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Investigation and Prediction of Material Removal Rate and Surface Roughness in CNC Turning of EN24 Alloy Steel

S. Dinesh
K. Rajaguru
V. Vijayan
Department of Mechanical Engineering
K. Ramakrishnan College of Technology
Tiruchirapalli, Tamil Nadu, India
dineshmechian@gmail.com

A. Godwin Antony
Department of Mechanical Engineering
Shivani College of Engineering and Technology
Samayapuram, Trichy, Tamilnadu, India

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Every manufacturing or production unit should concern about the quality of the product. Apart from quality, there exists other criterion, called productivity which is directly proportional to the profit level. Every manufacturing industry aims at producing a large number of products in relatively lesser time. In any machining process, it is most important to determine the optimal settings of machining parameters aiming at reduction of production costs and achieving the desired product quality. If the problem is related to a single quality attribute then it is called single objective optimization. If more than one attribute comes into consideration it is very difficult to select the optimal setting which can achieve all quality requirements simultaneously. . In this work, EN-24 alloy steel work pieces were turned on Computer Numerical Controlled (CNC) lathe by using Cemented carbide tool (coated). The influence of four cutting parameters, cutting speed, feed rate, depth of cut, and tool nose radius on minuscule surface roughness and material removal rate (MRR) were analyzed on the basis of Response Surface Methodology approach. The experimental results were collected by following the Taguchi's L16 mixed Orthogonal Array design.

Keywords: Material Removal Rate (MRR), surface roughness, EN24 alloy steel, cemented carbide tool, RSM approach.

1. Introduction

Datta S et al [1] attempted to solve the correlated multivariate optimization problem of submerged arc welding using PCA based hybrid Taguchi Method. The result of this method is compared with the grey Taguchi method results and proves to be satisfactory. Lan T et al [2] studied the effect of the cutting parameters feed, speed, depth of cut and tool nose runoff on the surface roughness and cutting force. This shows 95.87% of accuracy in dimension for the predicted optimized parameter values. Biswas C.K. et al [7] proposed their work on various methods used for predicting the surface roughness of the machined components. Their approaches were classified into machining theory, experimental investigation, designed experiments and artificial intelligence. Antony J et. al. [26] studied the problems faced by the Taguchi method of optimization. They found that this is best suited only for a single variable problem. For solving a multi variable optimization condition, the above method always brings some level of uncertainty in the results. For overcoming this problem, the author proposes a powerful multivariate statistical method called Principal Component Analysis (PCA). Feng et. al. [24] investigated for the prediction of surface roughness in finish turning operation by developing an empirical model through considering working parameters: work piece hardness (material), feed, cutting tool point angle, depth of cut, spindle speed, and cutting time. Data mining techniques, nonlinear regression analysis with logarithmic data transformation were employed for developing the empirical model to predict the surface roughness. Suresh et al (2002) focused on machining mild steel by Tin-coated tungsten carbide (CNMG) cutting tools for developing a surface roughness prediction model by using Response Surface Methodology (RSM). Genetic Algorithms (GA) used to optimize the objective function and compared with RSM results. It was observed that GA program provided minimum and maximum values of surface roughness and their respective optimal machining conditions.

Lee et. al. [25] highlighted on artificial neural networks (OSRR-ANN) using a sensing technique to monitor the effect of vibration produced by the motions of the cutting tool and work piece during the cutting process developed an on-line surface recognition system. The authors employed tri–axial accelerometer for determining the direction of vibration that significantly affected surface roughness then analyzed by using a statistical method and compared prediction accuracy of both the ANN and SMR. Kohli et. al. [17] proposed a neural–network based methodology with the acceleration of the radial vibration of the tool holder as feedback. For the surface roughness prediction in turning process the back–propagation algorithm was used for training the network model. The methodology was validated for dry and wet turning of steel using high speed steel and carbide tool and observed that the proposed methodology was able to make accurate prediction of surface roughness by utilizing small sized training and testing datasets. Al–Ahmari [12] developed empirical models for tool life, surface roughness and cutting force for turning operation. The process parameters used in the study were speed, feed, depth of cut and nose radius to develop the machinability model. The methods used for developing aforesaid models were Response Surface Methodology (RSM) and neural networks (NN).

