ResearchGate

See discussions, stats, and author profiles for this publication at: https://www.researchgate.net/publication/279848092

Assessment of surface roughness and MRR while machining brass with HSS tool and carbide inserts

Article *in* Indian Journal of Engineering and Materials Sciences · July 2015

CITATIONS
17

READS
388

4 authors, including:

Arun Vikram Kothapalli
GITAM (Deemed to be University)

29 PUBLICATIONS **290** CITATIONS

SEE PROFILE

Sankara Narayana
GITAM University

3 PUBLICATIONS **20** CITATIONS

SEE PROFILE

Satish Ben
National Institute of Technology, Warangal

58 PUBLICATIONS **670** CITATIONS

SEE PROFILE

All content following this page was uploaded by Arun Vikram Kothapalli on 07 July 2015.

The user has requested enhancement of the downloaded file.

Indian Journal of Engineering & Materials Sciences
Vol. 22, June 2015, pp. 321-330

Assessment of surface roughness and MRR while machining brass with HSS tool and carbide inserts

K Arun Vikram[a]*, Ch Ratnam[b], K Sankara Narayana[c] & B Satish Ben[d]

[a]Department of Industrial Engineering, GITAM Institute of Technology, GITAM University, Visakhapatnam 530 045, India
[b]Department of Mechanical Engineering, Andhra University College of Engineering (AUCE), Visakhapatnam 530 003 , India
[c]Department of Mechanical Engineering, GITAM Institute of Technology, GITAM University, Visakhapatnam 530 045, India
[d]Department of Mechanical Engineering, National Institute of Technology, Warangal 506 004, India

Received 9 June 2014; accepted 7 November 2014

This work focuses on study of surface roughness (R_a) and metal removal rate (MRR) produced in hard turning process under dry conditions using TiN-Al_2O_3-TiCN-TiN coated carbide inserts and high speed steel (HSS) tools. Two parameters are selected for the study: speed and feed with constant depth of cut. These machining parameters are adopted to analyze their influences, significance and contributions on the generated surface roughness and MRR. Full factorial design of experiments (DOE) is used for conducting the experiments and analysis of variance (ANOVA) is used to assess the significance and contribution of each parameter and also their interactions. Later, the optimal parameter combinations for generating surface roughness and MRR are determined. The data generated using DOE is used for regression analysis and to create model for predicting the average surface roughness and MRR as a function of speed and feed. A confirmation experiments are done yielding max of 5.93% and 6.17% error in regression, while machining with carbide and HSS tools respectively. Surface roughness of 1.42 µm and 2.37 µm while machining with carbide and HSS tools respectively are obtained at the optimal combination of machining parameters.

Keywords: Roughness, Dry machining, DOE, Two-Way ANOVA, Hard Turning, MRR

Metal cut technology has grown rapidly with a common goal of achieving higher machining process efficiencies in form of high productivity and high surface finish. Surface roughness is one of the most important properties and is an indicator of surface quality specified by most of the customer requirements in machining processes. It really necessitates the products to be of a very high surface quality to grab the product appearance, function, utility, heat transmission and reliability.

To have high surface finish, one has to do multiple machining cuts for each and every product, thereby making its processing time and production costs to be increasing. So, hard turning of various engineering materials in a single cut operation came into existence, in order to reduce processing time, production cost and setup time with high surface finish[1,2].

Several parameters contribute to develop surface roughness in machining operations, as illustrated in the Fig. 1[3] and some of the machining parameters like speed and feed are adopted for analysis in this study.

The quality of the produced components such as engine cylinder blocks, pistons etc. leads to failure of mechanical parts which in turn leads to high cost damage and hence the surface roughness is to be evaluated. In addition to surface finish, the amount of material removal during machining also is of much more importance which is an indication of quantity of production. In this paper, machining parameters like speed and feed with constant 0.50 mm depth of cut in hard turning operation under dry conditions are considered.

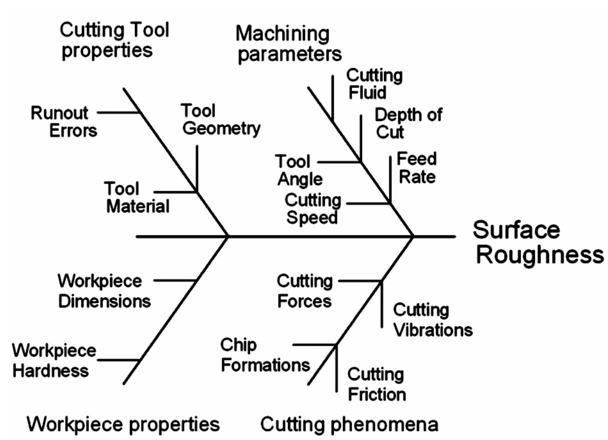

Fig. 1—Parameters effecting surface roughness in machining operation

*Corresponding author (E-mail: arunvikram@gmail.com)

Design of Experiments (DOE)

In order to produce any product with desired quality by machining, proper selection of process parameters is essential. This can be accomplished by DOE. DOE is a method to identify the important factors and the possibility of estimating interactions in a manufacturing process. DOE methods are now widely used in many industries to efficiently optimize the manufacturing process and also to allow multiple complex properties to be rapidly optimized at minimal cost. DOE supports the approach that asserts to move quality improvement upstream and thereby helps design engineers to build quality into products[4-7].

