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Research Article

Multiobjective Optimization of Hard Turning on OHNS Steel Using Desirability and TOPSIS Approaches

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Machining hard materials with 45–48 HRC is difficult in turning operation because of the improvident cutting parameter selections for the operation. The OHNS (AISI/SAE-01–48HRC) steel is mainly preferred for the production of shafts, gears, cams, and press tools. The OHNS material was turned at a dry state using VP-coated carbide inserts. The seventeen experimental trials were designed by central composite design (CCD) with different levels of cutting parameters, like feed rate, cutting speed, and depth of cut. Design Expert-11 software desirability approach and TOPSIS (Technique for Order Preference by Simulating the Ideal Solution) were used to analyse the experimental results to obtain a single optimal solution that defines better results on metal removal rate (MRR) and surface finish (Ra). RSM solution with 81.3% desirability, the cutting speed of 60 m/min, feed rate of 0.08 mm/rev, and depth of cut 1 mm as the optimal cutting parameters; similarly, TOPSIS algorithm calculation identifies the cutting parameter combinations, such as 40 m/min cutting speed, 0.09 mm/rev feed rate, and 1 mm depth cut to enrich the quality of the machined steel; however, the desirability approach cutting parameter setting is better for the surface finish achievement, while TOPSIS solution is better to obtain significant MRR. The confirmation test results validated for the predicted values of both approaches; as such, the experimental results were maintained better convenience than the predicted one. For the optimum cutting parameter combinations, an MRR of 22.032 gm/min and surface roughness of 0.781 μm were obtained at 60 m/min cutting speed, 0.08 mm/rev feed rate, and 1 mm depth of cut.

1. Introduction

Hard turning represents a crucial metal-cutting technique employed in manufacturing industries to uphold the quality standards of hard metal components. Typically, machining parameters are chosen from handbooks and operational data. However, the current approach to selecting cutting parameters often falls short of attaining optimal quality, resulting in energy wastage and escalating production costs [1, 2]. Conversely, high-speed turning operations yield superior surface finishes with moderate energy consumption. The quality of machined parts hinges on various factors, including machining parameters, work material, tool material, and machine condition [3]. Therefore, precise cutting parameters play a pivotal role in enhancing product quality. The permutations of input variables significantly impact responses such as surface finish and geometric parameters, consequently influencing energy consumption [4]. The functional efficiency of machined components is intricately linked to the surface finish achieved during machining. To augment quality, production costs and quality parameters of each machined part are meticulously scrutinized. Corrective measures can be implemented to uphold quality standards if these standards are not met.

In turning operations, cutting forces exert a substantial influence on tool life. At lower levels of machining parameters, radial components of cutting force are minimized. However, higher cutting speeds combined with a cryogenic environment result in reduced cutting forces. For instance, in the turning of hardened alloy steel AISI8660 using a PVD-coated ceramic tool, the feed rate notably impacts surface roughness, while the cutting speed exhibits independence in response [5, 6]. The surface finish of EN8 steel in turning operations is significantly influenced by cutting parameters, as confirmed by statistical and geometrical analyses. Notably, surface finish enhancement is achievable only at an optimal feed rate, while the contribution of cutting fluids to surface finish remains negligible.

Various factors associated with machining operations, both directly and indirectly, impact on surface finish, material removal rate (MRR), tool longevity, and geometrical precision of machined components; however, cutting parameters like cutting speed, feed rate, and depth of cut are the predominant factors in hard-turning operation [7, 8]. The insert CNMG120408-PM with DCLNL 2020K 12 tool holder, AlTiSiN-coated carbide inserts, and tungsten carbide-coated (WC) insert with chemical vapour deposition (CVD) coating with TiCN/Al2O3/TiN (ISO Designation: SNMM 120408) are used to machine AISI105 steel with hardness 206HB, AISID6 steel at dry condition, and AISI 1060 of 42 HRC, respectively. The low CBN content insert (ISO DESIGNATION: SNGA12 04 08 T01020) with the tool holder PSBNR 25 25 K12 is used to machine steel with hardness of 48 HRC [9–12]. To sustain hardness of the OHNS material, it is heat treated under the temperature range of 790°C to 820°C to obtain 48 HRC. It is suitable to produce press tools and die moulds [13]. Evaluating the performance of CBN and ceramic cutting tools in machining operations reveals that CBN tools yield superior results in surface roughness (Ra). At the same time, the increment in cutting force remains directly proportional to machining parameters [14]. In hard-turning operation, cutting fluids act as lubrication and cooling agent. The flood or deluge approach is practised in cutting fluids supplied methodology at the cutting edge during metal-cutting operation, and it ensures more quantity of cutting fluid and leads environment impacts and health hazards. By the application of minimal quantity of cutting fluid application route, the tool wear has been reduced such that surface finish of the work material is increased reasonably in hard-turning operation [15].

