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Empirical Modeling of Surface Roughness and Metal Removal Rate in CNC Milling Operation

CHARNJEET SINGH
Mechanical Engg. Department
Chd. College of Engg & Tech.
Chandigarh, India

Dr. B.S. PABLA
Mechanical Engg. Department
NITTTR
Chandigarh, India

SUKHDEV S. BHOGAL
Mechanical Engg. Department
Chd. College of Engg & Tech.
Chandigarh, India

PARDEEP KUMAR
Mechanical Engg. Department
Chd. College of Engg & Tech.
Chandigarh, India

Abstract- **Surface finish and material removal rate are two important factors in the manufacturing organization which affect acceptability of the product which in turn reflects on the profitability of the organization. Ability of the production setup to produce the components with high material removal rate without sacrificing the surface requirements can play vital role in sustainability and profitability of the organization. In this paper, the effect of process parameters on metal removal rate and surface roughness has been investigated in milling of SAE52100 tool steel. Cutting speed, feed and depth of cut have been taken as input factors in three level full factorial orthogonal arrays used for experimentation. Mathematical models have been developed using response surface methodology to predict surface finish, and metal removal rate in term of machining parameters. Depth of cut and feed rate are found to be a dominant parameter for surface roughness; whereas feed rate mainly effects the metal removal rate. The results of mathematical models have been compared with the experimental and found to be in good agreement. The results of predicted model can be used in selection of process parameters to insure desired quality and improved productivity.**

Keywords: **CNC milling, SAE52100, RSM, metal removal rate, surface roughness**

I. INTRODUCTION

With the development of high speed cutting technology [1], the high speed machining practice has become more important now a day as it increase productivity. The scientists doing machinability experiments regard the high-speed and hard machining as one of the most important issues. As technology is advancing, productivity has increased and the more precise surfaces have been obtained due to the development of cutting tools that are resistant to high temperatures [2]. Face milling is a widely used machining operation to produce various components. The finished component depends not only on the dimensional accuracy but also on the surface finish[14].Hakanet. Al. [2] carried out experiment to find out insert numbers, material removal rate and machining time. Nowadays, the manufacturing industries specially are focusing their attention on dimensional accuracy and surface finish[3]. K.Krishnamurthy et. Al. [3] used Taugchi method to find the optimal cutting factors for surface roughness (Ra) and material removal rate (MRR) on TiB2 particles reinforcedaluminum (Al6063) metal matrix composites. E. Budaket.al.[4] used analytical method in optimization of the milling conditions for increased chatter free material removal rate in a variety of other applications.. H. R. Ghan[5,7]Conducted a study on the effect of milling and turning parameters on manufacturing processes of parts of Aluminium LM-26 alloy and to find out its mathematical model to achieve better surface finish and material removal rate, its validation by ANOVA.Mandeep Chahalet.al. [6] investigated that in milling surface roughness increases with increase of feed and depth of cut and MRR directly increases with increase in spindle speed,feed, depth of cut and step over on work piece (H-11) and solid carbide four fluted tool. Kantheti Venkata MuraliKrishnam Raju[8] develop an integrated study of surface roughness to model and optimize the cutting parameters when end milling of 6061 aluminum alloy with HSS and carbide tools under dry and wet conditions using Genetic algorithm(GA).Tongchao Ding et.al.[9] investigated the effects of cutting parameters on cutting forces and surface roughness in hard milling of AISI H13 steel with coated carbide tools. Based on Taguchi's method. Ahmad Hamdan et.al.[10] determined that the effect of feed rate is found to be more significant followed by the cutting speed and the depthof cut, while, the lubrication mode was found to be statistically insignificant on surface roughness and cutting force on stainless steel using coated carbide tool. S. Jeyakumar et.al. [11] Investigated the machining parameters on the surface finish criteria have been determined through the response surface methodology (RSM) prediction model. B. Sidda Reddy et.al. [12] have investigated the minimization of surface roughness by integrating design of experiment method, Response surface methodology (RSM) and genetic algorithm. Bala Murugan Gopalsamy et.al. [13] applied Taguchi method to find optimum process parameters for end milling in machining of hardened steel. B. Lela et.al. [15] examined the influence of cutting speed, feed, and depth of cut on surface roughness in face milling process on the steel St 52-3 (DIN designation). Three different modelling methodologies, namely regression analysis (RA), support vector machines (SVM), and Bayesian neural network (BNN), have been applied to data experimentally determined by means of the design of experiment. This research has also shown that the feed has the largest affect on surface roughness and the depth of cut the least.

