SMOOTHENING EFFECT OF CUTTING TOOLS ON WORK PIECE MATERIALS USING SPLIT-PLOT DESIGN

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Abstract

There is an increasing high demand and preference for imported machined products to locally machined ones. It seems that this general and lingering drift away from homemade ones is as a result of the perceived high degree of surface roughness of the locally machined products. This study seeks to use designed experiment to determine the controllable cutting variables that best minimize surface roughness of some selected machined workpiece materials. Split-plot design matrix, fashioned to the Montgomery 2-level factorial design, was used to generate our experimental data. Again, Fisher-Yate's analysis approach was used to develop a model that generated a response surface roughness of 1.15µm. Also, Taguchi optimality array model was used to validate the output of the model whose specified range of values lie between 0.9µm and 1.3µm. Moreover, a number of null hypotheses averring lack of differential treatment for workpiece materials, tool type, depth of cut, on the one hand, and absence of interaction for each case of rake angle, depth of cut and feed rate, within tool type, on the other, were rejected at a p-value of 0.05, suggesting that the foregoing listed process parameters are critical to the minimization of surface roughness of machined workpiece material. The method proposed in this study seems robust and first rate.

Keywords: Split-plot design, Taguchi Optimality Array, Surface roughness, Fisher-Yates analysis.

Introduction

Mating parts such as piston and cylinder (engine bore), brake master cylinder and the fitting piston sliding within it and so forth require smooth machined surface textures. Polishing, as finish operation, can only be effective if turning operation has good surface finish. Achieving smooth surface texture via turning operation requires proper understanding of the mechanics of interplay of process parameters in relation to tooling and nature of workpiece material. When this theoretical basis is poorly understood, achievement of good surface finish would remain a challenge.

The research problem described in the foregoing had attracted the attention of past researchers and various theories had been put forth to address the issue. The studies Al and Zhang (2004), Celik (2007), Cheng and Vanness (1999), Donev (2004) are typical, and they attempt to use designed experiments to study main and interaction effects of process parameters in metal cutting operations. The efforts of past researchers to address this issue go to underscore the significance of machined surface quality that contributes to product quality.

Although surface roughness had been widely investigated, the application of elaborate nested design, Fisher-Yate's Algorithm incorporating Taguchi factorial model for validation had been infrequently studied.

This study employed several cutting variables – depth of cut, speed, tool geometry, feedrate, workpiece materials, cutting tool materials, and varying combinations of these variables in developing a model that can capture relevant parameters needed to enhance quality of machined surface. Various methods are available in the literature for improving the surface quality of machined workpiece. Fuller (1987) has employed four parameters namely current, pulse on-time, pulse off-time and gap voltage as process variables under electrical discharge machining (EDM) to investigate surface roughness.

Interest in using designed experiment to control surface roughness dates back to the late part of 20th century. Progress and William are generally credited with the development of experiments to study abrasive wear in mating surfaces. The study Hastings, Mathew and Oxley (1980) investigated how friction coefficient can be affected by elastic hysteresis losses when the materials, or some part of them, are relatively soft and reformable elastically. Academic interest in development of computer algorithms for surface roughness started in the 1970s, continuing to early 1980s with the publication of a number of papers which include Jones and Eccleston (1980), Kennard and Stone (1969), Moon and Kalmar-Nagy (2001), Patterson and Bailey (1978), Patterson, HD (1976), Porgess, PVK and Wilman, H. (1959).

Factorial design of experiments had been widely applied in the literature. The works Plackett (1981), Ranganathan, Senthilvelan and Sriram (2009); Rao and Murti (2000); Snee and Marquardt (1974); Wang (2004) employed different types of experimental design to study surface roughness. In particular Abdelbasit and Plackett (1981) reviewed questions of experimental design which arise in the analysis of categorized data. Early work by Wu (1981) studied experiments for non-linear functions. Again, Xu and Wu (2001) emphasized the importance of blocking in experiments, noting that it is an important tool for increasing precision of an experiment. More recent studies on surface roughness studies can be found in Fata and Nikuei (2010); Joshit and Kothiyal (2012); Abuthaker, Mohanram and Mohankumar (2011); Kosaraju, Venugopal and Venkateswararao (2011)

By and large, the sample literature consulted indicate that although statistical models had been widely applied in surface roughness investigation, the application of hierarchical design in conjunction with Fisher-Yates algorithm and Taguchi factorial model had been sparsely studied. This study seeks to breach this gap in knowledge by developing an appropriate split-plot experimental design matrix that can nest several process variables which in turn are crossed by several workpiece materials in one design setting. Arising from the design tableau, a model which completely captures the entire process variables is developed. The model can readily predict surface roughness level of the machined workpiece. Finally, the Taguchi experimental design matrix is used to validate the results of the designed experiment.

