Response Surface Regression Modelling of Orthogonal Cutting of Stainless Steel Using HSS Tool

Morakinyo Kehinde Onifade

Department of Management Technology, Bells University of Technology, Ota, Nigeria.

E-mail: morakinyo.onifade@yahoo.com
kmonifade@bellsuniversity.edu.ng

ABSTRACT

Quality control in turning operations is a complex undertaking that requires both in-process and out-of-process approaches. The broad application of stainless steel in the process industry has accounted for its wide utilization despite its high cost. The production shops tend to use High Speed Steel tools in fine cutting the stainless-steel workpiece, based on its affordability. Products from these operations are bound to fail while in use due to craters formed on the surfaces resulting from poor surface texture. Surface roughness has been commonly determined based on the arithmetic average value and this does not account for all the information about a machined surface.

A fifteen-run Box-Behnken design-based experiment was carried out using the three process parameters, cutting speed, feed rate and depth of cut. The experimental responses, surface roughness in four parameters, tool-life and machining time were modelled using the response surface regression modelling technique.

The developed response surface models have 0.7950, 0.7950, 0.5960, 0.5456, 0.9971 and 0.8589 coefficient of determination, respectively. The process parameters have global solutions with responses which have composite desirability of 0.712814 which indicates that the optimized response values are 28.7% close to their targets.

(Keywords: stainless steel; HSS tool; response surface regression; tool life; surface roughness)

INTRODUCTION

Machining is an age-old manufacturing process and turning operations on a lathe machine is one of the most widely carried out operations because most machine elements are cylindrical in shape. Local machinists tend to carry out their operations based on the most economical techniques and available resources. This practice cannot be totally discouraged due to the present economic condition in developing countries, and hence there is need to control the quality of the outputs from their operations.

One of the commonly machined workpiece materials is stainless steel which has a wide range of applicability in the food processing industry and High Speed Steel (HSS) cutting tool is widely utilised for low cutting speed machining in production of screws taps, reamers, broaching tools and cutting tools [1]. The quality of the surface texture of the produced machined elements is a major factor relating to their wear and tear.

The focus of surface roughness investigation has been the arithmetic average roughness value, Ra, which, according to [2], has a rather low significance because it hardly reacts to peaks due to the mean value formation from all profile values. In addition, the Ra does not provide all the information about a surface and machine elements with the same Ra values will perform very differently when subjected to similar industrial applications.

The prediction of responses from orthogonal metal cutting process provides information for the specified operations which in-turn serves as control medium for the prevention of in-process tool failure, and deviations from specified surface roughness of machined work-piece: machine tools are often damaged by in-process tool breakage while deviations from specified surface roughness lead to sudden failure of produced machine elements.

Studies have shown that some of the existing mathematical models postulated for this purpose are mostly theoretical formulations; others that were developed by Response Surface Methodology (RSM) and Expert System Techniques (EST) have some limitations by adopting the process parameters' dimensions without carrying out adequate dimensional analysis to convert all their units to International Standard (S.I.) form before carrying out the formulations that resulted into their establishment. Of particular significance are the works of [3, 4, 5].

In-process tool condition monitoring systems are now being employed in adaptive control of machining operations. The experimental set-up for this is quite expensive and cannot be easily deployed in most of the workshops existing in developing economies. Processes in the engineering industry are defined by standards, mainly developed by the International Standard Organisation (ISO). These standards carefully describe procedures for technical sciences which are shaped by local operating conditions. These conditions are normally due to the status of the country where the manufacturing operations are carried out, and moreover, most nations did not experience industrial revolution, they only adopted technologies from industrialised ones [6]. The present research was able to model the surface roughness of machined workpiece beyond the centre line average, Ra, as well as, collectively investigating the six major responses (Ra, Rz, Rq, Rt TL and m/ctime) from an orthogonal metal cutting process.

THEORETICAL BACKGROUND

The regression modelling was based on the response surface methodology and the D-optimality was employed to optimise the regression parameters. The D-optimality minimises the variance of the model coefficient estimates. According to [7], the response from our RSM model can be represented in vector matrix form as shown in Equation (1).

$$\mathbf{y} = \mathbf{x}\beta + \mathbf{z}\partial + \varepsilon \qquad \textbf{(1)}$$

where β is the px1 vector of fixed effect model parameter including the intercept; x is the Nxp fixed effects model matrix; z is an Nxa incidence matrix of ones, minus ones and zeroes where the ij^{th} entry is 1 if the i^{th} observation (i= 1, . . ,N) belongs to the j^{th} whole plot (j=1, . . ., a); ∂ is an ax1 vector of random effects where the elements are assumed i.i.d $\mathrm{N}(0, \sigma_\delta^2)$ with σ_δ^2 denoting the variability among whole plots; and ε is the Nx1vector of i.i.d $\mathrm{N}(0, \sigma_\varepsilon^2)$ residual errors for σ_ε^2 denoting the variation among subplot unit.

The obtained experimental data were fitted to a quadratic polynomial model and regression coefficients obtained. The non-linear quadratic model adopted by the response surface is represented in the expression in Equation (2).

$$\gamma = \beta_o + \sum_{j=1}^{k} \beta_j X_j + \sum_{j=1}^{k} \beta_{jj} X_j^2 + \sum\sum_{i<j} \beta_{ij} X_i X_j \qquad \textbf{(2)}$$

where γ is the estimated response, $\beta_o, \beta_j, \beta_{jj}$ and β_{ij} represent the regression coefficient for intercept, linearity, square and interaction, respectively, while X_i, X_j are the independent coded variables.