Doniavi et. al. [10] used response surface methodology (RSM) in order to develop empirical model for the prediction of surface roughness by deciding the optimum cutting condition in turning. The authors showed that the feed rate influenced surface roughness remarkably. With increase in feed rate surface roughness was found to be increased. With increase in cutting speed the surface roughness decreased. The analysis of variance was applied which showed that the influence of feed and speed were more in surface roughness than depth of cut. B. Sidda Reddy et al carried out the experimentation on CNC turning machine with carbide cutting tool for machining aluminum alloys covering a wide range of machining conditions. The ANFIS model has been developed in terms of machining parameters for the prediction of surface roughness using train data. The Response Surface Methodology (RSM) is also applied to model the same data. The ANFIS results are compared with the RSM results.

2. Experimential set up

The machining tests are carried out on the specimen material in cylindrical form which was 120 mm long and 35 mm in diameter with the help of coated cemented inserts of two different nose radii on Batliboy Sprint 16 TC CNC lathe with a variable speed of 50 to 50,000 rpm and a power rating of AC motor rated power (continuous/30min rating) 5.5/7.5. For the present experiment work the three process parameters at four levels and one parameter at two levels have been decided. It is desirable to have two minimum levels of process parameters to reflect the true behavior of output parameters of study. The method chosen here is the L16 orthogonal array of mixed level design. The tool inserts were made of cemented carbide material for the machining operation.

Figure 1 Computer numerical controlled lathes

2.1. *Work piece material – EN-24 alloy steel*

Steel bars of 35 mm diameter and 120 mm length were used for the experimentation processes. The chemical composition of the material is Carbon - 0.37%, Silicon - 0.29%, Manganese - 0.60%, Sulphur - 0.028%, Phosphorous - 0.028%, Nickel - 0.12%, Chromium - 1.20%, Molybdenum - 0.201%, Copper - 0.15%, Titanium - 0.005%, Vanadium - 0.03%, Aluminium - 0.026%, Niobium - 0.008%, and the rest is Iron.

2.2. *Process variables and their limits*

In the present experimental study, spindle speed, feed rate and depth of cut have been considered as process variables. The working range of each parameter with their units is listed in table 1.

Table 1 Process variables and their limits

Parameters	Levels			
	1	2	3	4
Cutting speed: N (m/min)	110	165	210	275
Feed: F (mm/rev)	0.10	0.15	0.20	0.25
Depth of cut: D (mm)	0.4	0.8	1.2	1.6
Nose radius: NR (mm)	0.8	1.2	-	-

2.3. *Selection of experimental design*

Based on Taguchi's Orthogonal Array (OA) design, the L16 mixed array have been selected and is mentioned in the Tab. 2.

Table 2 Process variables and their limits

Experiment No.	**Speed**	**Feed**	**Depth Of Cut**	**Nose Radius**
1	110	0.10	0.4	0.8
2	110	0.15	0.8	0.8
3	110	0.20	1.2	1.2
4	110	0.25	1.6	1.2
5	165	0.10	0.8	1.2
6	165	0.15	0.4	1.2
7	165	0.20	1.6	0.8
8	165	0.25	1.2	0.8
9	210	0.10	1.2	0.8
10	210	0.15	1.6	0.8
11	210	0.20	0.4	1.2
12	210	0.25	0.8	1.2
13	275	0.10	1.6	1.2
14	275	0.15	1.2	1.2
15	275	0.20	0.8	0.8
16	275	0.25	0.4	0.8

