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ORIGINAL RESEARCH ARTICLE

Multi-response optimization in cutting mild steels

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ABSTRACT

Machine tools are very important metal cutting process that used widely in manufacture/construction and energy sector. Material removal rate in any metal cutting process is very important because it significantly affects the production rate, generated energy/forces, tool life. Improper choice of the machine tools, cutting tools or parameters will lead to be produced early wear, more energy and deterioration of surface qualities of machined mechanical components. The cutting process should be controlled during cutting or shaping process. In this study, therefore, multi-response optimization is carried out on AISI 1040 hardened mild steels when machined with ceramic cutting tools using response surface methodology under different cutting conditions. It can be noted that there are two responses. One is the surface roughness (SR) while the second is the material removal rate (MRR). The experimental results exhibits that all three factors reveal significant influence on generating metal cutting energy. Optimal levels are found out in A3, B3 and C3 level. Namely; cutting tests are carried out at 170 m/min cutting speed, 0.15 mm/rev. feed rate and 0.5 mm depth of cut conditions in terms of multi response performance index (MRPI). Analysis of variance and Pareto chart indicate that besides basic factors, A × C, A × B, B × C interactions have also an influence on MRPI (combination of MRR with SR). It is concluded that the correlation coefficient is found about 99.06%. Therefore, MRPI approach is capable of providing good modelling results for the combination of SR and MRR.

Keywords: mild steel; cutting speed; feed rate; surface roughness; metal removal rate; muti-response optimization

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1. Introduction

The metal cutting process is a material removal process by means of usage of different cutting tools such as carbide, coated carbides, ceramics, coated ceramics and boron nitride. These tools are used because of their hot hardness/wear resistance[1]. In any metal cutting process, material removal rate (MRR) has played importance role because of significantly affecting the rate of production, consumption of energy, forces and tool's service life[2]. Surface roughness (SR) is also very vital parameter due to determine the quality of any components. The quality of products is one of costumers' requirements. SR affects the fatigue and fracture strength, friction/wear properties of mechanical parts surfaces[2]. Tool life is actively cutting service time for indicating a performance satisfactorily. Thus, to reduce the cost and improve productivity, more longer tool life should be provided[3]. Improper choice of these selection parameters affects the surface quality, lead to abrasive wear and process efficiency[4]. Therefore, optimum cutting parameters should be determined. In this case, a better way is to apply some methodology like Taguchi, factorial, response surface and artificial neural network approach to limit the experiment runs, hence, leading to save times, materials and tools[5–8] in spite of the fact that there are considerable differences among those methodologies. RSM is the most generally accepted optimization method that is employed in many engineering areas like chemical and manufacturing processes to fit an empirical and measured output. Taguchi method basically sorted out for single response optimization in terms of mean response/SNR[9]. Whereas, in practice we have more than one dependent variables. The observed data can be gathered from each response through Taguchi. In this study, we will discuss multi-response method which can be easily employed. Multi-response problems are converted into single response problem in this weight method (W). This term is called "multi response performance index (MRPI)". Some multi-response optimization problems were applied[10–12].

Many research studies have been investigated on optimum surface roughness when machined hard materials. Markopoulos et al.[13] searched the milling of hardened AISI O1 steel alloy and evaluated the surface roughness using main factors. Surface quality/energy usage on 1045 steel[14], the milling process optimization of high-strength steel[15], statistical evaluation on milling of Inconel 718[16] were conducted on surface roughness. Electro-discharge machining of super-alloy (Inconel-800)[17] applied with multi-criteria decision-making methods. Moreover, optimization/assessment of life cycle in turning of Ti-6Al-4V under N2 atmosphere, machinability of AISI 4140 by minimum quantity lubrication method, and optimization of cutting En-31 steel with Taguchi method were performed[18,19]. Apart from the hard-to-cut materials, effects of MQL and factors, on optimum roughness/tool wear/force in milling of Al alloys and SiCp composite[20–25]. Milling optimization, cutting condition, tool geometry effect, surface roughness on carbon steel by ceramic tool, cutting parameters on force/roughness and comparison of two tool's shapes were searched using Al alloy, alloyed steel, carbon steel of AISI 1045 and AISI 4140 steel[26–31]. In addition, multi-objective optimization of drilling parameters for K500 alloy, metal matrix composites, Al6061 alloy were studied using ANN, grey relation, and grey relation plus Data Envelopment Analysis Ranking (DEAR) technique[32–35] while surface characteristics of Ti-6Al-4V by RSM approaches and cutting ability of ceramic based composites in terms of energy consumption were investigated by optimizing the process[36,37].

