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PREDICTION AND OPTIMIZATION OF EN8 MILD STEEL MATERIAL REMOVAL RATE AND SURFACE ROUGHNESS USING RESPONSE SURFACE METHODOLOGY

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Abstract— The demand for EN8 mild steel in the industry is high due to its integral mechanical properties. However, conventional machining of EN8 mild steel is a challenging task. In this research work, prediction and optimization of EN8 mild steel Material Removal Rate (MRR) and Surface Roughness (Ra) using Response Surface Methodology (R.S. M) were investigated. The dimension of the EN8 mild steel material was 0.12 m diameter and 0.08 m in length. The turning operation of the ENS mild steel was carried out using an M42 HSS single-point cutting tool. To minimize any form of error, the machining operation was done in a dry environment. A TR 100 Surface Roughness Tester was used to carry out the surface roughness measurement of the EN8 mild steel in a transverse direction. This process was repeated three times, and the average value of three measurements recorded. The data generated were analyzed using Response Surface Methodology. The results obtained revealed an R2 value of 0.9985 and 0.9978 for Material Removal Rate (MRR) and Surface Roughness (Ra), respectively. Besides, it was observed that the feed rate, spindle speed, and depth of cut had a significant influence on the material removal rate. Nevertheless, unlike the other parameters evaluated, it was only feed rate that had a significant influence on surface roughness. The results obtained from the numerical optimization solution revealed that optimum machining setting of spindle speed of 220 rpm, the feed rate of 140 x 10^{-6} m/min and depth of cut of 1.5 x 10^{-3} m would result in a turning process with an optimum material removal rate of 12598.5 mm^3/min and surface roughness of 0.87785 µm, and with a composite desirability value of 98.9%.

I. Introduction

EN8 mild steels are versatile material in the manufacturing industry. The high demand for EN8 mild steel in the industry is a result of its good mechanical properties such as; high strength, toughness, ductility, and its ability to retains its high strength at high temperatures. Several machine components, such as bearings, cams, gears, shafts, etc., are produced from EN8 mild steel. However, before these machine elements are created, machine operation such as hard turning is required. The hard-turning machine operation provides numerous benefits, unlike grinding that had remained the standard finishing process for hardened steel surfaces over the years. Also, the high mechanical and thermal load that results from machining operations creates a severe environment for the tools to operate. Besides, during hard turning operations, complications and mutual interactions are formed between the tool and workpiece at the point of surface contact [1]-[6]. Also, significant cutting loads and extreme tribological conditions are developed because of severe dry friction and high surface contact interface temperatures between the workpiece and tool chip resulting in accelerated tool wear and eventual breakage of the tool. Thus, there is an alteration of the precisions on the surface roughness of the finished workpiece dimensions.

Several methods to curb several researchers had proposed the problem of Material Removal Rate (MRR) and Surface Roughness (Ra) in the past and their findings were aimed at analyzing the effect of cutting and turning conditions on the tool performance and optimization. In this line, Adarsh et al. [7] analyzed the optimum cutting conditions of EN8 alloy material using spindle speed, feed, and depth of cut as evaluated parameters. The performance of Ra was evaluated using Multiple Regression Analysis (MRA) and ANOVA Analysis (A.A.). The results of their findings depicted feed rate as the only significant factor affecting Ra. Barik and Mandal [8] in their strive to find a solution to Ra in turning of EN31 alloy decided to study the characteristics of the material as mentioned above using speed, feed and depth of cut as evaluated parameters. Genetic Algorithm (G.A.) was used for the optimization of the parameters discussed above. The results obtained by them suggested that an increase in feed rate led to a correspondingly increase in Ra.

