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Analysis of machining parameters for EN24 material in CNC vertical machining center by Ti-N coated HSS tool using GRG reinforced RSM technique

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Abstract: The goal of the present study is to evaluate the optimum machining parameters for EN24 material to achieve an increased material removal rate (MRR), low cutting force (CF), and surface roughness (SR). The total number of trial experiments for the three control parameters spindle speed (SS), feed rate (FR), and depth of cut (DOC) varying at three levels are designed based on the Taguchi L27 orthogonal array. To optimize the multiple machining parameters for EN24 steel based on the three experimentally measured responses such as MRR, CF, and SR, a contemporary and hybrid multi-objective optimization technique, grey relational grade (GRG) reinforced response surface methodology (RSM) is employed in the present study. Based on the results obtained from the integrated multi-objective optimization technique, the predicted optimum machining conditions for SS, FR, and DOC are 1383.47 rpm, 106.5 mm/min, and 0.79 mm respectively. The responses MRR – 21.56 mm3/min, CF – 195.56N, and SR- 0.53µm are obtained at optimum level. The percentage of improvement achieved in the preferred responses for milling the EN 24 material after implementing the GRG reinforced RSM technique are MRR - 5.19%, CF - 15.42%, and SR- 19.69%.

Keywords: Response Surface Methodology, Grey Relational Grade, Cutting Force, Material Removal Rate, Surface Roughness

1. Introduction

The intrinsic properties like good fatigue resistance, high mechanical strength, and greater durability under heavy load conditions made EN24 material more popular in aircraft, automobile, and general engineering industries. The practical application of EN24 material demands various machining processes on raw materials in making the end engineering component. Ni, Cr, and Mo alloying elements present in high strength EN24 steel alloy material enhance its ductility, wear resistance, and tensile strength [1]. Due to these desired properties, EN24 material finds application in automotive, aerospace, and general engineering applications. In general, while making dies and punches using EN 24 material, milling operation is carried out on the material to form various job profiles required [2]. For achieving a better cutting profile during the milling of EN24 material, the optimum machining parameters of the corresponding milling machine are to be evaluated by conducting numerous experiments at different levels and combinations of the preferred control parameters. Thus experimental evaluation of the optimum control parameters for a material on a particular machine requires a lot of trials that involve more time and money. A well-structured multi-objective optimization technique may be useful in finding the optimum control parameters with a limited number of predesigned trials. Particle swarm optimization, genetic algorithm, principal component analysis, and so many methods are available for multi-objective optimization [3]. In the present study, GRG implemented RSM technique is employed because of its ease of application and error-free nature. From an earlier study, it is revealed that when hardened steel is machined in non-lubricated conditions, titanium nitride (TiN) coated tools outperform uncoated cutting tools. The two most important factors in achieving high-quality surface roughness are low feed rate and elevated cutting speed. The rate at which material is removed is dependent on the coolant condition, feed rate, and cutting speed. The cutting force developed by the tool on the workpiece material is significantly controlled by parameters, spindle speed, and feed rate [4]. To improve the metal removal rate and achieve superior surface smoothness when milling composite material, optimization based on grey Taguchi analysis is applied [5]. Numerous real-world applications comprise multi-objective optimization challenges. The multi-objective optimization algorithms must provide solutions that give up on competing goals, even in single-objective optimization situations. Hybrid approaches were applied to model the response values of different processes and optimize the process parameters.

Combining the advantages of the various algorithms is now possible because of these integrated methods. For response modeling and optimization, the RSM technique was combined with grey relational analysis [6, 7]. An optimization method creates response surfaces to investigate how different design variables interact with one another. Typically, the two main reaction surface designs utilized are the central composite design (CCD) and the Box-Behnken design (BBD) [8, 9]. Traditionally, an RSM generates a quadratic model for every response using BBD or CCD for testing. This restricts the observations related to simultaneous optimization by limiting the analysis to the influence of design factors on individual responses [10]. Hybrid multi objective optimization with ratio assessment techniques and grey relational analysis are employed for the optimization research, with equal weighting assigned to each output [11]. In the current study, emphasis is given to optimizing the machining parameters for EN24 steel in a vertical CNC machining center with titanium nitride (TiN) coated high-speed steel (HSS) tool. Orthogonal arrays-based RSM has not received much attention in the literature, although manufacturing processes have used RSM with central composite design. Because of this, the suggested study expands the possibility of optimizing many responses at the same time by applying an integrated technique of GRG reinforced RSM for optimal parameter design.

2. Material and Methods

The current study attempts to optimize machining parameters like spindle speed, feed rate, and depth of cut for EN24 material in a vertical CNC machine to obtain the best machining characteristics such as cutting force, surface roughness, and metal removal rate. The composition of EN 24 steel is as follows : Ni-1.5%;Cr-1.25 %;Mn-0.6%;C-0.4%;Mo-0.3 %;Si-0.25%; S-0.04%; P-0.035%, and the rest Fe compounds. The TiN-coated (3µm thick layer) high speed steel (HSS) tool is used to machine EN24 material on the CNC vertical machining center (AMS Spark-ACE Micromatic) as shown in Figure 1. The composition of TiN coated HSS tool is as follows [12]: W-6.85%; Mo-5.1%; Cr-4.85%; V-1.95 %;C-0.83%, and the rest Fe compounds. TiN coating provides extremely good wear resistance and hardness for the HSS tool [13].

