Parametric Optimization of Martensitic Stainless Steel 440 C in CNC Turning Using Box-Behnken and Response Surface Method

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Abstract: Stainless steels are used in a wide range of applications such as aerospace, marine, and automotive, because of maintaining their mechanical properties at high temperature and high corrosion resistivity. In industry in order to obtain high product quality, better productivity and extended tool life it is essential to optimize the machining parameters such as (cutting speed, feed and depth of cut). The main purpose of this paper is to study the effect of turning parameters of martensitic stainless steel (AISI440) in CNC turning under dry conditions on surface roughness, material removal rate and temperature. A box-behnken design (BBD) approach in response surface methodology (RSM) was used to model the surface roughness material removal rate and temperature as a response of the cutting parameters. Design expert (v12) was used to generate 17 experimental runs needed to develop and verify the empirical mathematical model of the roughness, material removal rate and temperature. The results indicated that the roughness is strongly affected by the feed rate, additionally the cutting speed is the main factor followed by feed rate Influences the material removal rate, whilst, the depth of cut followed by feed rate has great effect on temperature.

Keywords: Parametric Optimization, CNCTurning, Box-Behnken, Response Surface Method

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1. Introduction

Martensitic stainless steel when hardened through the quenching and tempering process, It acquires high strength and hardness ratios [1]. Martensitic stainless steels usually have higher chromium and carbon content compared to austenitic and ferritic steels [2]. Stainless steel 440 C has been studied as a type of martensitic steel because it is used in a wide range of applications, including steam and water valves, turbines, pumps, bearings, compressor components, shafting, plastic moulds, cutlery, surgical tools, and applications of aerospace etc [3].

There are certain factors that must be considered in any manufacturing process in order to obtain excellent results. Surface roughness, temperatures, and amount of material removed were investigated in this study as responses obtained by stainless steel 440 C during the orthogonal cutting process. Surface roughness is affected by a variety of factors, including tool variables, workpiece variables (Internal chemical and mechanical compositions, as well as material components), and cutting conditions. [4]they have conducted an optimization study of surface roughness for turning a carbon steel AISI 1025 using a carbide cutting tool on a CNC machine and discovered that the feeding rate has the biggest impact on surface roughness. [5]studied the Machinability of both materials and tools was evaluated in terms of roughness, flank wear, cutting force, and specific cutting pressure for the hard martensitic stainless steel AISI 440 C and SCM 440 alloy steel with CBN and PCBN cutting tools. The results show that CBN tools yield lower surface roughness values at high cutting velocity and low feed rate than PCBN tools.

[6]they investigated the effect of cutting temperature on several parameters such as cutting speed, feed rate, and cut depth and used a single k-type thermocouple sensor for determining the average cutting tool temperature during turning operations on a lathe machine, using EN series grade 36 steel as the work piece and coated carbide as the cutting tool. established a mathematical empirical model of temperature measurement that were validated by experimental tests and discovered to have a temperature measurement error of less than 10%. [7]they tried to develop an artificial neural network model that can be successfully used for accurate cutting temperature prediction when turning biomedical stainless steel cutting temperature was calculated before modeling because it is one of the most important parameters in the turning process. Cutting temperature was measured during the turning of biomedical stainless steel using infrared thermography. Taguchi experimental designs were used to

determine the effect of cutting parameters on cutting temperature. Cutting temperature rises as cutting speed rises, according to the findings.

[8] studied the performance of titanium (Grade-5) alloy for turning by using response surface methodology (RSM). The investigations took into account machining parameters such as cutting speed, feed rate, depth of cut, and cutting edge approach angle. The response variables for investigations are surface roughness and tangential powers. Face-centered, central composite design (CCD) with RSM was used as the experimental plan for four factors at three stages. The obtained experimental results show that surface roughness increases with increasing cutting speed and feed rate and decreases with decreasing cutting speed and feed rate.[9] studied the specimens of EN8 alloy steel, determined the important input parameters to get influence on the response variables. Find out important parameters using the Taguchi method (for the data analysis, Statistical Techniques of ANOVA was used). Concluded that the spindle speed is the most influencing factor for roughness surface (Ra) and material removal rate (MRR) followed by feed and depth of cut. [10] studied the behavior of the austenitic stainless steels AISI 304, and optimize turning parameters to achieve the best performance. Turning tests have been performed in three different values for feed rates and cutting speed with and without fluid of cutting. It is being inferred by analysis of variance (ANOVA) that cutting speed has the main influence on the flank wear and the feed rate has the most important influence on the surface roughness. Many researchers have done extensive research on the optimization process of machining with different techniques can be found at [11],[12],[13]. This study's conclusions will be trying to assist CNC users in determining the ideal parameters for machining stainless steel 440 C.