The purpose of this current work has been, therefore, to develop the multi-response performance index based on material removal rate/surface roughness to predict AISI 1040 steel at various machining conditions in order to controlling the existing processes. The response surface methodology (L18) has been adopted for design of the experiment, quadratic and interaction effects has been developed with 95% confidence level.

2. Materials and methods

CNC lathe machine is used for these cutting tests because it allows you in wide ranges of variations from 50 rpm to 3500 rpm. A mixed ceramic based cutting tools with matrix of Al_2O_3 (70%) plus TiC (30%), designated by KY1615 grade is selected. The ceramic tools are supplied by Kennametal Inc which are commercially available inserts.

Materials used in the research is a mild steel (AISI 1040). Its carbon content ranged from 1.5% to 4.0%. Due to its lower tensile strength and its lower cost, it is widely used for plenty of applications such as gear wheel, crane wheel, flywheel and crankshaft. Application of heat treatment is also modified the structure of the steel. Thus, hardness of this steel is reached to about 56–60 HRC. Cylindrical bar's diameter is 99 mm and its length is 220 mm under dry conditions.

2.1. Experimental planning

To study SR/MRR of mild steel, response surface methodology (RSM) is selected. This design allows us for an efficient estimating the first-, second-order coefficient. Main control factors and levels are indicated in **Table 1** (level 1 = L1, level 3 = L3, level 5 = L5).

Second order MQR can be described as,

$$Y = \beta_o + \sum_{i=1}^{k} \beta_i + \sum_{i=1}^{k} \beta_{ii} x_{ii} + \sum_{i=1}^{k=1} \sum_{j=2}^{k} \beta_{ij} x_i x_j + \varepsilon \tag{1}$$

where, Y is desired response, β_o is constant, β_i and β_j are regression coefficients, x_i is input parameters and x_i, x_j is the interaction between input parameters and ε is error. Regression coefficients (quadratic, interactions) are calculated.

Table 1. Control parameters and un-coded levels.

Symbol	Control factors	Levels				
		L1	**L2**	**L3**	**L4**	**L5**
V	Cutting speed (m/min)	123	144	170	196	225
f	Feed rate (mm/rev.)	0.10	0.127	0.15	0.172	0.192
d	Depth of cut (mm)	0.361	0.425	0.50	0.575	0.66

2.2. Surface roughness/metal removal rate

Surface roughness. MAHR portable is chosen in measuring the surface roughness (SR), which is an arithmetic mean deviation of surface profile.

Theoretical surface roughness, SR can be estimated as the following formula.

$$\mathrm{SR}(\mu\mathrm{m}) = \frac{f^2}{8 \times r_c} \times 1000 \tag{2}$$

where SR (µm) is measured surface roughness of machined components, f (mm/rev.) is feed rate per revolution and r_c (mm) is insert corner radius.

Metal removal rate. Material removal rate (MRR) is calculated using Equation (3) for each run.

$$\mathrm{MRR}\left(\frac{\mathrm{mm}^3}{\mathrm{min}}\right) = V \times f \times d \times 1000 \tag{3}$$

where MRR is volume removed per unit time (mm^3/min), d is depth of cut (mm), f is feed rate (mm/min), V is cutting speed (m/min).

2.3. Multi-response method

There are two responses, one is surface roughness (SR) while other is material removal rate (MRR). MRR is larger, the better-quality characteristic but SR is smaller, the better-quality characteristic. Multi-response problems are converted into single response problem.