Conversely, increasing cutting speed has led to escalated flank wear on both cutters. A designated cutting tool, the WIDEX SCLCR 1212F09T3, is employed for machining EN-31 steel in turning operations under wet conditions. Utilizing grey relational analysis (GRA), optimal process parameters were forecasted [16]. In hard-turning operation, cutting fluids act as lubrication and cooling agent. The flood or deluge approach is practised in cutting fluids supplied methodology at the cutting edge during metal-cutting operation, and it ensures more quantity of cutting fluid and leads environment impacts and health hazards. By the application of minimal quantity of cutting fluid application route, the tool wear has been reduced such that surface finish of the work material is increased reasonably in hard-turning operation. The concentration system of lubricants contributes to improved surface finish by minimizing chip thickness and influencing geometrical parameters and cutting forces. By employing GRA and Taguchi's optimization methods, optimal cutting parameters for hard-turning processes are determined, with ANOVA indicating that the feed rate predominantly influences the surface finish of EN24 steel [17].

In the heat transfer dynamics during the cutting process of medium carbon steel in turning operations, it is observed that the flank face of the tool experiences low heat generation. This phenomenon allows for the resolution of multiresponse characteristics through grey relational analysis (GRA) as a singular solution [18, 19]. The impact of process variables on responses is elucidated by considering a higher-order degree of grey relational grade within variant machining environments, revealing that machinability is intricately linked to machining parameters. Research indicates that the thermal conductivity of tool materials plays a pivotal role in defining cutting tool erosion during machining. Employing cutting fluid emulsion enhances surface finish on machined parts, with the Jaya algorithm proving effective for solving both constrained and unconstrained optimization problems.

Optimization, as a methodology, aims to identify the optimal set of operating parameters to yield optimal results on responses. Techniques such as the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) serve as statistical methods to pinpoint the best solution for process parameters. Normalizing the solution of responses and applying optimization methods such as Taguchi and GRA optimize turning operations and the machinability of end milling operations through multiobjective function analysis [20, 21]. The highest value of the grey relational grade (GRG) signifies the optimal parameter settings to enhance the machinability of aluminium alloys.

The optimization of micromachining cutting parameters was achieved through response surface methodology (RSM), resulting in the enhancement of surface finish and metal removal rate. Optimal cutting parameters were selected to maximize these multiresponses, with the study revealing that the feed rate has the most significant impact. In the micromachining of Ti6Al4V, the abrasion and crater wear mechanisms are induced, while the magnitude of vibration influences the quality of the EN25 steel turning process [22]. Furthermore, cutting speed and depth of cut play pivotal roles in generating vibrations during hard turning, affecting performance characteristics. The cutting tool inclination angle, followed by the rake angle, significantly influences workpiece vibration, metal removal rate, and geometrical parameters. The central composite design (CCD) method was utilized to design the experiment for EV8 steel turning operations. Additionally, the artificial neural network (ANN) technique was employed to predict cutting forces and surface finish results [23].

In the hard-turning process, the machinability of AM alloy is predominantly influenced by the depth of cut and feed rate. Cryogenically treated cutting inserts have shown effectiveness in machining AISI M2 steel, employing optimization methods. By optimizing cutting parameters, such as feed rate, cutting speed, and depth of cut, machining efficiency is heightened, resulting in better surface finish and material removal rates (MRR) for stainless steel. The impacts of individual parameters on responses are forecasted through analysis of variance, with SEM images providing insights into the relationship between chip geometry and output responses [24]. Vibration induced during machining operations tends to degrade surface finish and productivity. It serves as an additional factor in cutting parameters influencing the overall machinability of the operation.

Identifying an optimal range of cutting parameters for metal-cutting operations may help minimize vibration induced during operations, improving overall efficiency and output quality. Hard ferrous materials with a hardness exceeding 45 HRC are commonly machined in turning operations under wet conditions. However, a comprehensive analysis of material removal rate (MRR), surface finish, tool wear, and energy consumption has been lacking [25, 26]. To address this, both the Taguchi method and grey relational analysis were employed to optimize the metal-cutting process.

In this work, a hybrid analysis methods utilizing response surface methodology (RSM) and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) approaches were uesd, although quantified references were not utilized. Specifically, OHNS metal with a hardness of 48 HRC, typically used for press tools, underwent hard-turning operations using carbide-coated inserts. To enhance the machinability characteristics of the process, a multiobjective functional analysis was adopted to predict the optimal parameter settings. This holistic approach aims to optimize various aspects of the machining process to achieve superior results.