Materials and methods

Materials

? 30mm × 700mm.

The following materials were used in the study:

(a) Workpiece Materials

These include – aluminium, copper, mild steel and stainless steel cylinders each roughly measuring There are 15pieces for each workpiece material.

(b) Lathe Machine and Surface Roughness Tester.

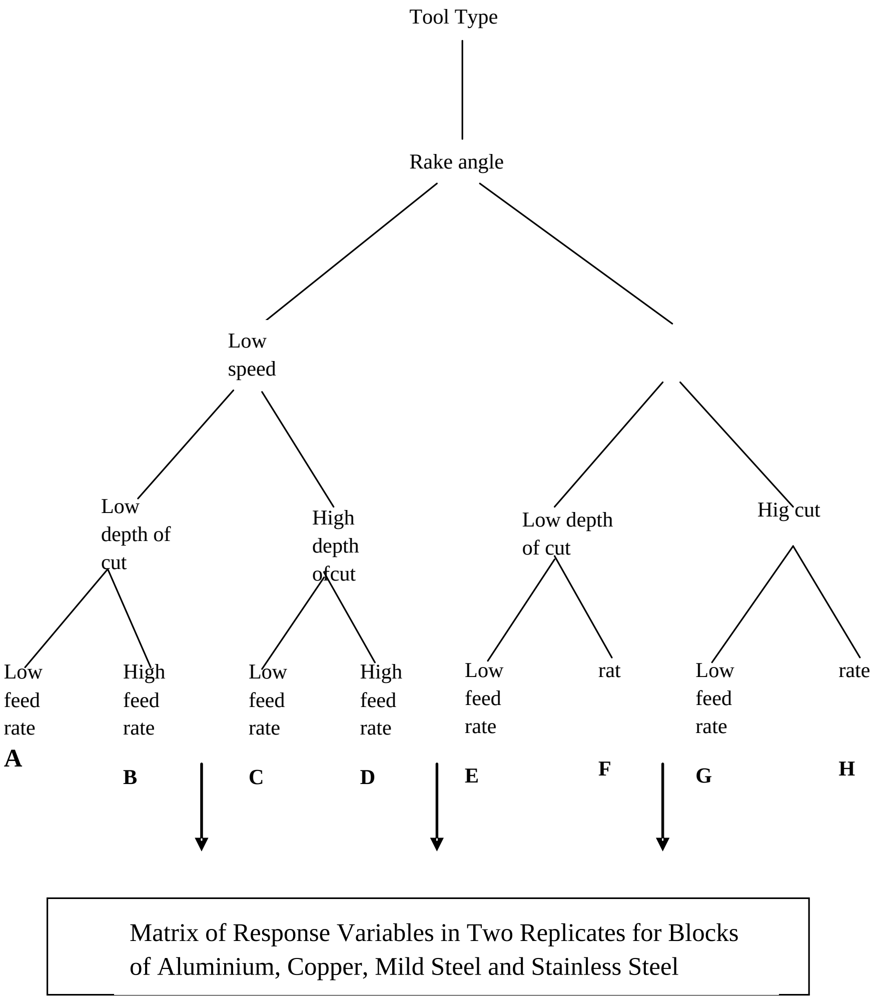
A medium size turret lathe was used in turning operation. Four types of tool materials were employed HSS, Carbide, Ceramic and Cobalt. The tools were ground to high and low rake angles (6^0 and 10^0 respectively)

(c) Cutting tools employed

These include: HSS, Ceramics, Carbide and Cobalt lathe cutting tools. Speed, feed rate and depth of cut were set at (210rpm, 140rpm), (0.12mm/sec., 0.04mm/sec.) and (0.25mm, 0.05mm) respectively representing high and low levels in that order.

Methods

The following controllable variables were considered: rake angle, depth of cut, feed rate and cutting speed. Data for the experimental design were obtained by surface roughness tester which is a measuring device for degree of surface roughness. Readings were taken in two replicates. Montgomery



2.2.1 Method of data analysis.

Computation of corrected sum of squares for the analysis of variance was done according to the method of Spiegel and Stephens (1998). A mathematical model was developed from the analysis of variance of the designed matrix and the numerical value for the final model was computed.