Sum of weighted response (W) will be single response,

$$\mathrm{W} = \mathrm{W}_1 \times \mathrm{R}_1 + \mathrm{W}_2 \times \mathrm{R}_2 \tag{4}$$

W is called "multi response performance index (MRPI)". Weights are determined in the following way. For example, for MRR, individual response is divided by total response (MRR). For SR, reverse normalization procedure is used. It can be noted that,

$$\mathrm{W}_{\mathrm{SR}} = \frac{\left(\frac{1}{\mathrm{SR}}\right)}{\sum \frac{1}{\mathrm{SR}}} \text{ and } \mathrm{W}_{\mathrm{MRR}} = \frac{\mathrm{MMR}}{\sum \mathrm{MMR}} \tag{5}$$

$$(\mathrm{MRPI})i = \mathrm{W}_1 \times \mathrm{Y}_{11} + \mathrm{W}_2 \times \mathrm{Y}_{12} + \cdots + \mathrm{W}_j \times \mathrm{Y}_i \tag{6}$$

(MRPI)i = MRPI of the i-th trial, W_j = weight of the j-th response/dependant variable, Y_{ij} = observed data of i-th trial under j-th response.

3. Results and discussion

Experimental factors, design and results are analyzed with MINITAB 17 software, shown in **Table 2**. Pareto chart is a basic quality tool to analyze data. **Figure 1** shows the Pareto chart with standardized influence on outputs. Length of bars in this chart indicates the degree of each factor effect. Increase of A, B, C factors has statistically significant on MRPI because of exhibiting a 2.31 value. Standardized effect shows an unitless measure. 2.31 value is considered as a reference, if each factor is lower than this value, this factor assumes not effective. Pareto chart indicated that increases in basic factors used are effective. Further, A × C, A × B, B × C interaction factors have statistically significant influence. This might be due to directly related to the main control factors invloved in Equation (3) because it was linearly proportional to $V \times f \times d$. Therefore, contributions mostly come from the metal removal rates. Among the each factor, speed is bigger effect than the other due to weight factor. Cutting speeds are found to be considerable in the previous works[27–29], but V indicates the minimum effect[30] and mostly f is significantly effective for wiper ceramic tool in cutting steel[3,31,32].

Figure 2 exhibits the normal probability plot for MRPI of machining tested specimens. It exhibits cumulative distribution of standardized residuals around ±3. Residual is scattered randomly around line of experimental trials. On the other hand, there is not any trend offering relationship between residuals/MRPI.

Table 2. Experimental factor, design and results of data.

	Control parameters			**Outputs**	
Trials	***V*** **(m/min)**	***f*** **(mm/rev.)**	***d*** **(mm)**	**Surface roughness, SR (μm)**	**Material removal rate, MRR (mm^3/min)**
1	144	0.1275	0.425	0.864	7803
2	196	0.1275	0.425	0.845	10620.75
3	144	0.1725	0.425	1.189	10557
4	196	0.1725	0.425	1.206	14369.25
5	144	0.1275	0.575	0.764	10557
6	196	0.1275	0.575	0.789	14369.25
7	144	0.1725	0.575	1.224	14283
8	196	0.1725	0.575	1.262	19440.75
9	123	0.15	0.5	0.965	9225
10	225	0.15	0.5	1.112	16875
11	170	0.108	0.5	0.624	9180
12	170	0.198	0.5	1.273	16830
13	170	0.15	0.361	0.889	9205.5
14	170	0.15	0.661	0.854	16855.5
15	170	0.15	0.5	0.859	12750
16	170	0.15	0.5	0.872	12750
17	170	0.15	0.5	0.864	12750
18	170	0.15	0.5	0.862	12750

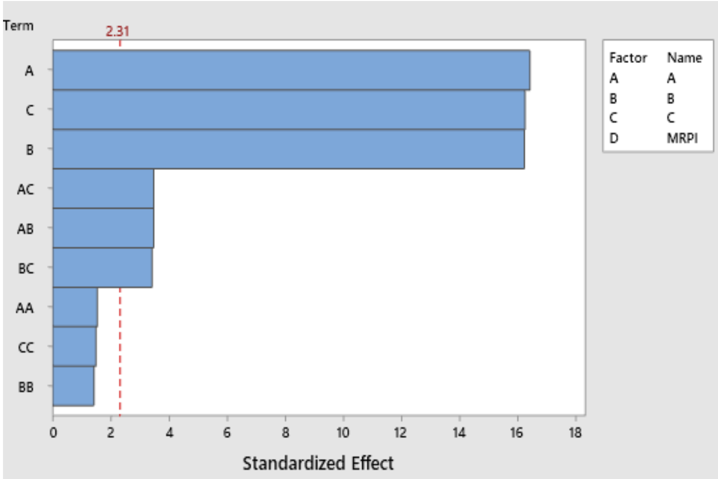

Figure 1. Pareto chart for its interactions/quadratic effects.