Experimental setup

The trials were carried out using a CNC machine Fig. (1), with three process parameters set for each of the three levels. Before starting the turning process, using a special digital weighing machine Fig. (2), each sample of stainless steel 440 C is weighed. The temperatures of the cutting zone were measured using a DT109A digital device via a thermocouple sensor of the type (k) was fixed under the cutting tool's and set at a distance of one millimeter from the cutting tool's tip Fig.(3). Cutting parameters such as speed, feed, and depth of cut are changed to create experimental machining. For each specimen, three turning operations with temperature measurement were performed in order to determine the cutting zone average temperature. The sample weight is re-measured when the turning process is completed using the same digital weighing machine. Then, roughness of surface is determined using an automated surface roughness tester (PCE-RT 1200) Fig. (4).

Figure -1-CNCturning machine of FANUC (series Oi Mate-TC)

Figure -2- A high sensitive balance of type precision balance KERN-PLS

Figure -3- temperature measuring device(D T 109)

Figure -4- surface roughness tester (PCE-RT 1200)

1.2 Work material

The sample in this investigation was taken of 440 C stainless steel was dimensions of 100 mm in length and 38 mm in diameter, tables (1, 2) shown the chemical composition and mechanical properties of this metal. [14],[15]

Table -1- Stainless Steel 440 C Chemical Composition

Elements	**weight%**
Carbon	0.95 to 1.20 %
Phosphorus	0.040 %
Silicon	1.00 %
Molybdenum	0.75 %
Manganese	1.00 %
Sulfur	0.030 %
Chromium	16.00 to 18.00 %
Iron	77.98 to 80.23 %

Table -2- Mechanical Properties of Stainless Steel 440 C

Grade	440 C	
Density (kg/m3)	7650	
Elastic Modulus (GPa)	200	
Mean Coefficient of Thermal Expansion (mm/m/°C)	(0-100) C°	10.1
	(0-200) C°	10.3
	(0-600) C°	11.7
Thermal Conductivity(W/m.K)	At 100 C°	24.2
	At 500 C°	-
Specific Heat(J/kg.K)	(0-100) C°	460
Electrical Resistivity (nW.m)	600	
Hardness (HRC)	45-55	
Tensile strength (MPa)	758	
Elongation %	14	

1.3 Experimental Design

Design of Experiments (DOE) is a series of strategies that revolve around the study of the effect on the result of a controlled experiment of various variables. The first step is usually to define the independent variables or variables influencing the substance or process and then to research their effects on a dependent variable or reaction. The Box-Behnken approach is a traditional method commonly used to improve the input factors during the turning process. The Box-Behnken designs make the influence of the different design factors to be studied sequentially if the other factors are held at a constant level throughout the analysis of the first factors. The table (3) shows the various levels and parameters of cutting that were chosen.

Table -3- The levels of cutting factors

Factors	Level -1-	Level -2-	Level -3-
Speed (RPM)	500	1000	1500
Feed (mm/rev)	0.05	0.125	0.2
Depth of cut (mm)	0.5	1	1.5

2. **Results and Discussion**

The response surface design was conducted using Design-Expert version 12 experimental design layout and the result an indicated in table (4).

Table -4- : Input parameters and responses

Test number	Cutting speed(rpm)	Feed (mm\rev)	Depth of cut(mm)	Roughness Ra(µ m)	Temperature (C°)	MRR mm^3\min
1	500	0.05	1	1.385	116	3248.2