2. Materials and Methods

2.1. Work Piece and Cutting Tool. The oil-hardened non-shrinking steel with 48 HRC (OHNS metal) is primarily used in press tools and dies. The cylindrical geometry of the workpiece with a diameter of 65 mm and length of 300 mm was used for the hard-turning operation experiment. The chemical composition of the work material in the datasheet provided by the supplier is given in Table 1. To maintain a uniform circularity on work material, a skin cut metal was removed to the entire length of work material and heat treated in an oil quenching process at 920°C followed by the tempering at 150°C. The hardness of the steel was measured with Rockwell hardness tester, and the average hardness value of 48 HRC was recorded on the entire length of work material [12, 13]. The cutting tool VP-coated carbide inserts (CNMG 120408 MJ) with the specifications of insert of rake angle $\alpha = 20^\circ$, cutting edge length = 12 mm, nose radius = 0.8 mm, and effective rake angle = 14° and tool holder (PCLNR 2020 K12 WIDAX) are used for the turning operation. The supplier recommended cutting parameters are feed rate: 0.05 mm/rev–0.25 mm/rev mm, cutting speed: 30 m/min–60 m/min, and depth of cut: 0.5 mm–1.45 mm.

Table 1: Chemical composition of OHNS material.

Composition	Percentage
C	0.75
Si	0.25
Mn	1.7
Cr	0.54
Ni	0.311
Cu	0.12
W	0.426
P	0.04
Fe	95.6

The cutting parameters range for the hard-turning operation was selected by reviewing the literature and the actual parameters used in industries [15].

2.2. Experimental Setup. The turning operation was performed on a KIRLOSKAR Turning Master-35 all-geared centre lathe with a computer access system. It has an independent drive for the spindle, feed rod, and coolant pump. The RPM indicator used is a microcontroller-based RPM transmitter with model number 14Dhaving a speed measuring range of 150 to 10000. Adynamometer of Kistler type: 9257 B with Multi-Channel Amplifier Make: Kistler Instruments, Switzerland Software: KisterDynoware–TYPE 2825 A1 are in cooperated with lathe machine to measure cutting forces. Figure 1 shows the process abstract of the machining operation.

The data acquisition system was used to observe the cutting forces during the machining operation. The electric prime mover used for the spindle running, and lead screw rotation was DC shunt motors that individually operate the spindle as well as carriage movements.

2.3. Experimental Design. The assignment of cutting parameters is an imperative one in hard turning. Proper selection of cutting parameters leads to better results on the quality of the products. The input factors such as cutting speed (V), feed rate (f), and depth of cut (d) with different levels were optioned based on the literature review and available standard data [1, 3, 8] given in Table 2. These three input-independent variables were combined to perform the experimental trials. The RSM-based centre composite design (CCD) method was followed, and experimental trials were performed by varying the cutting parameters under dry conditions.

The experimental trials were designed, and the experimental matrix was obtained using Design Expert-11 software. The coded and actual input-cutting parameters with the experimental results are shown in Table 3.

2.4. Experimental Procedure and Results. The OHNS cylindrical shaft is machined initially to reduce 1 mm in diameter to maintain circularity to the entire length of the workpiece. At both ends of the workpiece, a chamfer was formed to prevent any damage to the cutting tool at the imitation of the operation. The end pass of the cutting tool was maintained at a free ambient state to avoid unfavourable exodus circumstances [27]. The experiment was conducted based on

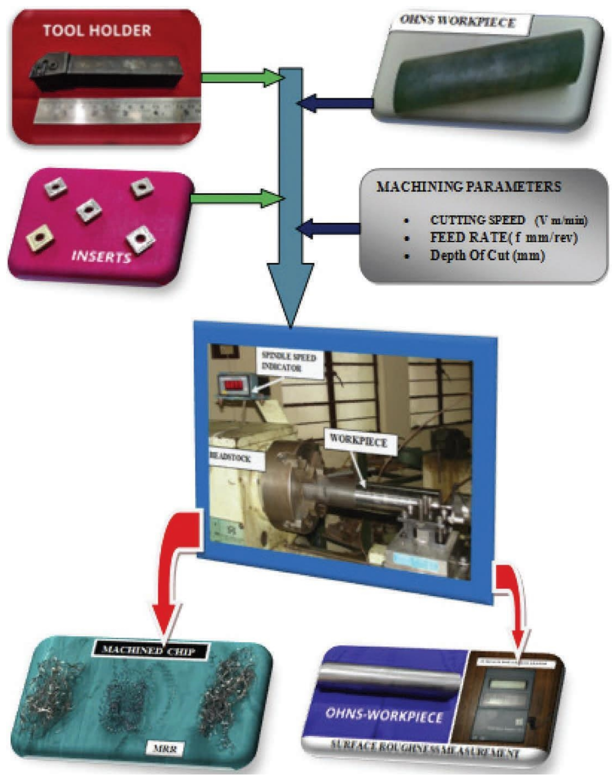

FIGURE 1: Experimental setup and results.

TABLE 2: Machining parameters.