In machining processes, a proper selection of cutting conditions generates high surface finished parts with less dimensional error, precision fits and aesthetic look. Many researchers focused on measurement of surface roughness and their regression models generated using single point and multi-point cutting tools with different machining parameter combinations are well documented.

Several researchers focused their studies on different steels machined with different cutting tools and inserts as mentioned by Feng *et al.*[8], who developed an empirical model for the prediction of surface roughness in finish turning basing on work-piece hardness (material), cutting parameters, tool geometry and cutting time by means of nonlinear regression with logarithmic data transformation and their applications in determining the optimum machining conditions. Çalışkan *et al.*[9] studied machining with hard coatings like nano-layer AlTiN/TiN, multilayer nano-composite TiAlSiN/TiSiN/TiAlN, and commercially available TiN/TiAlN. Machining parameters like cutting speed, feed rate, and depth of cut were analyzed on cutting forces and surface roughness during face milling of AISI O_2 cold work tool steel. The experiments were designed based on response surface methodology of 3^{13} factorial designs. The results showed that the interaction of coating type and depth of cut affects surface roughness, while the hard coating type has no significant effect on cutting forces. In addition, the different machining factors were analyzed for their significance and contributions based on ANOVA and regression models, like Khrais *et al.*[4] focused on evaluating surface roughness and developed a multiple regression model for surface roughness as a function of cutting parameters during the machining of flame hardened medium carbon steel with TiN-Al_2O_3-TiCN coated inserts. Taguchi methodology was adapted for experimental plan of work and signal-to-noise ratio (S/N) were used to relate the influence of turning parameters to the work-piece surface finish and the effects of turning parameters were studied by using the ANOVA. Motorcu[5] studied the surface roughness in the turning of AISI 8660 hardened alloy steels by ceramic based cutting tools with cutting parameters such as cutting speed, feed rate, depth of cut in addition tool's nose radius, using a statistical approach. An orthogonal design, signal-to-noise ratio and analysis of variance were employed to find out the effective cutting parameters and nose radius on the surface roughness. Yang and Tarng[6] studied optimal cutting parameters for turning operations based on orthogonal array, signal-to-noise (S/N) ratio, and the analysis of variance (ANOVA) to investigate the cutting characteristics of S45C steel bars using tungsten carbide cutting tools. Through this study, they found not only the optimal cutting parameters for turning operations can be obtained, but also the main cutting parameters that affect the cutting performance in turning operations. Singh and Rao[1] investigated the effects of cutting conditions and tool geometry on the surface roughness in the finish hard turning of the bearing steel (AISI 52100) with mixed ceramic inserts made up of aluminum oxide and titanium carbonitride (SNGA) and a mathematical model for the surface roughness were developed by using the response surface methodology.

Recently, researchers extended their studies to non-ferrous work-piece materials like alloys of aluminium, titanium etc. Vijian *et al.*[7] studied surface roughness in squeeze casting of LM6 aluminium alloy using Taguchi orthogonal array as DOE and predicted the significance of parameters based ANOVA and F-Tests. Ginta *et al.*[10] focused on developing an effective methodology to determine the performance of uncoated WC-Co inserts in predicting minimum surface roughness in end milling of titanium alloys Ti-6Al-4V under dry conditions. Response surface methodology was employed to create an efficient analytical model for surface roughness in terms of cutting parameters and surface roughness values were measured using Mitutoyo surface roughness measuring instrument.

Apart from multiple cut machining, research studies were focused on single cut machining like hard turning process under dry conditions for better response results and analyzed their performance. Tamizharasan *et al.*[2] analyzed the process of hard turning and its potential benefits compared to the conventional grinding operation. Additionally, tool wear, tool life, quality of surface turned, and amount of material removed are also predicted. Diniz and Micaroni[11] focused on working to find cutting conditions more suitable for dry cutting, without damaging the work-piece surface roughness and without increasing cutting power consumed by the process. The main conclusion of this work was that to remove the fluid from a finish turning process, without harming tool life and cutting time and improving surface roughness and power consumed, it is necessary to increase feed and tool nose radius and decrease cutting speed.

Research studies take the help of designed tests in order to reduce the number of experiments for faster completion of work and analysis. Computational data analysis of surface roughness, cutting parameters and dynamic cutting behavior are very helpful in analyzing the expected manufacturing outputs. Çolak *et al.*[12] studied gene expression programming method for predicting surface roughness of milling surface in relation to cutting parameters like cutting speed, feed and depth of cut. The collected data for predicting surface roughness was used to model a linear equation of the experimental study. Mahdavinejad and Bidgoli[3] highlighted the methods of predicting the surface roughness, like based on the trends of machining theories, based on the designed tests, based on artificial intelligence such as neural networks, GA, fuzzy etc and based on lab research such as statistics and regression model analysis. The combination of adaptive neural fuzzy intelligent system is used to predict the roughness of dried surface machined in turning process.