Model validation

Table 1 shows the Taguchi model structure adopted in the study.

Table 1: Taguchi Orthogonal Array

Runs	Rake angle (^{0}c)	Cutting speed (rev/mins)	Depth of cut (mm)	Feed rate (mm/sec)	Surface roughness Readings (µm)
1	+1	+1	+1	+1	
2	-1	-1	-1	-1	
3	+1	+1	+1	+1	
4	-1	-1	-1	-1	
5	+1	+1	+1	+1	
6	-1	-1	-1	-1	
7	+1	+1	+1	+1	
8	-1	-1	-1	-1	

The computations are generated as follows;

i. Rake angle: The high (+) and low (-) levels for each of the work piece are the average of the first eight and last eight observations (surface roughness) respectively.

ii. Cutting Speed: The high (+) and low (-) levels for each of the work piece are the average of the alternating four observations.

iii. Depth of cut: The high (+) and low (-) levels for each of the work piece are the average of the alternating two observations (surface roughness).

iv. Feed rate: The high (+) and low (-) levels for each of the work piece are the average of the alternating observations (surface roughness).

2.2.3 Taguchi Runs (L_n)

In this model, we considered the two levels of factorial design (high and low) and the four control variables (Rake angle, Cutting speed, Depth of cut and Feed rate). According to Taguchi Orthogonal array, this method will give us eight runs (L_8).

Hypotheses Employed

The following relevant six hypotheses were crafted.

I. Nature of Workpiece Material

a. $H^{(0)}_{\text{workpiece}}$: all $\alpha_i = 0$; the four types of workpiece specimens employed showed no significant differential effect under the cutting conditions adopted.

b. $H^{(1)}_{\text{workpiece}}$: some $\alpha_i \neq 0$; surface roughness observed on the workpiece varied according to the nature of the workpiece material.

ii. Tool Type

a. $H^{(0)}_{\text{tooltype}}$: all $\beta_j = 0$; the four tool specimens employed in the experiment impact similar surface roughness features under the same cutting conditions.

b. $H^{(1)}_{\text{tooltype}}$: some β_j ? 0; the four tool specimens exhibit different surface roughness characteristics under the prevailing experimental conditions.

ii. Rake angle

a. $H^{(0)}_{rakeangle}$: all $\gamma_k = 0$; within the range of rake angle to which specimen tools were ground, no significant differential treatment is evident.

b. $H^{(1)}_{rakeangle}$: some $\gamma_k \neq 0$; differential treatment with respect to rake angle is significantly evident.

iii. Speed Regime

a. $H^{(0)}_{cuttingspeed}$: all $\tau_l = 0$; the level of surface roughness perceived on the workpiece, under different speed settings used in the experiment, are essentially the same.

$H^{(1)}_{cuttingspeed}$: some $\tau_l \neq 0$; the level of surface roughness perceived on the workpiece, under different speed settings used in the experiment, are not the same

a.

ii. Depth of cut

a. $H^{(0)}_{depthofcut}$: all $\sigma_m = 0$; there is no noticeable difference in the degree of surface roughness perceived on workpiece specimens turned at different depths of cuts.

b. $H^{(1)}_{depthofcut}$: some $\sigma_m \neq 0$; there is noticeable difference in the degree of surface roughness perceived on workpiece specimens turned at different depths of cuts

iii. Feed rate

a. $H^{(0)}_{feedrate}$: all $\delta_n = 0$; there is no noticeable difference in the degree of surface roughness perceived on workpiece specimens turned at different feed rates.

b. $H^{(1)}_{feedrate}$: some $\delta_n \neq 0$; there is noticeable diffe rence in the degree of surface roughness perceived on workpiece specimens turned at different feed rates.