Table 1 lists the parameters along with their three levels considered for the present investigation. Taguchi L27 orthogonal array is utilized to determine the total number of trial experiments required for implementing the optimization procedure [14]. Every test was carried out on a vertical CNC machining center in dry condition. Figure 1 and Figure 2 show the images of the end milling operation performed on EN24 material in the CNC vertical machining center using a Ti-N coated HSS cutting tool. Figure 3 and Figure 4 show EN24 workpiece material of size 50mm x 50mm x 6mm after the end milling process.

Table 1. Preferred machining parameters with three levels considered

Parameter	Level 1	Level 2	Level 3
Depth of Cut (DOC) in mm	0.4	0.8	1.2
Spindle Speed (SS) in rpm	800	1200	1600
Feed Rate (FR) in mm/min	75	100	125

Figure 1. Image showing the Vertical CNC Machining Center used for the current study.

Figure 2. Image showing the end milling of EN24 specimen on CNC machine.

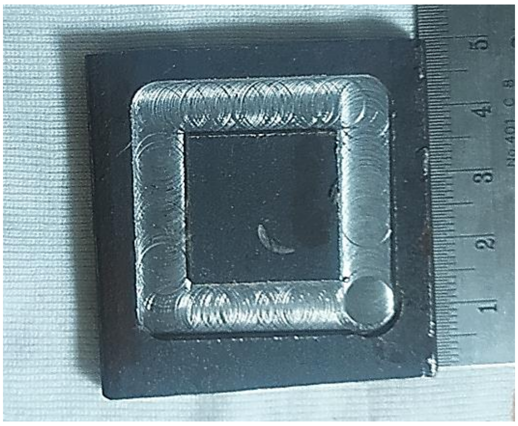


Figure 3. Image showing closure view of the profile of an EN24 specimen after milling with a TiN coated HSS tool.

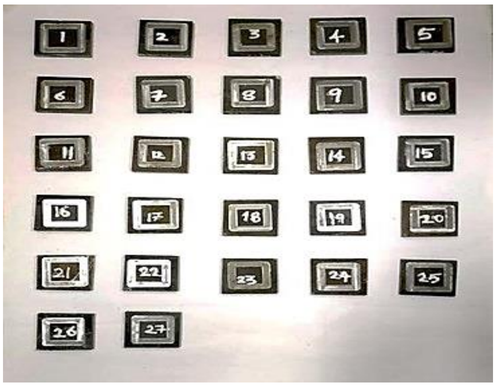


Figure 4. Image showing all EN24 specimens after completing the end milling process.

To measure the cutting forces Fx, Fy, and Fz, along the x, y, and z directions during milling the EN24 material, a standard tool dynamometer is attached to the machine. The resultant cutting force is evaluated as FR = $(Fx^2 + Fy^2 + Fz^2)^{1/2}$, and considered for further analysis [15]. An electronic watch is utilized to record the actual time taken accurately for machining each specimen. The mass of each EN24 specimen before and after the milling operation was measured precisely using an electronic weighing machine. Equation (1) is used to calculate the (MRR) of each specimen.

$$MRR = (m_b - m_a) / \rho \times t \tag{1}$$

where

m_b= Mass of the original workpiece in kg,

m_a= Mass of the workpiece after milling in kg,

ρ = Density of EN24 Material =7839 kg/m^3,

t = Machining time in Sec.

The surface roughness (SR) of the workpiece profile of each EN24 specimen was observed using a surfcoder (Mitutoyo SJ-210) instrument.

The surface roughness values were measured at 5 distinct locations along the machined profile and the average roughness value was used for further study. Table 2 lists the values of the three preferred machining parameters for all 27 trials of experiments and the corresponding measured responses.

3. GRG Reinforced RSM Method

Based on the required desirability analysis, the experimentally recorded responses are optimized using the statistical technique RSM. Through the reinforcement of GRG in RSM, the interdependence among the responses transforms the multi-objective elements into a single-objective function. The following is the step-by-step process of the grey reinforced response surface methodology.

3.1 Stage 1: Grey Relational Grade (GRG) Analysis

The signal to Noise ratio is computed for all the experimental data obtained through trial experiments carried out based on the L27orthoganal array [16]. To bring the computed S/N ratio values of the different responses closer to a normal distribution and also to improve the comparability of the design variable values, a linear normalization process was applied [17]. After being normalized, the normalized data is processed further to determine the significance of each parameter over the different output responses obtained from experiments [18]. The quality attributes found in terms of GRG were translated onto the design factors employed in the milling process.

