

Effect of Machining Parameters on Surface Roughness for Titanium Alloy

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Abstract—The current study presents an approach to the determination of the optimal cutting parameters to create high surface finish in the face milling of Titanium alloy. The surface roughness seriously varies with the change of machining parameter. This requires proper selection of the process parameter. The machining parameters taken for the study are cutting speed (rpm), feed rate (mm/tooth), depth of cut (mm) and coolant condition. Out of these four parameters the coolant used is a categorical parameter rest has numeric value. In present study the fractional factorial design technique is used to optimize the process parameter in face milling of Titanium alloy steel (Ti-6Al-4V) with PVD coated Cemented carbide face mill inserts. Two levels of 2^{4-1} fractional factorial designs of eight runs were selected for conducting the experiments. The mathematical models were developed from the data generated. The significance of coefficients and adequacy of developed models were tested by 't'-test and 'F'-test respectively. Out of four variables, feed contribute the highest effect on surface roughness, followed by speed, interaction effect of feed and speed, main effect of depth of cut, coolant, interaction effect of feed and coolant, interaction effect of feed and depth of cut, and finally on interaction effect of speed and depth of cut. The established equations clearly show that surface roughness increased with increasing the feed and depth of cut but decreased with increasing the cutting speed under wet condition.

Index Terms—Optimization, Titanium alloy (Ti-6Al-4V), Machining parameter, Face Milling, Fractional factorial design technique, PVD coated cemented carbide tool.

I. INTRODUCTION

Milling is the process for removing excess material from a work piece with a rotating cutting tool. Milling process is used for producing flat, contoured or helical surface, for cutting threads and toothed gears and for making helical grooves [2]. A face mill consists of a cutter body (with the appropriate machine taper) that is designed to hold multiple disposable carbide or ceramic tips or inserts, often golden in colour [6]. The tips are not designed to be re-sharpened and are selected from a range of types that may be determined by various criteria, some of which may be: tip shape, cutting action required, and material being cut. When the tips are blunt, they may be removed, rotated (indexed) and replaced to present a fresh, sharp face to the work piece. This increases the life of the tip and thus its economical cutting life [3]. In machining process, most of the mechanical energy used to remove material becomes heat. This heat generates high temperature in the cutting region. The higher the cutting speed, the faster the heat generation and higher temperature resulted. The new challenge in machining is to use high cutting speed in order to increase the productivity with high surface finish. This is the main reason for rapid tool wear and

surface roughness [1]. Another Conventional method used to reduce this surface roughness is by using cutting fluid. This cutting fluid acts as lubricant and coolant as well during the machining process. Usage of cutting fluid can increase the cutting speed up to 30% without affecting the surface roughness and tool life [1]. However the usage of cutting fluid has negative effect to the economy, environment and health [1]. Total elimination of cutting fluid seems to be not promising due the unsatisfactory tool life and poor surface finish [5]. This rapid tool wears not only gives higher surface roughness value, but also higher micro hardness and major microstructure alteration [6]. So it is better to optimize the variable parameters (coolant flow rate, cutting speed, feed rate and depth of cut) for surface finish to increase the productivity at good surface finish. For optimization factorial design technique is used In full factorial design the number of trials increases with increase in number or levels of the factors. Increased number of that is mainly due to higher order interactions which in most cases donot affect the response significantly [7]. The number of trials in a factorial experiment is considerably greater than the coefficients of a linear model to be determined. In other words a factorial experiment has a great surplus number of trials as a result increased cost of experimentation and wastage of time [8]. Obviously, it is desirable to reduce the number of trials and cost of running experiment. Often a large proportion of experimental effort is wasted in evaluating unimportant interactions and in determining the experimental error with unnecessary degree of precision [9]. Hence fractional factorial design enables the size of an experiment to be reduced to a fraction that of full factorial experiment, which still provide all the important information.

II. EXPERIMENTAL SETUP

Work piece

Titanium alloy (Ti-6Al-4V) is an alloy of high strength to the weight ratio. 16mm thick plate was used in this research work. The chemical composition of the material was determined with the spectrometer and tabulated in Table 1 also the Mechanical properties of work piece has been shown in Table 2. The work piece used for present study in the rectangular form with the dimensions as 97 X 75 X 16 mm³.

