

Response surface methodology (RSM)-based machining parameter optimization for minimization of burr in CNC turning of materials

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ABSTRACT

The complicated combined impacts of multiple parameters that affect the cutting process might make it challenging to describe burrs generated during face milling operations. The objective of the work is to study the influence of turning parameters such as depth of cut, spindle speed, and feed on three output performances such as machining time, surface roughness, and burr height. The three turning input parameters and three output turning performances are considered for machining three different materials, such as stainless steel, low-carbon steel, and high-carbon steel. The experimental design is planned as per the box-behnken design for six types of materials. Tungsten carbide is utilized as a cutting tool for all turning operations. Output parameters like machining time, burr height, and surface roughness are calculated. Machined (turned) samples are studied under the influence of a scanning electron microscope (SEM) for burr formation. Surface roughness is measured by the surface roughness meter, and machining time is calculated by the CNC machine itself. ANOVA is used to investigate and optimize machining parameters influence on output performances. The mathematical model for three output performances, such as machining time, burr height, and surface roughness, has been developed using response surface methodology.

Keywords: Turning Parameters; Machining Time; ANOVA; CNC; Optimize.

1. INTRODUCTION

Burrs are produced during machining processes in today's contemporary manufacturing industry. A burr is a portion of material that is plastically distorted and still attached to the workpiece [1]. The price is the result of the cost of the raw materials, transportation, loading, and unloading, as well as the cost of machining and shipping. Even when all the aforementioned expenditures contribute to the final product's cost, the production process has a significant impact on production costs. Presently, the CNC process (computer-numerical control) is crucial to manage parameters and avoid human interference [2]. An optimization strategy based on the desirability function approach (DFA) in combination with the Response Surface Methodology was used to determine the most important machining parameters and ideal CNC turning process parameters, such as cutting speed [3]. The effectiveness of electric discharge machining depends on processing the metal matrix composite made of AA6061 with 10% B4Cp. Response surface methodology (RSM) and Box-Behnken design (BBD) experiments were used to develop the modeling and optimization of electric discharge machining [4, 5]. Using the Taguchi approach, one can convert SCM 440 alloy steel while determining the ideal surface roughness value and cutting conditions. The experiment was planned using the Taguchi method, and after it was carried out, its findings were examined using the ANOVA (Analysis of Variance) method [6]. The study was to find a mild steel turning surface roughness prediction model. For experiments, CNMG cutting tools were utilized. Using the response surface approach, a second-order mathematical model for surface roughness was created. Many significant turning characteristics were also examined using ANOVA [7]. The author arrived at the ideal process parameter settings for multi-response optimization in the 17-4 PH stainless steel milling process by utilizing the Taguchi

gray relational technique. Several response outputs have been investigated, including cutting force, tool wear, temperature, and surface roughness. When 17-4 PH stainless steel is machined with a 0.8 mm cutting nose radius, the lowest surface roughness values were observed. Under all test conditions, it was discovered that the surface roughness values in the trials with the 0.8 mm cutting nose radius were on average 46.56% lower than those in the studies with the 0.4 mm cutting nose radius. In this investigation, metal cutting experiments were carried out using CVD (MT-TiCN + TiC + Al₂O₃ + TiN) and PVD (TiAlN) coated carbide tools NIMAX plastic mold steel in a universal lathe, under varying cutting conditions. During machining, variations in vibration, noise, cutting temperature, and surface roughness were investigated. Test specimens were machined with eighteen distinct parameters at three different feed rates (0.1, 0.15, and 0.2 mm / dev), three different cutting speeds (120, 160, and 200 m / min), and a constant depth of cut (0.6 mm). Following the testing, values for vibration, noise, cutting temperature, and surface roughness were analyzed; the PVD coated cutting tool demonstrated the best performance. The burr types that resulted from micromilling Inconel 718 were mostly determined by the feed rate ($\mu\text{m}/\text{tooth}$) and cut depth, whereas cutting velocity had little effect. Additionally, it was determined that the burr width discovered during confirmation trials at low-speed machining was likewise within an acceptable range, and the findings for the surface finish at low-speed machining are comparable to those of transition and high-speed machining. The objective of the work is to study the influence of turning parameters such as depth of cut, spindle speed, and feed on three output performances such as machining time, surface roughness, and burr height.

2. MATERIALS AND METHODS

2.1. High carbon steel

Contains between 1% and 1.4% carbon, along with small amounts of tungsten and chromium added for increased wear resistance. Due to its tendency to lose hardness at temperatures around 250°C, steel is not recommended for use in contemporary machining processes that typically involve high speeds and deep cuts.

2.2. High Speed Steel (HSS)

Steel has strong and shock-resistant qualities. It's hot hardness value is around 600°C. Drills, reamers, and milling cutters are examples of multi-point and single-point cutting instruments that are frequently utilized with it (Figure 1).