Erameh et al. [9] investigated Ra and Tool Wear Rate (TWR) in hard turning of EN8 mild steel. They used High-Speed Steel (HSS) cutting tool, and spindle speed, feed rate, and depth of cut were evaluated as determining parameters. The optimization was done using Response Surface Methodology (R.S. M). The outcome of the results obtained from their research work revealed feed rate as the only influencing parameters on Ra. Moreover, Nitin et al. [10] used ANOVA Analysis (A.A.) and combined signal to noise ratio to predict the Ra of turning AISI 410 steel using TiN coated P20 and P30 cutting tool. The parameters evaluated in their research work include; inserted radius, depth of cut, feed rate, and cutting speed. The results of their research work showed that insert radius and feed rate have a significant effect on Ra [11]. Their research work was further optimized using spindle speed, feed rate, and depth of cut in dry turning of mild steel HSS cutting tool. ANOVA Analysis, Signal to Noise Ratio, and Taguchi Methods were used to analyze and evaluate the Ra value. Their conclusion also goes in line with the results of the researchers mentioned above, and this was because the feed rate once again was the primary factor recorded.

Similarly, Samir et al. [12] investigated the Ra of mild steel using the HSS cutting tool. The parameters analyzed and evaluated include; feed rate, speed and depth of cut, and the cutting force. The approach adopted by them involved the full factorial design, and two repetitions were used to find the optimal solution. The outcome of the results obtained in their research work showed that feed rate and spindle speed were the influencing factors that were required to increase the Ra of mild steel. To find the optimal Ra of Al6351-T6, an experimental investigation was conducted by Rodrigues et al. [13]. The model used by this five-person team was predicted and validated using the regression technique and Taguchi Technique. Cutting speed, feed rate, and depth of cut were considered for the turning process and equally evaluated.

They conclude from their findings that cutting speed was found to be highest, and this agreed with the research work of Das et al. [14]. Nevertheless, this present research work is focused on the prediction and optimization of EN8 mild steel material removal rate and surface roughness using Response Surface Methodology.

II. Material And Methods

A. Material

The EN8 mild steel material was bought from the local market in Benin City, Nigeria. The mechanical properties of the EN 8 mild steel were determined at Petroleum Training Institute, Effurun, Delta State, Nigeria. Table 1 shows the experimental condition of EN8 mild steel. Table 2 shows the mechanical properties of the EN8 Mild Steel. The turning operation was carried out using the M42 HSS single-point cutting tool. The turned samples are shown in Figure 1. An ENC lathe machine with spindle speed, as shown in Figure 2, ranging from 100 rpm to 3000 rpm, was used for the experiment. A 6.5 hp electric motor drove the machining center, and the experiment was carried out under a dry machining environment. TR 100 Surface Roughness Tester equipment shown in Figure 3 was used for the measurement of the Ra of the machined EN8 mild steel material in the transverse direction. This process was repeated three times, and the average of three measurement values recorded.

Table 1: Experimental Condition of the EN8 Mild Steel

S/N	Parameters	Dimension
1	Length	80.00
2	Diameter	120.00

Table 2: Mechanical Properties of the EN8 Mild Steel

S/N	Parameters	Determined Value
1	Hardness value	235 Brinell
2	Elongation	16.87%
3	Yield Stress	464.95N/mm2
4	Maximum Stress	845.85N/mm2

Figure 1: Turned Samples

Figure 2: CNC Lathe Machine

Figure 3: TR100 Ra Tester

B. Methods

In this present research work, three main cutting parameters (i.e., spindle speed (A) in rev/min, feed rate (B), in mm/min, and depth of cut (C), in mm) were selected and considered for the turning process. Table 3 shows the process variables and their level, and Table 4 shows the experimental design matrix and output response for Material Removal Rate (MRR) and Surface Roughness (Ra). The mathematical model of MRR and Ra deduced from this research work is shown in (1) and (2).

$$(\mathrm{MRR} + 1400) = +31.67354 + 0.029293 * A - 96.59485 * B + 12.66684 * C + 0.93570 * A * B + 0.14815 * A * C + 156.67356 * B * C - 2.15601E-004 * A^2 + 166.40596 * B^2 - 9.32012 * C^2 \quad (1)$$