Table 1: Composition (Wt. %) of Work piece (Ti-6Al-4V)

Serial No.	Content	Weight %
1.	O	0.020
2.	H	0.005
3.	N	0.01

4.	C	0.05
5.	Fe	0.09
6.	V	4.40
7.	Al	6.15
8.	Ti	Balance

Table 2: Mechanical Properties of Work piece

Serial No.	Mechanical Property	Value
1.	Tensile strength (M Pa)	993
2.	Yield Strength (M Pa)	830
3.	Elongation	14
4.	Modulus of Elasticity (G Pa)	114
5.	Hardness (HRC)	36

III. CUTTING TOOL

PVD coated cemented carbide Tool was used in this experiment. The composition (Weight %), Physical & mechanical properties and Geometry of this Tool are shown in Tables 3, 4 and 5 respectively.

Table 3 Composition

Serial No.	Content	Weight %
1.	WC	87
2.	Co	13

Table 4 Physical & Mechanical Properties of cutting tool

Serial No.	Properties	Value
1.	Particle size	0.8µm
2.	Hardness	1470 Hv ₁₀
3.	Density	14.5 g/cm ³
4.	Modulus of Elasticity	580 G Pa
5.	Coefficient of thermal Expansion	5.5 x 10 ⁻⁶ /K

Cutting Fluid

Water immiscible cutting fluid was used during this experiment. However, this coolant is miscible with solvent or mineral oil. Desired coolant flow rate was achieved by regulating the supplied air pressure and the opening of

nozzle. Physical properties of cutting fluid are shown in table 5.

Table 5 Geometry of Cutting Tool

Serial No.	Angle	Value
1.	Cutting Rake	-4°-0°
2.	Axial Rake	+6°
3.	Radial Rake	-4°-0°

Table 6: Physical Properties of cutting fluid

Serial No.	Properties	Value
1	Specific Gravity	0.8754g/cm ³
2	Viscosity	22.2 mm ² /s
3	Flash point	178°C
4	Pour point	-30°C

IV. DESIGN OF EXPERIMENT

All the machining was carried out on 3-axis CNC milling machine. Type of machining done in this experiment is Face milling. Design of experiment was multilevel factorial design which is summarised below in table 6

Table 7: Design of Experiment

Name	Units	Type	Min. (1)	Max. (2)
Speed	m/min	Numeric	120	150
Feed	mm/tooth	Numeric	0.1	0.15
Depth of cut	mm	Numeric	2.0	2.50
Coolant	ml/hr	Categorical	on	off

The design matrix developed to conduct the eight trials runs of 2⁴ or 2³ fractional factorial design as given in Table 7

Table 8: Design matrix

S. no.	S	F	D	C
1	1	1	1	1
2	2	1	1	2
3	1	2	1	2
4	2	2	1	1
5	1	1	2	2
6	2	1	2	1
7	1	2	2	1
8	2	2	2	2

The models of the type $Y = f(S, F, D, C)$ could be developed to facilitate the prediction of a response within the specified dimensional tolerance for a particular set of direct process parameters. Assuming a linear relationship in the first instance and taking into account all the possible two factor

interaction and confounded interactions, it could be written as:

$$Y = b_0 + b_1S + b_2F + b_3D + b_4C + b_{12}SF + b_{13}SD + b_{14}SC + b_{23}FD + b_{24}FC + b_{34}DC \quad [\text{Eqn. 1}]$$

The regression coefficients of the selected model were calculated using Equation 3.2. This is based on the method of least squares.

$$b_j = \frac{\sum_{i=1}^N (X_{ji} Y_i)}{N}, \quad j = 0, 1, \dots, k \quad [\text{Eqn. 2}]$$

Where,

X_{ji} = Value of a factor or interaction in coded form

Y_i = Average value of response parameter

N = No. of observation

K = Number of coefficients of the model

Coefficients of model

V. CHECKING THE ADEQUACY OF THE DEVELOPED MODEL

The adequacy of the model was determined by the analysis of variance technique. The regression coefficients were determined by the method of least square, from which the 'F'- ratio for the polynomial was found. The variance of the response and the adequacies were calculated. The 'F'- ratio of the model were compared with the corresponding 'F'- ratio from the standard table and it was found that the model is adequate within 95% level of confidence, thus justifying the use of assumed polynomials. After calculating the coefficients of model, it must be tested for its fitness. Thus adequacy of the model was tested using analysis of variance technique. For this variance of optimization parameter (S^2y) was determined. It can be calculated with Equation 3 as follows

Further, the variance of adequacy, also called as residual variance was determined by using following Equation 4

$$S^2_{ad} = \frac{\sum_{i=1}^N (\Delta M^2)}{3} \quad [\text{Eqn. 4}]$$

Where,

S^2_{ad} = variance of adequacy

y_m = observed response

y_p = estimated / predicted value of response

f = $N - (K + 1)$ (Degree of freedom)

\sum = residual sum of square

K = number of independently controllable variables.