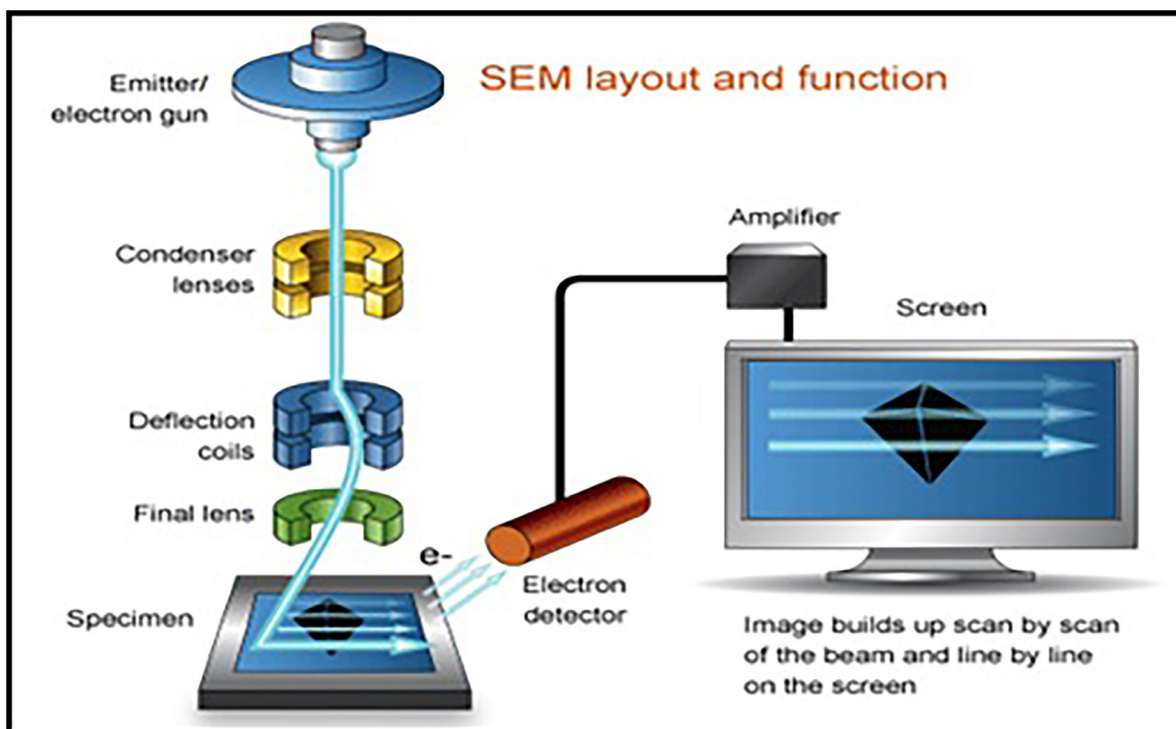


Figure 1: SEM layout diagram.

3. EXPERIMENTAL METHODOLOGY

A sample piece of 10 mm dia and 10 mm length was turned from the work pieces of all six materials (low carbon steel, high carbon steel, brass, aluminum copper, and stainless steel) of initial dimensions, which include a diameter 20 mm and a length 300 mm. A photograph of all six materials before and after machining is shown below.

Figure 2 illustrates the photos of stainless steel before and after machining. A stainless steel rod of 300 mm length and 20 mm diameter was turned into a sample piece of 10 mm diameter and 10 mm length. As there were 17 experimental runs, 17 sample pieces were cut and examined under SEM to measure burr height, and a surface roughness meter was used to find the surface roughness. The machining time was calculated on the CNC machine itself. All machining parameter readings were tabulated as per the Box Behnken Design in the corresponding tables.

3.1. Experimental design for stainless steel machining

Desirability (RSM) approach for optimization of processes. Table 1 shows the Box-Behnken Design for Stainless Steel and the corresponding standards of spindle speed, feed, and depth of cut [8–10].

Figure 3 shows the photos of low-carbon steel before and after machining. A low-carbon steel rod 300 mm long and 20 mm in diameter was turned into a sample piece of 10 mm in diameter and 10 mm in length. As

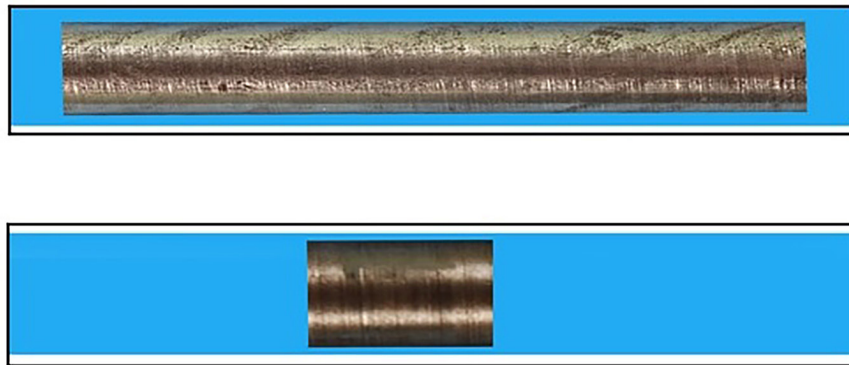


Figure 2: Photos of stainless steel before and after machining.