Step 1: S/N ratios for each response are calculated using a precise formula based on the quality standards. The smaller the best kind of quality features were employed to reduce CF and SR and the larger the best feature was employed to maximize MRR. Equations (2) and (3) are used to evaluate the S/N ratio (η) values for the experimentally measured responses.

Smaller-the-best:

$$S/N\ Ratio(\eta) = -10\log_{10}\left(\frac{1}{n}\cdot\sum_{i=1}^{n} y_{ij}^2\right) \tag{2}$$

Larger-the-best:

$$S/N\ Ratio(\eta) = -10\log_{10}\left(\frac{1}{n}\right)\sum_{i=1}^{n}\frac{1}{y_{ij}^2} \tag{3}$$

yij = observed output values, i = 1,2,3… n, and j = 1,2,…m,

Where, m = number of observations and n = number of replications

Step 2: Normalized values of the S/N ratio (Zij) are estimated using Equation (4)

Table 2. Experimental plan and corresponding measured output

S. No.	SS (rpm)	FR (mm/min)	DOC (mm)	Average CF (N)	MRR (mm3/s)	Average SR (µm)
1	800	75	0.4	100.36	4.21	0.63
2	800	100	0.4	154.30	5.37	0.75
3	800	125	0.4	171.42	5.45	0.9
4	800	75	0.8	133.43	11.07	0.65
5	800	100	0.8	200.35	15.45	0.79
6	800	125	0.8	219.33	16.70	0.85
7	800	75	1.2	131.94	7.33	0.64
8	800	100	1.2	170.88	9.21	0.76
9	800	125	1.2	200.35	12.95	0.89
10	1200	75	0.4	46.76	1.73	0.55
11	1200	100	0.4	72.50	6.15	0.65
12	1200	125	0.4	115.75	7.33	0.75
13	1200	75	0.8	118.24	7.33	0.54
14	1200	100	0.8	154.01	15.45	0.64
15	1200	125	0.8	160.86	19.83	0.74
16	1200	75	1.2	148.15	12.95	0.56
17	1200	100	1.2	230.61	20.44	0.66
18	1200	125	1.2	231.22	26.07	0.76
19	1600	75	0.4	36.91	1.71	0.26
20	1600	100	0.4	48.52	5.46	0.3
21	1600	125	0.4	62.31	10.45	0.4
22	1600	75	0.8	72.33	7.33	0.29
23	1600	100	0.8	84.95	10.46	0.3
24	1600	125	0.8	132.44	19.83	0.42
25	1600	75	1.2	113.75	7.33	0.37
26	1600	100	1.2	116.82	12.95	0.35
27	1600	125	1.2	147.01	22.95	0.34

$$Z_{ij} = \frac{y_{ij} - \min(y_{ij}, i = 1,2,\ldots\ldots, n)}{\max(y_{ij}, i = 1,2,\ldots\ldots, n) - \min(y_{ij}, i = 1,2,\ldots\ldots, n)} \quad (4)$$

Step 3: Grey relational coefficient (γ) values are evaluated using Equation (5)

$$\gamma_i^j = \frac{\Delta\min + \xi\Delta\max}{\Delta_{oj}(i) + \xi\Delta\max} \quad (5)$$

$\Delta_{oj} = \left\| z_o(i) - z_j(i) \right\|$, $z_o(i)$ is the reference order ($z_o(i)$ =1; i=1,2,…,n) and $z_j(i)$ is the smallest magnitude of $z_j(i)$, and 'ξ' is the distinguishing coefficient $(0 \le \xi \le 1)$ which is taken as 0.5 for the present case.

Step 4: Grey Relational Gradient values for every trial are calculated using Equation (6)

$$GRG_i = \frac{1}{n}\sum_{i=1}^{n}(\gamma_i) \tag{6}$$

3.2 Stage II: GRG Reinforced RSM

In the second stage, the GRG values obtained in the first stage are considered as input to the RSM technique, and a second order model was created [19]. The corresponding response surface plots were produced for a good understanding of the effects of input machining parameters on the preferred responses.

Step 5: Analysis of Variance (ANOVA) was carried out for the evaluated GRG values to identify the significant contribution of each parameter.

Step 6: A second order model was created in the RSM technique to relate the GRG inputs and their interactions.

Step 7: The best machining conditions are identified using the required desirability analysis. The response surface plot obtained from the RSM technique explains how input parameters affect GRG.

Table 3 provides the S/N ratios, normalized S/N ratio values, grey relational gradient (GRG), and grey relational coefficient (GRC) for the quality attributes of milling EN24 material. The greatest GRG value was 0.6805 (18th trial), which was in line with experimental settings that were almost ideal.

4. Results and Discussion

4.1 Model Analysis using ANOVA

Table 4 displays the results of the ANOVA performed for the GRG values evaluated for the 27 trial experiments. The table shows the sum of squares, Mean square, F-value, and p-value along with the model term [20].