The ratio of variance of adequacy to the variance of optimization parameter gives Fisher ratio:-

$$\text{'F' ratio} = S^2_{ad} / S^2_y \quad [\text{Eqn. 5}]$$

The F-value obtained and denoted as (F_m) was compared with the table value as (F_t). It was found that the model was adequate at 95% level of significance thus justifying the use of the assumed polynomial.

VI. CHECKING THE SIGNIFICANCE OF COEFFICIENTS OF MODEL

The statistical significance of the coefficients can be tested by applying 't' test. The level of significance of a particular

S. no.	Coefficient	Due to
1	b_0	Combined effect of all parameter
2	b_1	Cutting speed
3	b_2	Feed rate
4	b_3	Depth of cut
5	b_4	Coolant effect
6	b_{12}	Interaction of S and F
7	b_{13}	Interaction of S and D
8	b_{14}	Interaction of S and C
9	b_{23}	Interaction of F and D
10	b_{24}	Interaction of F and C
12	b_{34}	Interaction of D and C

$$S^2_y = 2 \frac{\sum_{i=1}^N (\Delta M^2)}{N} \quad [\text{Eqn. 3}]$$

Where,

$$\Delta Y^2 = (Y_{iq} - Y_m)^2$$

Y_m = Arithmetical mean of repetitions

Y_{iq} = Value of response in a repetition trial

N = Number of observations

i = No. of trials

q = No. of repetition

parameter can be assessed by the magnitude of the 't' value associated with it. Higher the value of 't', the more significant it becomes. 't' value for the given coefficients of the models were calculated using Equation 3.7 as follows.

$$t = |b_j| / S_{bj} \quad [\text{Eqn. 6}]$$

where,

$|b_j|$ = absolute value of coefficients

S_{bj} = standard deviation of coefficients

$$S_{bj} = S^2_y / N$$

Calculated 't' value were compared with the t-table value and statistically insignificant terms of the models were dropped. The value of 't' from the standard table for eight degree of freedom and 95% confidence level is 2.306. Coefficients having calculated 't' value less than or equal to 't' value from the standard table for eight degree of freedom and 95% confidence level, are the members of reference distribution i.e. due to the and hence, they cannot be significant.

Final Modal

The final model could be obtained by dropping statistically in-significant terms from the developed models. Only

significant decision variables are to be considered in the final model.

VII. OBSERVATION

According to design matrix, experiment has been done and three set of surface roughness (R) has been recorded as shown in table 8.

Table 9. Observational Table for Surface Roughness

Trial no.	Speed m/min	Feed mm/tooth	D.O.C mm	Coolant	(Set-1) R ₁ micron	(Set-2) R ₂ micron	(Set-3) R ₃ micron
1	150	0.15	2.5	On	0.28	0.29	0.31
2	120	0.15	2.5	Off	0.32	0.33	0.32
3	150	0.10	2.5	Off	0.42	0.43	0.44
4	120	0.10	2.5	On	0.41	0.41	0.40
5	150	0.15	2.0	Off	0.36	0.38	0.39
6	120	0.15	2.0	On	0.40	0.42	0.41
7	150	0.10	2.0	On	0.44	0.46	0.44
8	120	0.10	2.0	Off	0.52	0.50	0.49

The surface roughness of machined specimen has measured at Metrology lab of BGIET, SANGRUR, by piezoelectric type instrument.

Development of Mathematical Model

Coefficients of models were calculated using Equation 2 and presented in Table 9

Table 10: Coefficients of metal removal rate

Coefficient	Due to	b _i
b ₀	Combined effect of all parameters (main effect)	0.39980
b ₁	Speed	-0.01212
b ₂	Feed	-0.04862
b ₃	Depth of cut	-0.03612
b ₄	Coolant	-0.00962
b ₁₂	Interaction of Speed and Feed	-0.00362
b ₁₃	Interaction of Speed and Depth of cut	0.01037
b ₁₄	Interaction of Speed and Coolant	0.16062
b ₂₃	Interaction of Feed and Depth of cut	-0.00560
b ₂₄	Interaction of Feed and Coolant	-0.00460
b ₃₄	Interaction of Depth of cut and Coolant	-0.04560