Level	Coded factor	Cutting speed "V" (m/min) (A)	Feed rate "f" (mm/rev) (B)	Depth of cut "d" (mm) (C)
1	−1	40	0.07	0.5
2	0	50	0.08	0.75
3	1	60	0.09	1.0

TABLE 3: Experimental results.

Ex. no	Cutting parameters			MRR (gm/min)	Ra (μm)
	V (m/min)	(f) (mm/rev)	d (mm)		
1	40	0.07	0.5	16.835	0.98
2	40	0.08	0.75	18.695	0.96
3	40	0.09	1	26.665	1.09
4	50	0.07	0.75	11.488	0.96
5	50	0.08	1	17.405	0.89
6	50	0.09	0.75	13.125	0.95
7	60	0.07	1	19.305	0.83
8	60	0.08	0.75	20.262	0.76
9	60	0.09	0.5	11.932	0.79
10	50	0.08	0.75	12.358	0.91
11	50	0.08	0.5	10.958	0.89
12	50	0.08	0.75	13.865	0.89
13	40	0.07	1	14.876	1.02
14	40	0.09	0.5	17.858	0.97
15	50	0.08	0.75	16.975	0.93
16	60	0.09	1	20.385	0.87
17	60	0.07	0.5	18.568	0.85

CCD with varying cutting parameters using a new cutting edge of insert at a length of 100 mm. The average observation reading was taken into account to do further calculations. To avoid chip obstruction during machining, the TR 100 surface roughness tester is used to measure the surface roughness at a proper interval distance [28].

The chip removed from the workpiece was carefully collected, and the weight of the chip removal was calculated using a precision weighing machine. Figure 1 shows the turning operation, surface finish measurement, and chip formation in the turning operation. The hard-turning operation was performed on OHNS workpiece material by varying the input variables. The experimental results are noted in Table 3.

2.5. Multiobjective Optimization: Desirability Method (DOM) and TOPSIS Algorithm. Using a single process parameter setting is essential in the metal-cutting process to obtain multiple better responses. The response surface method (RSM) is a statistical optimization technique to obtain better results on the responses by selecting proper input process variables and their levels. The multiperformance characteristics analysing method followed in RSM is called the desirability optimization method (DOM). The identification of optimal input parameters to obtain multiple optimal responses is possible in desirability [29]. In the desirability function, all the experimental responses are converted as scale-free values, such as 0 and 1. The desirability value of 0 is referred to as an undesirable response, whereas the value of 1 means the response attains better quality through the optimal input parameters.

TOPSIS method is used to determine a solution for multiobjective problems. The optimal best solution can be obtained by evaluating the experimental results for the corresponding input variables and levels. The TOPSIS calculation for the optimal process parameter setting has been performed with the following steps.

Step 1: experimental results are arranged into matrix form

Step 2: determining the transformation value of the criteria

Step 3: assigning weightage to each criterion

Step 4: determination of standardized matrix

Step 5: determination of the best and worst solutions for each criterion

Step 6: determination of separation measures is calculated

Step 7: determination of the closeness coefficients

Step 8: ranking the TOPSIS results

3. Results and Discussion

3.1. Multiobjective Optimization Using Desirability Approach. The multiobjective function aims to identify the optimal process parameter setting that enhances the output responses of the process. The criteria for the optimum process parameters are given in Table 4. The desirability statistical analysis produces seventy-one results with different levels of the combination of the cutting parameters, responses, and desirability values.

Among that, the better solution of the desirability function with the highest desirability value is selected as the optimal process parameter setting for the machining operation. Figure 2 represents the graphical representation of the desirability with the combination of cutting speed (V) and feed rate (f).

The contour plot and surface plot of Figure 2 represent the effect of both V and f on desirability. It is observed that the 10% desirability obtained at 40 m/min of cutting speed and 0.09 mm/rev of feed rate means the combination of these parameters satisfies the required condition of the machinability of the process [30]. However, the maximum desirability value of 81.26% has been obtained at the interaction level of 60 m/min cutting speed and 0.08 mm/rev feed rate, respectively.

The interaction effect of cutting speed and depth of cut on desirability is given in Figure 3. The 42% desirability was obtained at 40 m/min cutting speed and a depth of cut 1 mm, but the 81.26% desirability was obtained at 60 m/min cutting speed and 0.7 mm depth of cut [31].

The feed rate and depth of cut interaction effect on Ra and MRR are represented in Figure 4. The increase of feed rate at 0.5 mm depth of cut reduces the desirability value, whereas at 1 mm depth and 0.08 mm/rev feed rate, notice the significant desirability value of the hard-turning operation, as shown in Figure 5. The ramp function graph represents the level and variation of input parameters and responses of the hard-turning process. The input variables are designed as one increment, which maintains the linearity scale. In contrast, the dependent variables of responses, such as metal removal rate and surface roughness, vary with the satisfaction of the second-order regression model [32]. The optimal cutting parameters are marked as a red dot on the horizontal line of corresponding input parameters, and the optimal response value is marked as a blue dot on the ramp-up line.