The regression coefficients of the response surface models for the four surface roughness parameters, tool life and machining time were determined using the technique of least squares estimation, and the experimental data for the various work-piece data for the various work-piece materials and tool combinations. The response surface models were represented in matrix form, according to [8], as shown in Equation (3).

$$\mathbf{y} = \mathbf{X\beta} + \varepsilon \qquad \textbf{(3)}$$

The least square estimator of $\boldsymbol{\beta}$ is shown in Equation (4):

$$\mathbf{b} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{y} \qquad \textbf{(4)}$$

The fitted regression model is shown in Equation (5):

$$\hat{\mathbf{y}} = \mathbf{Xb} \qquad \textbf{(5)}$$

The expression for the residual to the response surface regression models is shown in Equation (6):

$$\hat{\mathbf{y}} = \mathbf{Xb} \quad (6)$$

Hypothesis testing begins with some theories, claims, or assertions about a parameter of a population [9]. The developed models were tested for their deficiencies with regards to their predictions. The status quo is a claim that there is no lack-of-fit and this was set as the null hypothesis (H_o). Even though information is available only from the sample, the null hypothesis is written in terms of the population. The focus is on the population of all the experimental observations for each of the six (6) developed response surface models, namely, Ra, Rz, Rq, Rt, TL and M/ctime.

The alternative hypothesis (H_A) is the opposite of the null hypothesis. The alternative hypothesis represents the conclusion reached by rejecting the null hypothesis. The null hypothesis is rejected when there is sufficient evidence from the sample information that the null hypothesis is false.

The significance of the independent variable for the various responses was determined using analysis of variance (ANOVA). The P–values of the lack-of-fit, and the process parameters were examined and compared with the stipulated level of significance $(\alpha = 0.05)$.

There are risks associated with decision making about a population parameter based on hypothesis testing. These can lead to incorrect conclusion about the population parameter. In this light, two different types of errors lurk for the model development related decision-making process. These are Type I and Type II errors. Type I error occurs when a true null hypothesis is rejected. The probability of a Type I error occurring is α . Type II error occurs when the null hypothesis was not rejected when it is false and should be rejected. The probability of a Type II error occurring is β .

MATERIALS AND METHODS

The nature of the workpiece material as well as that of the cutting tool was highlighted in this section. Also, the chosen experimental design and its features were discussed as well.

Materials

The experiment was carried out based on the Box-Behnken's response surface design. Stainless steel was machined during the experiment and the chemical composition of the stainless steel machined justified its classification as Austenitic stainless-steel type AISI 304. The High Speed Steel (HSS) cutting tool which is widely used was selected based on its predominance in the Nigerian machine tool industry. The chemical compositions of the tool material are based on the information provided by the manufacturer.

Methods

Figure 1 shows the schematic diagram of the experimental procedure.

The developed design, shown in Table 1, was based on [10] response surface design. The Box-Behnken design was selected because it allows efficient estimation of the first and second order coefficients of the response surface regression model. Since the experiment was planned to be performed without replicates, Box-Behnken design is very relevant and appropriate because it is used when performing non-sequential experiments. The design is applicable to this experiment since the safe operating zones of the process parameters are known and established.

Table 2 illustrates the levels of process parameters for the selected tool and work-piece material in fine cut turning operation.

Dimensional Analysis for the Process Parameters

The process parameters for the orthogonal metal cutting process are normally programmed in units that are not standardized, and hence the need for appropriate dimensional analysis, before incorporating them into the response surface modelling framework.

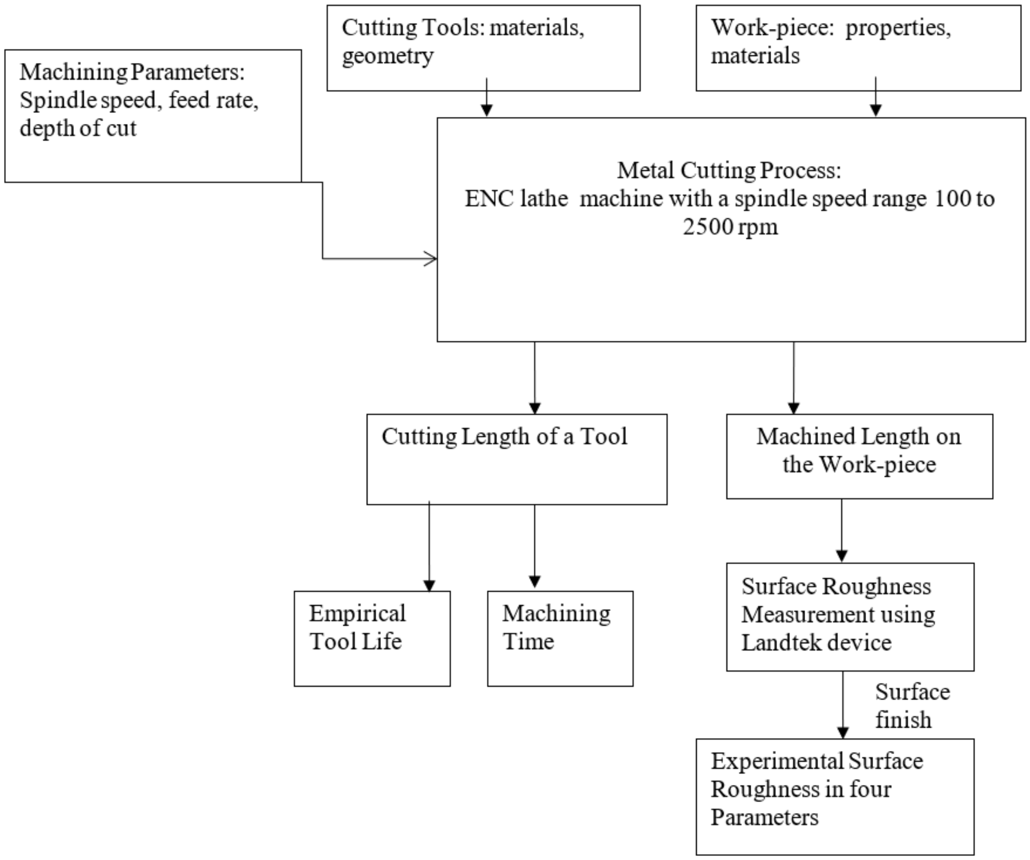

Figure 1: Experimental Setup.