Inserting the values of coefficients in the Equation 1, the model for Surface Roughness can be obtained as:

$$R_a = 0.3998 - 0.01212S - 0.04862F - 0.03612D - 0.00962C - 0.003625SF + 0.010375SD + 0.160625SC - 0.00560FD - 0.0046FC - 0.04560DC \text{ [Eqn. 7]}$$

Variance of optimization (S²y) for Surface Roughness is obtained by putting the values of Surface Roughness from two set of reading in Equations 3. Table 10 shows the variance of optimization for surface Roughness.

Table 11: Variance of optimization (S²y) for Surface Roughness

Surface Roughness R (micron)					S ² y
R ₁	R ₂	R _m	ΔR	ΔR ²	
0.28	0.31	0.294	0.03	0.0009	
0.32	0.32	0.324	0.00	0.0000	
0.42	0.44	0.430	0.02	0.0004	
0.41	0.40	0.407	-0.01	0.0001	
0.36	0.39	0.377	0.03	0.0009	
0.40	0.41	0.410	0.01	0.0001	

0.44	0.44	0.450	0.00	0.0000	
0.52	0.49	0.507	-0.03	0.0009	
				0.0033	0.000825

Using the Equation 6, 't' – values were calculated and are shown in Table 5.4. These values were compared with the 't'–values taken from standard table. The value of 't' from standard table at (8,0.05) is 2.306, hence statistically in significant terms i.e. having values less than 2.306 were dropped.

't'-VALUES FOR THE COEFFICIENTS OF METAL REMOVAL RATE

Table 12: 't' –values for the Surface Roughness

Coefficient	Due to	$ b_t $	't' –value	Decision
b ₀	Combined effect of all parameters (main effect)	0.3998	39.36	Significant
b ₁	Speed	0.0121	1.192	Insignificant
b ₂	Feed	0.0486	4.788	Significant
b ₃	Depth of cut	0.0361	3.557	Significant
b ₄	Coolant	0.0096	0.9458	Insignificant
b ₁₂	Interaction of Speed and Feed	0.0036	0.354	Insignificant
b ₁₃	Interaction of Speed and Depth of cut	0.0103	1.015	Insignificant
b ₁₄	Interaction of Speed and Coolant	0.1606	15.822	Significant
b ₂₃	Interaction of Feed and Depth of cut	0.0056	0.5517	Insignificant
b ₂₄	Interaction of Feed and Coolant	0.0046	0.4532	Insignificant
b ₃₄	Interaction of Depth of cut and Coolant	0.0456	4.4926	Significant

The Table 12 shows that coefficients b₄, b₁₄ and b₂₃ are insignificant, so these coefficients are to be dropped from model. After dropping these insignificant coefficients, the Equation 8 shows the final model.

$$R_a = 0.3998 - 0.048F - 0.036D + 0.1606SC - 0.046DC \text{ [Eqn. 8]}$$

VIII. VARIANCE OF ADEQUACY (S² ad) FOR SURFACE ROUGHNESS

Variance of adequacy value for metal removal rate, obtained by inserting the estimated and observed values of metal removal rate in Equation 4 are as shown in Table 12.

Table 13: Variance of adequacy (S² ad) for Surface Roughness

Surface Roughness, (micron)				S ² ad
Estimated values	Observed values	ΔR	ΔR ²	
0.35	0.294	0.056	0.00314	
0.36	0.324	0.036	0.00130	
0.39	0.430	-0.040	0.00160	
0.37	0.407	-0.037	0.00137	
0.39	0.377	0.013	0.00017	
0.37	0.410	-0.040	0.00160	
0.41	0.450	-0.040	0.00160	
0.43	0.507	0.077	0.00593	0.00557

IX. ANALYSIS OF VARIANCE FOR SURFACE ROUGHNESS (R)

'F'-values, thus, obtained and denoted as F_m were compared from the standard 'F' value (F_t) obtained from table of at (3,8, 0.05). As F_m < F_t, it was found that the model was adequate at 95% level of significant thus justifying the use of assumed polynomial.