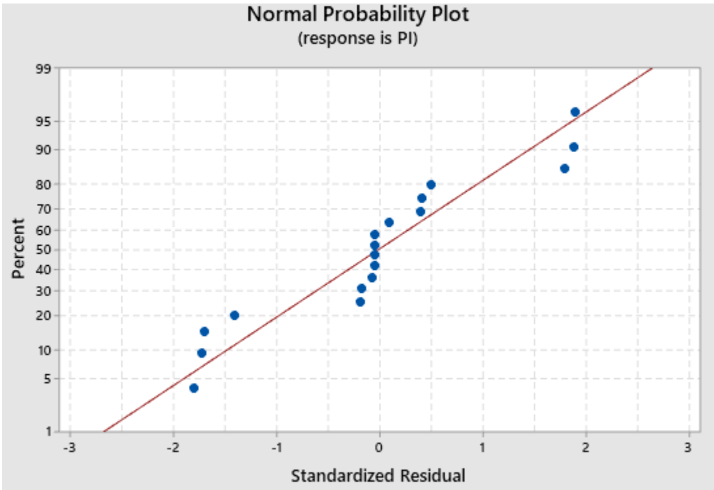

Figure 2. Normal probability plot for MRPI when machining the mild steel specimens.

3.1. Comparison of measured and theoretical results

The experiment results obtained under the cutting tests are given in **Table 2**. This table indicated that experimental design, control parameters, their five levels used in the model and results of output such as SR and MRR. It can be noted that there are two responses, which are the surface roughness (SR) and the material removal rate (MRR).

MRPIs calculated in terms of the weight approach for all trials are shown in **Table 3**. This data also reveals the normalization of data, estimation of MRPI, experimental and predicted values, and their percentage errors in cutting mild steels by the mixed ceramic tools. Percentage error (PE) is calculated from experimental data minus theoretical data, divided by theoretical data, finally multiplied by 100. In other words, PE = [(approximate value − exact value)/exact value] × 100. PE reaches to 5.94% in some conditions like 4, 7, 11 trials. Whereas, mean error is estimated about 2.81%, which is lower than 5%. Therefore, it is considered an acceptable level.

Figure 3 shows the experimental and prediction results using second order regression model from the present data. Since distributions of data are quite close each other, correlation coefficient is found quite high (99.06%). It is shown that there is quite less difference between the experimental and theoretical prediction values when machined with ceramic tools. As a result, this model may be used efficiently in predicting combinations of the metal cutting tests of any types of steels or other hard materials. **Table 4** also indicates the level totals of MRPI. All three factors were indicated significant effect on MRPI. Among them, feed rate is dominant, whereas, optimum level is at level 3 in all cutting parameters. Namely, A3, B3 and C3 are the optimized levels.

Table 3. Normalization of data, estimation of MRP, experimental/predicted values, and errors in cutting mild steels.

Normalization		**Multi-response performans index**		**KY1615 cutting tool**		
1/SR	**WSR**	**MRPI = WMR × Y1 + WSR × Y2**	**MRPI**	**MRPI**	**Predicted MRPI**	**PE, %**
1.1574074	0.059523	263.384287	0.051427	263.435714	260.55326	1.106280
1.1834319	0.060861	487.9519082	0.051427	488.003336	472.82462	3.210219
0.841042	0.043253	482.1117225	0.051427	482.16315	469.67445	2.659011
0.8291873	0.042643	893.1714859	0.051427	893.222913	945.87413	5.566409
1.3089005	0.067314	482.1117225	0.051427	482.163150	470.09012	2.568236
1.2674271	0.065181	893.1714859	0.051427	893.222913	946.28980	5.607890
0.8169934	0.042016	882.481319	0.051427	882.532746	938.28965	5.942398
0.7923930	0.040751	1634.905592	0.051427	1634.9570	1678.4176	2.589382
1.0362694	0.053293	368.1284633	0.051427	368.179891	370.90780	0.735469
0.8992805	0.046248	1231.839742	0.051427	1231.8911	1171.7770	5.130169
1.6025641	0.082416	364.5457259	0.051427	364.597153	370.52404	1.59959
0.7855459	0.040398	1225.27869	0.051427	1225.33011	1162.0169	5.448554
1.1248593	0.057849	366.5737928	0.051427	366.625220	373.046432	1.721290
1.1709601	0.060220	1228.994468	0.051427	1229.04589	1165.2384	5.475913
1.1641443	0.059869	703.2132058	0.051427	703.264633	705.72611	0.348786
1.1467889	0.058976	703.2132058	0.051427	703.264633	705.726114	0.348786
1.1574074	0.059523	703.2132058	0.051427	703.264633	705.72611	0.348786
1.1600928	0.059661	703.2132058	0.051427	703.264633	705.72611	0.348786
						2.819776