Not only ferrous and non-ferrous metals machining, but also recent trend focuses on composites matrix machining[13-16]. Bhushan *et al.*[13] attempted to investigate the influence of cutting speed, depth of cut, and feed rate on surface roughness during machining of 7075 Al alloy and 10 wt% SiC particulate metal-matrix composites using tungsten carbide and polycrystalline diamond (PCD) inserts on a CNC turning machine. Anandakrishnan and Mahamani[14] investigated on the machinability parameters such as cutting speed, feed rate, and depth of cut on flank wear, cutting force and surface roughness were analyzed during turning operations of a in situ Al-6061–TiB2 metal matrix composite (MMC) prepared by flux-assisted synthesis basing on the composites characterization using scanning electron microscopy, X-ray diffraction, and micro-hardness analysis. Zhou *et al.*[15] investigated a two-dimensional orthogonal cutting experiments and simulation analysis on the machining of SiCp/Al composites with a polycrystalline diamond tool. Using two kinds of finite element models, the cutting force and Von-Mises equivalent stress at different cutting conditions were studied in detail. Manna and Bhattacharya[16] investigated influence of cutting conditions on surface finish during turning of Al/SiC-MMC with a fixed rhombic tooling system using Taguchi method for optimizing the cutting parameters for effective turning and using multiple linear regression mathematical models relating to surface roughness height R_a and R_t were established.

The literature shows that researchers focused more on combination of various cutting parameters in turning operations and the regression model generation of surface roughness using factorial design of experiments. However, the effect of machining parameters interactions on various types of cutting tools in turning operation using full factorial DOE are less explored. Hence, this paper focuses on study of combination of machining parameters with full factorial study in turning operation taking into account on surface roughness, MRR, regression model generation and comparison of two different types of cutting tool (like HSS and Carbide) based on machining parameters like feed and speed with constant depth of cut.

Experimental Procedure

Surface roughness and MRR

In this work, turning operations were conducted on fully automated all geared headstock lathe machining center under dry conditions. Each turning operation was carried out with new carbide inserts and HSS tools for avoiding impact of tool geometry wear and crater impact on disturbing the surface roughness finish in hard turning operations.

Brass material (ISO:319) was chosen for studying the impact of speed and feed with constant depth of cut. In turning operation, their influence on the generated surface roughness, MRR and regression models were investigated based on full factorial DOE. In addition, a comparative study was also been done and analyzed.

Surface roughness tester of Mitutoyo SJ-301 as shown in Fig. 2 with Stylus (diamond) differential induction method detection unit, measuring in the range of -200 μm to 150 μm is used for measuring surface roughness on three diametrical points of the machined surfaces.

Work-piece material and cutting tools

Brass (ISO:319) extrusions find application in the manufacture of various items like shafts, lock bodies, gears, pinions, automotive parts, screws, nuts etc is taken as work-piece material with 70 mm length and 46.57 mm average diameter rod each, for hard turning operation. The chemical composition of ISO: 319 Brass has 56-59% of Cu, 2.0-3.5% of Pb, 0.35% max of Fe and remaining Zn.

Composition of brass as mentioned above provides good strength, more tensile strength, excellent corrosion resistance and good thermal conductivity. In addition, the alloy is completely recyclable and is a close substitute to leaded steel (formerly AISI 12L14) for screw machine products. The extruded brass is of α-β brass (or yellow brass) which has 32-40% zinc. Addition of lead improves its machinability and as it is insoluble, the chips of brass material breaks into fine particles thereby making it easy for disposal.

Cemented carbides increase considerably the working capacity of the tool and can be used for operations which require high number of revolutions, thereby reducing working time with good smooth surface roughness. Hence, commercially available multi layer coated cemented carbide by (TiN-Al_2O_3-TiCN-TiN) from WIDIA with an ISO Designation: CNMG120408-Grade: TN4000 were used.

High-speed steel not a new material, but basically an innovative tool developed from heat treatment procedures. The metallurgical composition of HSS T1 grade is 18% W, 4% Cr, 1% V, 0.7% C and remaining Fe. The HSS tool and carbide inserts are shown in Fig. 3.

Experimental design based on full factorial DOE

Full factorial designs are the simplest form of factorial designs in which all possible combinations of a set of factors are tested. This is the most fool proof design approach, but it is also the most costly in experimental resources. The advantage of this design is that, maximum information about factors can be obtained, provides possibility to identify interactions between factors and their effect on the experimental response.

This work predicts the model for the surface roughness and MRR as a function of two control factors using full factorial DOE with replicates. The two control factors like speed (560 rpm, 900 rpm and 1250 rpm) and feed (0.14 mm/rev, 0.17 mm/rev and 0.20 mm/rev) with three levels each were chosen.

The statistical measure of performance called signal-to-noise (S/N) ratio developed by Taguchi is applied to identify the optimal set of parameters for better quality and quantity characteristics[4-7].

Surface roughness is required to be of minimum and hence for S/N ratio smaller-is-better is selected**.** MRR is required to be of maximum and hence for S/N ratio larger-is-better is selected[5].

Analysis of variance (ANOVA)

ANOVA is used to investigate the significant effect of design parameters on the characteristic of the response. It also depicts the contribution of parameters on generating the required response. The statistical *F*-test is used to identify the significance of machining parameters[7].