Table 1: A Design Matrix for the Experimental Block.

Runs	Block	Cutting Speed	Feed Rate	Depth of Cut
1	Stainless Steel x HSS	-	-	0
2	Stainless Steel x HSS	+	-	0
3	Stainless Steel x HSS	-	+	0
4	Stainless Steel x HSS	+	+	0
5	Stainless Steel x HSS	-	0	-
6	Stainless Steel x HSS	+	0	-
7	Stainless Steel x HSS	-	0	+
8	Stainless Steel x HSS	+	0	+
9	Stainless Steel x HSS	0	-	-
10	Stainless Steel x HSS	0	+	-
11	Stainless Steel x HSS	0	-	+
12	Stainless Steel x HSS	0	+	+
13	Stainless Steel x HSS	0	0	0
14	Stainless Steel x HSS	0	0	0
15	Stainless Steel x HSS	0	0	0

Table 2: Process Parameters for the Turning Operations [11].

Cutting Speed			Feed Rate			Depth of Cut		
Low mpm (rpm)	Medium mpm (rpm)	High mpm (rpm)	Low mm/rev	Medium mm/rev	High mm/rev	Low mm	Medium Mm	High mm
45 (179.0)	55 (218.8)	75 (298.4)	0.05	0.1	0.15	0.1	0.2	0.4

The response surface analyser in Minitab 16 allows the design to be carried out in coded and un-coded units. The coded units utilize the – 0 + codes for the process parameters while the un-coded units utilize the exact values for low, medium and high input process parameters. Since the modelling was carried out in un-coded units, there is need to standardize the units of these process parameters before carrying out the response surface modelling.

Cutting Speed (v) in m/s

The cutting speed is a derivative of the spindle speed (N) which is in rev/min (rpm). The spindle speed is the parameter which the machinist configures on the ENC based on the information provided by the optimum process parameter chart for the specified work-piece and tool materials as well as the cutting operation. The machinist uses the expression in Equation 1 to obtain the corresponding spindle speed using the diameter of the work-piece. The cutting speed provided based on this relationship has a unit (m/min) which is not in S.I. unit. The modelling of the orthogonal cutting process was carried out in S.I. unit, thus the need to standardize the units of all process parameters. The cutting speed in m/min was converted to m/s using the expression in Equation 7, derived by multiplying the m/min with $\frac{1}{60}$ which converts the minutes to seconds.

$$m/s = 0.016667 m/min \quad \textbf{(7)}$$

Feed Rate (f) in m/s

The feed rate is a process parameter recognized in mm/rev by the ENC lathe machining centre. Also, the optimum process parameter chart provided the feed rate in mm/rev. Since the modelling of the orthogonal cutting process was carried out in S.I. unit, the feed rate in mm/rev for machining a work-piece of 80mm diameter was converted to m/s based on the expressions in Equations 8 to 11.

$$feedrate\,(mm/min) = \left(\frac{0.10472xv\,(m/s)}{40x1000}\right) xfeedrate\,(mm/rev) \quad \textbf{(8)}$$

The multiplicative factor was obtained thus:

$$(mm/min) = rev/\min x\, mm/rev \quad \textbf{(9)}$$

and,

$40x1000$ is the radius of the work-piece in metres, while 0.10472 is $\frac{2\pi}{60}$ which converts the angular (ω) speed to its linear components, using the work-piece radius as the radius of the angular motion.

Recall, $rev/\min = \frac{2\pi}{60}\omega$ and linear velocity $v = \omega r$ then $\frac{60}{2\pi} x \frac{rev}{min} r$.

Hence,

$$rev/min = \frac{0.10472(v)}{r} \quad \textbf{(10)}$$

The feed rate in m/s was derived from the expression in Equation (11).

$$feedrate\,(m/s) = \frac{f\,(mm/min)\,x60}{1000} \quad \textbf{(11)}$$

The input parameters developed are shown in Table 3.

The values of these input parameters were developed based on the dimensional analysis carried out and standardisation of obtained values. L (mm) is the cutting length, v (mpm) is the cutting speed in metre per minute, f (mm/rev) is the feed rate in millimetre per revolution, ap is the depth of cut, f (mmPm) is the feed rate in millimetre per minute.

Table 3: Developed Input Process Parameters for the Experiment.

Runs	L(mm)	Input Process Parameters						
		v(mpm)	f(mm/rev)	ap(mm)	v(m/s)	f(mmPM)	f(m/s)	ap(m)
1	10	45	0.05	0.2	0.750015	0.098177	0.005891	0.0002
2	10	75	0.05	0.2	1.250025	0.163628	0.009818	0.0002
3	10	45	0.15	0.2	0.750015	0.294531	0.017672	0.0002
4	10	75	0.15	0.2	1.250025	0.490885	0.029453	0.0002
5	10	45	0.1	0.1	0.750015	0.196354	0.011781	0.0001
6	10	75	0.1	0.1	1.250025	0.327257	0.019635	0.0001
7	10	45	0.1	0.4	0.750015	0.196354	0.011781	0.0004
8	10	75	0.1	0.4	1.250025	0.327257	0.019635	0.0004
9	10	55	0.05	0.1	0.916685	0.119994	0.0072	0.0001
10	10	55	0.15	0.1	0.916685	0.359982	0.021599	0.0001
11	10	55	0.05	0.4	0.916685	0.119994	0.0072	0.0004
12	10	55	0.15	0.4	0.916685	0.359982	0.021599	0.0004
13	10	55	0.1	0.2	0.916685	0.239988	0.014399	0.0002
14	10	55	0.1	0.2	0.916685	0.239988	0.014399	0.0002
15	10	55	0.1	0.2	0.916685	0.239988	0.014399	0.0002