2	1500	0.05	1	1.35	143	9758.0
3	500	0.2	1	1.9	153	13186.8
4	1500	0.2	1	1.582	150	38646.2
5	500	0.125	0.5	1.5	120	4212.3
6	1500	0.125	0.5	1.507	124	12467.8
7	500	0.125	1.5	1.432	172	12344.6
8	1500	0.125	1.5	1.95	140	35893.6
9	1000	0.05	0.5	1.824	109	3384.0
10	1000	0.2	0.5	1.347	125	12984.7
11	1000	0.05	1.5	1.35	176	9557.7
12	1000	0.2	1.5	2.107	169	38330.1
13	1000	0.125	1	1.136	150	16439.6
14	1000	0.125	1	1.189	148	16141.7
15	1000	0.125	1	1.311	152	16292.9
16	1000	0.125	1	1.217	155	16390.9
17	1000	0.125	1	1.118	158	16040.3

Tables 5, 6, and 7(a&b) summarize the results of the quadratic model utilized in this experiment. This illustrates the importance of each factor, such as speed, feeding, and depth of cut, and they effect on surface roughness, temperature, and material removal rate.

Several key points can be found in these tables, including the F-value, P-value, and R^2.

F-values are used to assess the overall significance of an ANOVA model rather than just one variable. The greater the F-value better the model.

The p-value indicates if the model describes a significant relationship, the model's importance is determined by a p-value of less than 0.05.

R^2 indicates how well the data is explained by the model, whenever the R^2 is higher that is mean the model is better.

Table (5a) show the model F-value of 6.66 indicates that the model is significant. An F-value of this magnitude has a 1.03% chance of occurring due to noise. Model terms with P-value less than 0.05 are significant. B is important model term in this scenario. The model terms are not important if the p-value is bigger than 0.1

Table -5a- Surface roughness: an analysis of variance

Source	Sum of squares	df	Mean square	F-value	P-value	
Model	1.27	9	0.1408	6.66	0.0103	Significant
A	0.0037	1	0.0037	0.1749	0.6883	
B	0.1318	1	0.1318	6.24	0.0412	
C	0.0546	1	0.0546	2.58	0.1520	
AB	0.0200	1	0.0200	0.9470	0.3629	
AC	0.0653	1	0.0653	3.09	0.1223	
BC	0.3807	1	0.3807	18.01	0.0038	

A^2	0.0949	1	0.0949	4.49	0.0718	
B^2	0.1855	1	0.1855	8.77	0.0210	
C^2	0.2693	1	0.2693	12.74	0.0091	
Residual	0.1480	7	0.0211			
Lake of Fit	0.1246	3	0.0415	7.11	0.0443	Significant
Pure Error	0.0234	4	0.0058			
Cor. Total	1.41	16				

By noting the value of R^2 the 89.54% in table (5b), the acceptability of the model can be confirmed. The design space can be navigated using this model.

Table -5b- Surface roughness: an analysis of variance

Std.Dev.	0.1454
Mean	1.48
C.V.%	9.81
$\mathbf{R^2}$	0.8954
Adjusted$\mathbf{R^2}$	0.7609
Predicted $\mathbf{R^2}$	-0.4351
Adeq. Precision	8.8084

Table (6a) show the model F-value of 5.50 indicates that the model is significant. An F-value of this magnitude has a 1.76% chance of occurring due to noise. Model terms with P-value less than 0.05 are significant. C is important model term in this scenario. The model terms are not important if the value is bigger than 0.1

Table -6a- Cutting temperature: an analysis of variance

Source	Sum of squares	df	Mean square	F-value	P-value	
Model	5552.08	9	616.90	5.50	0.0176	Significant
A	2.00	1	2.00	0.0178	0.8975	
B	351.13	1	351.13	3.13	0.1202	
C	4005.13	1	4005.13	35.69	0.0006	
AB	225.00	1	225.00	2.01	0.1997	
AC	324.00	1	324.00	2.89	0.1331	
BC	132.25	1	132.25	1.18	0.3136	
$\mathbf{A^2}$	335.39	1	335.39	2.99	0.1275	
$\mathbf{B^2}$	42.44	1	42.44	0.3783	0.5580	
$\mathbf{C^2}$	92.02	1	92.02	0.8201	0.3952	
Residual	785.45	7	112.21			
Lake of Fit	722.25	3	240.75	15.24	0.0118	Significant

Pure Error	63.20	4	15.80			

The model's acceptance can be checked by noting the value of R^2 of 87.61% in table (6b). This model can be used to navigate the design space.