Two-way ANOVA is used to determine the significances of the factors and their interaction using the following equations:

$$SS_{Total} = \sum X^2 - \frac{\left(\sum X\right)^2}{N} \;\&\; DF = N-1 \qquad \ldots (1)$$

$$SS_{Between} = \frac{\left(\sum X_1\right)^2}{n_1} + \frac{\left(\sum X_2\right)^2}{n_2} + .. + \frac{\left(\sum X_{AC}\right)^2}{n_{AC}} - \frac{\left(\sum X\right)^2}{N} \qquad \ldots (2)$$

$$SS_C = \sum \frac{\left(\sum for \quad each \quad column\right)^2}{n \quad for \quad each \quad column} - \frac{\left(\sum X\right)^2}{N} \qquad \ldots (3)$$

$$SS_A = \sum \frac{\left(\sum for\ each\ row\right)^2}{n\ for\ each\ row} - \frac{\left(\sum X\right)^2}{N} \qquad \ldots (4)$$

$$SS_{Within} = SS_{Total} - SS_{Between} \qquad \ldots (5)$$

$$\%Contribution = {MS}/{MS_{Total}} \qquad \ldots (6)$$

Where SS is sum of squares, MS is mean square, 'DF' is degree of freedom, *N* is total observations, *n* is size of population.

Regression model

$$R_a = C{*}f^{k}{*}v^{h} \qquad \ldots (7)$$

Where R_a is average surface roughness (μm), *v* is the spindle speed (rpm) and *f* is the feed (mm/rev). *C*,*k*,*h* are model parameters to be estimated from experimental results. Converting the exponential form of surface roughness R_a to linear model with the help of logarithmic transformation and modeled as:

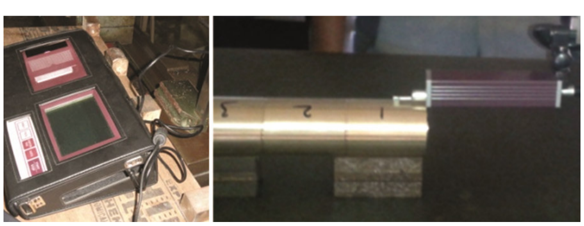

Fig. 2—Set-up of surface roughness tester

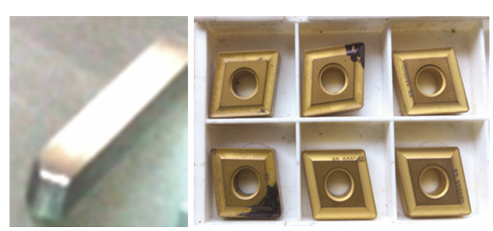

Fig. 3—HSS tool and carbide inserts

$$\log R_a = \log C + k^* \log f + h^* \log v \qquad \dots (8)$$

The proposed second order model developed from the above functional relationship is:

$$Y = \beta_o x_o + \beta_1 x_1 + \beta_2 x_2\ \beta_3 x_1^2 + \beta_4 x_4^2 + \varepsilon \qquad \dots (9)$$

Where Y is the true response of surface roughness on a logarithmic scale x_o=1 (dummy variable), x_1,x_2,x_3,x_4 are logarithmic transformations of feed and speed respectively, while β_o, β_1, β_2, β_4 are the parameters to be estimated, Where ε is the experimental error and the b values are estimates of the β parameters.

Experimental set-up

Work-piece material of length 210 mm was divided into 3 equal parts (i.e. 3 × 70 mm). Based on full factorial DOE, combinations of the speed and feed with constant depth of cut were considered, as shown in Table 1.

As the machined surfaces are cylindrical, the work-piece with same dimensions was machined three times to record the replicates of the surface roughness and MRR and averages of them were considered.

In this study, 9 experiments were conducted with three replicates. The surface roughness readings were measured using surface roughness tester and MRR values were calculated, as shown in the Table 2. The

Table 1—Full factorial design of experiments with 2 factors and 3 levels

Exp. No.	Control factors		Actual setting values	
	A	B	A: Spindle speed (rpm)	B: Feed (mm/rev)
1	1	1		0.14
2	1	2	560	0.17
3	1	3		0.20
4	2	1		0.14
5	2	2	900	0.17
6	2	3		0.20
7	3	1		0.14
8	3	2	1250	0.17
9	3	3		0.20

Table 2—Experimental values of turning brass using TiN-Al_2O_3-TiCN-TiN carbide insert and HSS Tools

Exp No.	A: Speed (rpm)	B: Feed (mm/rev)	Carbide insert				HSS Tools			
			R_a (microns)	MRR (mm^3/min)	S/N ratio (R_a)	S/N ratio (MRR)	R_a (microns)	MRR (mm^3/min)	S/N Ratio (R_a)	S/N ratio (MRR)
1	1	1	1.43	5732.2	-3.29	75.35	2.99	5855.3	-9.33	75.17
			1.47	5729.7			2.81	5852.8		
			1.48	5734.6			2.98	5857.8		
2	1	2	1.66	6960.5	-4.44	77.04	3.12	7110.0	-10.00	76.85
			1.65	6957.3			3.14	7107.0		
			1.69	6963.5			3.10	7113.0		
3	1	3	1.97	8188.8	-6.11	78.45	3.40	8364.7	-10.72	78.26
			2.10	8185.3			3.39	8361.2		
			1.99	8192.3			3.43	8368.2		
4	2	1	1.41	9212.4	-3.13	79.47	2.44	9410.3	-7.87	79.29
			1.45	9208.5			2.50	9406.3		
			1.44	9216.4			2.48	9414.3		
5	2	2	1.62	11186.5	-4.35	81.16	2.68	11426.8	-8.56	80.97
			1.66	11181.7			2.65	11422.0		
			1.67	11191.3			2.71	11431.6		
6	2	3	1.98	13160.6	-5.98	82.57	2.76	13443.3	-8.80	82.39
			1.99	13155.0			2.78	13437.6		
			2.00	13166.3			2.74	13448.9		
7	3	1	1.44	12795.1	-3.03	82.33	2.40	13069.9	-7.48	82.14
			1.42	12789.6			2.36	13064.4		
			1.39	12800.6			2.34	13075.4		
8	3	2	1.60	15536.9	-3.99	84.01	2.65	15870.5	-8.44	83.83
			1.55	15530.2			2.61	15863.9		
			1.60	15543.5			2.60	15877.2		
9	3	3	1.95	18278.7	-5.85	85.42	2.67	18671.2	-8.77	85.24
			1.99	18270.8			2.69	18663.4		
			1.94	18286.5			2.64	18679.1		