Table 1: DoE experimental runs for stainless steel using Box-Behnken design.

RUN	SPINDLE SPEED IN RPM	FEED IN MM/REV	DEPTH OF CUT IN MM
1	2050.00	0.06	0.35
2	100.00	0.01	0.35
3	100.00	0.10	0.35
4	4000.00	0.10	0.35
5	2050.00	0.01	0.60
6	2050.00	0.06	0.35
7	2050.00	0.01	0.10
8	100.00	0.06	0.10
9	4000.00	0.01	0.35
10	2050.00	0.06	0.35
11	2050.00	0.10	0.10
12	2050.00	0.06	0.35
13	4000.00	0.06	0.60
14	2050.00	0.10	0.60
15	100.00	0.06	0.60
16	2050.00	0.06	0.35
17	4000.00	0.06	0.10

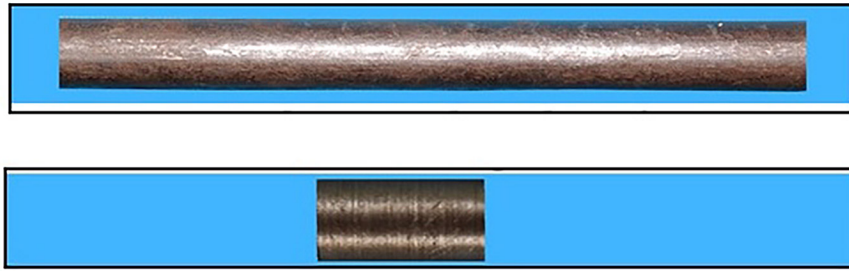


Figure 3: Photos of low carbon steel before and after machining.

Table 2: DoE experimental runs of low carbon steel using Box-Behnken design.

RUN	SPINDLE SPEED IN RPM	FEED IN MM/REV	DEPTH OF CUT IN MM
1	2050	0.06	0.35
2	4000	0.10	0.35
3	4000	0.06	0.60
4	2050	0.06	0.35
5	2050	0.01	0.60
6	100	0.06	0.10
7	2050	0.06	0.35
8	100	0.10	0.35
9	4000	0.06	0.10
10	100	0.01	0.35
11	2050	0.06	0.35
12	100	0.06	0.60
13	4000	0.01	0.35
14	2050	0.06	0.35
15	2050	0.10	0.10
16	2050	0.10	0.60
17	2050	0.01	0.10

there were 17 experimental runs, 17 sample pieces were cut and examined under SEM to measure burr height, while a surface roughness meter was used to find the surface roughness, with the machining time being calculated by the CNC machine itself. All readings were tabulated in the corresponding Table 2.

Figure 4 shows photos of high-carbon steel before and after machining. A high-carbon steel rod of 300 mm length and 20 mm diameter was turned into a sample piece of 10 mm diameter and 10 mm length. As there were 17 experimental runs, 17 sample pieces were cut and examined under SEM to measure burr height, while a surface roughness meter was used to find surface roughness, with the machining time being calculated by the CNC machine. All readings were tabulated in the corresponding Table 3.

4. RESULT AND DISCUSSION

4.1. Response Surface Methodology (RSM)

4.1.2. Desirability approach

Numerous industrial challenges call for optimization with multiple interesting responses. For such issues, techniques including restricted optimization, the desirability approach, and overlaying the response contour plots were applied. Among other benefits, the desirability approach had the capacity to easily and flexibly weigh and prioritize individual responses. The desirability technique was used by many academics [11] to optimize processes. Optimization of laser welding parameters like laser beam power density, shielding gas, flow rate, welding speed, and incident beam angle for the measured responses (depth of penetration, bead width, and depth to width ratio) was done in this work using a desirability approach based on the RSM.

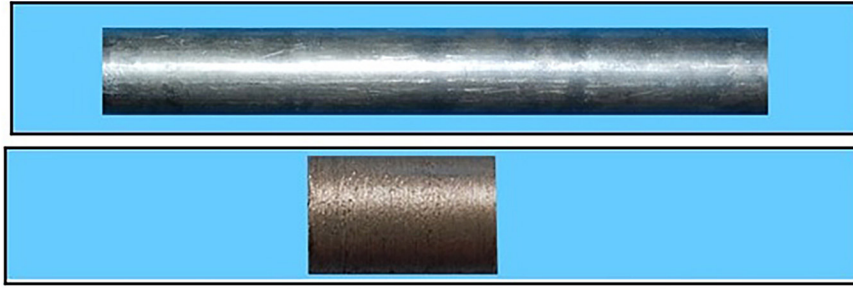


Figure 4: Photos of high carbon steel before and after.

Table 3: DoE experimental runs of high carbon steel using Box-Behnken design.