Table -6b- Cutting temperature: an analysis of variance

Std.Dev.	10.59
Mean	144.71
C.V.%	7.32
$\mathbf{R^2}$	0.8761
Adjusted$\mathbf{R^2}$	0.7167
Predicted $\mathbf{R^2}$	-0.8390
Adeq. Precision	7.7237

Table (7a) show the model F-value of 10901.75 indicates that the model is significant. An F-value of this magnitude has a 0.01% chance of occurring due to noise. Model terms with P-value less than 0.05 are significant. A is important model term in this scenario. The model terms are not important if the p-value is bigger than 0.1

Table -7a- material removed rate (MRR): an analysis of variance

Source	Sum of squares	df	Mean square	F-value	P-value	
Model	1.991E+09	9	2.212E+08	10901.75	< 0.0001	Significant
A	5.084E+08	1	5.084E+08	25053.87	< 0.0001	
B	7.450E+08	1	7.450E+08	36713.44	< 0.0001	
C	4.973E+08	1	4.973E+08	24509.61	< 0.0001	
AB	8.977E+07	1	8.977E+07	4424.07	< 0.0001	
AC	5.847E+07	1	5.847E+07	2881.61	< 0.0001	
BC	9.189E+07	1	9.189E+07	4528.38	< 0.0001	
A^2	13720.83	1	13720.83	0.6762	0.4380	
B^2	49444.10	1	49444.10	2.44	0.1625	
C^2	33045.00	1	33045.00	1.63	0.2426	

Residual	1.420E+05	7	20291.70			
Lake of Fit	29311.35	3	9770.45	0.3467	0.7947	not significant
Pure Error	1.127E+05	4	28182.63			

The acceptability of the model can be checked by noticing the value of R^2 of 99.99% in table (7b). This model can be used to navigate the design space.

Table -7b- material removed rate (MRR): an analysis of variance

Std.Dev.	142.45
Mean	16195.26
C.V.%	0.8796
R^2	0.9999
AdjustedR^2	0.9998
Predicted R^2	0.9997
Adeq. Precision	322.6125

The distribution of actual and predicted values of surface roughness, temperatures, and material removal rate are shown in Figures 3, 4, and 5. It is clear that most of the points are located on either side of the 45°slope line.

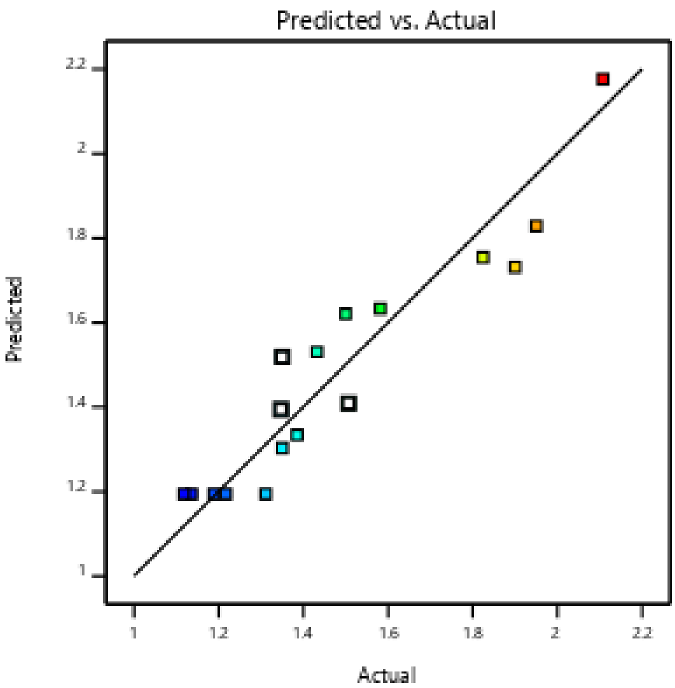

Figure -5- predicted vs. actual value of surface roughness (Ra)