surface roughness and MRR values were used to generate the parametric non-linear regression equations based on LSM with help of data mining technique.

Results and Discussion

Analysis of variance

The “F” and “P” values are measured statistical test values of machining parameters, whereas F-critical is obtained from statistical data table. When the F-statistical value measured is greater than the F-critical value then the parameter is said to be significant on the response with a confidence level of P-statistics.

Tables 3 and 5 present the result of ANOVA of surface roughness and MRR obtained with carbide inserts at 95% ($P<0.05$) confidence level. The feed values while machining with carbide inserts are highly significant followed by speeds, while the interaction is less significant.

Tables 4 and 6 shows the result of ANOVA of surface roughness and MRR generated with HSS tools at 95% confidence level. The speed values while machining with HSS tools are highly significant followed by feeds, while the interaction is significant.

Tables 3 and 4 presents the result of ANOVA of surface roughness generated with carbide and HSS tools

Table 3—Two-way ANOVA for carbide inserts: roughness versus speed, feed including interactions

Source	DF	SS	MS	F	P	$F_{Critical}$	% Contribution	Remarks
A	2	0.018	0.009	8.4	0.003	3.55	1.25	Less significant
B	2	1.416	0.708	675	0.000	3.55	98.5	Highly significant
A*B	4	0.002	0.001	0.54	0.712	2.93	0.13	Not significant
Error	18	0.019	0.001					
Total	26	1.455	0.719				100	

S = 0.03238 R-Sq = 98.70% R-Sq(adj) = 98.13%

Table 4—Two-way ANOVA for HSS: roughness versus speed, feed including interactions

Source	DF	SS	MS	F	P	$F_{Critical}$	% Contribution	Remarks
A	2	1.893	0.946	547	0.00	3.55	75.6	Highly Significant
B	2	0.578	0.289	167	0.00	3.55	23.1	Significant
A*B	4	0.059	0.015	8.5	0.00	2.93	1.19	Less significant
Error	18	0.031	0.002					
Total	26	2.56	1.252				100	

S = 0.04159 R-Sq = 98.78% R-Sq(adj) = 98.24%

Table 5—Two-way ANOVA for carbide inserts: MRR versus speed, feed including interactions

Source	DF	SS	MS	F	P	$F_{Critical}$	% Contribution	Remarks
A	2	345385938	172692969	6633796	0.00	3.55	81.7	Highly Significant
B	2	73735563	36867781	1416232	0.00	3.55	17.5	Highly Significant
A*B	4	7170666	1792667	68863	0.00	2.93	0.85	Significant
Error	18	469	26					
Total	26	426292636	211353443				100	

S = 5.102 R-Sq = 100.00% R-Sq(adj) = 100.00%

Table 6—Two-way ANOVA for HSS: MRR versus speed, feed including interactions

Source	DF	SS	MS	F	P	$F_{Critical}$	% Contribution	Remarks
A	2	331021594	165510797	6320606	0.00	3.55	81.7	Highly Significant
B	2	70670039	35335020	1349390	0.00	3.55	17.5	Highly Significant
A*B	4	6871609	1717902	62604	0.00	2.93	0.85	Significant
Error	18	471	26					
Total	26	408563713	202563745				100	

S = 5.117 R-Sq = 100.00% R-Sq(adj) = 100.00%

respectively. The tables indicate that the spindle speeds and feeds are significant, whereas interactions are not significant.

Tables 5 and 6 presents the result of ANOVA analysis of MRR generated with carbide and HSS tools respectively. The tables indicate that the spindle speeds and feeds are highly significant, whereas interactions are significant.

Regression analysis

Non-Linear equations are generated and used to predict the regression constants and exponents. The regression equation of surface roughness and MRR are generated as shown in Tables 7-10.

Tables 7-10 present the roughness regression model and MRR regression models respectively and indicates that the model depicts a significance more than 95% confidence level (P<0.05).

Tables 7 and 9 predict the regression to be 95.9% and 85.0% which indicates the better performance fit of carbide insert machining rather than HSS tools in generating surface roughness.

Tables 8 and 10 predict the regression to be 98.3% which indicates the equal performance fit of carbide insert machining rather than HSS tools in generating MRR.

Based on the regression fitness values as shown in Tables 7-10 indicate that the carbide inserts are well suitable for higher surface finish and MRR

generation, while machining on brass material, rather than HSS tools.