From the literature it was observed that the cutting parameters in milling operations like feed rate, cutting speed and depth of cut influence both surface roughness and material removal rate. The research was mainly focused on determining the cutting force, tool wear and surface roughness of the milling process. A few studies have been reported to maximize the material removal rate and surface roughness during machining. The main aim in this work is to find out the best combination of cutting parameters in machining of high carbon alloy steel using tungsten carbide tool to achieve low surface roughness and maximize material removal rate. To achieve the objective, mathematical models have been developed using the experimental data and developed models are tested for its adequacy.

II. PROPOSED METHODOLOGY

In this present study, response surface methodology (RSM) has been used to develop mathematical model to determine suitable combination of cutting parameters to achieve minimum surface roughness and maximum material removal rate. The predictive mathematical models were developed to optimize the machining process.

A. Design of experiment

The design of experiments is an important technique, which allows us to perform the modelling and analysis of effect of cutting parameters on the response factors. The response factors are function of the process parameters, which are known as design factors. Large numbers of machining parameters are there which can be considered for machining of a material in end milling operation. In the present study machining parameters cutting speed, feed and depth of cut are considered as design factors. The range of values of each factor is given in Table 2. A 3K full factorial design orthogonal array is used to design factors so that all the interactions between the response factors and cutting parameters can be carried out.

B. Work Material

TABLE 1: CHEMICAL COMPOSITION OF SAE 52100 HIGH CARBON ALLOY STEEL (WT %)

C	Mn	Si	S	P	Cr
1.1	.5	.2	.04	.04	1.3

A SAE 52100 high carbon alloy steel work piece were used in present study. The size of work piece was 105×115×32 mm and chemical composition is shown in Table 1

C. Tool and equipments

A two phase cutter of 40 mm diameter is used for face milling. The tool holder used for end mill cutter is BT40 and cutting tool selected for present work is triangular carbide inserts having thickness 4.76 mm and Clearance angle $11^{0.}$ The machine used for experimentation is CNC Vertical Milling Centre (VM 10, HURCO). The surface roughness was measured by using a portable surface roughness tester (Mitutoyo Surftest SJ301) and material removal rate was measured by formulae = area× total depth of cut/cutting time (mm^3/min) up to measure of flank wear till V_B = 300 µm in accordance with the ISO standard for tool life testing of end milling (ISO Standard 8688-2, 1989), by machine vision.

TABLE 2: LEVELS OF CONTROL FACTORS

Parameter	Designation	Level -1	Level -2	Level -3
Speed (m/min)	A	100	140	180
Feed (mm/tooth)	B	0.1	0.15	0.2
Depth of Cut (mm)	C	0.75	1.00	1.25

TABLE 3: DESIGN MATRIX

	Coded Parameters			Responses	
Sr. No.	Speed (m/min)	Feed (mm/tooth)	Depth of Cut (mm)	Surface Roughness (µm)	MRR (mm³/min)
1	-1	-1	-1	0.48	2780.85
2	-1	-1	0	0.35	3984.37
3	-1	-1	1	0.34	4634.76
4	-1	0	-1	0.84	4148.38
5	-1	0	0	0.36	5550

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6	-1	0	1	0.49	7065.5
7	-1	1	-1	0.38	6356.25
8	-1	1	0	0.88	8625
9	-1	1	1	1.08	10781.25
10	0	-1	-1	0.55	4116.47
11	0	-1	0	0.36	5488.63
12	0	-1	1	0.37	6860.79
13	0	0	-1	0.32	6468.75
14	0	0	0	0.41	8625
15	0	0	1	0.24	10781.25
16	0	1	-1	0.28	8085.93
17	0	1	0	0.37	9937.5
18	0	1	1	0.65	12421.87
19	1	-1	-1	0.18	5565
20	1	-1	0	0.41	7420
21	1	-1	1	0.53	8385.41
22	1	0	-1	0.91	7875
23	1	0	0	0.32	10500
24	1	0	1	2.59	13125
25	1	1	-1	0.25	9951.92
26	1	1	0	0.39	13269.23
27	1	1	1	2.01	16586