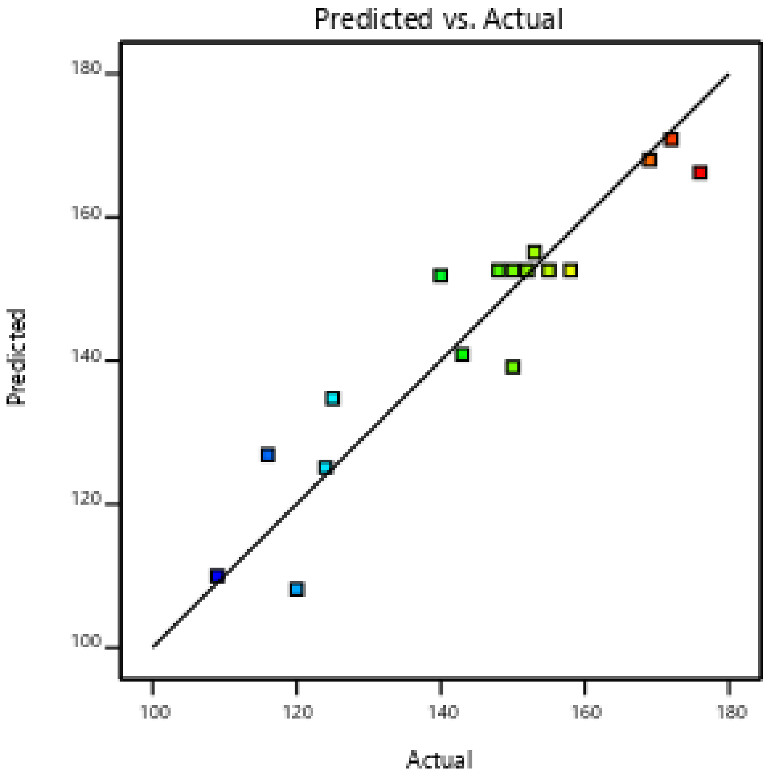

Figure -6- predicted vs. actusl of temperature (T)

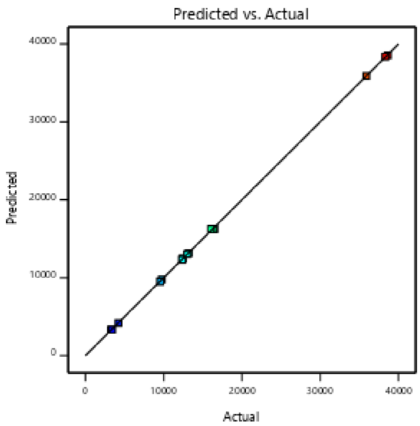

Figure -7- predicted vs. actual value of material removal rate (MRR)

From the analysis of contour plot 8(a), 8(c) & 3D-plots 8(b), 8(d.) for surface roughness, the lowest value of surface roughness 1,385 µm was apparent at a cutting speed of 613.26 rpm, feed 0.06 mm/rev, and cutting depth of 0.834 mm.

