2.93%	0.099	0.0985	0.51	0.506
A^2	1	0.289	0.14%	0.398	0.3983	2.07	0.209
B^2	1	0.002	0.00%	0.03	0.03	0.16	0.709
C^2	1	0.075	0.04%	0.092	0.0916	0.48	0.521
AB	1	0.004	0.00%	0.017	0.0171	0.09	0.777
AC	1	0.212	0.10%	0.198	0.1984	1.03	0.356
BC	1	0.011	0.01%	0.011	0.0106	0.06	0.824
Error	5	0.961	0.47%	0.961	0.1921		
Total	14	206.507	100.00%				

effective parameter of Ra, vibration, and energy consumption is feed rate. The contribution of feed rate to the results is 97.63% for Ra, 89.35% for vibration, and 95.87% for energy consumption.

Figure 3 graphically presents the percentage contribution rates in Tables 5–7. Feed rate is regarded as the most contributing parameter for Ra, vibration, and energy consumption. If an optimum point is to be chosen for Ra, vibration, and energy consumption, it is the optimum factor feed rate.

Figure 4 shows the contour graphs for Ra. The graphs illustrate the effects of the cutting parameters (V-f-a) on Ra. The line directions and dark colors on the graph show the directions where Ra increases. Feed rate is the cutting parameter that affects Ra the most.

Figure 5 shows the contour graphs for vibration.

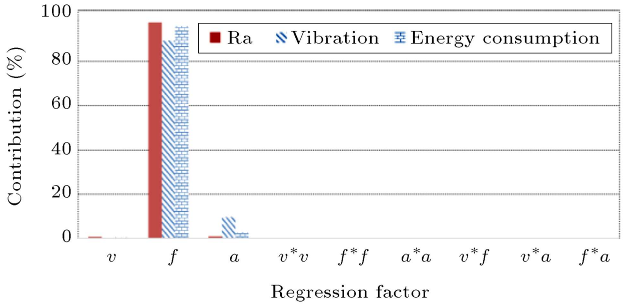

Figure 3. Percentage (%) contribution for regression factors.

The graphs show the effects of cutting parameters (V-f-a) on the vibration. The line directions and dark colors on the graph indicate the directions where the vibration increases. Feed rate is the cutting parameter that affects vibration the most.

Figure 6 shows the contour graphs for energy consumption. The graphs shows the effects of cutting parameters (V-f-a) on energy consumption. The line directions and dark colors on the graph show the directions where energy consumption increases. Feed rate is the cutting parameter that affects energy consumption the most.

Figure 7 shows the experimental (actual) and predicted values of RSM models for Ra, vibration, and energy consumption. In this figure, the actual and predicted results are in good agreement.

Figure 8 presents the perturbation graphs of RSM models designed for Ra, vibration, and energy consumption. While analyzing the graph for Ra, vibration, and energy consumption, it was observed that the B line was more open than the other factors. It was found that the feed rate was more effective for Ra, vibration, and energy consumption.

Figure 9 shows the optimum cutting parameters as well as the results of Ra, vibration, and energy consumption. Optimum cutting parameters were determined as $V = 100$ m/min, $f = 0.12$ mm/rev, and $a = 3.9$ mm. The values obtained for the optimum cutting parameters were Ra $= 2.85$ μm,

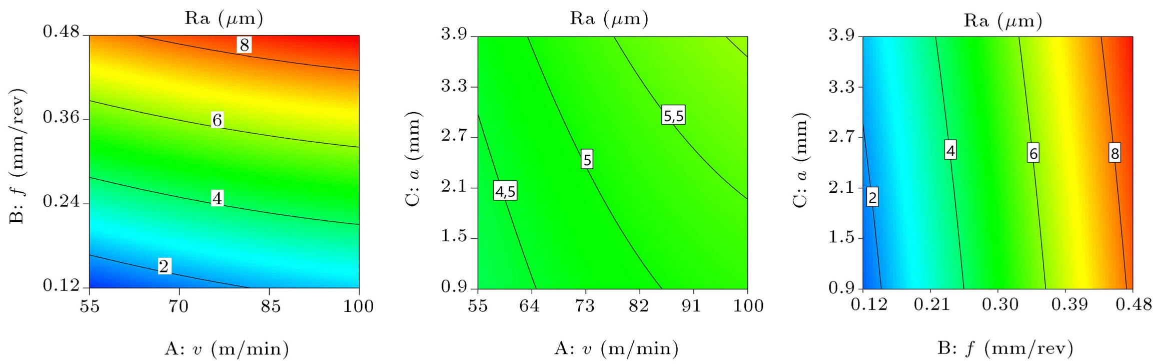

Figure 4. Contour graphics for Ra.