The model stability and the statistical significance of various machining parameters were confirmed using the ANOVA, which is displayed in Table 4 for the response GRG. The results showed that the model was significant with main factors A, B, and C and interaction factors AB and BC as 'p' values less than 0.05, and the three machining parameters considered for the study, SS, FR, and DOC, are significantly affecting the three responses of CF, MRR, and SR. The main factors A, B, and C contributing to influence the responses are 23.24%, 21.3%, and 29.65% respectively. The interaction factors AB and BC contribution to influence the responses are 4.72% and 8.66% respectively. The individual factors play a greater influence than the interaction factors for machining responses. The entire response variability is displayed by the R^2 value, which accounts for the significant variables. The entire number of predictors in the model is taken into consideration in the adjusted R^2 value [21]. Both numbers indicate that the model provides a precise fit to the data. The Adjusted R^2 of 0.7916 and the Predicted R^2 of 0.6623 are reasonably in agreement with one another that is, the difference is less than 0.2. A regression model was created for the quadratic model to understand the level of significance of individual parameters and their interaction with GRG values. Equation (4.1) shows the mathematical model of the present study after neglecting the insignificant model terms with p values more than 0.05. This equation helps to predict GRG values theoretically and this includes individual factors and interaction factors.

GRG = 0.5895-0.0326 A+0.0073 B+0.0485 C-0.0181 AB+0.024 BC-0.0351 A^2 (4.1)

The comparison plot of actual and predicted values is shown in Figure 5 and the normal plot of residuals is shown in Figure 6. The residual plot in Figure 5 shows that only very few points are deviated from the center line which suggests that some expected values may differ from actual values. However, the majority of the predicted points in the graph generally match the values of the real points which confirms the validity of the present mathematical model.

4.2 Optimization Study using RSM

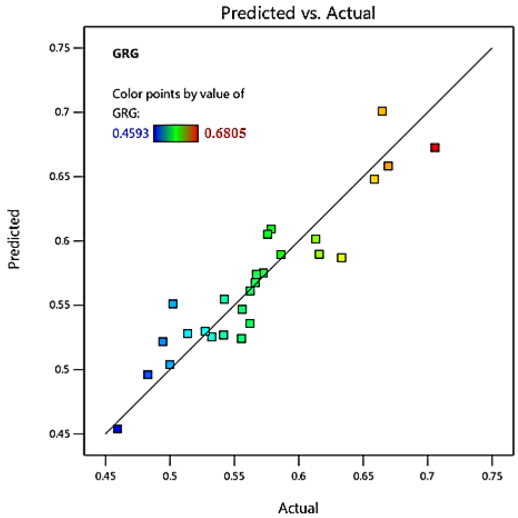
Numerous optimization techniques offer the required solutions of interest for many real-life problems. Some of the techniques used for optimization include overlaying the contour plots for each response, the desirability approach, and constrained optimization issues. Among all these, the desirability technique has been shown to have added benefits such as ease of use, software accessibility, adaptability in weighing, and the capacity to lend legitimacy to each response [22]. In the present work, the preferred input variables, including SS, DOC, and FR are optimized using an RSM-based desirability technique using Design Expert software [23]. The responses like CF, MRR, and SR are all included in the GRG analysis. The optimal conditions obtained based on the highest value of desirability in the RSM method are as follows: SS – 1383.47 rpm, DOC -0.79 mm, and FR -106.5 mm/min. The desirability analysis output is listed in Table 5. Figure 7 shows the ramp graph with the optimal level of input parameters. The input parameters with the highest desirability are shown in the ramp graph. The highest desirable level of all input parameters in the range of permissible levels is marked as the red dot hence informing the highest value of GRG is 0.6953.

Table 3. S/N Ratio, Normalized S/N Ratio, GRC, and GRG for Milling of EN 24 Material with TiNcoated HSS