RESULTS

Experimental Results

The obtained experimental results, based on the Box-Behnken design, for the six responses are shown in Table 4. The response model for the empirical tool life was based on relationship developed by [12] in which the cutting length and the feed rate in mm/min utilized. The present research was able to carry out dimensional analysis for the feed rate as shown in Equation (11). Hence, the tool life was estimated using the expression in Equation (12).

$$TL = \frac{60xL}{\left(\frac{0.10472xv(m/s)}{\frac{D}{2}x1000}\right)xfeedrate(mm/rev)}$$

(12)

where D is work-piece diameter, v is the cutting speed, L is the cutting length.

Response Surface Regression Models Developed

The obtained coefficients for the response surface regression model for the stainless steel work-piece and HSS tool turning operation were incorporated as shown in Equations 13 to 18 for the four surface roughness parameters, tool life and machining time respectively.

$$R_a = 0.0523884 + 4.18702v - 23.3834f - 15907(ap) - 6.79547v^2 - 12763.8f^2 - 4247978(ap)^2 + 430.17vf + 20845.7v(ap) + 11856.6f(ap)$$

(13)

The dependent variable, Ra, for this model has three independent variables. The Ra is expected to increase by 4.18702 units when the cutting speed is increased by unity, holding all the other independent variables constant. However, when the feed rate and depth of cut is increased by unity, the Ra value is expected to reduce by 23.3834 and 15907 units, respectively, holding all the other independent variables constant.

Table 4: Experimental Results Obtained.

Runs	L(mm)	Experimental Responses					
		M/Ctime	Ra	Rz	Rq	Rt	TL(sec)
1	10	47.28	0.372	1.053	1.21	2.913	6111.413
2	10	29.76	0.302	0.855	2.13	5.255	3666.848
3	10	18.18	0.68	1.923	1.35	3.099	2037.138
4	10	12	0.695	1.965	1.49	3.827	1222.283
5	10	25.14	0.925	2.616	2.35	5.883	3055.707
6	10	16.68	0.83	2.347	2.35	5.569	1833.424
7	10	23.46	0.452	1.279	1.28	2.684	3055.707
8	10	16.86	3.38	9.559	1.105	2.585	1833.424
9	10	35.34	0.675	1.909	0.347	0.792	5000.247
10	10	13.8	0.497	1.407	0.305	0.906	1666.749
11	10	36.6	0.825	2.333	1.37	3.441	5000.247
12	10	14.7	0.82	2.319	1.095	2.699	1666.749
13	10	19.68	1.195	3.379	2.25	5.455	2500.124
14	10	19.62	1.73	4.892	2.4	4.884	2500.124
15	10	19.68	1.18	3.337	1.67	4.284	2500.124

The cutting speed and feed rate interaction, cutting speed and depth of cut interaction, as well as feed rate depth of cut interaction have positive coefficients of 430.17, 20845.7 and 11856.6 respectively which indicate that they acted synergistically towards the dependent variable, Ra.

$$R_z = 0.155939 + 11.8255v - 65.9477f - 44997.1(ap) - 19.2080v^2 - 36089.4f^2 - 11995852(ap)^2 + 1216.15vf + 58957.2v(ap) + 33371.9f(ap) \quad \textbf{(14)}$$

The dependent variable, Rz, for this model has three independent variables. The Rz is expected to increase by 11.8255 units when the cutting speed is increased by unity, holding all the other independent variables constant. The Rz is expected to decrease by 65.9477 units if the feed rate is increased by unity, holding all the other independent variables constant. Also, when

the depth of cut is increased by unity, the Rz value is expected to decrease by 44997.1 units, holding all the other independent variables constant. The cutting speed and feed rate interaction, cutting speed and depth of cut interaction, as well as, feed rate depth of cut have positive coefficients of 1216.15, 58957.2 and 33371.9 respectively which indicate that they acted synergistically towards the dependent variable, Rz.

$$R_q = 1.41145 - 5.98015v + 81.0004f + 21624.6(ap) + 2.37399v^2 - 10843.2f^2 - 29598620(ap)^2 + 258.530vf - 6637.89v(ap) - 58600.4f(ap) \quad \textbf{(15)}$$

The dependent variable, Rq, for this model has three independent variables. The Rq is expected to decrease by 5.98015 units when the cutting speed is increased by unity, holding all the other independent variables constant. The Rq is expected to increase by 81.0004 units if the feed rate is increased by unity, holding all the other independent variables constant. Also, when the depth of cut is increased by unity, the Rq value is expected to increase by 21624.6 units, holding all the other independent variables constant. The cutting speed and feed rate interaction have positive coefficients of 258.530 which indicate that they both acted synergistically towards the dependent variable, Rq. The cutting speed and depth of cut, and feed rate and depth of cut with negative coefficients of -6637.89and -58600.4 respectively are antagonist towards each other while contributing to the response (dependent) variable, Rq.

$$R_t = 4.55047 - 15.5300v + 191.03f + 45592.7(ap) + 6.64869v^2 - 22202.4f^2 - 65187168(ap)^2 + 518.165vf - 11990.1v(ap) - 196579f(ap) \quad \textbf{(16)}$$