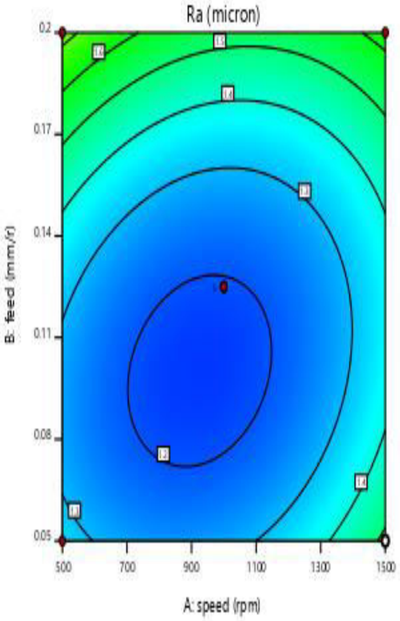

Figure -8a- contour plot of intercation speed and feed for surface rpughness

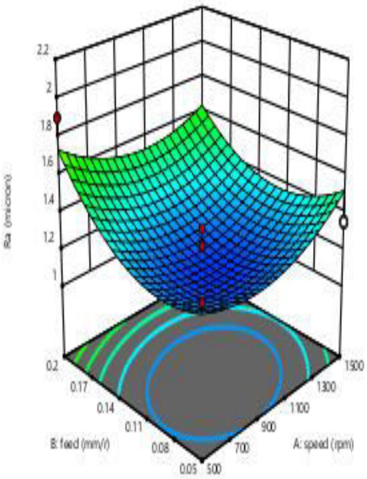

Figure -8b- 3D plot for surface roughness of interaction between speed and feed

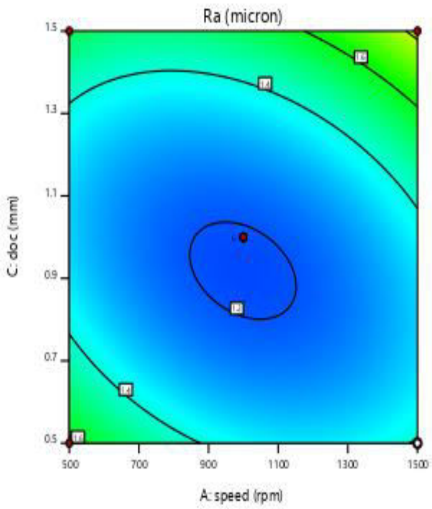

Figure -8c- contour plot of intercation speed and depth of cut for surface roughness

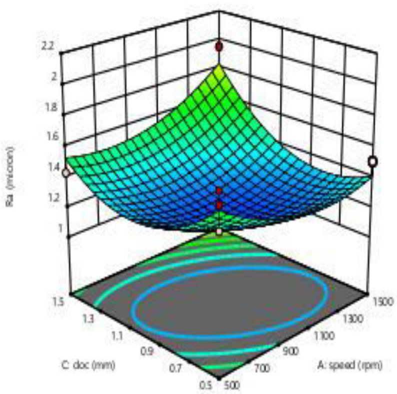

Figure -8d- 3D plot for surface roughness of interaction between speed and depth of cut

From the analysis of contour plot 9(a), 9(c) & 3D-plots 9(b), 9(d.) for temperature, the lowest value of temperature 126.875 C° was apparent at a cutting speed of 500 rpm, feed 0.05 mm/rev, and cutting depth of 0.5 mm.

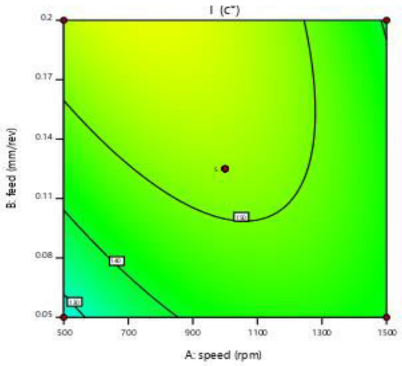

Figure -9a- contour plot of interaction speed and feed for temperature

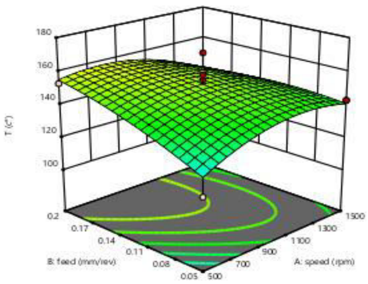

Figure -9b- 3D plot for temperature of interaction between speed and feed

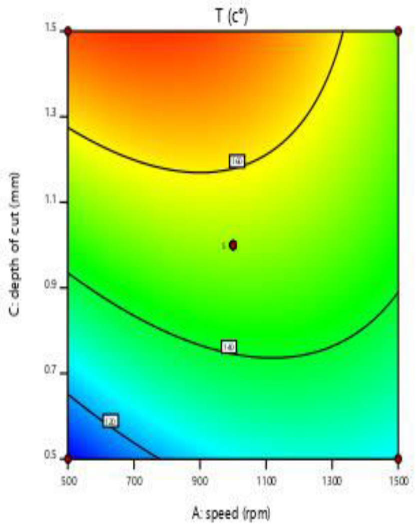

Figure -9c- contour plot of interaction speed and depth of cut for temperature

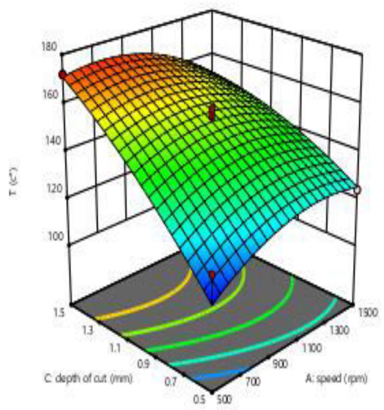

Figure -9d- 3D plot for temperature of interaction between speed and depth of cut

From the analysis of contour plot 10(a), 10(c) & 3D-plots 10(b), 10(d) for material removal rate, the biggest value of material removal rate 38646.2 mm³/min was apparent at a cutting speed of 1500 rpm, feed 0.2 mm/rev, and cutting depth of 1.5 mm.