RUN	SPINDLE SPEED IN RPM	FEED IN MM/REV	DEPTH OF CUT IN MM
1	100	0.10	0.35
2	2050	0.01	0.10
3	2050	0.06	0.35
4	2050	0.06	0.35
5	100	0.01	0.35
6	100	0.06	0.10
7	4000	0.01	0.35
8	2050	0.06	0.35
9	4000	0.06	0.10
10	2050	0.10	0.10
11	2050	0.06	0.35
12	2050	0.06	0.35
13	2050	0.10	0.60
14	4000	0.10	0.35
15	100	0.06	0.60
16	2050	0.01	0.60
17	4000	0.06	0.60

Optimization was carried out by means of the Design Expert program, with each response being converted to a desirability value (d_i), which varied from 0 to 1. Accordingly, when $d_i = 0$, the response was entirely unwanted, and when $d_i = 1$, the response was the most desirable. Depending on the nature of the problem, the goal of each response might be set as either to maximize, minimize, target, in the range, or equal to. The following equations can be used to determine each response's attractiveness in relation to its intended outcome [12].

For a goal of maximum, desirability will be defined by

$$d_i = 0 \text{ when response } (Y_i) \leq \text{low value } (Low_i)$$

$$d_i = 1 \text{ when response } (Y_i) \geq \text{high value } (High_i)$$

$$d_i = \left(\frac{Y_i - Low_i}{High_i - Low_i} \right)^{wt_i}, \text{ When low value } (Low_i) < Y_i < \text{high value } (High_i)$$

For the goal of minimum, desirability will be defined by

$$d_i = 1 \text{ when response } (Y_i) \leq \text{low value } (Low_i);$$

$$d_i = 0 \text{ when } Y_i \geq High_i; \text{ and}$$

$$d_i = \left(\frac{High_i - Y_i}{High_i - Low_i} \right)^{wt_i}, \text{ When low value } (Low_i) < Y_i < \text{high value } (High_i)$$

For a goal as target, $d_i = 0$ when $Y_i < \text{low value } (Low_i)$; and $Y_i > \text{high value } (High_i)$

$$d_i = \left(\frac{Y_i - Low_i}{T_i - Low_i} \right)^{wt_i}, \text{ When low value } (Low_i) < Y_i < T_i$$

$$d_i = \left(\frac{Y_i - \text{High}_i}{T_i - \text{High}_i} \right)^{w_i} \quad \text{When } T_i < Y_i < \text{high value (High}_i) \text{ and}$$

For the goal within the range, $d_i = 1$ when low value (Low_i) $i < Y_i < \text{high value (High}_i)$ and $d_i = 0$ otherwise.

Here, “i” stands for the response, “Y” for the response’s value, “low” for the response’s lower limit, “high” for its upper limit, “T” for the response’s goal value, and “w” for the response’s weight. The weight field has the power to modify the desirability function’s shape for each response. Weights were used to emphasize the target value or to draw attention to the upper and lower boundaries. Thus, d_i will linearly range from 0 to 1 with a weight of 1.

Weights above 1 (with a maximum weight of 10) emphasize the objective more. Weights below 1 (the lowest weight is 0.1) place less focus on the objective. The overall desirability function, D ($0 \leq D \leq 1$), was generated by merging several responses into a dimensionless measure of performance to solve multiple response optimization problems using the desirability approach, which was calculated by

$$D = \left(\prod_{i=1}^n d_i^{r_i} \right)^{\frac{1}{\sum r_i}}$$

Each response can be given a relative significance (r_i) in the overall desirability objective function (D), based on how important it is compared to other responses. Each included parameter had a minimum and a maximum setting. Each objective can be given a weight to change the shape of its own desirability function. Each goal’s “importance” with respect to the other goals could be altered. The value of importance (r_i) ranged from least important (+), which had a value of 1, to most important (++++), with a value of 5. The best and most desirable features of the system, which were regarded as the best possible solution, were designated by a high value for D [13]. The value of each desired function (d) that maximized D was used to calculate the optimal factor value. The pursuit of a goal started at a random location and moved up the steepest slope until it reached its peak. Due to the curvature of the response surfaces and how they are combined with the desire function, there might be two or more maximums. The probability of discovering the “best” local maximum can be increased by beginning from a variety of positions in design space.

The mathematical formulation of the current optimization problem can be stated as follows [14]:

Min: $F_1(x) = \text{SR}$

Min: $F_2(x) = \text{BH}$

Min: $F_3(x) = \text{MT}$

Subject to $100 \leq x_1 \leq 4000$

$0.01 \leq x_2 \leq 0.1$

$0.1 \leq x_3 \leq 0.6$

Here, such kind of search based optimization technique was popularized by KARA et al [15].

4.2. Stainless steel

Table 4 shows the constraints of machining parameters for turning stainless steel. It also shows the lower and upper limits of the input machining parameter (spindle speed, feed, and depth of cut) range and the output parameter (surface roughness, burr height, and machining time) range.