Trial	S/N Ratio			Normalized S/N Ratio			GRC			GRG
	CF	SR	MRR	CF	SR	MRR	CF	SR	MRR	GRG
1	-40.032	-4.013	12.487	0.455	0.713	0.331	0.478	0.635	0.428	0.5137
2	-43.767	-2.499	14.597	0.220	0.853	0.420	0.391	0.773	0.463	0.5422
3	-44.682	-0.915	14.730	0.163	1.000	0.426	0.374	1.000	0.465	0.6131
4	-42.506	-3.742	20.887	0.300	0.738	0.685	0.417	0.656	0.614	0.5621
5	-46.036	-2.047	23.776	0.078	0.895	0.807	0.352	0.826	0.722	0.6332
6	-46.822	-1.412	24.453	0.029	0.954	0.836	0.340	0.916	0.753	0.6694
7	-42.408	-3.876	17.302	0.306	0.725	0.534	0.419	0.646	0.518	0.5273
8	-44.654	-2.384	19.283	0.165	0.864	0.618	0.374	0.786	0.567	0.5757
9	-46.036	-1.012	22.247	0.078	0.991	0.743	0.352	0.982	0.660	0.6647
10	-33.399	-5.193	4.760	0.871	0.603	0.005	0.795	0.558	0.334	0.5623
11	-37.208	-3.742	15.775	0.632	0.738	0.470	0.576	0.656	0.485	0.5725
12	-41.271	-2.499	17.302	0.377	0.853	0.534	0.445	0.773	0.518	0.5786
13	-41.456	-5.352	17.302	0.365	0.589	0.534	0.441	0.549	0.518	0.5023
14	-43.751	-3.876	23.776	0.221	0.725	0.807	0.391	0.646	0.722	0.5861
15	-44.129	-2.615	25.946	0.198	0.842	0.899	0.384	0.760	0.831	0.6586
16	-43.414	-5.036	22.247	0.243	0.618	0.743	0.398	0.567	0.660	0.5416
17	-47.258	-3.609	26.211	0.001	0.750	0.910	0.334	0.667	0.847	0.6159
18	-47.281	-2.384	28.322	0.000	0.864	1.000	0.333	0.708	1.000	0.6805
19	-31.343	-11.701	4.641	1.000	0.000	0.000	1.000	0.333	0.333	0.5555
20	-33.718	-10.451	14.749	0.851	0.115	0.426	0.770	0.361	0.466	0.5324
21	-35.892	-7.959	20.381	0.715	0.347	0.664	0.637	0.434	0.598	0.5561
22	-37.187	-10.752	17.302	0.633	0.088	0.534	0.577	0.354	0.518	0.4829
23	-38.583	-10.458	20.391	0.546	0.115	0.664	0.524	0.361	0.598	0.4945
24	-42.440	-7.535	25.946	0.304	0.386	0.899	0.418	0.449	0.831	0.5661
25	-41.120	-8.636	17.302	0.387	0.284	0.534	0.449	0.411	0.518	0.4593
26	-41.350	-9.119	22.247	0.372	0.239	0.743	0.443	0.397	0.660	0.5000
27	-43.347	-9.370	27.215	0.247	0.216	0.952	0.399	0.389	0.913	0.5670

Table 4. ANOVA for Quadratic model

Source	SS	DOF	MS	F-value	p-value	% Contribution
Model Terms	0.0837	9	0.0093	11.97	<0.0001	-
SPEED-A	0.0192	1	0.0192	24.69	0.0001	23.24
DEPTH OF CUT-B	0.0181	1	0.0181	22.63	0.0001	21.3
FEED RATE- C	0.0252	1	0.0252	31.5	<0.0001	29.65
AB	0.0039	1	0.0039	5.02	0.0386	4.72
AC	0.0019	1	0.0019	2.50	0.1324	2.35
BC	0.0071	1	0.0071	9.20	0.0075	8.66
A^2	0.0074	1	0.0074	9.52	0.0067	8.96
B^2	0.0003	1	0.0003	0.3833	0.5441	0.36
C^2	0.0006	1	0.0006	0.7836	0.3884	0.73
Residual	0.0132	17	0.0008			
Cor Total	0.0969	26				



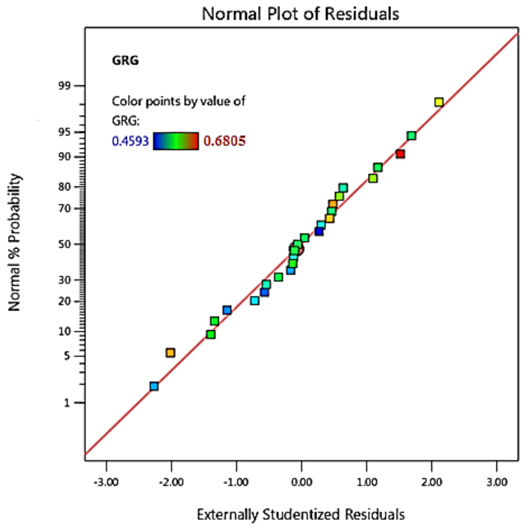


Figure 5. Plot of Actual vs. predicted GRG Values. **Figure 6.** Normal plot of residuals of GRG values.

Table 5. Milling Input Parameters at Optimal Level for EN24 material by RSM

Milling Inputs	Symbol	Low Level	High Level	Optimum Level
Spindle speed (rpm)	A	800	1600	1383.47
Depth of cut (mm)	B	0.4	1.2	0.79
Feed rate (mm/min)	C	75	125	106.5