2.4. *Material Removal Rate*

Initial and final weights of work piece were noted. Machining time was also recorded. Following equation is used to calculate the response Material Removal Rate (MRR).

$$\mathrm{MRR} = \frac{\text{Initial weight of workpiece} - \text{Final weight of workpiece}}{\text{Density} \times \text{Machining time}}$$

2.5. *Surface Roughness*

Surface roughness can generally be described as the geometric features of the surface. Surface roughness measurement is carried out by using TR 100 surface roughness tester. The Roughness measurements, in the transverse direction, on the work pieces has been repeated three times and average of three measurements of surface roughness parameter values has been recorded in table.

3. Analysis of results

The experiments were conducted to study the effect of process parameters over the output response as designed in the table. The experimental results of Surface Roughness and Material Removal Rate are given in the table 3.

Table 3 Response values from experimental work

S. No.	MRR (mm^3/min)	SR (μm)
1	2883.79	0.43
2	10710.34	0.66
3	19617.83	1.32
4	31528.66	1.31
5	9372.42	0.50
6	5661.71	0.61
7	40245.46	1.39
8	33970.27	1.46
9	20544.24	0.45
10	36746.60	0.71
11	9002.70	1.14
12	34444.10	1.51
13	31705.50	0.53
14	32134.40	0.66
15	25207.62	1.43
16	12974.70	1.99

3.1. *Analysis of variance*

ANOVA is the statistical technique used to calculate the size of the difference between data set. The elements of ANOVA table are source of variance, sum of squares, degrees of freedom, mean square, f ratio, and the probability associated with the F ratio. Table 3 shows the ANOVA table for experimental data of Material Removal Rate and Surface Roughness as dependent variables, and Speed, Feed, Depth of cut & Nose radius as independent variables.

3.1.1. *Material Removal Rate data analysis*

The F-value of 35.86 implies the model is significant. There is only a 0.05% chance that a "Model F-Value" this large could occur due to noise. Values of "Prob > F" less than 0.0500 indicate model terms are significant. The "Adj R-Squared" of

0.9587. "Adeq Precision" measures the signal to noise ratio. A ratio greater than 4 is desirable. For this model, the ratio of 17.197 indicates an adequate signal. Therefore the model can be used to navigate the design space.

3.1.2. *Surface Roughness data analysis*

The F-value of 11.92 implies the model is significant. There is only a 0.68% chance that a "Model F-Value" this large could occur due to noise. Values of "Prob > F" greater than 0.1000 indicate the model terms are not significant. The "Adj R-Squared" of 0.8792. "Adeq Precision" measures the signal to noise ratio. For this model the ratio of 11.929 indicates an adequate signal. Therefore the model can be used to navigate the design space.

Table 4 ANOVA table for the responses

Material Removal Rate (MRR)					
Source	Sum of Squares	DOF	Mean square	F-value	p-value Prob > F
Model	2.29E+09	10	2.29E+08	35.855	0.0005
A-Speed	48843193	1	48843193	7.6456	0.0396
B-Feed	1216640	1	1216640	0.1904	0.6807
C-Depth of cut	62882939	1	62882939	9.8433	0.0257
D-Nose radius	950277.5	1	950277.5	0.1488	0.7156
AB	37931016	1	37931016	5.9375	0.0589
AC	38903873	1	38903873	6.0898	0.0567
AD	1238504	1	1238504	0.1939	0.6781
BC	27474757	1	27474757	4.3007	0.0928
BD	15018596	1	15018596	2.3509	0.1858
CD	38755726	1	38755726	6.0666	0.0570
Residual	31941915	5	6388383		
Surface Roughness (SR)					
Source	Sum of Squares	DOF	Mean square	F-value	p-value Prob > F
Model	3.428187	10	0.342819	11.921	0.0068
A-Speed	0.002938	1	0.002938	0.1022	0.7622
B-Feed	0.226503	1	0.226503	7.8763	0.0377
C-Depth of cut	0.002923	1	0.002923	0.1016	0.7628
D-Nose radius	0.003359	1	0.003359	0.1168	0.7464
AB	0.047427	1	0.047427	1.6492	0.2553
AC	0.002365	1	0.002365	0.0823	0.7858
AD	0.009445	1	0.009445	0.3284	0.5914
BC	0.028654	1	0.028654	0.9964	0.3640
BD	0.032114	1	0.032114	1.1167	0.3390
CD	0.023937	1	0.023937	0.8324	0.4034
Residual	0.143788	5	0.028758		