3.0 Results

3.1 Fisher-Yate Analysis of Data

(i) HSS data matrix

The experimental data are presented in keeping with the format of design matrix of Figure 1

Table 2: Response Variables for HSS (J=1)

Workpiece Material	A		B		C		D		E		F		G		H	
	H	L	H	L	H	L	H	L	H	L	H	L	H	L	H	L
Al	0.68	0.77	1.11	1.09	0.88	0.81	0.93	0.92	0.94	0.91	1.20	0.91	0.78	0.68	0.81	0.88
Cu	1.07	1.01	1.20	1.14	0.80	0.85	1.60	1.88	0.86	1.11	0.68	0.85	0.93	1.20	0.67	0.68
Mild steel	0.90	0.88	1.25	1.03	0.85	0.90	0.99	1.81	0.81	0.57	1.03	1.16	0.80	0.57	0.78	1.09
Stainless Steel	0.65	0.73	1.12	1.03	0.86	0.81	1.11	1.45	0.73	0.85	1.76	1.24	0.68	0.73	0.81	0.94

(ii)Ceramic data matrix

Table 3: Response Variables for ceramic (J=2)

Work piece Material	A		B		C		D		E		F		G		H	
	H	L	H	L	H	L	H	L	H	L	H	L	H	L	H	L
Al	0.69	0.68	0.83	0.90	1.27	1.43	0.85	0.77	0.99	1.27	1.22	0.77	1.03	1.14	1.77	1.38
Cu	1.22	1.30	0.86	1.69	0.93	0.98	1.11	1.01	1.22	1.86	1.17	1.11	1.42	1.09	1.81	1.16
Mild steel	1.24	0.86	1.76	1.43	0.85	0.87	0.89	1.01	2.15	2.07	0.96	1.56	1.04	1.32	0.94	0.88
Stainless Steel	0.85	0.92	0.94	0.98	0.99	1.38	0.67	1.40	1.84	1.79	1.27	1.31	1.25	1.32	1.64	1.42

(iii)Carbide data matrix

Table 4: Response Variables for carbide (J=3)

Work piece Material	A		B		C		D		E		F		G		H	
	H	L	H	L	H	L	H	L	H	L	H	L	H	L	H	L
Al	0.57	0.90	1.11	1.06	0.89	0.90	0.77	0.88	1.04	0.68	1.12	1.24	1.07	1.01	1.11	1.14
Cu	0.73	0.65	1.20	1.01	0.78	0.57	1.01	0.80	0.99	0.72	1.17	1.64	1.09	0.90	1.20	1.35
Mild steel	1.24	1.07	0.68	0.90	0.92	0.90	0.99	1.81	0.81	0.57	1.03	1.16	0.80	0.57	0.78	1.09
Stainless Steel	1.64	1.09	1.12	1.60	1.88	0.81	1.11	1.45	0.73	0.85	1.76	1.24	0.68	0.73	0.81	0.94

(iv) Cobalt data matrix

Table 5: Response Variable for cobalt (J=4

Work piece Material	A		B		C		D		E		F		G		H	
	H	L	H	L	H	L	H	L	H	L	H	L	H	L	H	L
Al	0.92	0.68	1.10	1.09	0.90	0.78	0.95	0.97	0.92	0.94	1.18	1.01	2.15	0.71	0.85	0.85
Cu	1.62	0.78	0.80	0.99	1.69	1.01	1.61	0.78	1.09	1.17	0.73	1.40	1.87	1.19	1.87	0.86
Mild steel (MS)	0.82	0.84	1.81	0.81	0.68	1.12	1.02	0.80	0.99	0.59	1.06	1.14	0.72	0.54	0.72	1.12
Stainless Steel (SS)	0.69	0.83	1.12	1.02	0.72	1.17	1.19	0.57	1.03	0.93	1.24	1.21	0.64	0.76	0.84	0.99

Fisher-Yate's algorithm was applied to obtain the sum of squares (SS) for the main effects, effects within cutting tool types and interaction effects. These computations are shown in equations (1) to (13). Higher order interactions are practically insignificant and hence were not considered in keeping with the procedure by Ranganathan [15]

$$ss_{total} = \sum_{n=1}^{n=2} \sum_{m=1}^{n=2} \sum_{l=1}^{n=2} \sum_{k=1}^{n=2} \sum_{j=1}^{J=4} \sum_{i=1}^{I=4} X^2_{ijklmn} - \frac{X^2_{......}}{IJKLMN} \qquad (1)$$

$$\therefore SS_{Total} = 309.80 - 282.198 = 27.602$$

$$SS_{Workpiece} = \sum_{i=1}^{i=4} \frac{X^2_{i.....}}{JKLMN} - \frac{X^2_{......}}{IJKLMN}$$

$$SS_{Workpiece} \; 282.19 - 282.198 = 0.721$$

$$SS_{Tool\ Type} = \sum_{j=1}^{J=4} \frac{X^2 j...}{IKLMN} - \frac{X^2}{IJKLMN} \qquad (2)$$