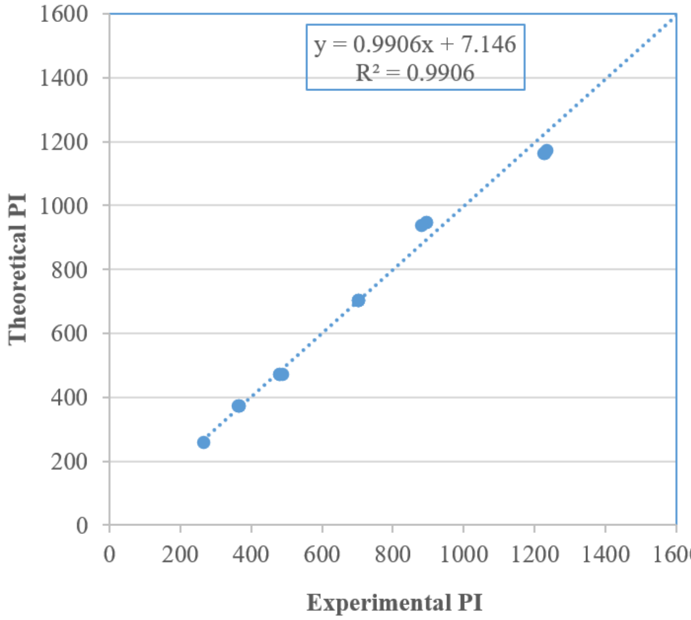

Figure 3. Experimental and predicted results of machining by KY1615 cutting tools for MRPI index.

Table 4. Level totals of MRPI.

Parameters	L1	L2	L3	L4	L5
Cutting speed, A	368.1799	2110.2947	5998.6569	3909.4061	1231.8911
Feed rate, B	368.1798	2126.825	6008.800	3892.876	1225.33
Depth of cut, C	366.6252	2126.825	6003.0568	3892.876	1229.0458

3.2. Regression model

Regression model was used to study MRPI with cutting mild steels.

Regression equation is given by,

$$\begin{aligned}\mathrm{MRPI} = {} & 705.7 + 238.1 \times \mathrm{A} + 235.3 \times \mathrm{B} + 235.5 \times \mathrm{C} + 23.2 \times \mathrm{A} \times \mathrm{A} + 21.4 \times \mathrm{B} \times \mathrm{B} + 22.4 \times \mathrm{C} \times \mathrm{C} \\ & + 66.0 \times \mathrm{A} \times \mathrm{B} + 66.0 \times \mathrm{A} \times \mathrm{C} + 64.8 \times \mathrm{B} \times \mathrm{C}\end{aligned} \tag{7}$$

where MRPI = multi response performance index, A = speed (m/min), B = feed rate (mm/rev.), C = depth of cut (mm). Coefficients of A, B and C are all positive. Higher coefficient will be higher influence to response, but no significant difference was obtained between factor C and factor B, respectively. MRPI is estimated through Equation (6) and given in **Figure 3**. Coefficient determination is found to be 99.06% while adjusted R^2 is 97.99%. This shows the that there is a good correlation between input parameteres such as factor A, B, factor C and output of MRPI that also represent the association of SR and MRR based on the weight method. However, it reveals that MRR contribution is more than that of SR contribution. For SR, feed rate mostly is effective parameter among the other, which is followed by tool tip's radius (see Equation (2))[3]. As for the case of MRR, cutting speed, feed rate and depth of cut are all effective because they all involves during the machining process (see Equation (3)).