Table 14: Analysis of Variance for Surface Roughness

Degree of freedom		Variance of Adequacy	Variance of response	'F'-ratio model (F _m)	'F'-ratio table (F _t)	Adequacy of model
F	N	S^2_{ad}	S^2_y	$F_m = \frac{S^2_{ad}}{S^2_y}$	At 3,8,0.05	Whether F _m < F _t
3	8	0.00557	0.000825	6.75	4.12	Yes

X. RESULT AND DISCUSSION

The proposed models for the prediction of Surface roughness after dropping the statistically insignificant terms, in coded form as given below:-

$$R_a = 0.3998 - 0.0486F - 0.0361D + 0.1606SC - 0.046DC$$

The hypothesis adopted for identifying the parameters, which were mainly and predominantly responsible for the interaction effect in a confounded pattern was to first drop those interactions that were due to parameter having insignificant effects and if there were still two or more interactions left in the confounded pattern then the interaction due to parameter which the most predominant effect was selected. The mathematical models furnished above can be used to predict the surface roughness by substituting the values of respective factors in coded form.

INFLUENCE OF CUTTING SPEED (rpm) ON SURFACE ROUGHNESS

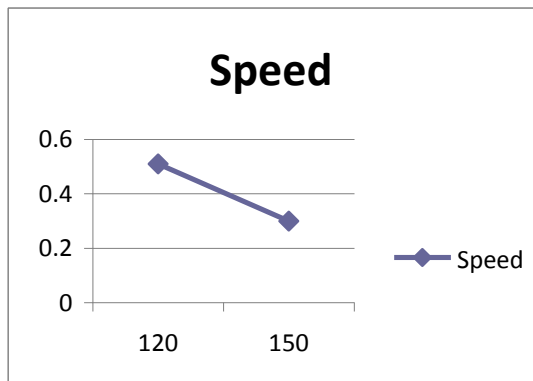


Fig.1: Plot between cutting speed & surface roughness

The relationship between the cutting speed and surface roughness for a given model of surface roughness has been shown in Fig.1. It could be concluded from this figure that with increase in cutting speed from 120 m/min to 150 m/min, there is decrease in surface roughness from 0.51 micron to 0.29 micron. Because as cutting speed increases the temperature also increases, which softens the material to enhance the cutting performance leading to reduced surface roughness also the decreasing built up edge (BUE) formation tendency with increasing cutting speed which leads to decreasing surface roughness.

XI. INFLUENCE OF FEED (MM/TOOTH) ON SURFACE ROUGHNESS

The relationship between the feed and surface roughness for a given model of surface roughness has been shown in Fig. 2. It could be concluded from this figure that with increase in feed from 0.1 mm/tooth to 0.15 mm/tooth, there is increase in surface roughness from 0.29 microns to 0.51 microns. Because higher feed rate tool traverses the work piece too speedily resulting in deteriorated surface quality and also high feed increase the chatter, which leads to higher surface roughness.

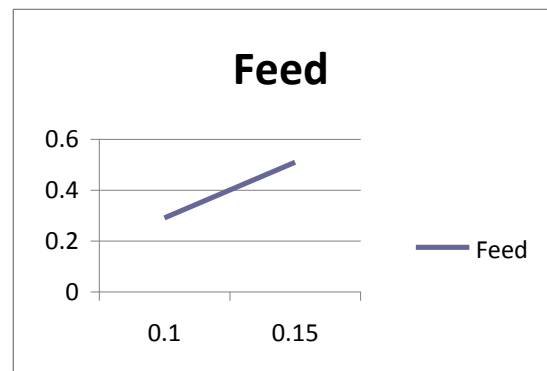


Fig.2: Plot between feed & surface roughness
INFLUENCE OF DEPTH OF CUT (mm) ON SURFACE ROUGHNESS

The relationship between the depth of cut and surface roughness for a given model of surface roughness has been shown in Fig.3. It could be concluded from this figure that with increase in depth of cut from 2.00 mm to 2.5 mm, there is increase in surface roughness from 0.29 microns to 0.51 microns. Because as the depth of cut increases the cutting forces also increases resulting in deteriorated surface quality.