The final equation for MRR in terms of actual factors:

$$\mathrm{Ra} = +0.23546 - 3.62871 * B + 75.55179 * B^2 \quad (2)$$

Table 3: Process Variables and their Level

Factor	**Range**	
	Low	**High**
Spindle speed, A, (rpm)	110 rpm (32.85m/min)	220 rpm (62.13m/min)
Feed rate, B, (mm/min)	0.10 mm/min	0.14 mm/min
Depth of cut, C, (mm)	0.25 mm	1.50 mm

Table 4: Experimental Design Matrix and Output Response for Material Removal Rate (MRR) and Surface Roughness (Ra)

Std.	Run	Block	Factor			Response		
			Spindle Speed (rpm)	Feed Rate (mm/min)	Depth Of Cut (mm)	Material Removal Rate (mm^3/min	Av. Surface Roughness, Ra (µm)	Machining Time (MT)min
1	1	Block1	163.5	0.10	0.8	1024.69	1.39	2.46
2	2	Block1	163.5	0.10	1.2	7091.04	1.41	1.59
3	3	Block1	260.2	0.10	1.1	12228.9	1.42	1.53
4	12	Block1	110.0	0.10	0.7	2954.34	2.03	3.17
20	5	Block1	162.5	0.10	1.0	7502.04	1.33	2.11
18	6	Block1	162.5	0.10	1.5	7502.78	1.42	2.01
6	7	Block1	110.5	0.15	1.2	5849.3	0.94	4.76
19	8	Block1	162.5	0.10	1.1	7680.04	1.33	2.46
9	9	Block1	165.8	0.10	1.0	2935.16	1.41	6.36
12	10	Block1	162.5	0.10	1.1	10208.5	2.55	1.83
11	11	Block1	162.5	0.10	1.1	4955.54	0.63	3.77
7	12	Block1	115.0	0.14	1.5	8773.96	2.03	3.18
15	13	Block1	162.5	0.13	1.0	7182.65	1.34	2.46
8	14	Block1	220.0	0.16	1.5	18383.5	2.03	1.52
1	15	Block1	115.0	0.90	1.1	1969.56	0.91	4.76
4	16	Block1	220.0	0.18	0.5	6190.05	2.03	1.52
16	17	Block1	162.5	0.13	1.1	7382.04	1.52	1.94
14	18	Block1	162.5	0.10	1.8	14024.5	1.41	2.46
6	19	Block1	220.0	0.14	1.5	12255.7	0.94	2.27
2	20	Block1	220.0	0.85	0.5	4126.7	0.93	2.27

III. Result And Discussion

The quadratic model was suggested from the sequential model sum of squares [Type II] for the two responses, as shown in Table 5. The experimental data were analyzed with ANOVA Analysis (A.A.), and this was mainly to identify the factor(s) that significantly influence the performance measure as depicted in Tables 6 and 7. Transformation was carried out because of the ratio of the maximum to the minimum, which was obtained as 18383.5 and 1024.69, respectively. A transform square root constant of 1400 was obtained. The ANOVA generated at a 95% confidence level for the cutting parameters, and the response (i.e., MRR) is shown in Table 4. The present model F-value was obtained as 266.59, and this implies that the model is significant. Besides, it was observed that there is a 0.01% chance that the model with an F-Value could only occur because of noise. Also, in this model, it was found that factors A, B, C, AB, A.C., BC, and C2 are the significant model terms for the maximization of MRR, and this is because of their possessing values of "Prob. > F" is less than 0.050.

Similarly, the probability value associated with the lack of fit was 0.0522, thus, not significant. It is, therefore, desirable to have an insignificant lack of fit. Table 5 shows the ANOVA Analysis (A.A.) for testing the significance of the quadratic model in predicting Ra. The model has a P value of 0.0001, and this suggests that the mode is significant, and it was observed that B and B2 are the model term that has a significant influence on Ra. Moreover, the probability value associated with the lack of fit was 1.0000, which is not significant.