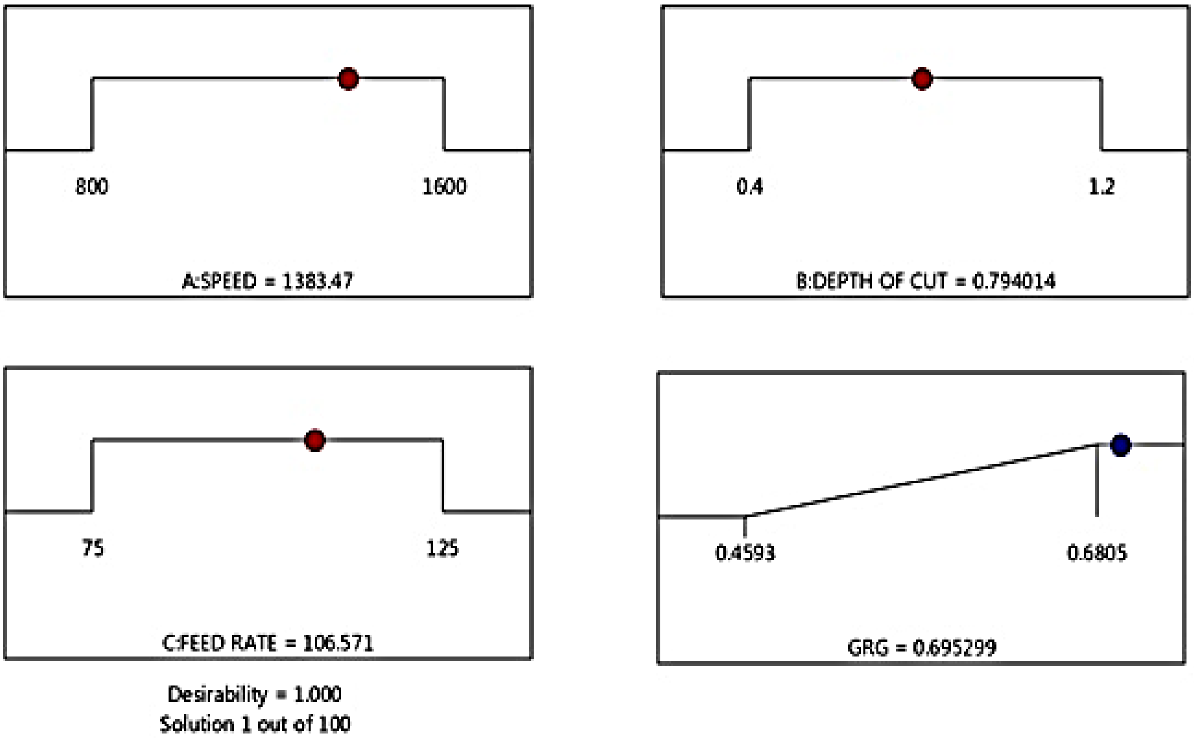


Figure 7. Ramp function graph showing the optimal machining parameters

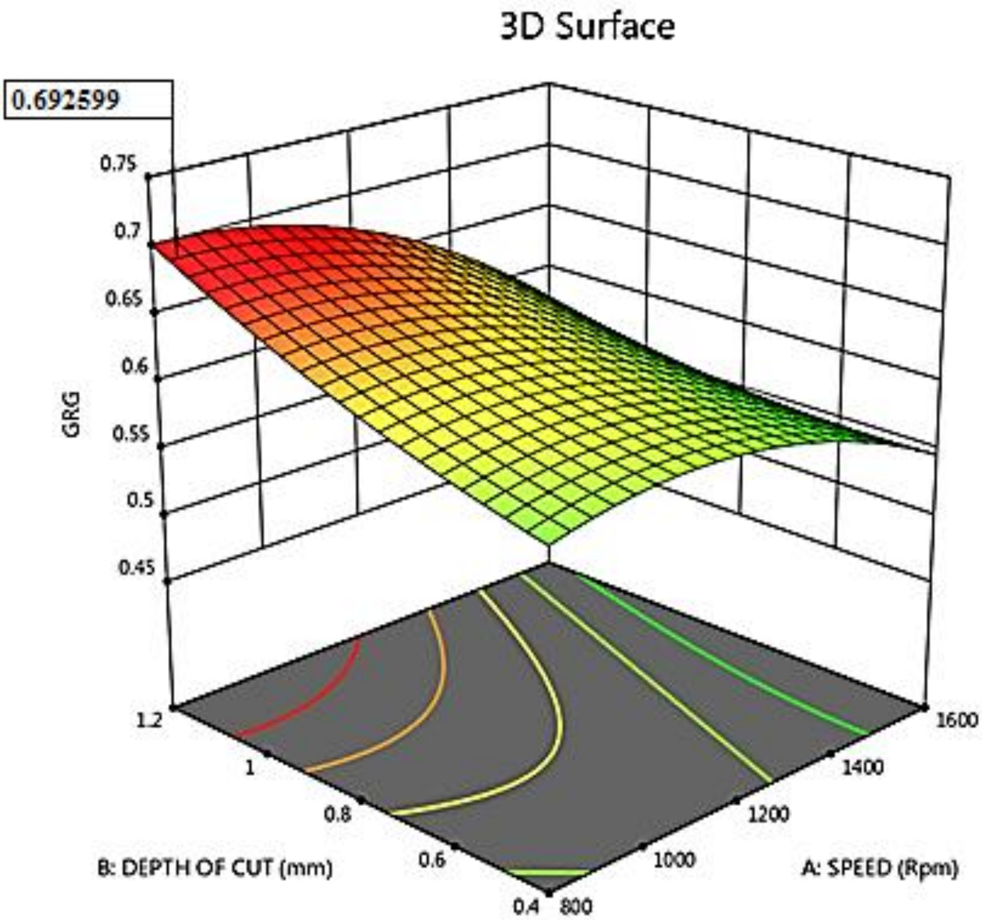


Figure 8. Optimum condition prediction graph for Depth of cut vs. Speed

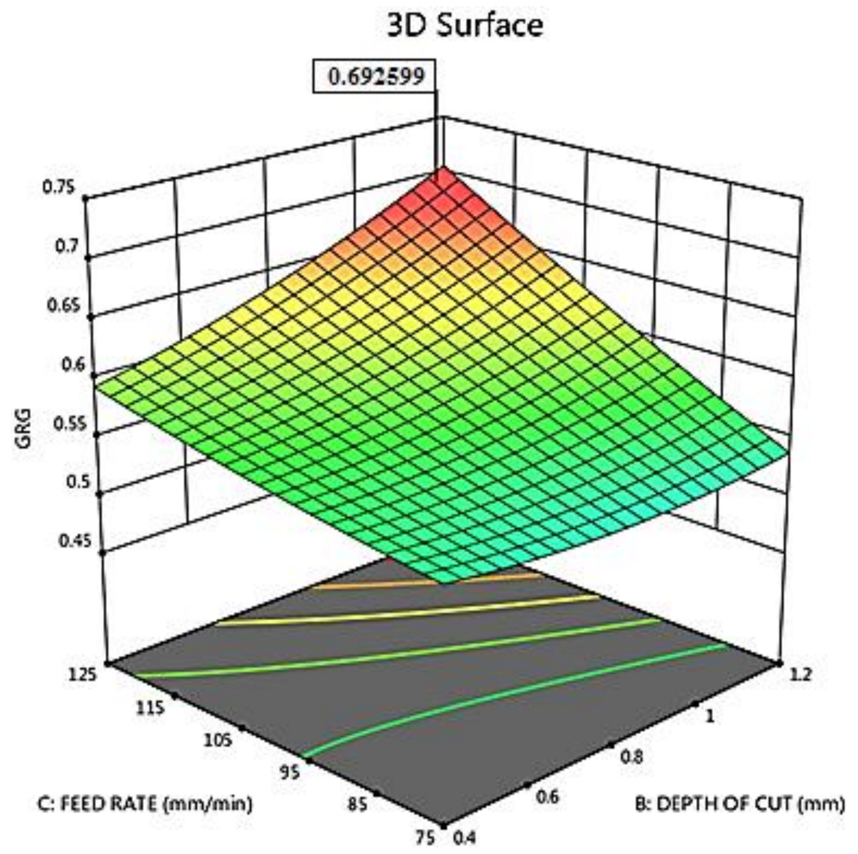


Figure 9. Optimum condition prediction graph for Feed rate vs. depth of cut

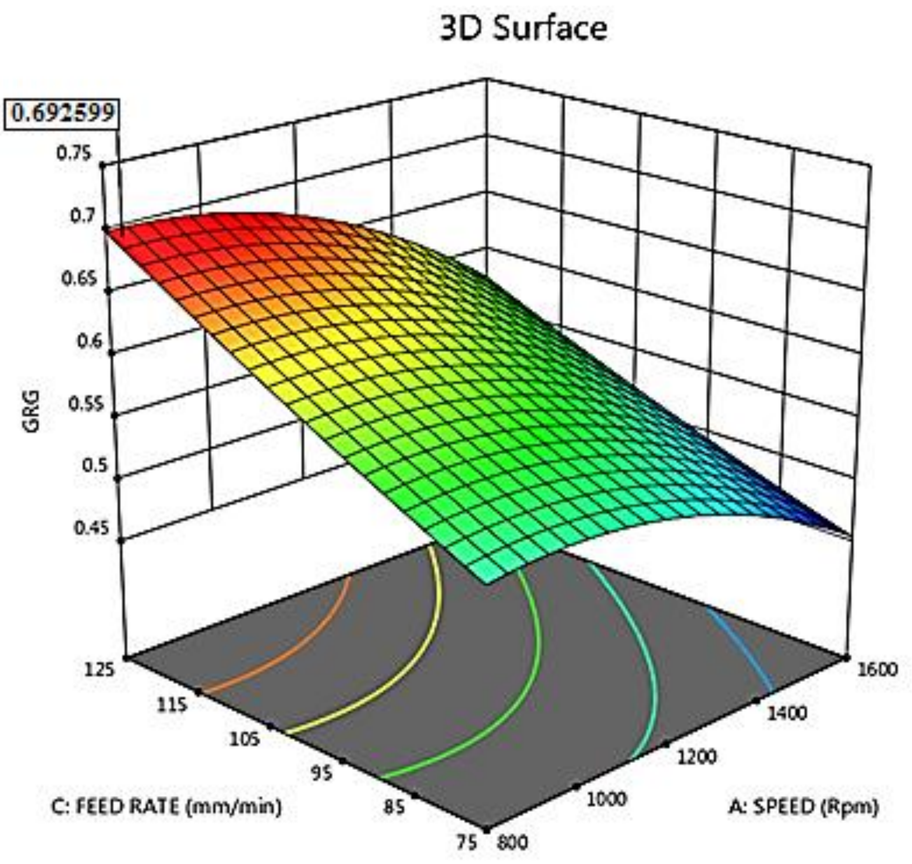


Figure 10. Optimum condition prediction graph for Speed vs. feed rate

Table 6. Responses Predicted with Optimal Conditions

Responses	Maximum Condition	Optimal Condition	Improvement
GRG	0.6805	0.6952	0.0147
MRR (mm^3/min)	20.44	21.56	1.12
SR (µm)	0.66	0.53	0.13
CF (N)	231.22	195.56	35.66

The variation plots of GRG in 3D for the different process parameters considered are shown in Figures 8, 9, and 10. The optimum values of preferred parameters were displayed by the apex of the response surfaces. From RSM analysis, the main and interaction effects of various machining parameters on the responses are graphically depicted.

The output results predicted by the grey incidence reinforced response surface approach with the optimum configuration of milling inputs were compared to the outputs of the actual trial (No. 18) with the highest computed value of GRG (0.6805). At maximum GRG condition, the machining characteristics were found to be 231.22 N for CF, 0.66 µm for SR, and 20.44 mm^3/min for MRR. At optimum conditions, the machining characteristics were found to be 195.56 N for CF, 0.53 µm for SR, and 21.56 mm^3/min for MRR. The percentage of improvement achieved in the preferred responses for milling the EN 24 material after implementing GRG reinforced RSM technique are as follows: MRR - 5.19%, CF - 15.42%and SR- 19.69%.