Confirmation experiments

Table 11 shows the determined % error in between the experimental and the regression equation values. The results show the calculated error maximum 5.93% and minimum 1.51% while machining with carbide and calculated error maximum 6.17% and minimum 0% while machining with HSS.

Discussion on graphs

The minimum surface roughness values with carbide and HSS tools were observed as 1.42 μm and 2.37 μm, while the maximum MRR values with carbide and HSS tools were observed as 18278.3 mm^3/min and 18671.2 mm^3/min.

Figures 4 and 6 interpret main effects plot and interaction plots based on SN ratios of surface roughness while machining with carbide and HSS respectively. The surface roughness which is an important property preferred by customers, has to be smaller and based on the smaller is better characteristic, the figures propose that

Table 7—Regression analysis for roughness with carbide inserts

Source	DF	SS	MS	*F*	*P*	$F_{Critical}$	% Contribution	Remarks
Regression	2	1.39	0.69	280	0.00	3.44	99.5	Highly significant
Error	24	0.06	0.003					

S = 0.0498 R-Sq = 95.9% R-Sq(adj) = 95.6% & R_a=2.6+7.3*10^{-5}*A-20.6*B-5.2*10^{-8}*A^2+88.9*B^2

Table 8—Regression analysis for MRR with carbide inserts

Source	DF	SS	MS	*F*	*P*	$F_{Critical}$	% Contribution	Remarks
Regression	2	419121501	209560750	701	0.00	3.44	99.86	Highly significant
Error	24	7171135	298797					

S = 546.6 R-Sq = 98.3% R-Sq(adj) = 98.2% & MRR=0.04-3.7*10^{-5}*A-0.37*B+8.82*10^{-9}*A^2+0.8*B^2

Table 9—Regression analysis for roughness with HSS tools

Source	DF	SS	MS	*F*	*P*	$F_{Critical}$	% Contribution	Remarks
Regression	2	2.18	1.09	68.0	0.00	3.44	98.19	Highly significant
Error	24	0.38	0.02					

S = 0.126 R-Sq =85.0% R-Sq(adj) = 83.8% & R_a= 2.6-0.0042*A+21.03*B+1.82*10^{-6}*A^2-44.4*B^2

Table 10—Regression analysis for MRR with HSS tools

Source	DF	SS	MS	*F*	*P*	$F_{Critical}$	% Contribution	Remarks
Regression	2	401691633	200845817	701.4	0.00	3.44	99.86	Highly significant
Error	24	6872080	286337					

S = 535.1 R-Sq = 98.3% R-Sq(adj) = 98.2% & MRR=1.9+0.001*A+14.9*B-2.2*10^{-7}*A^2 -30.9*B^2

in order to achieve the best surface finish, the highest spindle speed (1250rpm) and lowest value of feed (0.14mm/rev) should be selected (**A3B1**). The literature mentions that the higher surface finish can be obtained at higher speeds and lower feeds, which is proved by these observations. Hence, the optimum combination of spindle speed and feed gives a roughness of 1.42 μm and 2.37 μm, for carbide and HSS tools respectively.

Table 11—Confirmation tests and foreseen results of surface roughness generated

Exp. No.	Feed (mm/rev)	Spindle speed (rpm)	Experimental roughness (microns)	Predicted (microns)	Error %
With carbide inserts					
4	0.17	560	1.67	1.69	1.51
6	0.17	1250	1.58	1.68	5.93
With HSS tools					
1	0.14	560	2.93	3.11	6.17
8	0.17	1250	2.62	2.62	0.00

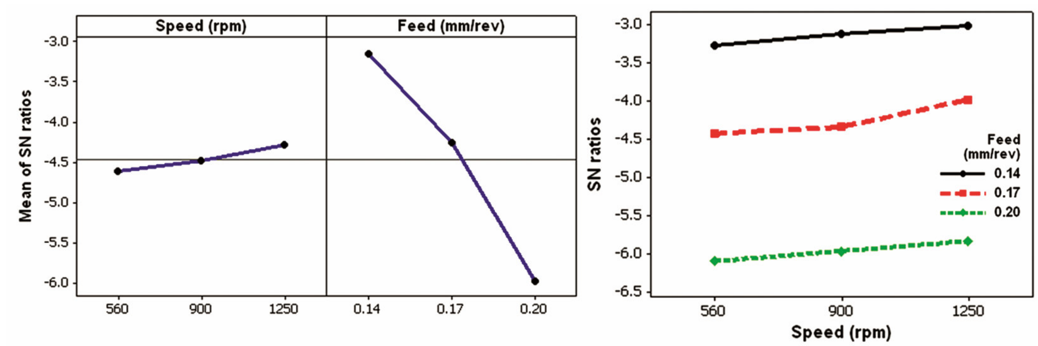

Fig. 4—Main effects and interactions of parameters on surface roughness S/N ratio while machining with carbide