Table 5: Sequential Model Sum of Squares [Type II]

Response	Source	Sum of Squares	df	Mean Square	F Value	P-value Prob. > F	
Material Removal Rate (MRR)	Quadratic VS 2FI	84.26	3	28.09	6.86	0.0086	Suggested
Surface Roughness (Ra).	Quadratic VS 2FI	0.071	3	0.024	7.31	0.007	Suggested

Table 6: ANOVA for Material Removal Rate (MRR)

Source	Sum of Squares	df	Mean Square	F Value	P-value Prob. > F	
Model	9818.74	9	1090.97	266.59	< 0.0001	significant
A-Spindle Speed	2771.05	1	2771.05	677.14	< 0.0001	
B-Feed Rate	844.04	1	844.04	206.25	< 0.0001	
C-Depth of cut	5.91E+03	1	5.91E+03	1.44E+03	< 0.0001	
AB	20.84	1	20.84	5.09	0.0476	
AC	145.14	1	145.14	35.47	0.0001	
BC	44.18	1	44.18	10.8	0.0082	
A^2	7.32E+00	1	7.32E+00	1.79	0.2106	
B^2	3.20E-01	1	3.20E-01	0.079	0.7844	
C^2	7.82E+01	1	7.82E+01	19.12	0.0014	
Residual	40.92	10	4.09E+00	4.94	0.0522	not significant
Lack of Fit	3.40E+01	5	6.81E+00			
Pure Error	6.89	5	1.38E+00			
Cor Total	9859.66	19				

Table 7: ANOVA for Surface Roughness (Ra)

Source	Sum of Squares	df	Mean Square	F Value	P-value Prob. > F	
Model	4.52	2	2.26	1085.94	< 0.0001	significant
B-Feed Rate	4.45	1	4.45	2139.29	< 0.0001	
B^2	0.068	1	0.068	32.59	< 0.0001	
Residual	3.50E-02	17	2.08E-03			
Lack of Fit	3.85E-03	12	3.21E-04	0.051	1	not significant
Pure Error	0.032	5	6.31E-03			
Cor Total	4.56	19				

To evaluate how best the quadratic model fits the observed data and its ability to predict MRR and Ra, the goodness of fit statistics presented in Tables 8 and Table 9 were generated. From results analysis as depicted in Tables 6 and 7, the R2 value of 0.9985 and 0.9978 for MRR and Ra respectively are more significant than 0.9, implying a high correlation. Thus, the model can explain 99.85% and 99.78% variability MRR and Ra. For an agreement to be accomplished, their adjusted R-squared and predicted R-squared should be within approximately 0.20. Therefore, since this condition is meant for their respective values, which are in the stipulated range, they are in good agreement. An adequate precision is a measure of the range of a predicted response relative to its associated error (i.e., signal to noise ratio). The desired value should be four or more. For these two models, it is more than four, and this simply showed that it could be used to navigate the design space. The predicted values of MRR and Ra based on (1) and (2) are presented in Tables 10 and 11, respectively.

Table 8: GOF Statistics for Validating Model Significance towards Maximizing Material Removal Rate

Std. Dev.	2.02	R-Squared	0.9958
Mean	91.75	Adj. R-Squared	0.9921
C.V. %	2.2	Pred. R-Squared	0.9726
PRESS	270.4	Adeq. Precision	62.786

Table 9: GOF Statistics for Validating Model Significance towards Minimizing Surface Roughness

Std. Dev.	0.046	R-Squared	0.9922
Mean	1.44	Adj. R-Squared	0.9913
C.V.%	3.17	Pred. R-Squared	0.9902
PRESS	0.044	Adeq. Precision	108.697

Table 10: Prediction Result for Material Removal Rate (MRR)

Standard Order	Actual value	Predicted Value	Residual	Run Order
1	58.05	56.15	1.9	15
2	74.34	72.89	1.45	20
3	65.99	63.94	2.04	4
4	87.12	87.14	-0.021	16
5	85.14	84.53	0.61	7
6	116.86	118.31	-1.45	19
7	100.87	101.73	-0.86	12
8	140.65	141.96	-1.31	14
9	65.84	67.75	-1.91	9
10	116.7	115.67	1.08	3
11	79.72	80.93	-1.21	11
12	107.74	107.37	0.37	10
13	49.24	52.1593.73	-2.91	1
14	124.2	122.12	2.08	18
15	92.674	93.73	-1.08	13
16	93.71	93.73	-1.-013	17
17	94.35	93.73	0.63	6
18	92.15	93.73	-1.58	2
19	95.29	93.73	1.56	8
20	94.35	93.73	0.63	5