Figure 6 shows the desirability value of individual responses and multiperformance characteristics. The optimal cutting parameters produce better surface roughness; however, the improvement in metal removal rate is less compared to the former. The desirability of 81.3% of better results on multiresponses can be achieved by adopting the optimal level of cutting parameters in the hard-turning process. Table 5 shows optimal cutting parameters with desirability values.

It has been observed that the desirability value of the lowest defines that the process is not perfect. In contrast, the greater value of desirability produces better response results with the identification of optimal cutting parameters.

3.2. Multiobjective Optimization Using TOPSIS. TOPSIS algorithm is used to calculate the optimal parameters to build up multiple responses in a better quality of the hard-turning operation. The MRR and Ra experimental results for

Table 4: Criteria for the optimal cutting parameters.

Name	Objective	Lower limit	Upper limit	Weightage
V: cutting speed (m/min)	Is in range	40	60	3
f: feed (mm/rev)	Is in range	0.07	0.09	3
d: depth of cut (mm)	Is in range	0.5	1	3
MRR: metal removal rate (gm/min)	Maximize	10.958	26.665	5
Ra: surface roughness (μm)	Minimize	0.76	1.09	5

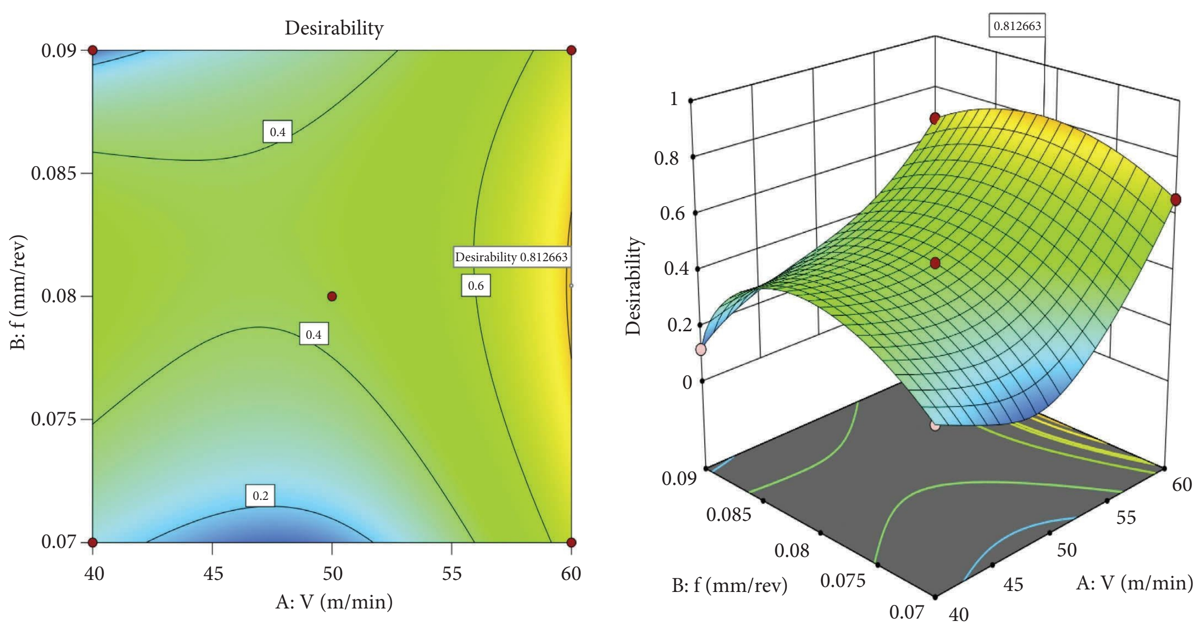

Figure 2: Contour and surface plot (V vs f).