The dependent variable, Rt, for this model has three independent variables. The Rt is expected to decrease by 15.5300 units when the cutting speed is increased by unity, holding all the other independent variables constant. When the feed rate is increased by unity, the Rt value is expected to increase by 191.03 units, holding all the other independent variables constant. Also, the Rt is expected to increase by 45592.7 units if the depth of cut is increased by unity, holding all the other independent variables constant. The cutting speed and feed rate interaction has positive coefficient of 518.165 which indicates that they both acted synergistically towards the dependent variable, Rt. The cutting speed and depth of cut, and feed rate depth of cut interactions with negative coefficients of -11990.1 and 196579 respectively, are antagonist towards one another while contributing to the response (dependent) variable Rt.

$$TL = 9057.09 - 537.23v - 614474f - 3879070(ap) - 750.62v^2 + 11526532f^2 + 3828995910(ap)^2 + 28766.3vf + 1496746v(ap) + 35217845f(ap) \quad \textbf{(17)}$$

The dependent variable, TL, for this model has three independent variables. The TL is expected to decrease by 537.23, 614474 and 193614 units when the cutting speed, feed rate and depth of cut are increased by unity respectively, holding all the other independent variables constant. The cutting speed and feed rate, cutting speed depth of cut, as well as, feed rate depth of cut interactions have positive coefficients of 28766.3, 1496746 and 35217845 respectively which indicate that the interaction acted synergistically towards the dependent variable, TL.

$$\mathrm{M/CTime} = 95.5832 - 61.3523v - 4108.08f - 23274.4(ap) + 27.4441v^2 + 79786.8f^2 + 744243(ap)^2 + 57.6468vf + 19723.5v(ap) + 302260f(ap) \quad \textbf{(18)}$$

The dependent variable, M/Ctime, for this model has three independent variables. The M/Ctime is expected to decrease by 61.3523, 4108.08 and 4894.61 units when the cutting speed, feed rate and depth of cut are increased by unity respectively, holding all the other independent variables constant. The cutting speed and feed rate, cutting speed and depth of cut as well as, feed rate and depth of cut interactions have positive coefficients of 57.6468, 19723.5, and 302260, respectively, which indicate that the interaction acted synergistically towards the dependent variable, M/Ctime.

Response Surface Optimization

The response surface optimisation carried out on the experimental data for the Stainless Steel and HSS tool combination provided Global Solution for the process parameters. The cutting speed, v in m/s, feed rate, f in m/s and depth of cut, ap in m have global solutions of 1.03285, 0.0066046 and 0.0001 respectively. These optimum process parameter settings for the turning operation on ENC lathe were converted to their common units using dimensional analysis, and are 61.97mpm, 0.041 mm/rev and 0.1mm for the cutting speed, feed rate and depth of cut, respectively.

The optimum predicted responses from the orthogonal cutting process for the optimal process parameters are 0.12 micron, 0.34 micron, 0.74 micron, 1.97 micron, 5280.12 seconds and 38.15 seconds for the Ra, Rz, Rq, Rt, TL and M/Ctime, respectively. The associated desirability for these optimum responses are 1.000000, 1.000000, 0.794632, 0.768606, 0.829970, and 0.258777, respectively. Also, the composite desirability for the stainless steel work-piece and HSS tool turning operation on ENC lathe machine is 0.712814. The response optimisation plot is shown in Figure 2.

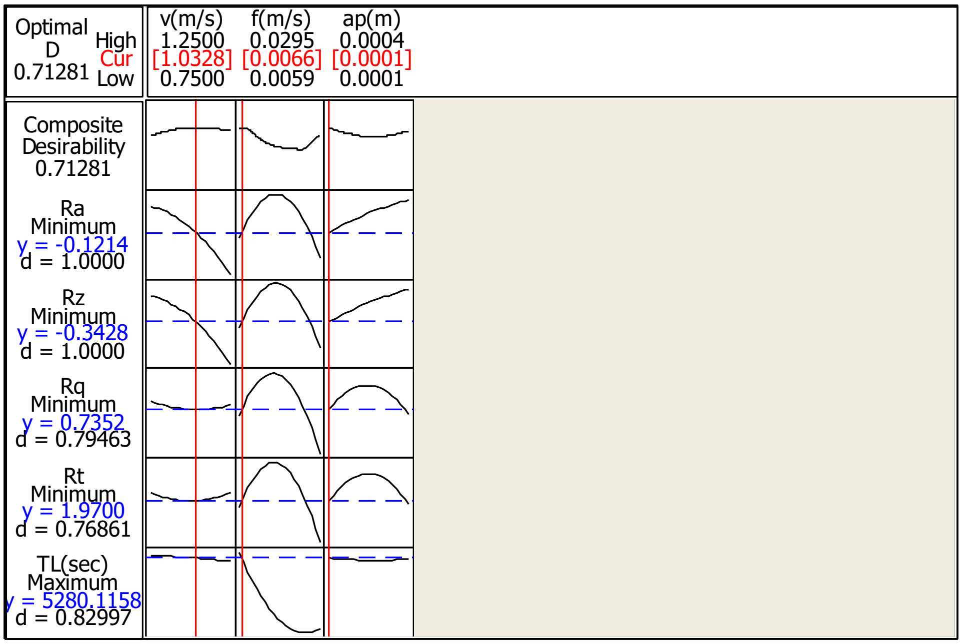

Figure 2: Response Optimization Plot for Stainless steel and HSS Combination Response Surface Plot.

Figures 3 to 11 show the contour plots for the six modelled using response surface regression modelling technique. They are Ra, Rq, Rz, Rt, TL and M/ctime.

The contour plots were plotted against cutting speed and another process parameters interchangeably to illustrate the relationship between each response and the combination of process parameters.