Table 11: Prediction Result for Surface Roughness (Ra)

Standard Order	Actual value	Predicted Value	Residual	Run Order
1	0.9	0.89	0.012	15
2	0.9	0.89	0.012	20
3	2.03	2.03	-1.71E-04	4
4	2.03	2.03	-1.71E-04	16
5	0.9	0.89	0.61	7
6	0.9	0.89	-1.45	19
7	2.03	2.03	-1.71E-04	12
8	2.03	2.03	-1.71E-04	14
9	1.41	1.39	0.019	9

10	1.41	1.39	0.019	3
11	0.6	0.62	-0.023	11
12	2.55	2.54	6.13E-03	10
13	1.4	1.39	8.93E-03	1
14	1.41	1.39	0.019	18
15	1.3	1.39	-0.091	13
16	1.5	1.39	0.11	17
17	1.42	1.39	0.029	6
18	1.4	1.39	8.93E-03	2
19	1.33	1.39	-0.061	8
20	1.3	1.39	-0.091	5

The optimization was done using the Numerical Optimization Approach, and this was to ascertain the desirability of the overall model. In the numerical optimization phase, a design expert was used to maximize MRR and minimize Ra. The optimum values for the parameters (spindle speed, feed rate, and depth of cut) were determined. Table 12 shows the constraints used for numerical optimization. The outcome of the results obtained showed that numerical optimization produces twelve optimal solutions, as presented in Table 3. Figure 4 shows the three-dimensional (3D) surface plot of MRR as a function of A and B. Figure 5 shows the 3D surface plot of MRR as a function of A and C.

Table 12: Constraints for the Numerical optimization

Name	Goal	Lower Limit	Upper Limit	Lower Weight	Upper Weight	Importance
Spindle Speed (rpm)	Is in range	110	220	1	1	3
Feed Rate (mm/min.)	Is in range	0.10	0.14	1	1	3
Depth of Cut (mm)	Is in range	0.50	1.50	1	1	3
Material Removal Rate (MRR)	Maximize	1024.69	18383.5	0.1	1	5
Surface Roughness	Minimize	0.60	2.55	1	0.1	5

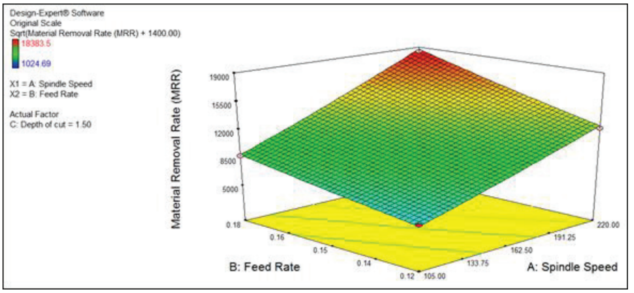

Figure 4: Three Dimensional (3D) Surface Plot of Material Removal Rate (MRR) as a Function of A and B

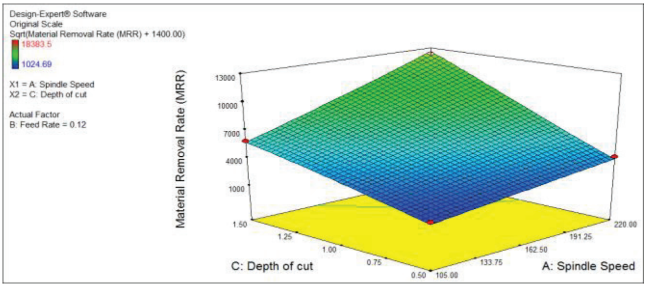

Figure 5: Three Dimensional (3D) Surface Plot of Material Removal Rate (MRR) as a Function of A and C

Figure 6 and Figure 7 shows the 3D surface plot of MRR as a function of B and C. The 3D surface plot of MRR as a function of B. From the 3 D surface plots in Figures 4, 5 and 6, it was observed that as the spindle speed, feed rate and depth of cut increase, the rate at which unwanted material is removed from the surface of the rotating workpiece also increase. However, only a decrease in feed rate brings about a reduction in Ra, as shown in Figure 7.