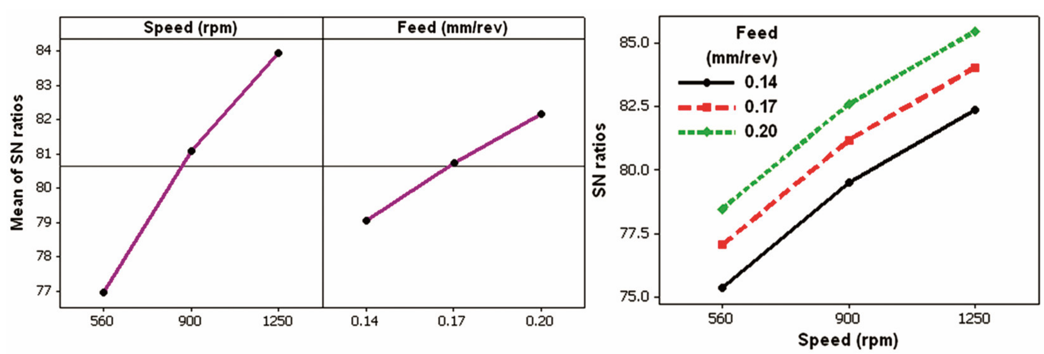

Fig. 5—Main effects and interactions of parameters on MRR S/N ratio while machining with carbide

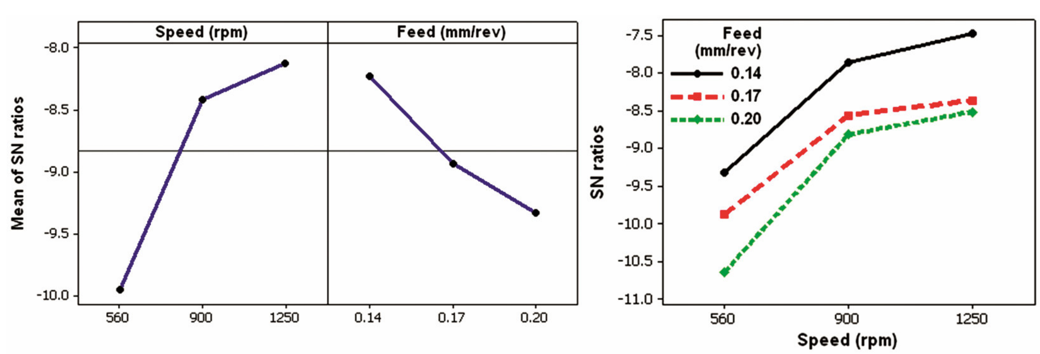

Fig. 6—Main effects and interactions of parameters on surface roughness S/N ratio while machining with HSS

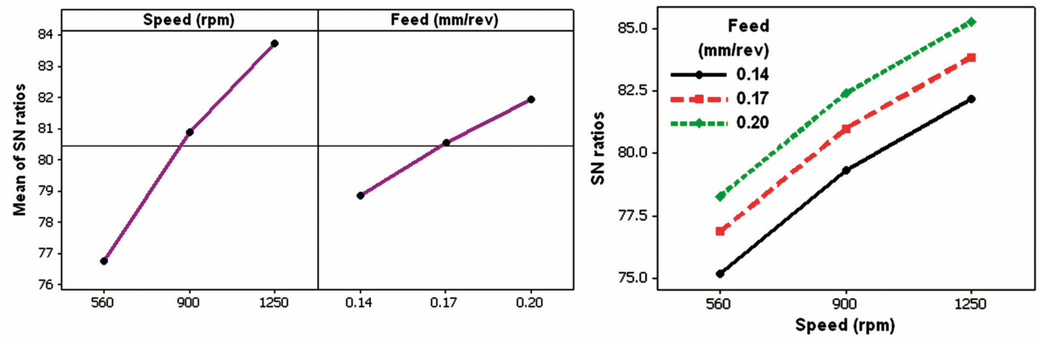

Fig. 7—Main effects and interactions of parameters on MRR S/N ratio while machining with HSS

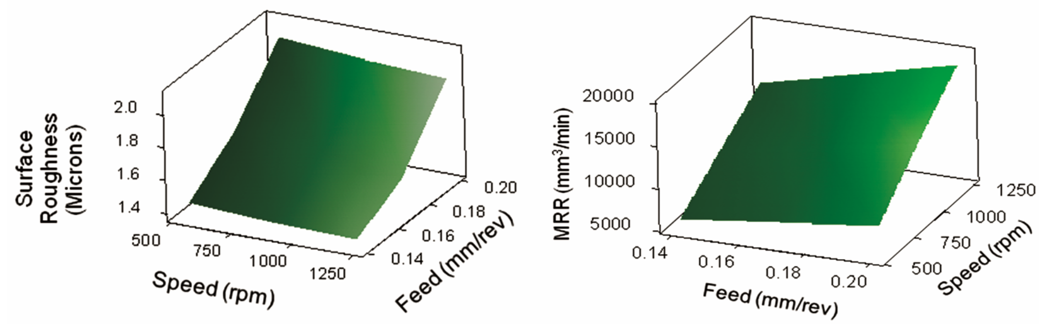

Fig. 8—Surface plots of parameters on surface roughness and MRR while machining with carbide inserts