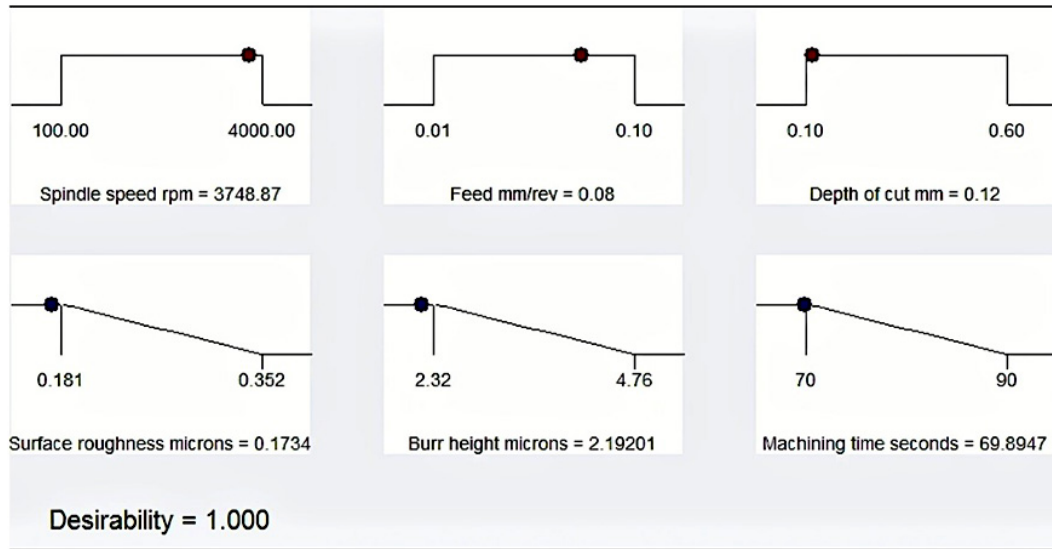
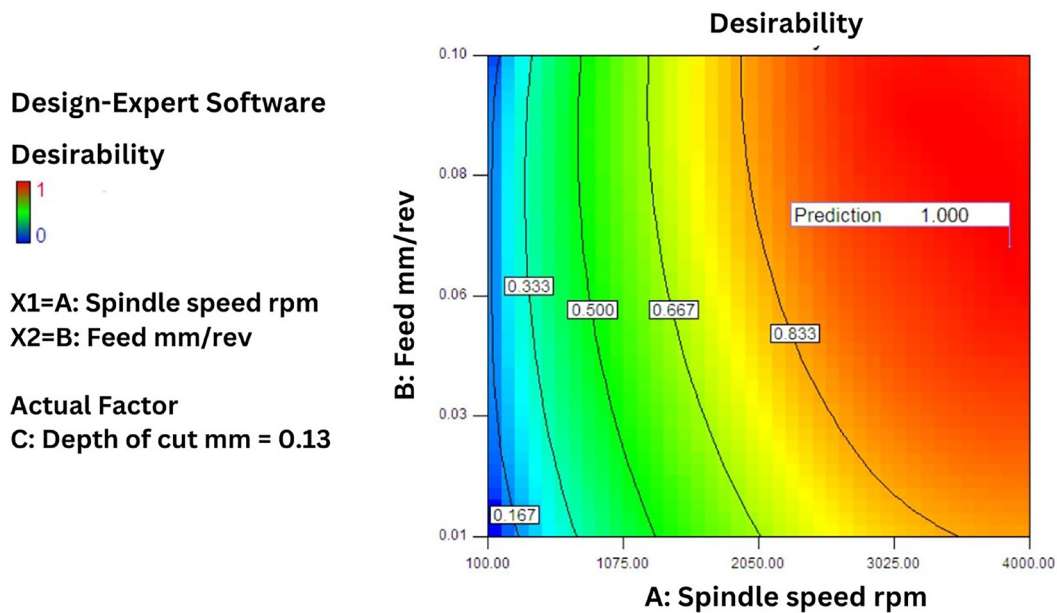
Table 5 shows the optimized turning parameters during the machining of stainless steel. In the desirability function approach to optimization, the optimized solutions were obtained by taking the combined objective

Table 4: Constraints of machining parameters for stainless steel.

NAME	UNIT	GOAL	LOWER LIMIT	UPPER LIMIT	LOWER WEIGHT	UPPER WEIGHT	IMPORTANCE
Spindle speed	rpm	In range	100	4000	1	1	3
Feed	mm/rev	In range	0.01	0.1	1	1	3
Depth of cut	mm	In range	0.1	0.6	1	1	1
Surface roughness	microns	minimize	0.181	0.352	1	1	3
Burr height	microns	minimize	2.32	4.76	1	1	3
Machining time	seconds	minimize	70	90	1	1	3

Table 5: Optimized machining parameters of stainless steel.

SPINDLE SPEED IN (RPM)	FEED IN (MM/REV)	DEPTH OF CUT IN (MM)	SURFACE ROUGHNESS IN (MICRONS)	BURR HEIGHT IN (MICRONS)	MACHINING TIME IN (SECONDS)	DESIRABILITY
3748.87	0.08	0.12	0.1734	2.19201	69.8947	1

**Figure 5:** RAMP graph for stainless steel.**Figure 6:** Contour plot of optimized machining parameters for stainless steel.

minimization function. The optimized parameters included surface roughness of 0.1734 microns, burr height of 2.19201 microns, and machining time of 69.8947 seconds [16].