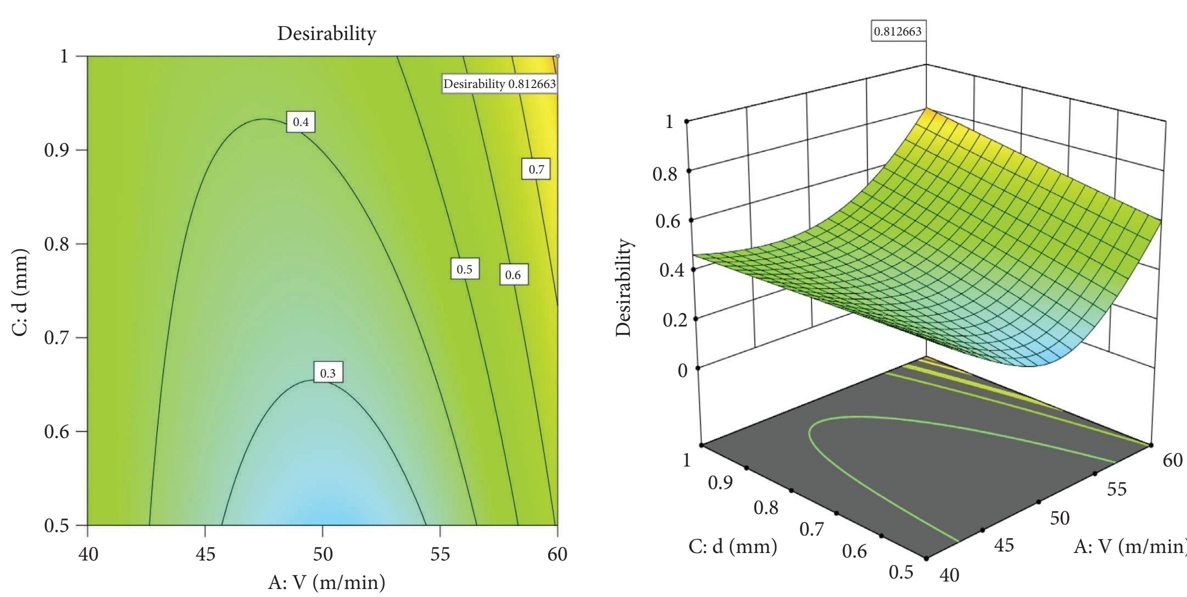

Figure 3: Contour plot and surface plot (V vs d).

the respective input variable levels were formulated as a matrix and as an equation, and the formulated values were converted into criterion, which is also given in Table 6.

The transformed TOPSIS values undergo conversion into a standardized matrix, incorporating measures of separation and closeness coefficients. The resultant values for both metal

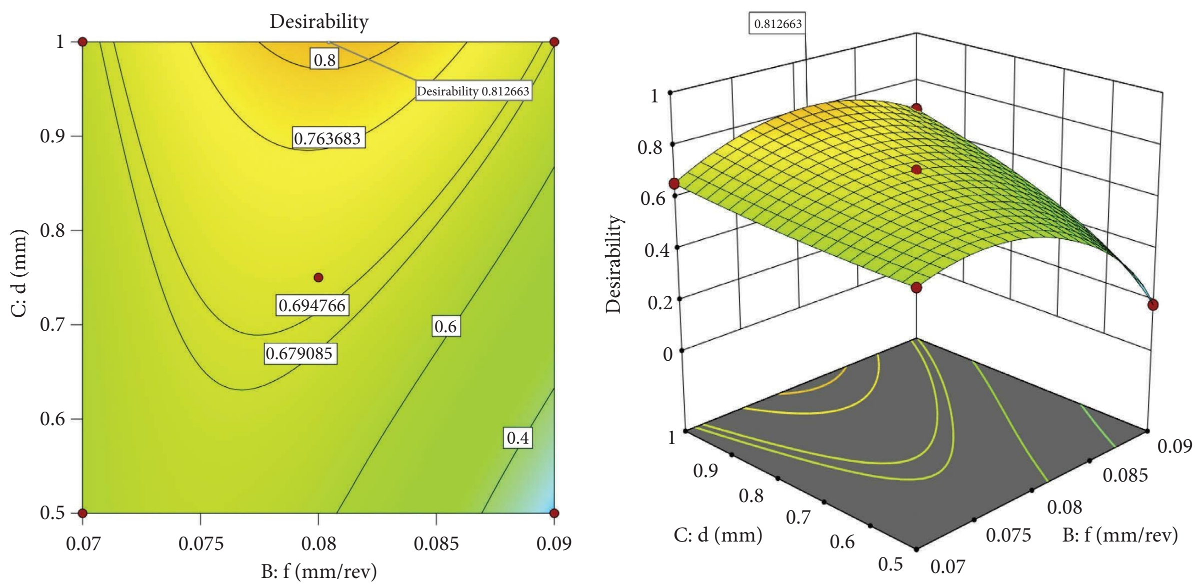

Figure 4: Contour plot and surface plot (f vs d).

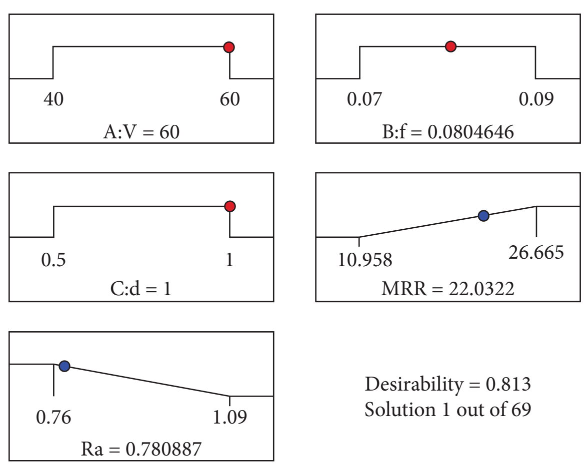

Figure 5: Ramp function graph for desirability.