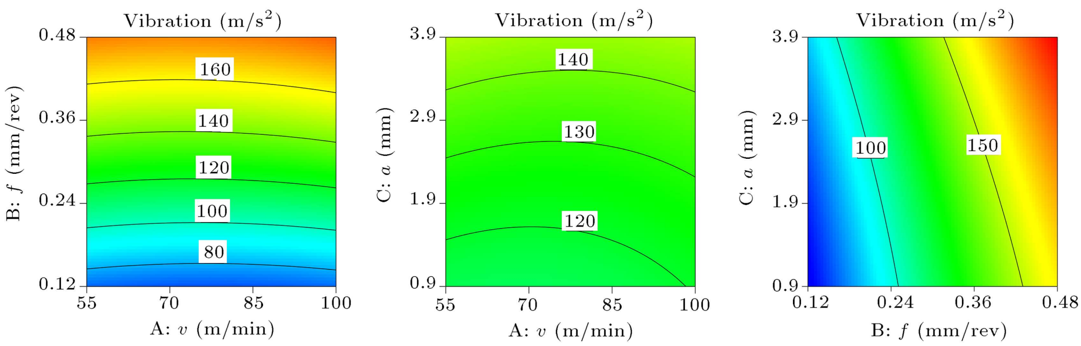

Figure 5. Contour graphics for vibration.

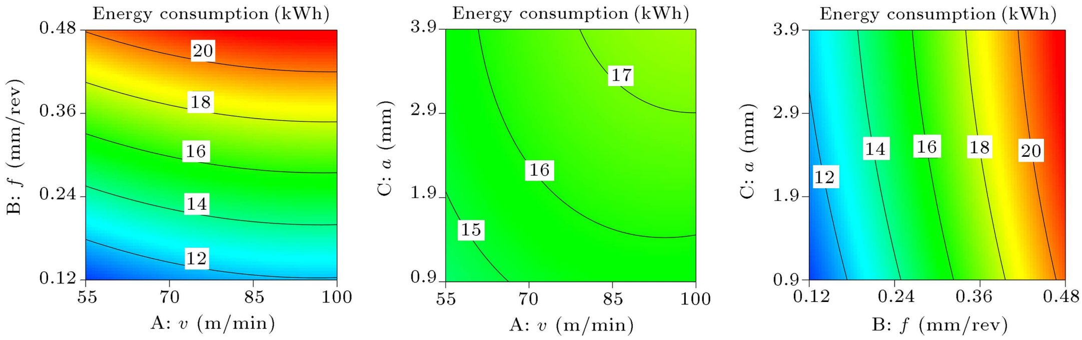

Figure 6. Contour graphics for energy consumption.

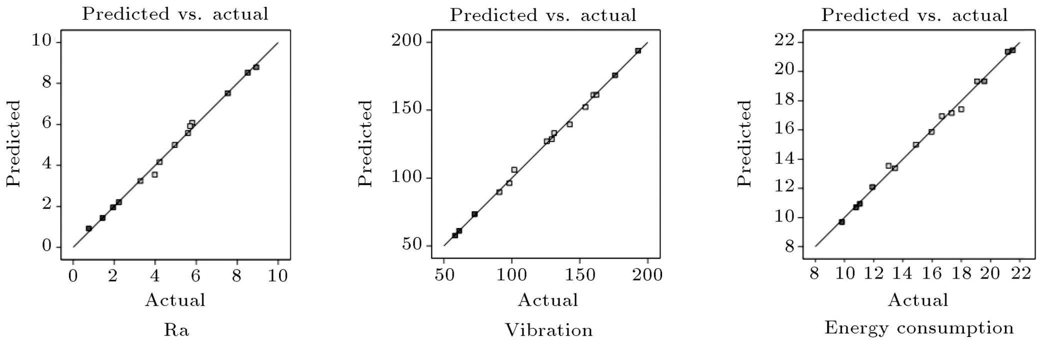

Figure 7. Predicted vs. actual values for responses.