3.2. *Effect of process parameters on MRR*

The Figs. 2–7 shows the effect of various process parameter combinations on the Material Removal Rate in turning of EN24 alloy steel work piece turned using coated cemented carbide.

The Fig. 2 shows the effect of speed and feed on MRR. Based on the graph, if the speed is increased the MRR decreases. The minimum speed of 110m/min produces higher MRR. The minimum feed of 0.10 mm/min produces higher MRR. Hence higher MRR is achieved by the combination of minimum feed and minimum speed. The Fig. 3 shows the effect of speed and Depth of cut on MRR. Based on the graph, it is clear that MRR decreases with increase in speed. The minimum speed of 110m/min produces higher MRR. The depth of cut has an inverse effect on MRR. The maximum depth of cut of 1.0 mm produces higher MRR. Hence higher MRR is achieved by the combination of minimum feed and maximum depth of cut.

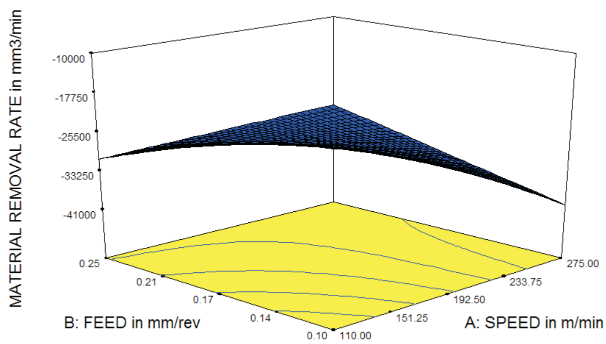

Figure 2 Effect of speed and feed on MRR

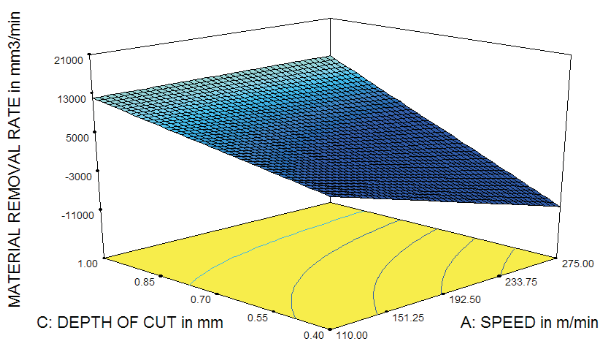

Figure 3 Effect of speed and depth of cut on MRR

The Fig. 4 shows the effect of speed and Nose radius on MRR. From the graph, the increase in speed decreases MRR. The minimum speed of 110m/min produces higher MRR. The Nose radius has a less significant effect on MRR. Hence higher MRR is achieved by the combination of minimum feed and at all Nose radius values. The Fig. 5 shows the effect of feed and Depth of cut on MRR. From the graph, increase in feed increases the MRR. The maximum feed of 0.25 mm/rev produces higher MRR. Similarly, increase in depth of cut increases MRR. The maximum depth of cut of 1.0 mm produces higher MRR. The highest value of MRR is achieved from the combination of maximum feed and maximum depth of cut.