Table 6 depicts the comparison of the various machine responses obtained for the highest GRG and optimum conditions obtained after implementing the GRG reinforced RSM technique. The surface roughness of 0.66µm was obtained at the speed of 1200 rpm and 0.53 µm at 1383 rpm. The surge in speed drops the surface roughness [24]. This is because, at high speed of rotation, the chances of creation of a built up edge on the surface are reduced which in turn decreases the surface roughness. The MRR in the machining process decides the machining time and cost of machining. The high speed of rotation of the spindle often tends to the formation of smaller chips, this smaller chips reduce the cutting resistance and heat generation, allowing for smoother cutting and more efficient material removal [25]. The high cutting force in machining tends to more wear on the tool and high heat generation which affects the properties of the material. Cutting force is decreased as a result of decreasing chip thickness and shear area as cutting speed increases. The decrease in depth of cut from 1.2 mm to 0.79 mm could be the reason for the reduction in cutting force and surface roughness at optimum conditions. During the machining process, smaller chips are usually created for a small depth of cut. Smaller chips may result in a less aggressive cutting operation, which would lower surface roughness [26]. The area of contact between the tool and the specimen reduces as the depth of cut decreases. Because less material is lost in each pass, the force needed to shear the material also reduces [27].

5. Conclusion

In the present study, the GRG reinforced RSM technique is employed to predict the optimum machining conditions for the milling of EN24 material on a CNC vertical machining center. The following conclusions were arrived at based on the experimental and statistical analyses:

The preferred GRG reinforced RSM technique is very effective in envisaging the optimum milling parameters for EN24 material to achieve desirable responses like high material removal rate, low surface roughness, and low cutting force.

The optimum solution obtained through GRG reinforced RSM technique yielded an MRR of 21.56 mm^3/min, SR of 0.53 µm, and CF of 195.56 N for the machining parameters level of DOC 0.79 mm, FR 106.5 mm/min, and SS 1383.47 rpm.

The percentage of improvement achieved in the preferred responses for milling the EN 24 material after implementing GRG reinforced RSM technique are as follows: MRR - 5.19%, CF - 15.42%and SR- 19.69%.

The preferred machining parameters, SS, FR, and DOC were found to be most significantly affecting the characteristics CF, SR, and MRR.

The current research outcomes established a better set of guidelines for milling EN24 material in CNC vertical machining centers using the TiN-coated HSS tool.

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Authors Contribution Statement

R. Murugan: Conceptualization, Writing. G. Senthilkumar: Data Curation, Investigation, Writing – original draft. V. Vinodkumar: Software, Methodology. G. Rathinasabapathi: Conceptualization, Supervision. B. Dhanasakkaravarthi: Validation. V. Sivaraman: Formal Analysis and Project Administration. All the authors read and approved the final version of the manuscript.

Competing Interests

The authors declare that there are no conflicts of interest regarding the publication of this manuscript.

Data Availability

The data supporting the findings of this study can be obtained from the corresponding author upon reasonable request.

Has this article screened for similarity?

Yes

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