III. ANALYSIS OF PROCESS FACTOR

A. Response Surface Methodology

The response surface methodology is a widely adopted tool for the quality engineering field. The Response surface methodology (Montgomery, 1984) is a collection of mathematical and statistical techniques that are useful for modeling, analysis and optimizing the process in which response of interest is influenced by several variables and the objective is to optimize this response. Response Surface Methodology uses data from experiments to determine and solve multi-variable equation. The response surface methodology comprises regression surface fitting to obtain approximate responses, design of experiments to obtain minimum variances of the responses and optimizations using the approximated responses. In statistical modeling to develop an appropriate approximating model between the response 'Y' and independent variables $\{x_1, x_2, \text{------} x_n\}$ in general, the relationship is written in the form of

$$Y = f(x_1, x_2, \text{-------} x_n) + \varepsilon \; ; \qquad (1)$$

where the form of the true response function Y is unknown and perhaps very complicated, and ε is a term that represents error or noise in Y. Usually ε is treated as statistical error, often assuming it to have a normal distribution with mean zero and variance σ2.

$$E(y) = Y = E\,[f\,(x_1, x_2, \ldots, x_n)] + E\,(\varepsilon) = f\,(x_1, x_2, \ldots, x_n); \qquad (2)$$

is called a response surface.

The variables x1, x2, …, xn Eq.(2) are usually called the natural variables, because they are expressed in the natural units of measurements. In most of the RSM problems the form of relationship between the response and the independent variable is unknown. Thus the first step in RSM is to find a suitable approximation for the true functional relationship between Y and set of independent variables employed. Usually a second order model is utilized in RSM.

$$Y = \beta_0 + \sum^{k}_{i=1}\beta_i X_i + \sum^{k}_{i=1}\beta_{ii} X_i^2 + \sum\sum\beta_{ij} X_{ij} + \varepsilon \qquad (3)$$

The β coefficients, used in the above model can be calculated by means of using least squares technique. The second order mode is normally used when the response function is not known or nonlinear [12].

TABLE 4: ANALYSIS OF ANOVA

	Surface roughness				
Source	Sum of Squares	df	Mean Square	F Value	p-value
Model	4.60	9	0.51	2.85	0.0301
A-s	0.32	1	0.32	1.77	0.2010
B-f	0.41	1	0.41	2.29	0.1484
C-d	0.94	1	0.94	5.23	0.0352
AB	0.011	1	0.011	0.06	0.8091
AC	1.07	1	1.07	5.96	0.0259
BC	0.65	1	0.65	3.64	0.0733
A^2	0.60	1	0.60	3.34	0.0851
B^2	0.18	1	0.18	0.99	0.3331
C^2	0.42	1	0.42	2.37	0.1421
Residual	3.05	17	0.18		

TABLE 5: ANALYSIS OF ANOVA

	Material Removal Rate				
Source	Sum of Squares	df	Mean Square	F Value	p-value
Model	2.8E+08	9	3.151E+007	137.25	0.0001
A-s	8.3E+07	1	8.343E+007	363.35	0.0001
B-f	1.2E+08	1	1.216E+008	529.47	0.0001
C-d	6.9E+07	1	6.920E+007	301.39	0.0001
AB	1.3E+06	1	1.383E+006	6.02	0.0252
AC	2.5E+06	1	2.529E+006	11.01	0.0041
BC	5.3E+06	1	5.302E+006	23.09	0.0002
A^2	19705.09	1	19705.09	0.086	0.7731
B^2	1.6E+05	1	1.696E+005	0.74	0.4020
C^2	12122.42	1	12122.42	0.053	0.8210
Residual	3.9E+06	17	2.296E+005		

In this study, RSM (Design Expert 9.0 version software) was used to develop mathematical models using experimental outcome. The aim of developing mathematical models for machining responses and their process parameter is to make easy the optimization of the machining process. The experiments were performed on SAE 52100 Tool Steel for its face mill and response factor R_a and MRR were measured by changing the factors speed (s), feed (f) and depth of cut (d). The machining performances for the milling process were analyzed to estimate the machinability using RSM to develop the prediction model for the response parameters for the required range of design factors.