Table 13 shows the numerical optimization solution. The analysis of the results showed that optimum machining setting of spindle speed of 220 rpm, the feed rate of 0.14 mm/rev and depth of cut of 1.5 mm were required for a turning process that produced an optimum (maximized) MRR of 12598.5 mm3/min and minimum Ra of 0.87785 µm, and with a composite desirability value of 98.9%.

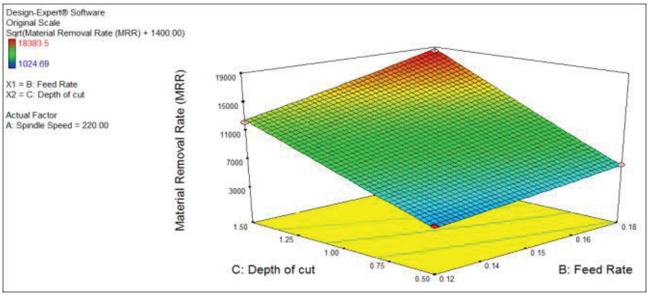

Figure 6: Three-Dimensional(3D) Surface Plot of Material Removal Rate (MRR) as a Function of B and C

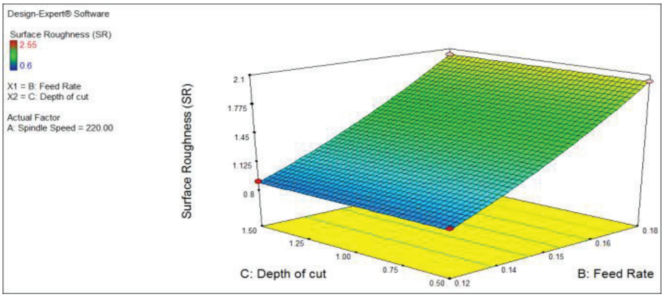

Figure 7: Three Dimensional (3D) Surface Plot of Material Removal Rate (MRR) as a Function of B and C

Table 13: Numerical Optimization Solution

S/N	Spindle Speed	Feed Rate	Depth of cut	Material Removal Rate (MRR)	Surface Roughness (Ra)	Desira-bility	
1	220	0.14	1.5	12598.5	0.87785	0.989	Selected
2	220	0.12	1.5	12598.5	0.893749	0.978	
3	219.36	0.12	1.5	12557	0.887969	0.978	
4	218.82	0.12	1.5	12522.7	0.888006	0.978	
5	220	0.12	1.5	12707.4	0.907012	0.978	
6	219.98	0.12	1.49	12518.5	0.888177	0.978	
7	218.30	0.121.5	1.5	12489.8	0.88803	0.978	
8	220	0.12	1.48	12420.3	0.887991	0.978	
9	216.27	0.12	1.5	12362.4	0.888305	0.978	
10	219.99	0.12	1.5	13005.6	0.954007	0.977	
11	220	0.13	1.5	13638.8	1.05981	0.976	
12	219.23	0.12	1.41	11763.4	0.887987	0.976	

IV. Conclusion

In this research work, the prediction and optimization of EN8 mild steel Material Removal Rate (MRR) and Surface Roughness (Ra) using Response Surface Methodology (R.S. M) were investigated. The results obtained revealed that the spindle speed, feed rate, and depth of cut have a significant influence on the MRR. However, the only feed rate is found to have a significant influence on Ra. It was also observed, that optimum machining setting of spindle speed of 220 rpm, the feed rate of 0.14 mm/rev and depth of cut of 1.5 mm resulted to a turning process with an optimum MRR of 12598.5 mm3/min and minimum Ra of 0.87785 µm, and with a composite desirability value of 98.9%.

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