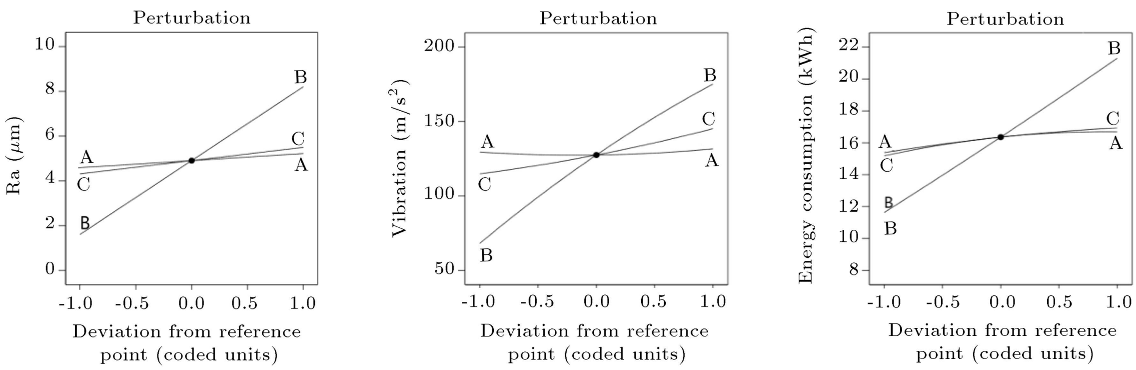

Figure 8. Pertubrtion graphics for Ra, vibration and energy consumption.

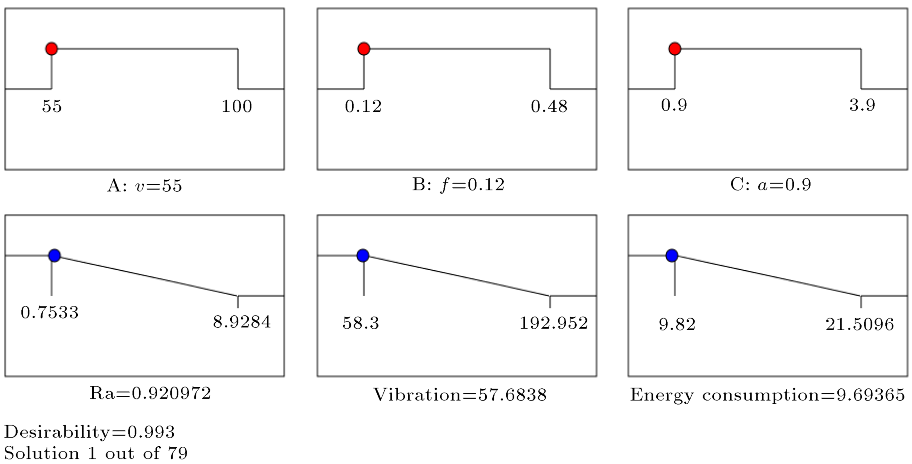

Figure 9. Ramp function graph for optimization.

vibration = 86.71 m/s^2, and energy consumption = 12.7 kWh. Combined desirability ratio was obtained as 0.993. This high desirability ratio is indicative of the reliability of the created RSM optimization model.

4.2. Grey relational analysis

Grey relational analysis consists of the basic steps found in multi-criteria (qualified) decision-making methods [22,23]. These steps are described below. In the last stage, the calculated values are given in line with these steps.

Step 1: Decision matrices are created. Eq. (1) is formed as follows: m alternatives and n criteria.

$$X = \begin{bmatrix} x_1(1) & x_1(2) & \cdots & x_1(n) \\ x_2(1) & x_2(2) & \cdots & x_2(n) \\ \vdots & \vdots & \ddots & \vdots \\ x_m(1) & x_m(2) & \cdots & x_m(n) \end{bmatrix}. \tag{1}$$

Step 2: This step is the normalization process of the data. In order for the criteria to be compared with each other, the unit differences among them must be eliminated. In this step, it is determined whether the dependent variables are minimum, mean or maximum according to expert opinions.

If the variable is desirable at the maximum value, Eq. (2) is as follows:

$$x_i'(j) = \frac{x_i(j) - \min x_i(j)}{\max x_i(j) - \min x_i(j)}$$

$$i = 1, 2, \cdots, m, \quad j = 1, 2, \cdots, m. \tag{2}$$

If the variable is desirable at the minimum value, Eq. (3) is as follows:

$$x_i'(j) = \frac{\max x_i(j) - x_i(j)}{\max x_i(j) - \min x_i(j)}$$

$$i = 1, 2, \cdots, m \quad j = 1, 2, \cdots, m. \tag{3}$$

If the variable is desirable at the ideal value, Eq. (4) is as follows:

$$x_i'(j) = 1 - \frac{|x_i(j) - x_0(j)|}{\max x_i(j) - x_0(j)}$$

$$i = 1, 2, \cdots, m \quad j = 1, 2, \cdots, m. \tag{4}$$

After normalization, the unit differences between the variables disappear. Results take values between 0 and 1. Hence, the results become comparable.