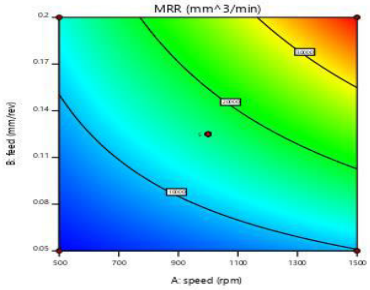

Figure -10a- contour plot of interaction speed and feed for material removal rate

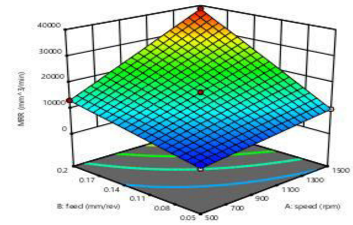

Figure -10b- 3D plot for material removal rate of interaction between speed and feed

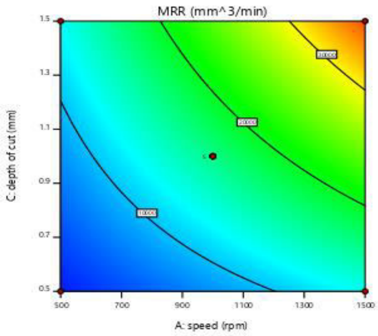

Figure -10c- contour plot of interaction speed and depth of cut for material removal rate

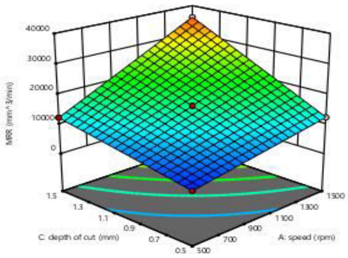

Figure -10d- 3D plot for material removal rate of interaction between speed and depth of cut

Mathematical Models

RSM is a set of statistical and mathematical methodologies for modeling and analyzing problems in which several input factors influence a process response, with the purpose of optimizing the output parameters. The success of the RSM technique is heavily influenced by the correct experimental design and selection of input parameters. The fundamental advantage of RSM is the ability to understand and estimate the relationship between input parameters and their impact on outputs (responses). Second-order RSM is used in this study to define the relationship between each of the output parameters, namely temperature, surface roughness, and material removal rate (MRR), and the input process parameters, by regression analysis which is a reliable way for determining whether variables have an impact on a particular problem. Regression analysis allows to confidently establish which elements are most important, which factors may be neglected, and how these factors interact. After the data were entered into the analytical program, which includes the inputs and outputs obtained through the experiment, the relationships that join all factors with the responses are obtained, as shown in the equations below.

The quadratic equation below shows the regression relationship for Ra (output) with speed, feeding, and cutting depth (inputs).

$$Ra= 1.19+0.0215\ A+0.1284\ B+0.0826\ C-0.0708\ AB+0.1278\ AC+0.3085\ BC+0.1501\ A^2+0.2099\ B^2+0.2529\ C^2$$

The quadratic equation below shows the regression relationship for Temperature (output) with speed, feeding, and cutting depth (inputs).

$$T= 152.60-0.5000\ A+6.63\ B+22.38\ C-7.50\ AB-9.00\ AC-5.75\ BC-8.93\ A^2-3.18\ B^2-4.67\ C^2$$

The quadratic equation below shows the regression relationship for metal removal rate (output) with speed, feeding, and cutting depth (inputs).

$$MRR= 16261.08+7971.71\ A+9649.99\ B+7884.65\ C+4737.40\ AB+3823.38\ AC+4792.92\ BC+57.08\ A^2-108.37\ B^2-88.59\ C^2$$

Where: Ra=Surface Roughness, T=Temperature, MRR=Material Removal Rate, A=Speed, B=Feed, C=Depth of cut

Conclusion

May deduce from the tables and graphs of a response factors that the factor that affects the material removal rate significantly and clearly is the cutting speed. As the cutting speed is increased, the rate of material removal increases. The ideal input parameters for getting material removal rate (MRR) are cutting speed of 1500 RPM, feed of 0.2 mm/rev, and cut depth of 1.5 mm. The optimal input parameters for the lowest surface roughness (Ra) are 613.26 RPM, 0.06 mm/rev feed, and 0.84 mm cut depth. The optimal temperature input parameters are cutting speed 500 RPM, feed 0.05mm/rev, and cut depth 0.5mm. Based on the aforementioned results, can apply the optimal cutting conditions for turning stainless steel 440 C, which will result in a better surface finish, lower machining costs, manufacturing time, as well as material squanders, among other benefits. Overall productivity increases, as a result, resulting in higher earnings.