3.3. Analysis of variance (ANOVA)

ANOVA is chosen to determine control factors affecting on MRPI, results are indicated in **Table 5**. This analysis is carried out at 95% confidence level. Probability (*P*) values were about 0.0, 0.0, 0.0 for A, B, C, respectively. This analysis is confirmed with Pareto results, as shown in **Figure 1**. Further, interaction factors of A × B, A × C and B × C significantly influenced the MRPI since the *P*-values were 0.008, 0.008, 0.009 lower than 0.05 on the response. Therefore, these basic factors are significantly affected the coming out results.

Table 5. ANOVA for MRPI when machined the steels by mixed ceramics.

Source	DF	Adj SS	Adj MS	*F*-value	*P*-value
Model	9	2404.570	267.174	93.22	0
Linear	3	2287.975	762.658	266.11	0
A	1	774.228	774.228	270.14	0
B	1	756.205	756.205	263.85	0
C	1	757.542	757.542	264.32	0
Square	3	13.376	4.459	1.56	0.274
A × A	1	6808	6808	2.38	0.162
B × B	1	5796	5796	2.02	0.193
C × C	1	6359	6359	2.22	0.175
2-way interaction	3	103.219	34.406	12	0.002
A × B	1	34.829	34.829	12.15	0.008
A × C	1	34.829	34.829	12.15	0.008
B × C	1	33.561	33.561	11.71	0.009
Error	8	22.928	2.861	-	-
Total	17	2427.498	-	-	-

4. Conclusions

The prediction modelling of material removal rate/surface roughness was studied with RSM in machining mild steels through mixed ceramic tools. Multi regression equation and multi-response performance index (MRPI) was developed and determined the optimal levels.

1) It is observed that all involved control factors indicated effective factors on MRPI, but speed generated more cutting energy than other factors. In addition to this, A × C, A × B, B × C interactions had also statistically significant influence on the combination of material removal rate with surface finish.

2) Maximum/minimum MRPI produced were about 1634.957/263.435, which are corresponding to 19440.75 mm^3/min and 7803 mm^3/min for 8th run and 1st run of the experiment. These results were obtained under cutting parameters of 196 m/min cutting speed, 0.1725 mm/rev. feed rate, 0.575 mm depth of cut, and of 144 m/min cutting speed, 0.1275 mm/rev. feed rate and 0.425 mm depth of cut, respectively.

3) Optimal levels were found in terms of MRPI that were A3, B3, C3. It meant that the hardened mild steel tested at a cutting speed of 170 m/min, feed rate of 0.15 mm/rev. and depth of cut of 0.5 mm cutting conditions for multi-response characteristics index.

4) It was concluded that the percentage errors estimated from the data obtained were about 2.81% for regression model and, correlation coefficient was around 99.06%. This is because the main three factors of A, B, C were found to be effective in addition to interactions effects like A × C, A × B, B × C on the response. It does not show any relation between SR and MRR since it represented the weightage approach, but MRR contribution was significantly large compared to SR output on the multi-response.

5) This experimental and theoretical based of the study indicated that MRPI method was capable of quite good modelling for the evaluation of surface roughness/material removal rate based on the determining the weight method.

Author contributions

Conceptualization, YŞ and DA; methodology, YŞ; software, DA; validation, YŞ; formal analysis, YŞ; investigation, YŞ; resources, YŞ; data curation, DA; writing—original draft preparation, YŞ; writing—review and editing, DA; visualization, YŞ; supervision, DA; project administration, YŞ; funding acquisition, YŞ. All authors have read and agreed to the published version of the manuscript.

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Conflict of interest

The authors declare no conflict of interest.

Abbreviations

Al_2O_3	Aluminum oxide based ceramic cutting tool
BB	Box-Behnken method
CBN	Cubic boron nitride based cutting tool
CC650	Conventional mixed ceramic cutting tool
CC650WG	Wiper mixed ceramic cutting tool
CNC	Turning machine controlled by numerically

CVD	Chemical vapor deposition coating method
d	Depth of cut (mm)
f	Feed rate (mm/rev.)
MQR	Quadratic model
Quadratic 2nd order regression model	
PE	Percentage error (%)
PVD	Physical vapor deposition coating method
R^2	Coefficient of determination
RSM	Response surface methodology
SR	Average surface roughness (μm)
V	Cutting speed (m/min)

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