Step 3: This step is taken when the reference series are created. In the third step, the normalized decision matrix (X') of Eq. (5) with the values is normalized:

$$X = \begin{bmatrix} x_1'(1) & x_1'(2) & \cdots & x_1'(n) \\ x_2'(1) & x_2'(2) & \cdots & x_2'(n) \\ \vdots & \vdots & \ddots & \vdots \\ x'_m(1) & x'_m(2) & \cdots & x'_m(n) \end{bmatrix}. \tag{5}$$

Eq. (6) is the reference matrix (X_0) for the reference values determined for each of the n criteria:

$$X_0 = \{x_0(1), x_0(2), x_0(3), \cdots, x_0(n)\}. \tag{6}$$

Step 4: It is the step required to obtain the difference matrix. Difference matrix values are obtained by calculating the difference between the values in the normalized decision matrix and the reference series calculated for each criterion using Eq. (7):

$$\Delta_{0i}(j) = |x_0(j) - x_i'(j)|$$

$$i = 1, 2, \cdots, m, \quad j = 1, 2, \cdots, m. \tag{7}$$

Step 5: This step is to obtain the grey relational coefficients. Grey relational coefficients are calculated based on Eq. (8). The grey relational coefficient between $x_0(j)$ and $x_i(j)$ is expressed as $\varepsilon(x_0(j), x_i(j))$, and its value is calculated as equating between 0 and 1.

$$\varepsilon(x_0(j), x_i(j)) = \frac{\Delta_{\min} + \xi\Delta_{\max}}{\Delta_{0i}(j) + \xi\Delta_{\max}},$$

$$\Delta_{\min} = \min_i \min_j |x_0(j) - x_i(j)|,$$

$$\Delta_{\max} = \max_i \max_j |x_0(j) - x_i(j)|,$$

$$i = 1, 2, \cdots, m, \quad j = 1, 2, \cdots, m. \tag{8}$$

The expression ξ is expressed as the coefficient of separation whose value is between 0 and 1. It is usually taken as 0.5 in scientific papers;

Step 6: Grey relational degree expresses the weighted sums of grey relational coefficients for each criterion which is calculated through Eq. (9):

$$\gamma(x_0, x_i) = \sum_{j=1}^{n} \varepsilon(x_0(j), x_i(j) * w_i(j)). \tag{9}$$

The value of $w_i(j)$ equals the weights determined for each criterion. If the criteria have equal weight values, the formula in Eq. (10) turns into the following:

$$\gamma(x_0, x_i) = \frac{1}{n} \sum_{j=1}^{n} \varepsilon(x_0(j), x_i(j)). \tag{10}$$

The grey relational degree measures the degree of similarity between the series for each alternative and reference series. The more similar the alternative series is to the reference series, the greater the grey relational degree becomes. This way, each alternative is ranked from the best to worst.

Table 8 shows the results calculated based on the mentioned steps. The minimum value equation is used

Table 8. Calculation results for grey relational analysis.

No	Normalized values			Deviance sequences			Grey relation coefficient			GRG	Rank
	Ra	Vibration	Energy	Ra	Vibration	Energy	Ra	Vibration	Energy		
1	0.819	0.894	0.821	0.181	0.106	0.179	0.734	0.825	0.736	0.765	4
2	0.050	0.000	0.000	0.950	1.000	1.000	0.345	0.333	0.333	0.337	15
3	0.917	0.758	0.895	0.083	0.242	0.105	0.858	0.674	0.827	0.786	3
4	0.169	0.229	0.208	0.831	0.771	0.792	0.376	0.393	0.387	0.385	12
5	0.486	0.472	0.475	0.514	0.528	0.525	0.493	0.486	0.488	0.489	8
6	0.576	0.499	0.566	0.424	0.501	0.434	0.541	0.500	0.536	0.525	7
7	0.407	0.288	0.414	0.593	0.712	0.586	0.458	0.413	0.461	0.444	10
8	0.854	0.978	0.917	0.146	0.022	0.083	0.774	0.958	0.858	0.863	2
9	0.691	0.677	0.689	0.309	0.323	0.311	0.618	0.608	0.617	0.614	5
10	0.605	0.704	0.726	0.395	0.296	0.274	0.559	0.628	0.646	0.611	6
11	0.169	0.244	0.165	0.831	0.756	0.835	0.376	0.398	0.375	0.383	13
12	0.000	0.127	0.028	1.000	0.873	0.972	0.333	0.364	0.340	0.346	14
13	1.000	1.000	1.000	0.000	0.000	0.000	1.000	1.000	1.000	1.000	1
14	0.382	0.459	0.357	0.618	0.541	0.643	0.447	0.480	0.437	0.455	9
15	0.394	0.373	0.301	0.606	0.627	0.699	0.452	0.444	0.417	0.438	11