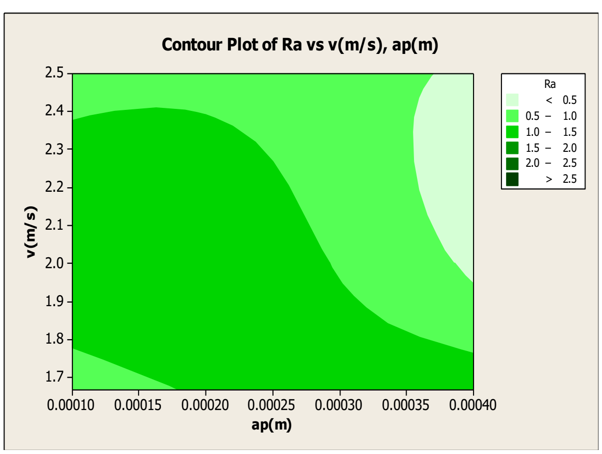

Figure 3: Plot of Ra vs v(m/s), ap(m).

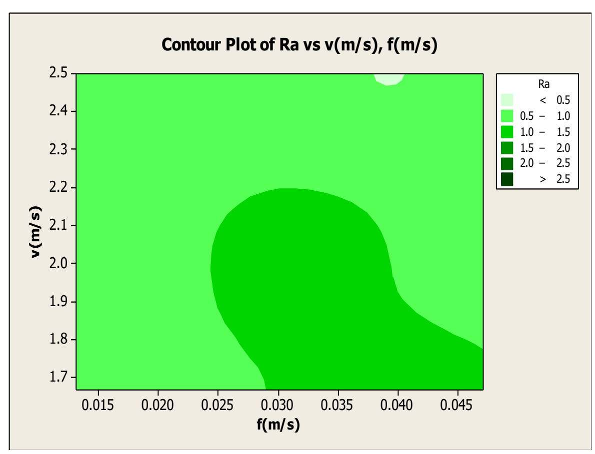

Figure 4: Plot of Ra vs v(m/s), f(m/s).

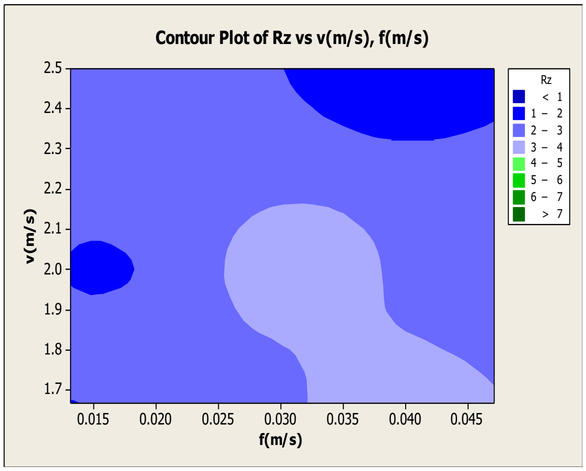

Figure 5: Plot of Rzvs v(m/s), f(m/s).

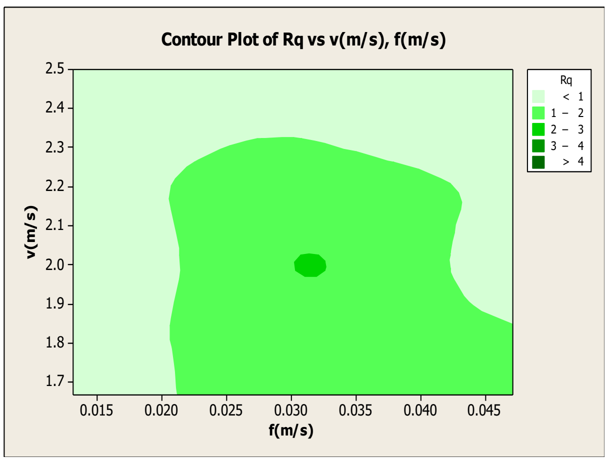

Figure 6: Plot of Rq vs v(m/s), f(m/s).

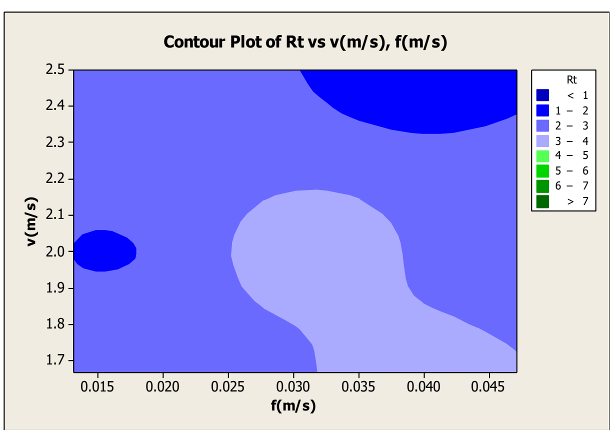

Figure 7: Plot of Rt vs v(m/s), f(m/s).

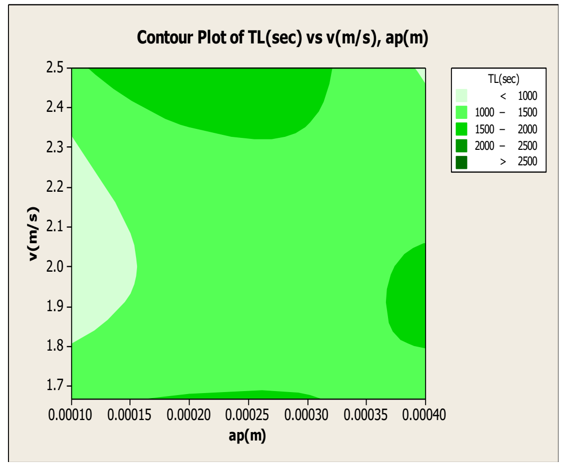

Figure 8: Plot of TL vs v(m/s), ap(m).