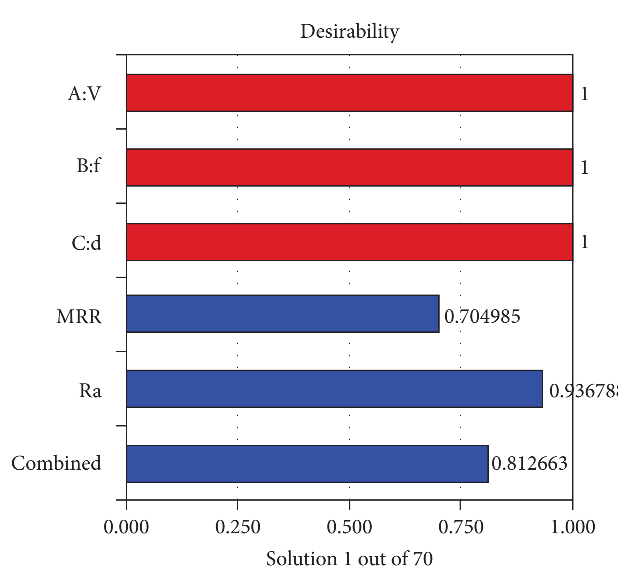

Figure 6: Bar chart for the compound desirability.

Table 5: Optimal parameters in DOM.

V: cutting speed (m/min)	f: feed (mm/rev)	d: depth of cut (mm)	MRR (gm/min)	Ra (μm)	Desirability
60	0.08	1.00	22.032	0.781	0.813

Table 6: Converted TOPSIS values.

Ex. no	Cutting parameters			MRR (gms/min)	Ra (μm)	MRR^2 (gms/min)	Ra^2 (μm)	TOPSIS value	
	V	f	d					MRR	Ra
1	40	0.07	0.5	16.835	0.95	283.42	0.9025	4.6198	0.2377
2	40	0.08	0.75	15.25	1.04	232.56	1.0816	3.7908	0.2849
3	40	0.09	1	26.66	1.09	710.76	1.1881	11.5855	0.3129
4	50	0.07	0.75	11.488	0.98	131.97	0.9604	2.1512	0.2529
5	50	0.08	1	17.405	0.85	302.93	0.7225	4.9379	0.1903
6	50	0.09	0.75	14.125	0.94	199.52	0.8836	3.2522	0.2327
7	60	0.07	1	14.305	0.83	204.63	0.6889	3.3356	0.1814
8	60	0.08	0.75	20.262	0.72	410.55	0.5184	6.6921	0.1365
9	60	0.09	0.5	11.932	0.78	142.37	0.6084	2.3207	0.1602
10	50	0.08	0.75	11.253	0.87	126.63	0.7569	2.0641	0.1993
11	50	0.08	0.5	10.958	0.92	120.08	0.8464	1.9573	0.2229
12	50	0.08	0.75	11.305	0.91	127.80	0.8281	2.0832	0.2181
13	40	0.07	1	12.256	1.02	150.21	1.0404	2.4485	0.2740
14	40	0.09	0.5	13.858	0.96	192.04	0.9216	3.1304	0.2427
15	50	0.08	0.75	10.975	0.93	120.45	0.8649	1.9634	0.2278
16	60	0.09	1	12.545	0.94	157.38	0.8836	2.5653	0.2327
17	60	0.07	0.5	12.262	0.86	150.36	0.7396	2.4509	0.1948

removal rate (MRR) and surface roughness (Ra) are detailed in Table 7. Subsequently, all calculated coefficients are ranked accordingly, with the highest coefficient designated as rank (1). The cutting parameter setting corresponding to this top-ranked coefficient is then deemed the optimal process parameter configuration for the hard-turning operation. Following this methodology, it is determined that a cutting speed of 40 m/min, a feed rate of 0.9 mm/rev, and a depth of cut of 1 mm emerge as the optimal process parameters for the machining operation. These parameters are identified as yielding the most favourable combination of MRR and surface roughness, thus optimizing the efficiency and quality of the hard-turning process.

The multiresponse optimization solution reveals that while the metal removal rate (MRR) aligns with acceptable standards, the Ra value falls outside the acceptable range. Conversely, employing the desirability optimization method yields optimal parameters, including a cutting speed of 60 m/min, a feed rate of 0.08 mm/rev, and a depth of cut of 1 mm. These settings correspond to predicted responses of 22.032 gm/min for MRR and 0.781 μm for surface roughness. Subsequent confirmation tests are conducted to validate the derived optimal parameter settings against actual experimental data [33]. This comparison provides insights into the performance of the optimization methods in real-world conditions. Notably, the cutting speed is the most influential factor affecting responses, exerting a more pronounced impact than other input-cutting parameters. By maintaining the exact depth of cut as in the TOPSIS method and increasing the feed rate, there is a noticeable improvement in the predicted surface roughness (Ra) value. This finding underscores the relationship between cutting parameters and their impact on surface finish, suggesting that a change in feed rate can yield significant improvements in surface quality [34, 35].