=284.21-282.198 =2.012

$$SS_{Rake\ Angle} = \sum_{k=1}^{k=2} \frac{X^2..k..}{IJLMN} - \frac{X^2}{IJKLMN}$$

$$= 282.321 - 282.198 = 0.123 \quad (3)$$

$$SS_{Cutting\ Speed} = \sum_{l=1}^{l=2} \frac{X^2..l..}{IJKMN} - \frac{X^2}{IJKLMN} \quad (4)$$

$$= 282.293 - 282.198 = 0.095$$

$$SS_{Depth\ of\ Cut} = \sum_{m=1}^{M=2} \frac{X^2...m}{IJKLN} - \frac{X^2}{IJKLMN} \quad (5)$$

$$= 283.073 - 282.198 = 0.875$$

$$SS_{Feed\ rate} = \sum_{n=1}^{n=2} \frac{X^2...n}{IJKLM} - \frac{X^2...}{IJKLMN} \quad (6)$$

$$= 282.259 - 282.198 = 0.061$$

$$SS_{Rake\ angle\ within\ tool\ type} = \frac{X^2.jk.}{ILMN} - \frac{X^2.j..}{IKLMN} \quad (7)$$

$$= 286.018 - 284.21 = 1.81$$

$$SS_{Cutting\ speed\ within\ tool\ type} = \frac{X^2.j.l}{IKMN} - \frac{X^2.j..}{IKLMN} \quad (8)$$

$$=284.3749 - 284.21 = 0.16$$

SS_{Feed}

$$SS_{Depth\ of\ cut\ within\ tool\ type} = \frac{X^2.j.m.}{IKLN} - \frac{X^2.j..}{IKLMN} \quad 9 \quad = 304.58 - 284.21$$

$$= 20.37$$

$$rate\ within\ tool\ type = \frac{X^2.j...n}{IKLM} - \frac{X^2.j..}{IKLMN} \quad (10)$$

$$= 284.82 - 284.21 = 0.67$$

$$SS_{Error} SS_{Workpiece\ \times tooltype} = \sum_{i=1}^{I=4}\sum_{j=1}^{J=4} \frac{X^2ij...}{KLMN} - \frac{X^2}{IJKLMN} - SS_{Workpiece} - SS_{Tooltype} \quad (11)$$

$SS_{Feedrate}$

$$SS_{Feedratewithintooltype} = 286.05 - 282.198 - 2.012 - 0.722 = 1.118$$

(12) $= SS_{Total} - SS_{Workpiece} - SS_{Tooltype} - SS_{Rakeangle} - SS_{Cuttingspeed} - SS_{Depthofcut} -$

$SS \quad - SS_{Rakeanglewithintooltype} - SS_{Cuttingspeedwithintooltype} - SS_{Depth\ of\ cut\ withintooltype} -$

$- SS_{Workpiece\ \times tooltype}$

Error

$$= 27.60 - 0.72 - 2.01 - 0.12 - 0.09 - 0.87 - 0.06 - 1.81 - 0.16 - 20.37 - 0.67 - 1.118$$

$$= - 0.398 \quad (13)$$

ANOVA Results

Table 6 that follow is a collation of ANOVA results.