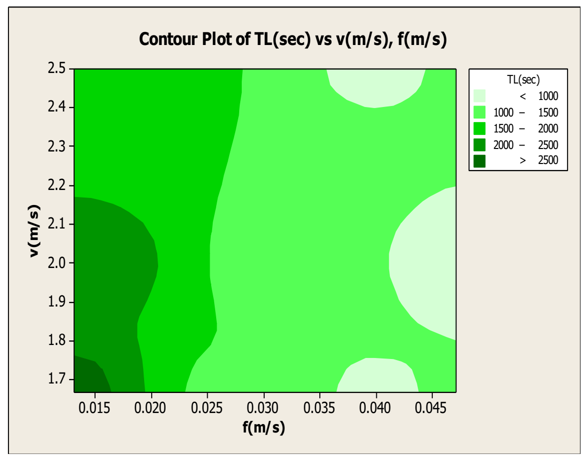

Figure 9: Plot of TL(sec) vs v(m/s), f(m/s).

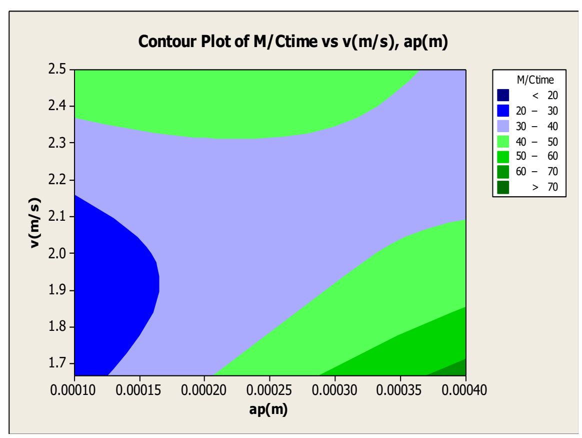

Figure 10: Plot of M/CTime vs v(m/s), ap(m).

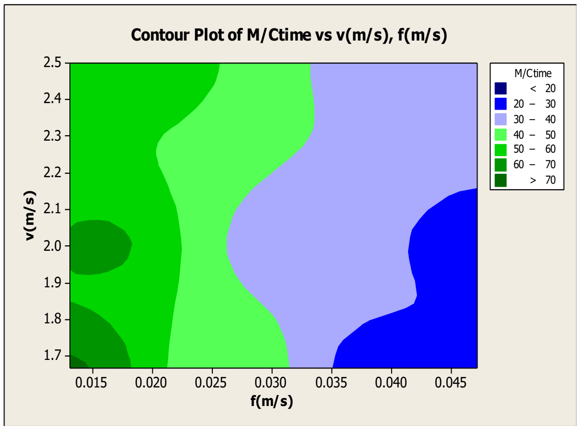

Figure 11: Plot of M/CTime vs v(m/s), f(m/s).

Table 5 shows the lack-of-fit test carried out on the developed Response Surface Models based on quadratic regression models using the experimental data obtained from the B-B design showed that the model for M/ctime did not fit appropriately. The summary of the lack of fit test for the quadratic regression models for the six responses from the orthogonal fine cutting experiments.

There was enough evidence, based on lack-of-fit test, to refit the model for the M/ctime response. Hence, the second-order two-factor interaction (2FI) model with p-value of 0.7355 was suggested for the M/ctime response, because it is an improvement on the quadratic model with p-value of 0.000, since the cubic model was aliased as shown in Table 6.

Table 5: Summary of Lack-of-Fit for Stainless steel and HSS Combination.

Responses	Models	Source	p-value	Decision
Ra	RaHat	Lack-of-fit	0.735	Evidence not enough
Rz	RzHat	Lack-of-fit	0.735	Evidence not enough
Rq	RqHat	Lack-of-fit	0.146	Evidence not enough
Rt	RtHat	Lack-of-fit	0.055	Evidence not Enough
TL	TLHat	Lack-of-fit	*	No basis
M/Ctime	M/CtimeHat	Lack-of-fit	0.000	Evidence enough

Table 6: Model Selection for M/ctime.

	Sequential	Lack of Fit for M/ctime	Adjusted	Predicted	
Source	p-value	p-value	R-Squared	R-Squared	Comments
Linear	0.0001	0.2751	0.7913	0.7100	
2FI	0.7355	0.7152	0.7531	0.5059	Suggested
Quadratic	0.0145	0.2218	0.9441	0.8364	
Cubic	0.7152		0.9208		Aliased

The revised model for the M/ctime response is shown in Equation 19.

$$M / ctime = 22.92 - 4.85v - 11.29f + 0.082(ap) + 2.84vf + 0.46v(ap) - 0.090f(ap) \quad \textbf{(19)}$$

The plot shown in Figure 12 that the revised model predicted better than the quadratic models for M/ctime experimental response.

Table 7 shows the diagnostic checks carried out for the models developed for the responses. It consists of the coefficient of determination, adjusted coefficient of determination, BIC and AIC test statistic which show that the developed and the suggested model predicted fairly.