Figure 5 shows a ramp graph for stainless steel material. In this graph, the ranges of input and output parameters, as well as the optimized values of these corresponding input and output parameter values, were also indicated [17].

Figure 6 shows the contour plot of the optimized machining parameters with respect to the desirability function optimization approach during the machining of stainless steel. The predicted desirability value was 1. It illustrates the optimized machining parameter values.

4.3. Low carbon steel

Table 6 reveals the constraints of machining parameters for turning low-carbon steel. It also depicts the lower and upper limits of both the input machining parameter (spindle speed, feed, and depth of cut) range and the output parameter (surface roughness, burr height, and machining time) range.

Table 7 shows the optimized turning parameters during the machining of low-carbon steel material. In the desirability function approach to optimization, the optimized solutions were obtained by taking the combined objective minimization function. The optimized parameters were surface roughness of 2.22665 microns, burr height of 27.137 microns, and machining time of 91.7292 seconds.

Figure 7 shows the ramp graph of low-carbon steel. In this graph, the ranges of input and output parameters, as well as the optimized values of the corresponding input and output parameter values, were also indicated.

Figure 8 shows the contour plot of the optimized machining parameters with respect to the desirability function optimization approach during the machining of low-carbon steel. The predicted desirability value was 0.932, which illustrates the optimized machining parameter values.

Table 6: Constraints of machining parameters for low carbon steel.

NAME	UNIT	GOAL	LOWER LIMIT	UPPER LIMIT	LOWER WEIGHT	UPPER WEIGHT	IMPORTANCE
Spindle speed	rpm	In range	100	4000	1	1	3
Feed	mm/rev	In range	0.01	0.1	1	1	3
Depth of cut	mm	In range	0.1	0.6	1	1	3
Surface roughness	microns	minimize	2.236	0.375	1	1	5
Burr height	microns	minimize	27.13	31.13	1	1	5
Machining time	seconds	minimize	88	95	1	1	1

Table 7: Optimized machining parameters of low carbon steel.

SPINDLE SPEED IN (RPM)	FEED IN (MM/REV)	DEPTH OF CUT IN (MM)	SURFACE ROUGHNESS IN (MICRONS)	BURR HEIGHT IN (MICRONS)	MACHINING TIME IN (SECONDS)	DESIRABILITY
3999.97	0.08	0.17	2.22665	27.137	91.7292	1

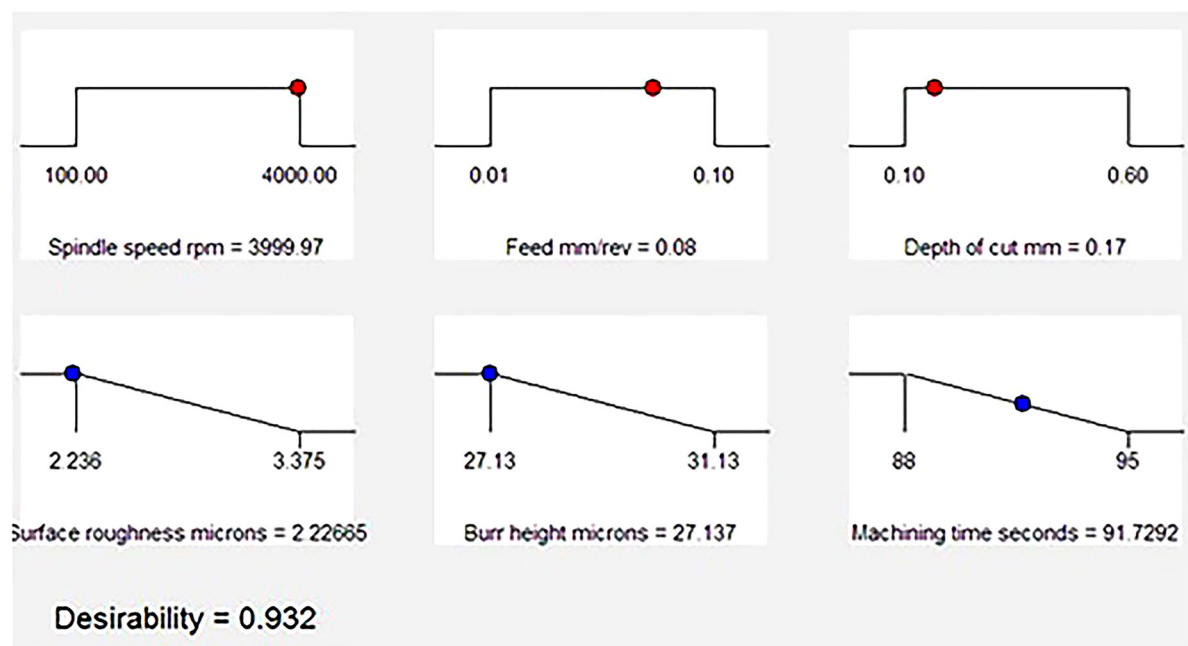


Figure 7: RAMP graph for low carbon steel.