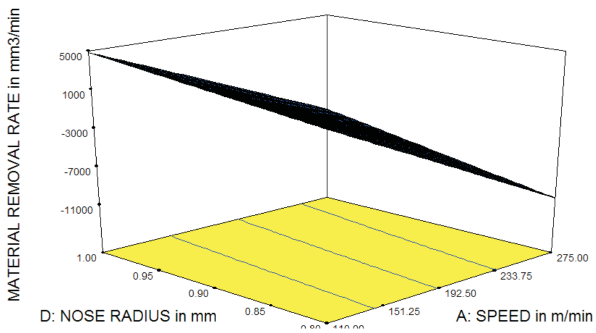

Figure 4 Effect of speed and nose radius on MRR

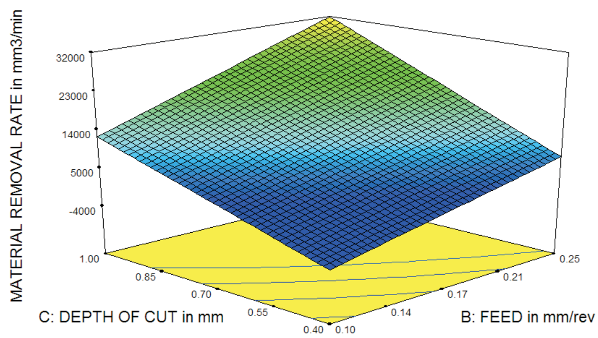

Figure 5 Effect of feed and depth of cut on MRR

The Fig. 6 shows the effect of feed and nose radius on MRR. From the graph, it is clear that MRR increases with increased feed. The maximum feed of 0.25mm/rev produces higher MRR. The MRR remains same throughout the range of nose radius. So, the nose radius has no significant effect on MRR. Hence higher MRR is achieved by the combination of minimum nose radius and maximum feed. Fig. 7 shows the effect of nose radius and depth of cut on MRR. The MRR tends to increase with the increase in depth of cut where the maximum MRR is achevied at 1 mm. The MRR remains constant with variying nose radius. The maximim MRR is achievied with the combination of maximum depth of cut and minimum nose radius.

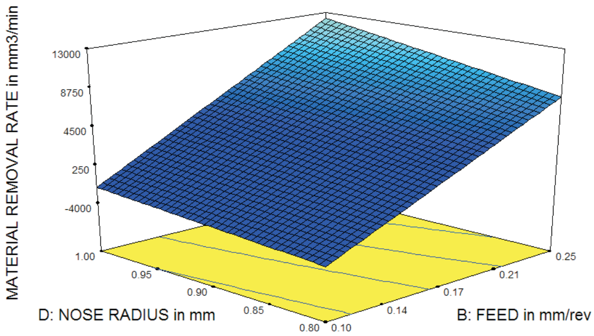

Figure 6 Effect of feed and nose radius on MRR

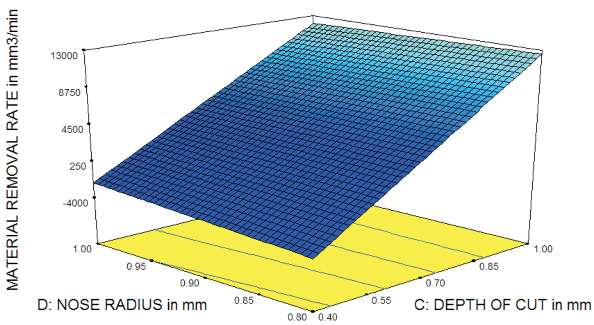

Figure 7 Effect of depth of cut and nose radius on MRR

3.3. *Effect of process parameters on SR*

The effect of speed and feed over SR is shown in the Fig. 8. The minimum SR occurs at a speed of 150 m/min and feed rate of 0.10 mm/rev. The SR tends to increase with increasing feed. The SR remains constant through the range of speed which proves that speed does not have any significant effect on SR. Hence, the minimum SR is obtained at the combination of minimum feed and minimum speed.