Table 6: ANOVA Table

S/No	Sources of Variation	Sum of Squares (SS)	Degree of Freedom, (DoF)	Mean Square(MS)=SS/DoF	F_{cal}	F_{tab}	Decision
1	SS_{total}	27.60		0.11	2.5	5.12	
2	$SS_{workpiece}$	0.72	(I – 1) = 3	0.24	5.46	3.86	$F_{cal} > F_{tab}$ Reject H_0
3	$SS_{tooltype}$	2.01	(J – 1) = 3	0.67	15.23	3.86	$F_{cal} > F_{tab}$ Reject H_0
4	$SS_{rakeangle}$	0.12	(K – 1) = 1	0.12	2.73	5.12	$F_{cal} < F_{tab}$ Accept H_0
5	$SS_{cuttingspeed}$	0.09	(L – 1) = 1	0.09	2.05	5.12	$F_{cal} < F_{tab}$ Accept H_0
6	$SS_{depthofcut}$	0.87	(M – 1) = 1	0.87	19.77	5.12	$F_{cal} > F_{tab}$ Reject H_0
7	$SS_{feedrate}$	0.06	(N– 1) = 1	0.06	1.36	5.12	$F_{cal} < F_{tab}$ Accept H_0
8	$SS_{rakeanglewithintooltype}$	1.81	J(K – 1) = 4	0.45	10.23	3.63	$F_{cal} > F_{tab}$ Reject H_0
9	$SS_{cuttingspeedwithintooltype}$	0.16	J(L – 1) = 4	0.04	0.91	3.63	$F_{cal} < F_{tab}$ Accept H_0
10	$SS_{depthofcutwithintooltype}$	20.37	J(M – 1) = 4	6.79	154.32	3.63	$F_{cal} > F_{tab}$ Reject H_0
11	$SS_{feedratewithintooltype}$	0.61	J(N – 1) = 4	0.20	4.55	3.63	$F_{cal} > F_{tab}$ Reject H_0
12	$SS_{workpieceXtooltype}$	1.118	(I – 1)(J – 1) = 9	0.124	2.82	3.19	$F_{cal} < F_{tab}$ Accept H_0
13	SS_{error}	-0.398	(I – 1)(J –1)(K – 1)(L– 1)(M – 1)(N – 1) = 9	0.044			

Table 7 shows the summary of the decisions made based on the ANOVA table results.

Table 7: Summary of ANOVA Decisions

EFFECTS	Accepted The Null Hypothesis	Rejected The Null Hypothesis
Main Effects	(i)Rake Angle (ii) Cutting Angle (iii) Feed Rate	(i) Work Piece (ii) Tool type (iii) Depth of cut
Interaction Effects	(iv) Cutting Speed within the tool type (v) Workpiece X tool type interaction	(iv) Rake angle within tool type (v) Depth of cut within tool type (vi) Feed rate within tool type

3.3 Computation of the Developed model

$$= \mu + \alpha_i + \beta_j + \gamma_k + \tau_l + \sigma_m + \delta_n + ?_{k(j)} + \varphi_{l(j)} + \omega_{m(j)} + \psi_{n(j)} + (\alpha\beta)_{ij} + \varepsilon_{ijklmn}$$

where

$$\mu = \frac{X_{......}}{IJKLMN} = \frac{61.75 + 76.73 + 65.06 + 65.24}{4 \times 4 \times 2 \times 2 \times 2 \times 2} = \frac{268.78}{256} = 1.05$$

$$\alpha_i = SS_{Workpiece} = 0.72$$

$$\beta_j = SS_{Tooltype} = 2.01$$

$$\gamma_k = SS_{rakeangle} = 0.12$$

$$\tau_l = SS_{cuttingspeed} = 0.09$$

$$\sigma_m = SS_{depthofcut} = 0.87$$

$$\delta_n = SS_{feedrate} = 0.06$$

$$?_{k\ j} = SS_{Rakeanglewithintooltype} = 1.81$$

$$\varphi_{l\ j} = SS_{cuttingspeedwithintooltype} = 0.16$$

$$\omega_{m(j)} = SS_{feedratewithintooltype} = 0.61$$

$$\psi_{n(j)} = SS_{depthofcutwith\ intooltype} = 20.37$$

$$(\alpha\beta)_{ij} = SS_{workpieceXtooltype} = 1.18$$

$$\varepsilon_{ijklmn} = SS_{Error} = -0.398$$

The sum of squares of sources of variation whose hypothesis were accepted is used to formulate the model.

= 0.12 + 0.09 + 0.06 + 0.16 + 1.118 - 0.398 = 1.15µm

Model Validation using Taguchi Model

Table 8 to 11 show the values generated based on the observations across four cutting tool types (HSS, Ceramics, Carbide and Cobalt). For each of the cutting tool type, the + or – signs attached to each of the various workpiece indicates the high and low levels respectively.