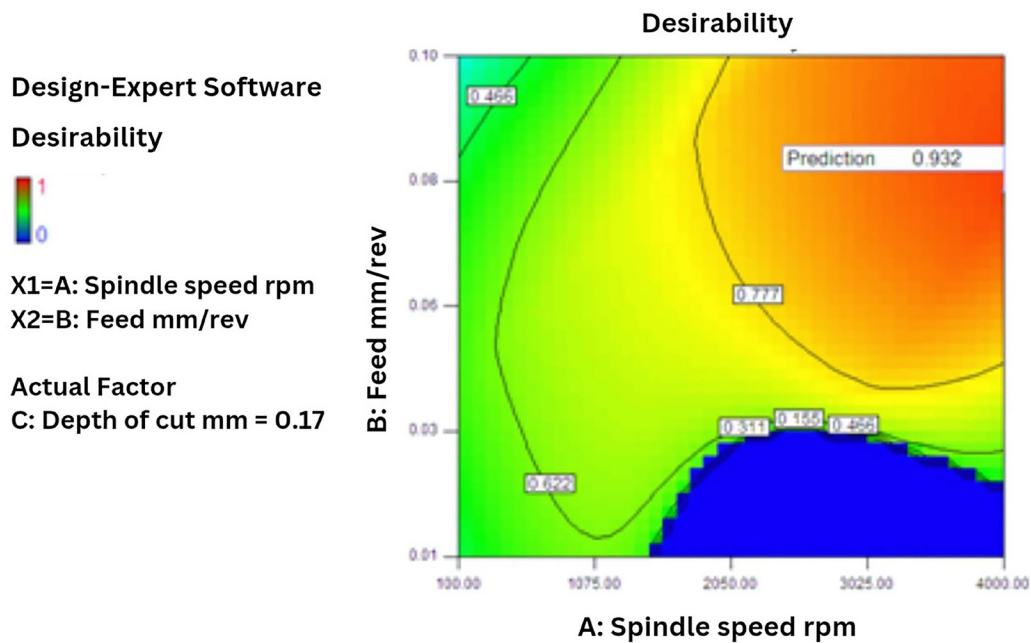


Figure 8: Contour plot of optimized machining parameters for low carbon steel.

Table 8: Constraints of machining parameters for high carbon steel.

NAME	UNIT	GOAL	LOWER LIMIT	UPPER LIMIT	LOWER WEIGHT	UPPER WEIGHT	IMPORTANCE
Spindle speed	rpm	In range	100	4000	1	1	3
Feed	mm/rev	In range	0.01	0.1	1	1	3
Depth of cut	mm	In range	0.1	0.6	1	1	3
Surface roughness	microns	minimize	0.569	0.583	1	1	5
Burr height	microns	minimize	5.12	5.66	1	1	1
Machining time	seconds	minimize	91	99	1	1	1

Table 9: Optimized machining parameters of high carbon steel.

SPINDLE SPEED IN (RPM)	FEED IN (MM/REV)	DEPTH OF CUT IN (MM)	SURFACE ROUGHNESS IN (MICRONS)	BURR HEIGHT IN (MICRONS)	MACHINING TIME IN (SECONDS)	DESIRABILITY
3999.98	0.10	0.20	0.571096	5.31988	96.371	0.711

4.4. High carbon steel

Table 8 shows the constraints of machining parameters for turning high-carbon steel. It also depicts the lower and upper limits of both the input machining parameters (spindle speed, feed, and depth of cut) range and the output parameters (surface roughness, burr height, and machining time) range.

Table 9 shows the optimized turning parameters during the machining of high-carbon steel. In the desirability function approach to optimization, the optimized solutions were obtained by taking the combined objective minimization function. The optimized parameters were surface roughness of 0.571096 microns, burr height of 5.31988 microns, and machining time of 96.371 seconds.

Figure 9 shows the ramp graph for low-carbon steel, where the ranges of input and output parameters as well as the optimized values of the corresponding input and output parameter values are indicated.

Figure 10 shows the contour plot for the optimized machining parameters with respect to the desirability function optimization approach during the machining of high-carbon steel. The predicted desirability value was 0.932, which illustrated the optimized machining parameter values (Table 10).