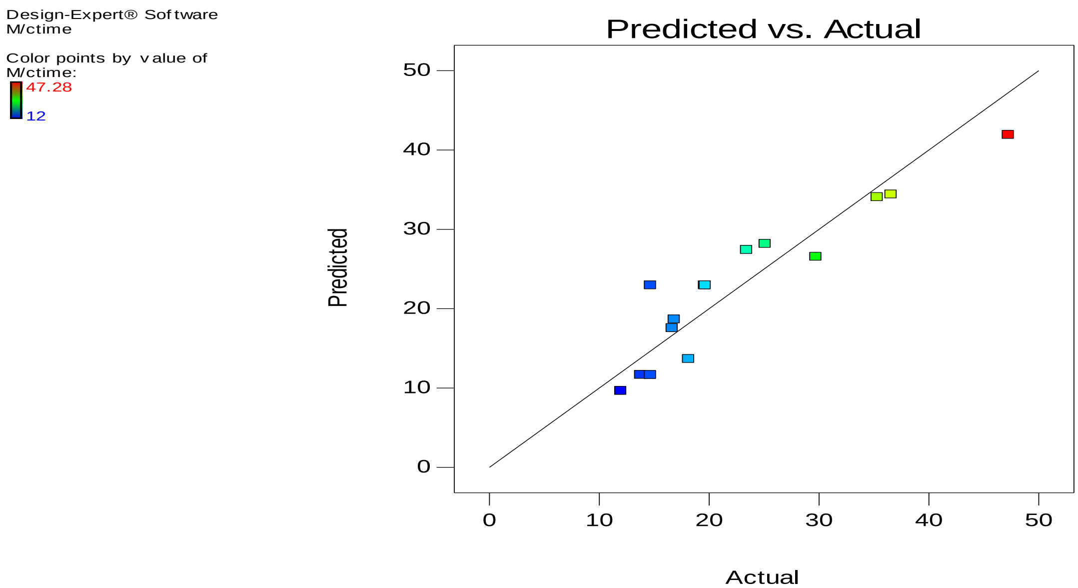

Figure 12: Plot of Actual and Predicted M/ctime Based on the 2FI Model.

Table 7: Diagnostic Checks for Models developed for Stainless steel and HSS.

Model	Rsq	Adj Rsq	BIC	AIC
Ra (quadratic)	0.7950	0.4260	36.61	84.53
Rz (quadratic)	0.7950	0.4260	67.80	115.72
Rq (quadratic)	0.5960	-0.1313	43.49	91.41
Rt (quadratic)	0.5456	-0.2724	70.95	118.87
TL (quadratic)	0.9971	0.9918	199.41	247.33
M/ctime (2FI)	0.8589	0.7531	100.66	111.70

DISCUSSION

The models showed that surface roughness (Ra, Rz) while fine cutting stainless steel using HSS tool will increase by (4.18702,11.8255) respectively when the cutting speed is increased by unity all other process parameters retain their values. The surface roughness (Rq, Rt) will decrease by (5.98015, 15.5300) when the cutting speed is increased by unity all other process parameters retain their values. The tool-life and machining time will decrease by 537.23 and 61.3523 units when the cutting speed is increased by unity while all other process parameters retain their values. These results suggested that the surface roughness parameters were not affected in a similar manner by the cutting speed when fine cutting stainless steel using HSS cutting tool.

In the same vein, the surface roughness parameter (Ra, Rz), tool-life and Mc/time decrease in values by (23.3834, 65.9477) and 614474 and 61.3523 units when the feed rate is increased by unity. The root mean squared values, Rq and maximum height of the profile, Rt, of the surface roughness will increase by 81.0004 and 191.03 units respectively when the feed rate is increased by unity when fine cutting stainless steel using HSS cutting tool.

The surface roughness parameters (Ra, Rz) will decrease in values by (15907, 44997.1) when the depth of cut is increased by unity. The surface roughness (Rq, Rt) will increase by 21624.6 and 45592.7 units respectively when the depth of cut is increased by unity. The tool life and M/ctime will decrease by 3879070 and 23274.4 units when the depth of cut is increased by unity.

The imports of these findings are that the surface roughness parameters were not affected in a similar manner by the cutting speed, feed rate and depth of cut for this combination.

CONCLUSION

The response optimization carried out, for the experimental observations from fine cutting stainless steel using HSS tool, showed that the global solutions of the response parameters, cutting speed, feed rate and depth of cut are 1.03285m/s (61.97mpm), 0.0066046 m/s (0.041 mm/rev) and 0.00066046m (0.1mm). Hence, the optimized (minimized) values for the surface roughness (Ra, Rz, Rq, Rt) are 0.12, 0.34, 0.74 and 1.97 microns.

The optimized (maximum) values for the tool life and machining time are 5280.12 and 38.15 seconds. These results indicated the recommended values for the process parameters when fine cutting stainless steel work-piece using HSS cutting tool. The work-piece materials produced with these optimized surface roughness values will have minimum flaws and there will be no crater formed on their surfaces while in use.

The produced work-piece can be used as machine element in equipment that requires high quality surface texture. Similarly, the information provided by the response optimization on tool life and machining time can enable machine shop production planners to carry out near accurate estimates on the cost of production of machine elements made of stainless steel and fine cut using High Speed Steel cutting tool. The process parameters have global solutions with responses which have composite desirability of 0.712814 which indicates that the optimized response values are 28.7% close to their targets.

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NOMENCLATURE, SYMBOLS AND NOTATIONS

Ra: Arithmetic average of absolute values
Rz: Average distance between highest peak and lowest valley in each length
Rq: Root mean squared
Rt: Maximum height of the profile
TL: Tool Life
M/ctime: Machining time

ABOUT THE AUTHOR

Morakinyo Kehinde Onifade, is a Senior Lecturer at the Bells University of Technology. He holds a Ph.D. degree in Industrial Engineering at the University of Benin, Nigeria. His research interests are in areas of operations research and management, as well as program and project management.

SUGGESTED CITATION

Onifade, M.K. 2019. "Response Surface Regression Modelling of Orthogonal Cutting of Stainless Steel Using HSS Tool". *Pacific Journal of Science and Technology*. 20(2):5-18.