3.4 Results of model validation by Taguchi method

Table 8: Generated values for HSS TOOL

HSS TOOL						
	RUNS	SURFACE ROUGHNESS (?m)				AVERAGESURFACE ROUGHNESS (?m)
		RAKE ANGLE	CUTTING SPEED	DEPTH OF CUT	FEED RATE	
Al (+)	1	0.90	0.95	0.81	0.92	0.90
Al (-)	2	0.89	0.84	0.98	0.87	0.90
Cu (+)	3	1.19	0.99	0.98	0.98	1.04
Cu (-)	4	0.87	1.08	1.09	1.09	1.03
MILD STEEL(+)	5	1.08	0.95	0.79	0.93	0.94
MILD STEEL(-)	6	0.85	0.97	1.14	1.00	0.99
STAINLESS STEEL(+)	7	0.97	1.01	0.76	0.97	0.93
STAINLESS STEEL(-)	8	0.97	0.92	1.18	0.97	1.01

Table 9: Generated values for CERAMICS TOOL

CERAMIC TOOL						
	RUNS	SURFACE ROUGHNESS (?m)				AVERAGESURFACE ROUGHNESS (?m)
		RAKE ANGLE	CUTTING SPEED	DEPTH OF CUT	FEED RATE	
Al (+)	1	0.93	0.92	1.06	1.08	1.00
Al (-)	2	1.20	1.21	1.06	1.04	1.13
Cu (+)	3	1.14	1.30	1.25	1.22	1.23
Cu (-)	4	1.36	1.19	1.24	1.28	1.27
MILD STEEL(+)	5	1.11	1.50	1.30	1.23	1.29
MILD STEEL(-)	6	1.37	0.98	1.18	1.25	1.20
STAINLESS STEEL(+)	7	1.02	1.24	1.29	1.18	1.18
STAINLESS STEEL(-)	8	1.48	1.26	1.20	1.32	1.32

Table 10: Generated values for Carbide Tool

CARBIDE TOOL						
	RUNS	SURFACE ROUGHNESS (?m)				AVERAGESURFACE ROUGHNESS (?m)
		RAKE ANGLE	CUTTING SPEED	DEPTH OF CUT	FEED RATE	
Al (+)	1	0.89	0.97	0.88	0.96	0.93
Al (-)	2	1.05	0.97	1.05	0.98	1.01
Cu (+)	3	0.84	1.01	0.80	1.02	0.92
Cu (-)	4	1.13	0.96	1.17	0.96	1.06
MILD STEEL(+)	5	1.06	0.93	0.86	0.91	0.94
MILD STEEL(-)	6	0.85	0.98	1.06	1.01	0.98
STAINLESS STEEL(+)	7	1.34	1.25	1.05	1.22	1.22
STAINLESS STEEL(-)	8	0.97	1.05	1.25	1.09	1.09

Table 11: Generated values for COBALT TOOL

COBALT TOOL						
	RUNS	SURFACE ROUGHNESS (μm)				AVERAGESURFACE ROUGHNESS (μm)
		RAKE ANGLE	CUTTING SPEED	DEPTH OF CUT	FEED RATE	
Al (+)	1	0.92	0.98	1.00	1.12	1.01
Al (-)	2	1.08	1.02	1.00	0.89	1.00
Cu (+)	3	1.16	1.07	1.30	1.41	1.24
Cu (-)	4	1.27	1.36	1.13	1.02	1.20
MILD STEEL(+)	5	0.99	1.01	0.79	0.96	0.94
MILD STEEL(-)	6	0.87	0.85	1.06	0.87	0.91
STAINLESS STEEL(+)	7	0.91	1.01	0.85	0.93	0.93
STAINLESS STEEL(-)	8	0.96	0.86	1.02	0.94	0.95

4.0 Discussion

At the onset, it was stated that the research work sought to determine the combination of controllable variables that minimize most the surface roughness of machined work piece. It was also claimed that the study would resolve the divide between aesthetics of imported products and the home-grown product based on their surface texture. It is evident from the study that our model gave a surface roughness response value $X_{ijklmn} = 1.15\mu M$ of that compares favourably with the range of values of 0.9μm – 1.32 obtained by Taguchi approach. Our research result thus has justified the foregoing claim. Thus, the objective of the study has been fully achieved. The combination of controllable factors that should be considered in minimizing the surface roughness of machined work piece are tool type, depth of cut, rake angle within tool type and depth of cut within tool type.

Conclusion

The application of split-plot experimental design that incorporated four process parameters, work piece materials and tool types factors in one experimental setting, seeking to explain the dynamics of the mutual interaction of the controllable variables in influencing the surface quality of machined work piece, has been well illustrated.

The decisions on the null hypothesis for the main effects of this experiment indicated that work piece materials, cutting tool type and selected depth of cut are the most important factors to be considered for the achievement of optimal surface finish of machined work piece materials.

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