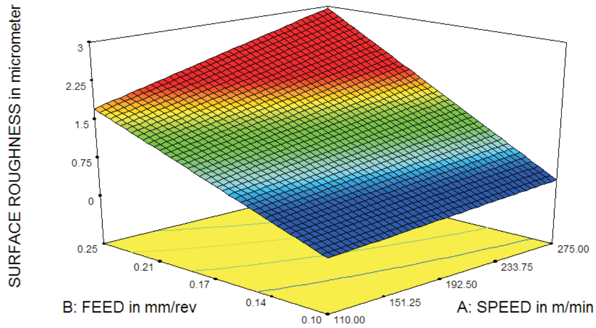

Figure 8 Effect of speed and feed on SR

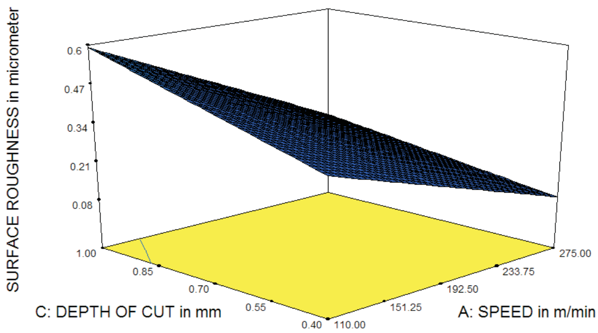

Figure 9 Effect of speed and depth of cut on SR

Fig. 9 illustrates the effect of speed and depth of cut over SR. The SR tends to decrease with the increase in speed with the minimum SR occuring at maximum speed of 275 m/min. when feed increases, the SR increases. Therefore, the minimum SR prevails with the combination of maximum speed and maximum depth of cut.

Fig. 10 indicates the effect of speed and nose radius on SR in which the SR decreases with the increase in speed. The minimum SR ouccred at the maximum speed of 275 m/min. The increase in nose radius leads to simulatnious decrease in SR. Howerver, the cobination of maximum speed and maximum nose radius proved to establish minimum SR. Fig. 11 shows the effect of feed and depth of cut on SR. The SR tends to increase with the increase in feed where in the minimum SR is obtained at minimum feed of 0.10 mm/rev. The SR remains constant with repesct to variying depth of cut which proves that depth of cut has no significant effect on SR. Henceforth, the combination of minimum feed and miniumum depth of cut produced the minimum SR.

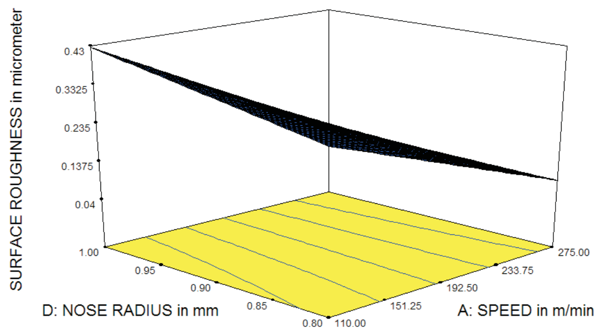

Figure 10 Effect of speed and nose radius on SR

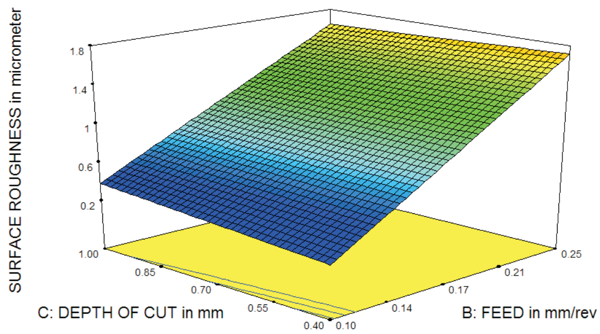

Figure 11 Effect of feed and depth of cut on SR

Fig. 12 depicts the impact of feed and nose radius on SR. The SR tends to increase with increasing feed. The minimum SR was obtained at a minimum feed of 0.10 mm/rev. The nose radius had no significatnt effect on SR, since the SR remains constant over the range of nose radius. In combination, the minimum SR is obtained at minimum feed and minimum nose radius.