References

[1] S. Y. Lu, K. F. Yao, Y. B. Chen, M. H. Wang, Y. Shao, and X. Y. Ge, "Effects of austenitizing temperature on the microstructure and electrochemical behavior of a martensitic stainless steel," J. Appl. Electrochem., vol. 45, no. 4, pp. 375–383, 2015, doi: 10.1007/s10800-015-0796-1.

[2] H. A. Youssef, Machining of Stainless Steels and Super Alloys. John Wiley & Sons, Ltd, The Atrium, Southern Gate, Chichester, West Sussex, PO19 8SQ, United Kingdom, 2015.

[3] S. Hasan and S. Thamizhmanii, "Tool flank wear analyses on AISI 440 C martensitic stainless steel by turning," Int. J. Mater. Form., vol. 3, no. SUPPL. 1, pp. 427–430, 2010, doi: 10.1007/s12289-010-0798-9.

[4] H. E. Radhi, M. jammel alsalhy "Multi-Objective Optimization of Turning Process during Machining of AISI 1025 on CNC machine Using Multi-objective particle swarm optimization," University of Thi_Qar Journal for Engineering Sciences, vol. 10, no. 1, 2019.

[5] S. Thamizhmanii and S. Hasan, "Machinability of hard martensitic stainless steel and hard alloy steel by CBN and PCBN tools by turning process," Proc. World Congr. Eng. 2011, WCE 2011, vol. 1, no. April 2015, pp. 554–559, 2011.

[6] M. Gosai and S. N. Bhavsar, "Experimental Study on Temperature Measurement in Turning Operation of Hardened Steel (EN36)," Procedia Technol., vol. 23, pp. 311–318, 2016, doi: 10.1016/j.protcy.2016.03.032.

[7] D. L. Petković, M. J. Madić, M. R. Radovanović, P. L. Janković, and G. M. Radenković, "Modeling of cutting temperature in the biomedical stainless steel turning process," Therm. Sci., vol. 20, no. January, pp. S1345–S1354, 2016, doi: 10.2298/TSCI16S5345P.

[8] S. R. Chauhan and K. Dass, "Optimization of machining parameters in turning of titanium (Grade-5) alloy using response surface methodology," Mater. Manuf. Process., vol. 27, no. 5, pp. 531–537, 2012, doi: 10.1080/10426914.2011.593236.

[9] R. R. Deshpande and R. Pant, "Optimization of Process Parameters for CNC Turning using Taguchi Methods for EN8 Alloy Steel with Coated / Uncoated Tool Inserts," Int. Res. J. Eng. Technol., pp. 180–188, 2017.

[10] R. A. Mahdavinejad and S. Saeedy, "Investigation of the influential parameters of machining of AISI 304 stainless steel," Sadhana - Acad. Proc. Eng. Sci., vol. 36, no. 6, pp. 963–970, 2011, doi: 10.1007/s12046-011-0055-z.

[11] H. E. Radhi, Barrans, S. M. "Comparison between multiobjective optimization algorithms," Lviv Polytechnic Publishing House 2011(handle / ntb / 28784)

[12] N. H. Majeed, H. E. Radhi, and H. J. Abid, "Optimization of MIG welding parameters," University of Thi_Qar Journal for Engineering Sciences, vol. 11, no. April, 2021.

[13] H. E. Radhi and S. Barrans, "Diversity metric assessment for multi-objective optimization," Conference 2013 : CEARC'13 ,University of Huddersfield, pp. 171-175. ISBN 9781862181212.

[14] Datasheet, "Carpenter Stainless Type 440C Carpenter Stainless Type 440C Identification Carpenter Stainless Type 440C," Corrosion, pp. 1–5, 2007.

[15] Wikipedia, "What is 440C Stainless Steel," J. Chem. Inf. Model., vol. 53, no. 9, pp. 1689–1699, 2013.

. Kinetic Learning , Mosul: Dar Al-Fikr for Printing and Publishing, 1989.