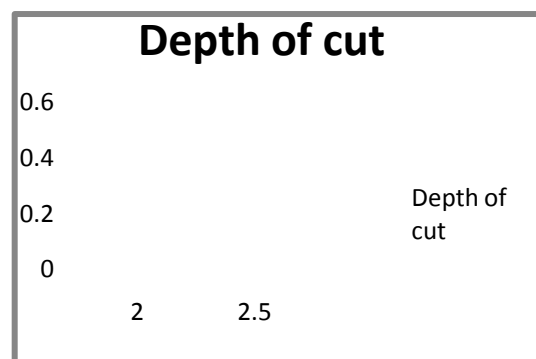


Fig.3: Plot between depth of cut & surface roughness

INFLUENCE OF COOLANT (on and off) ON SURFACE ROUGHNESS

The relationship between the level of coolant and surface roughness for a given model of surface roughness has been shown in Fig.4. It is clear from the plot that the value of surface roughness is less when coolant is on as compare to the condition of coolant off. From figure it is clear surface roughness decrease from 0.51 micron to 0.29 micron when coolant is on. Because coolant decreases the friction between tool and work piece during cutting thus improve the surface finish.

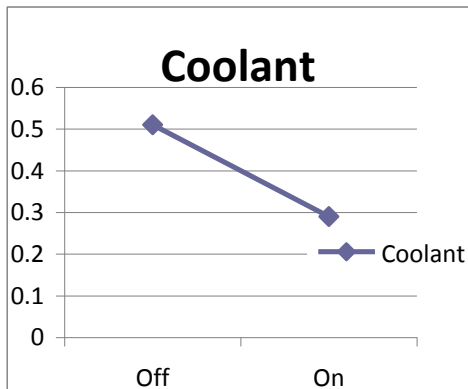


Fig.4: Plot between coolant levels & surface roughness

INFLUENCE OF CUTTING SPEED (rpm) AND FEED (mm/tooth) ON SURFACE ROUGHNESS

Influence of cutting speed and feed on the surface roughness is shown in Fig.6.5. The plot clearly explains that at constant speed, the surface roughness increases as the feed rate increases because higher feed rate tool traverses the work piece too speedily resulting in deteriorated surface quality and also high feed increase the chatter, which leads to higher surface roughness. Also, at constant feed rate, the surface roughness decreases as the cutting speed increases resulting in better surface quality.

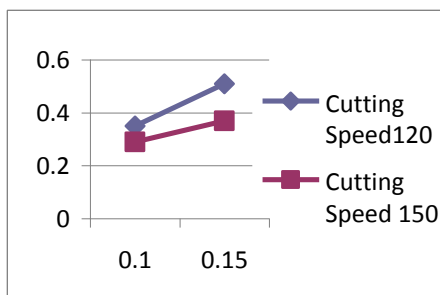


Fig.5: Interaction plot between cutting speed & feed for surface roughness

INFLUENCE OF DEPTH OF CUT (mm) AND COOLANT (on and off) ON SURFACE ROUGHNESS

Influence of depth of cut and coolant on the surface roughness is shown in Fig. 6. The plot clearly explains that at constant depth of cut, the surface roughness is higher when the coolant is off as compared to when coolant is on because coolant decrease the friction between tool and work piece during cutting thus improve the surface finish. Also, at constant level of coolant, the surface roughness increases as the depth of cut increases.

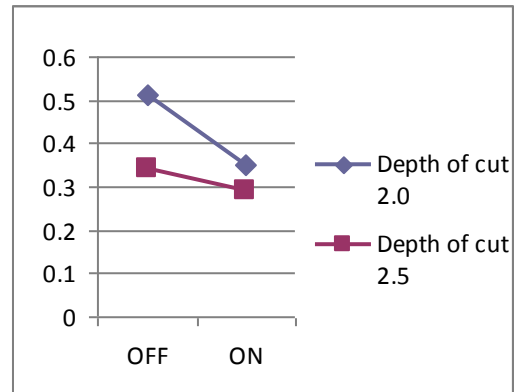


Fig. 6: Interaction plot between coolant condition & depth of cut for surface roughness

It is clear from all of the plot that minimum surface roughness is achieved at low level of feed , low level of depth of cut, higher level of cutting speed and level of coolant is on.

XII. CONCLUSION

Out of four variables, feed contribute the highest effect on surface roughness , followed by speed, interaction effect of feed and speed, main effect of depth of cut, coolant, interaction effect of feed and coolant, interaction effect of feed and depth of cut, and finally on interaction effect of speed and depth of cut.The established equations clearly show that surface roughness increased with increasing the feed and depth of cut but decreased with increasing the cutting speed under wet condition.The confirmation runs verify that the developed mathematical model for surface roughness shows excellent fit and provide predicted values of surface roughness that are close to the experimental values, with a 95 per cent confidence level.