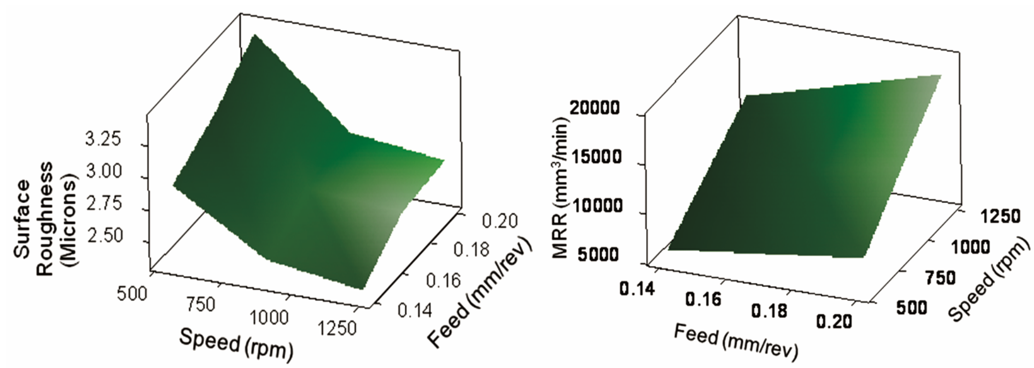

Fig. 9—Surface plots of parameters on surface roughness and MRR while machining with HSS tools

Figures 5 and 7 interpret main effects plot and interaction plots based on S/N ratios of MRR while machining with carbide and HSS, respectively. MRR which is an important property for most of the producer has to be larger, for minimal time of production with bulk quantity. Based on the larger is better characteristic; the graphs propose that in order to achieve the best metal removal rate, the highest spindle speed (1250 rpm) and highest value of feed (0.20 mm/rev) should be selected (A3B3). The literature mentions that the higher MRR can be obtained at higher speeds and higher feeds, which is proved by these observations. Hence, the optimum combination of spindle speed and feed gives a MRR of 18278.7 mm^3/min and 18671.2 mm^3/min for carbide and HSS, respectively.

Figures 8 and 9 interpret relation between responses and factors while machining with carbide and HSS, respectively. Observing Fig. 8, the surface roughness is inversely proportional to spindle speed, while observing Fig. 9, the MRR is directly proportional to spindle speeds and feeds for carbide and HSS, respectively.

Conclusions

The investigations of this study indicate that most significant parameters on surface roughness are speed and feed, while the interaction was less significant.

While on MRR the spindle speed, feed and the interaction were very significant.

The study indicates combination of high speed (A3) and low feed (B1) generates optimal surface roughness of 1.42 µm and 2.37 µm while machining with carbide and HSS tools, respectively. The combination of high speed (A3) and high feed (B3) generates optimal MRR of 18278.7 mm^3/min and 18671.2 mm^3/min while machining with carbide and HSS tools, respectively.

Empirical model for surface roughness developed in this paper based on full factorial DOE with three levels of speeds and feeds was very compromising and correlating. It can be used to estimate the values of surface roughness and MRR at certain turning parameters like speeds and feeds or to aid the selection of optimal working parameters, when given a required surface roughness and MRR.

Observing the regression fitness values, it can be concluded that for achieving higher surface finish, choosing the best tool material is helpful and in Tables 7 and 9 the carbide inserts are better than HSS tools while machining. Observing Tables 8 and 10, for MRR the tool variations may not be of much importance, as it depends on the machining factors only but not the tool material, when the tool wear is not considered.

References

1 Singh Dilbag & Venkateswara Rao P, *Int J Adv Manuf Technol*, 32(2007) 1115-1124.
2 Tamizharasan T, Selvaraj T & Noorul Haq A, *Int J Adv Manuf Technol*, 28 (2006) 671-679.
3 Mahdavinejad R A & Bidgoli Sharifi H, *J Achieve Mater Manuf Eng*, 37 (2) (2009) 571-577.
4 Khrais Samir, Hassan Adel Mahammod & Gazawi Amro, *World Acad Sci, Eng Technol*, 59 (2011) 2137-2141.
5 Motorcu Ali Riza, *J Mech Eng*, 56 (6) (2010) 391-401.
6 Yang W H & Tarng Y S, *J Mater Process Technol*, 84 (1998) 122-129.
7 Vijian P, Arunachalam V P & Charles S, *Indian J Eng Mater Sci*, 14, (2007) 7-11.
8 Feng C X J & Wang X, *Int J Adv Manuf Technol*, 20 (2002) 348-356.
9 Çalışkan H, Kurbanoğlu C, Panjan P, Kramar D, *Int J Adv Manuf Technol*, 66 (2013) 883-893.
10 Ginta Turnad L, Nurul Amin A K M, Mohd Radzi H C D & Lajis Mohd Amri, *Eur J Sci Res*, 28 (4) (2009) 542-551.
11 Diniz A E & Micaroni R, *Int J Mach Tools Manuf*, 42(8) (2002) 899-904.
12 Çolak O, Kurbanoglu C & Kayacan M C, *Mater Des*, 28(2) (2007) 657-666.
13 Bhushan Rajesh Kumar, Kumar Sudhir & Das S, *Int J Adv Manuf Techno*l, 50 (2010) 459-469.
14 Anandakrishnan V & Mahamani A, *Int J Adv Manuf Technol*, 55 (2011) 65-73.
15 Zhou Li, Huang S T, Wang D & Yu X L, *Int J Adv Manuf Technol*, 52 (2011) 619-626.
16 Manna A & Bhattacharyya B, *Int J Adv Manuf Technol*, 23 (2004) 658-665z.

View publication stats