Fig. 13 indicates the effect of nose radius and depth of cut on SR wherein the SR increases with the increase in depth of cut with the minimum SR encontered at the minimum depth of cut of 0.10 mm. The nose radius had no significance over SR. Hence in combination, the miniumum SR was obtained at minimum depth of cut and minimum nose radius.

3.4. *Regression analysis*

The relationship between dependent and independent variable requires a statement of statistical model. This work contains more than one independent variable, so that it needed a regression model. The following equations are the empirical relationship between independent and dependent variables. Here, N, F, D and NR are known as Speed, Feed, Depth of cut and Nose radius respectively.

$$\begin{aligned} SR &= -0.82916 - 2.22854E-003 * N + 6.95788 * F + 0.45341 * D \\ &\quad +1.01623 * NR + 0.038829 * N * F - 1.15533E-003 * N * D \\ &\quad -3.49357E-003 * N * NR - 2.78279 * F * D \\ &\quad -4.47157 * F * NR + 0.43331 * D * NR \end{aligned} \tag{1}$$

$$\begin{aligned} MRR &= 34142.69796 - 287.32334 * N - 2.53741E+005 * F \\ &\quad +2980.26857 * D - 2660.60951 * NR + 1098.08365 * N * F \\ &\quad +148.16659 * N * D + 40.00489 * N * NR + 86169.40215 * F * D \\ &\quad +96699.89809 * F * NR - 17435.41323 * D * NR \end{aligned} \tag{2}$$

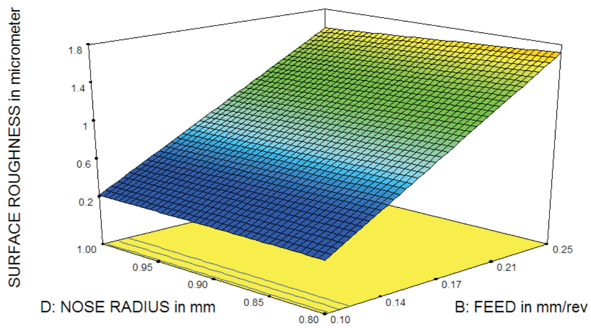

Figure 12 Effect of feed and nose radius on SR

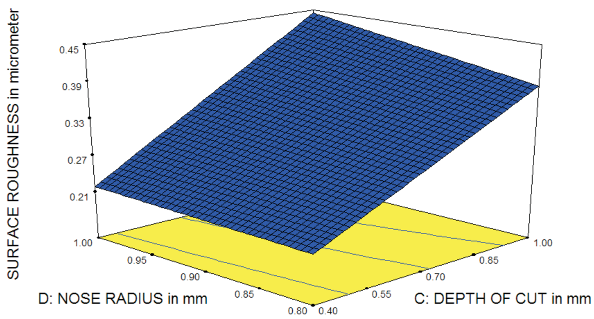

Figure 13 Effect of depth of cut and nose radius on SR

3.5. *Comparison between experimental and RSM value for MRR*

The developed models were validated with 16 data sets of experimental design used for the model development. The predicted values of Material Removal Rate were compared with the corresponding experimental values and the percentage of deviation is tabulated in Tab. 5.