REFERENCES

- [1] Kapil Kumar Chauhan & Dinesh Kumar Chauhan (2013) "Optimization of Machining Parameters of Titanium Alloy for Tool Life" in "Journal of Engineering, Computers & Applied Sciences (JEC&AS)" Volume 2, No.6, June 2013 (ISSN No: 2319-5606).
- [2] Dinesh Kumar Chauhan, Kapil Kumar Chauhan, Amit Morey, Preeti Singh (2014). "Optimization of Milling Process by the effects of Machining Parameters for high carbon alloy steel" in "Journal of Engineering, Computers & Applied Sciences (JEC&AS)" Volume 3, No.9, September 2014 (ISSN No: 2319-5606).pp.41-49
- [3] Benardos, P.G. & Vosniakos, G.C.(2002). Prediction of surface roughness in CNC face milling using neural networks and Taguchi's design of experiments,Robotics and Computer Integrated Manufacturing, Vol.18, pp.343-354.
- [4] Dweiri, F. & Al-Jarrah, M.(2003).Fuzzy surface roughness modeling of CNC down milling of Aluminic-79, Journal of Materials Processing Technology, Vol.133, pp.266-275.
- [5] Lo, ship-peng. (2003). An adaptive-network based fuzzy inference system for prediction of work piece surface roughness in end milling, Journal of Materials Processing Technology, Vol.142, pp.665-675.
- [6] Wang, Ming-Yung & Chang, Hung-yen.(2004).Experimental study of surface roughness in slot end milling AL2014-T6,

International Journal of Machine Tools & Manufacture,
Vol.44, pp.51-57.

AUTHOR'S PROFILE

- [7] Brezocnik, M. & Kovacic, M. (2004). Prediction of surface roughness with genetic programming, Journal of Materials Processing Technology, Vol. 157-158, pp. 28-36.
- [8] Oktem, Hasan. & Erzurumlu, Tuncay. (2005). Prediction of minimum surface roughness in end milling mold parts using neural network and genetic algorithm, Materials and design, Vol. 27, pp. 735-744.
- [9] Chang, Ching-Kao & Lu, H. S. (2005). Study on the prediction model of surface roughness for side milling operations, Int J AdvManufTechnol, Vol. 29, pp. 867-878.
- [10] Zhang, Julie Z. & Chen, Joseph C. (2006). Surface roughness optimization in an end-milling operation using the Taguchi design method, Journal of Materials Processing Technology, Vol. 184, pp. 233-239.
- [11] Iqbal, Asif & Dar, Naeem. (2007). Modeling the effects of cutting parameters in MQL-employed finish hard-milling process using D-optimal method, Journal of materials processing technology, Vol. 199, pp. 370-390.
- [12] Savas & Ozay, (2007). The optimization of the surface roughness in the process of tangential turn-milling using genetic algorithm Int J AdvManufTechnol, Vol. 37, pp. 335-340.
- [13] Yang, Yung-Kuang. & Chuang, Ming-Tsan. (2008). Optimization of dry machining parameters for high-purity graphite in end milling process via design of experiments methods, Journal of materials processing technology, Vol. 209, pp. 4395-4400.
- [14] Ho, Wen-Hsein. & Tsai, Jinn-Tsong. (2009). Adaptive network-based fuzzy inference system for prediction of surface roughness in end milling process using hybrid Taguchi-genetic learning algorithm, Expert Systems with Applications, Vol. 36, pp. 3216-3222.
- [15] Gopalswamy, Bala & Mandal, Biswanath. (2009) Optimization of machining parameters for hard machining: grey relational theory approach and ANOVA, Int J AdvManuf Technol, Vol. 45, pp. 1068-1086.
- [16] Gopalswamy, Bala & Mandal, Biswanath. (2009). Taguchi method and ANOVA: An approach for process parameters optimization of hard machining while machining hardened steel, Journal of Scientific & Industrial Research, Vol. 68, pp. 686-695.
- [17] Razfar, Reza. (2010). Optimum Surface roughness prediction in face milling by using neural network & harmony search algorithm, International Journal of Advanced Manufacturing Technology, Vol. 52, pp. 487-495.
- [18] Zain, Haron & Sharif. (2010). Prediction of surface roughness in the end milling machining using Artificial Neural Network, Expert system with application, Vol. 37, pp. 1755-1768.
- [19] Kadirgama, K. & Noor, M.M. (2010). End milling surface roughness optimization using Response ant colony optimization, Sensors, Vol. 10, pp. 2054-2063.



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