for Ra, vibration, and energy consumption. According to the grey relational analysis, experiment number 13 contains optimum parameters. The optimum parameters according to the grey relational analysis is determined with the cutting speed of 55 m/min, feed rate of 0.12 mm/rev, and cut depth of 0.9 mm.

5. Conclusions, discussion, and suggestions

In this study, Ti 6Al-4V alloy workpiece was machined on the CNC lathe. The cutting parameters were selected containing three factors (V-f-a) and four levels. The RSM optimal (custom) design method was employed to decrease the number of experiments. While 64 experiments should be conducted with full factorial experiment design, the number of experiments was reduced to 15 using the RSM. In addition, the values for Ra, vibration, and energy consumption were determined. Evaluation of these results was as significant as that of the results obtained in the study. The present study employed two statistical methods. The experimental results were then evaluated using RSM and grey relational analysis method. A summary of the experimental and statistical findings is given below:

- When turning titanium material, low cutting speeds or cutting fluid should be used; otherwise, high tool wear would occur. As a result, the vibration increases, which in turn leads to deterioration of surface quality and increase in energy consumption;
- This study analyzes the relationship among Ra, vibration, and energy consumption in terms of the machinability of titanium alloy;
- While examining the experimental results, it was concluded that the Ra, vibration, and energy consumption values were directly proportional. In other words, an increase in the one that affected the others. In the opposite case, it is true;
- Regression equations were established for Ra, vibration, and energy consumption. The R^2 value for Ra, vibration, and energy consumption was 0.99. In addition, the values for the regression equations exhibited the reliability of these models;
- ANOVA results were determined for the effective parameters including Ra, vibration, and energy consumption. Feed rate was proved to be an effective parameter of about 98% for Ra, about 89% for vibration, and 96% for energy consumption;
- While examining the contour, perturbation, and contribution charts, it was found that Ra, vibration, and energy consumption were more affected by the feed rate;
- The optimum cutting parameters were determined using RSM. These parameters for Ra, vibration, and energy consumption were calculated as $V = 100$ m/min, $f = 0.12$ mm/rev, and $a = 3.9$ mm. Further, the optimized Ra, vibration, and energy consumption values were determined (Ra $= 2.85$ μm, vibration $= 86.71$ m/s^2, and energy consumption = 12.7 kWh);
- The desirability ratio was calculated as 0.993 using

the RSM. This desirability ratio was indicative of the optimization reliability;

- The optimum cutting parameters were determined through the grey relational analysis. These parameters for Ra, vibration, and energy consumption were calculated as $V = 55$ m/min, $f = 0.12$ mm/rev, and $a = 0.9$ mm. The optimized Ra, vibration, and energy consumption were also calculated ($Ra = 0,75$ μm, vibration $= 58,30$ m/s^2, and energy consumption $= 9,82$ kWh);
- It was concluded that the vibration and energy consumption could be controlled by Ra;
- Since the results were positive, the methods used in the study could be applied to future studies (both in industrial and academic fields);
- Statistical approaches (Taguchi, artificial intelligence methods, etc.), experimental designs (DOE, full factorial, Box Behnken, Taguchi, etc.), parameters (cutting tool, cutting speed, feed, chip depth, coolant, cutting tool angles, cutting tool material, etc.), and measurement results (wear, acoustic emission, vibration, cutting forces, sound, temperature, etc.) are recommended for further studies.

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Nomenclature

RSM	Response Surface Method
Ra	Average surface roughness
ANOVA	Analysis of variance
ELI	Extra Low Interstitials
CNC	Computer Numerical Control
R^2	Coefficient of determination
V	Cutting speed
f	Feed rate
a	Depth of cut

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Biography

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