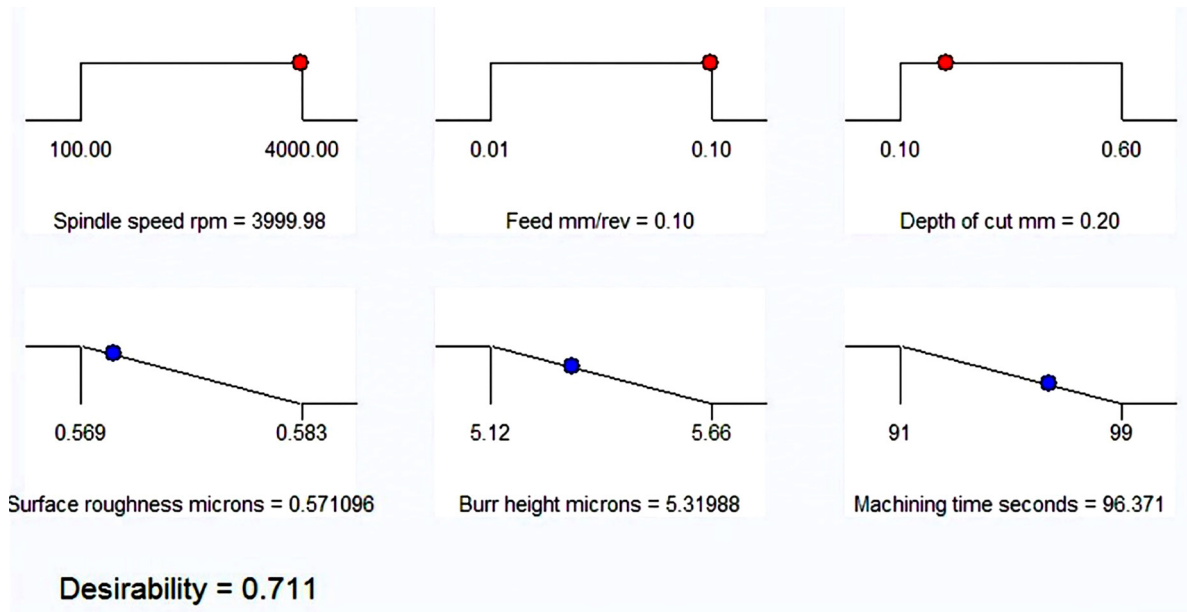


Figure 9: RAMP graph for low carbon steel.

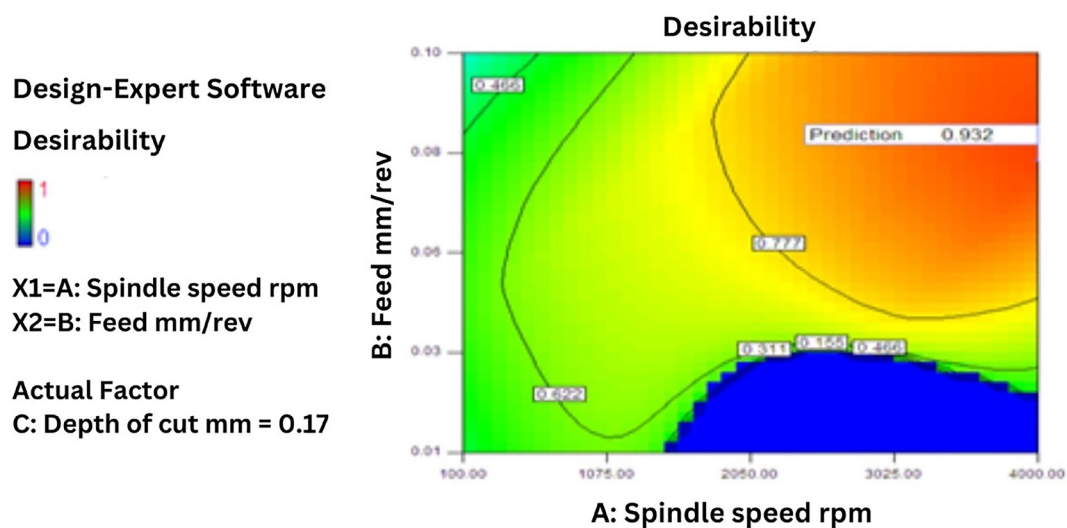


Figure 10: Contour plot of optimized machining parameters for high carbon steel.

Table 10: Evaluation of hardness value.

(HARDNESS. HRB)	TAGUCHI METHOD	EXPERIMENTAL ANALYSIS	RSM METHOD
Initial ($A_1B_1C_1$)	83.20	85.00	85.63
Optimum ($A_2B_3C_1$)	89.85	92.00	92.11
Gain	6.65	7.00	6.48

Table 11: Comparison between the parameters of three materials using (RSM) desirable function approach.

MATERIAL	SPINDLE SPEED IN (RPM)	FEED IN (MM/REV)	DEPTH OF CUT IN (MM)	SURFACE ROUGHNESS IN (MICRONS)	BURR HEIGHT IN (MICRONS)	MACHINING TIME IN (SEC)
Stainless steel	3748.87	0.08	0.12	0.1734	2.19201	69.8947
Low carbon steel	3999.97	0.08	0.17	2.22665	27.137	91.7292
High carbon steel	3999.98	0.10	0.20	0.571096	5.31988	96.371

5. CONCLUSION

Table 11 shows the optimized values of input and output parameters for all materials using RSM. Stainless steel was the best material in this optimization approach. It was concluded from the above tabulations that stainless steel provided minimized burr and better surface (finish) roughness, along with the minimum machining time among all other materials. The reason for this included cutting parameters, spindle speed (3748.87rpm), feed (0.08 mm/rev), and depth of cut (0.12 mm), as well as the physical, chemical, and mechanical properties of work piece materials, which also played a deciding factor in burr formation. As the research work was to optimize the cutting parameters to minimize burr and get a better surface-finished material, stainless steel was the best material among the three materials. In the future, the same materials may be experimented on with some other tool and with other optimization algorithms to ensure reduced burr formation.

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