Comparing the efficacy of the optimization methods, the Technique for Order of Preference by Similarity to the Ideal Solution (TOPSIS) method demonstrates superior performance in optimizing MRR [36, 37]. In contrast, the desirability optimization method achieves more satisfactory surface roughness results. Moreover, within the desirability optimization method, it is observed that maintaining the same depth of cut as in TOPSIS but increasing the feed rate leads to an improvement in the predicted Ra value [38]. Furthermore, analysis reveals that the optimal cutting speed levels identified in both optimization approaches tend to be relatively high compared to the levels of feed and depth of cut. This suggests that maximizing cutting speed may be crucial for enhancing overall machining performance.

4. Confirmation Test

The validation tests were conducted for the optimal cutting parameters determined in DOM and TOPSIS, and the results of the confirmation tests are represented in Table 8.

The validated results are under an acceptable percentage of error. The optimal parameters predicted in DOM and TOPSIS optimization techniques are acceptable for performing the hard-turning operation on a hard steed to enhance better machinability results [39, 40].

Table 7: Standardized matrix and rank.

Ex. no	Standard matrix		Separation measure		Closeness coefficient	Rank
	MRR	Ra	$S+$	$S-$	(C^*)	
1	2.3099	0.1188	3.4833	1.3315	0.2765	4
2	1.8954	0.1424	3.8981	0.9168	0.1904	5
3	5.7928	0.1565	0.0882	4.8142	0.9820	1
4	1.0756	0.1265	4.7176	0.0983	0.0204	13
5	2.4690	0.0951	3.3240	1.4911	0.3097	3
6	1.6261	0.1164	4.1670	0.6480	0.1346	7
7	1.6678	0.0907	4.1251	0.6911	0.1435	6
8	3.3460	0.0683	2.4468	2.3686	0.4919	2
9	1.1604	0.0801	4.6325	0.1921	0.0398	12
10	1.0321	0.0997	4.7609	0.0685	0.0142	15
11	0.9786	0.1115	4.8143	0.0310	0.0064	17
12	1.0416	0.1090	4.7514	0.0713	0.0148	14
13	1.2242	0.1370	4.5691	0.2457	0.0510	11
14	1.5652	0.1214	4.2279	0.5870	0.1219	8
15	0.9817	0.1139	4.8113	0.0287	0.0059	16
26	1.2826	0.1164	4.5104	0.3052	0.0634	9
17	1.2254	0.1164	4.5674	0.2577	0.0534	10

Table 8: Confirmation tests.

Optimization method	Optimal cutting parameters			Predicted responses		Confirmation test responses		% of error	
	V (m/min)	f (mm/rev)	d (mm)	MRR (gm/min)	Ra (μm)	MRR (gm/min)	Ra (μm)	MRR (gm/min)	Ra (μm)
DOM	60	0.08	1	22.032	0.781	22.568	0.792	2.1	1.4
TOPSIS	40	0.09	1	26.665	1.09	25.895	1.065	2.8	2.7

5. Conclusions

The hard-turning operation on OHNS material with VA-coated carbide inserts was performed by varying the cutting parameters of cutting speed, feed rate, and depth of cut. The central composite design in RSM followed to design the experimental trials. The responses of MRR and Ra values were obtained such that the mean values of each response were determined with respect to the input variables, which were then calculated. A multiobjective function analysis was determined using RSM—desirability and TOPSIS approaches.

(i) The optimal cutting parameters to obtain multiple responses of MRR and Ra in DOM are 60 m/min cutting speed, 0.08 mm/rev feed rate, and 1 mm depth of cut; these settings correspond to the MRR of 22.032 gm/min and a surface roughness of 0.781 μm.

(ii) TOPSIS calculation mentioned the cutting speed 40 m/min; feed rate 0.09 mm/rev, and depth of cut 1 mm are optimal cutting parameters to enhance results in the hard-turning operation. These parameters provide an MRR of 26.665 gm/min and a surface roughness of 1.09 μm.

(iii) The variations between predicted and actual are within permissible limits. Using these optimal cutting parameters to machine OHNS material to produce spindles, pulleys, and other automobile elements will obtain better results on the components with less energy consumption.

(iv) The cutting tool wear, energy consumption, cutting tool temperature, cutting forces generated during operation, geometrical tolerance on OHNS parts, different coatings on inserts, and ability to sustain the OHNS turning process are the future scope of this research article.

Data Availability

All the data used to support the findings of this study are included in this article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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