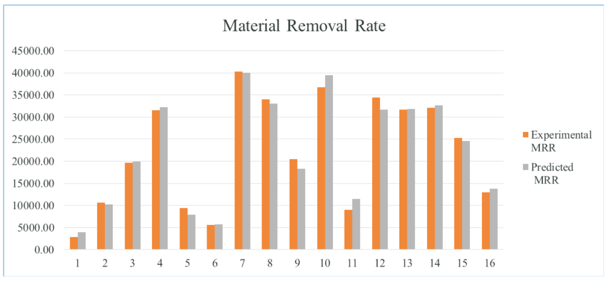

Figure 14 Comparison plot for Experimental & Predicted MRR

The average deviation between experimental results and RSM model results are -1.1117. Thus the equation 1 can be used to predict the MRR for any combinations of the turning parameters within the range of experiments. The Fig. 14 shows the validation results of experimental and RSM value. The validation results show that the experimental and RSM value has smaller deviation.

Table 5 Actual vs predicted MRR values

Exp. No.	Experimental MRR	Predicted MRR	% of Deviation
1	2883.79	3948.77	-26.97
2	10710.34	10194.83	5.06
3	19617.83	19950.63	-1.67
4	31528.66	32234.58	-2.19
5	9372.42	7908.61	18.51
6	5661.71	5757.25	-1.66
7	40245.46	39988.34	0.64
8	33970.27	33113.32	2.59
9	20544.24	18335.41	12.05
10	36746.60	39445.33	-6.84
11	9002.70	11435.24	-21.27
12	34444.10	31689.49	8.69
13	31705.50	31837.69	-0.42
14	32134.40	32653.24	-1.59
15	25207.62	24529.06	2.77
16	12974.70	13727.39	-5.48

3.6. *Comparison between experimental and RSM value for SR*

The developed models were validated with 16 data sets of experimental design used for the model development. The predicted values of Surface roughness were compared with the corresponding experimental values and the percentage of deviation is tabulated in Tab. 6.

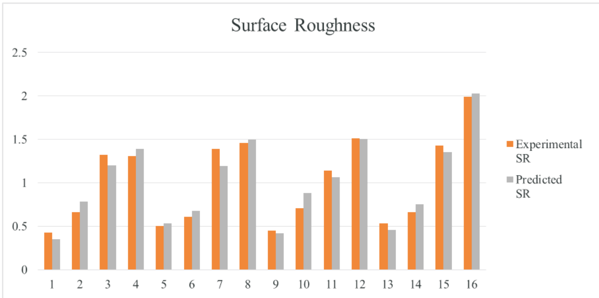

Figure 15 Comparison plot for experimental and predicted SR

The average deviation between experimental results and RSM model results are 0.645911. Thus the equations can be used to predict the surface roughness value for turning of EN24 with any combinations of chosen parameters within the range of experiments. The figure 15 shows the validation results of experimental and RSM value. The validation results show that the experimental and RSM value has smaller deviation.

Table 6 Actual vs predicted SR

Exp. No.	Experimental SR	Predicted SR	% of Deviation
1	0.43	0.35	21.36
2	0.66	0.78	-15.76
3	1.32	1.20	9.60
4	1.31	1.39	-5.81
5	0.5	0.53	-6.43
6	0.61	0.68	-9.87
7	1.39	1.20	16.12
8	1.46	1.50	-2.56
9	0.45	0.42	7.82
10	0.71	0.88	-19.61
11	1.14	1.06	7.46
12	1.51	1.51	0.23
13	0.53	0.46	16.38
14	0.66	0.75	-12.12
15	1.43	1.35	5.56
16	1.99	2.03	-2.05

4. Conclusion

The past works revealed the dominance of various parameters for different process which involved the study of MRR, surface roughness and tool wear. In our work, the experimental investigation involves turning of EN24 alloy steel using coated cemented carbide inserts. The main objective is to develop an empirical model using Response Surface Methodology. The parameter Speed and Depth of cut has significant effect on MRR. The parameter Feed has significant effect on Surface Roughness. The RSM model has smaller deviation from experimental data. This confirms that the developed model can be used to predict the MRR and surface roughness value in an effective manner. The empirical model for predicting the values of surface roughness and Material Removal Rate is developed successfully. Also the interaction effects of various parameters on the output variables were studied.

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