The analytical method for the approximation of the response was achieved by developing regression analysis Equation which represents a model of machining response. These are formed from Table 7 estimated coefficient.

TABLE 6: SUMMARY OF REGRESSION ANALYSIS

	R^2	Adjusted R^2
Ra	0.6015	0.5905
MRR	0.9864	0.9792

TABLE 7: ESTIMATED COEFFICIENT

Factor	coefficient	P-Value	coefficient	P-Value
constant	0.33	0.0301	8229.41	0.0001
A-s	0.13	0.2010	2152.84	0.0001
B-f	0.15	0.1484	2598.82	0.0001
C-d	0.23	0.0352	1960.74	0.0001
AB	0.030	0.8091	339.52	0.0252
AC	0.30	0.0259	459.04	0.0041
BC	0.23	0.0733	664.70	0.0002
A^2	0.32	0.0851	57.31	0.7731
B^2	-0.17	0.3331	-168.14	0.4020
C^2	0.33	0.1421	-44.95	0.8210

Ra $= 0.33 + 0.13\times A + 0.15\times B + 0.23\times C + 0.030\times A\times B + 0.30\times A\times C + 0.23\times B\times C + 0.32\times A^2 – 0.17\times B^2 + 0.33\times C^2$

MRR $= 8229.41+2152.84\times A +2598.82\times B +1960.74\times C +339.52\times A\times B +459.04\times A\times C +664.70\times B\times C +57.31\times A^2 –168.14\times B^2 – 44.95\times C^2$

From examining the Table 4 and 5, on the basis of F-value 2.85 for surface roughness and F- value 137.25 for material removal rate, it was checked that the second order model is fit for responses surface roughness and material removal rate. Further, values of R^2 (0.6015 for Ra and0.9864 for MRR) is greater than Adjusted R^2 (0.9864 for Ra and 0.9792) also shows adequacy of models of surface roughness and material removal rate. The comparison of experimental and predicted model for Surface roughness and material removal rate can be seen in fig. 3 and fig. 4. After analyzing the design factors and responses the Design Expert 9.0 version suggested following optimum process parameter entered in Table 8

TABLE 8: SUGGESTED OPTIMUM CUTTING PARAMETERS

Speed	FR	DOC	Ra	MRR
177.72	0.20	1.16	1.32	14995.43

After finding optimum parameter, final step is to perform confirmation experiments. So confirmation experiments were conducted whose values were

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tabulated in Table 9, which shows that experimental values are very close to predicted models.

TABLE 9: COMPARISONS BETWEEN EXPERIMENTAL AND PREDICTED VALUE

No.	Exp no. 1	Exp. no. 2	Exp. no. 3	Avg. value	Predicted value	% Residual
Ra	1.29	1.27	1.33	1.29	1.32	-2.32
MRR	15156.23	15100.35	15186.56	15147.71	14995.43	1.01

IV. RESULT AND DISCUSSION

A 3*3 full factorial design was used in order to get the output data uniformly distributed all over the ranges of the input parameters. the experiments were based on three input factors and two outputs. After analyze the influences of speed, feed and depth of cut it was observed that depth of cut is found most influencing factor on surface roughness and fig. 1(c) shows that surface roughness increases with the increase in depth of cut. The feed and speed have least effect on surface roughness as shown in fig. 1 (b) and (a). Further it is observed that speed and feed are most influencing factors on MRR as compared to depth of cut as shown in fig. 2(a), (b) and (c).

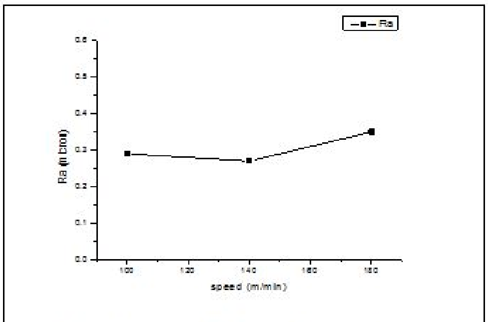

Figure 1(a): speed vs. surface roughness

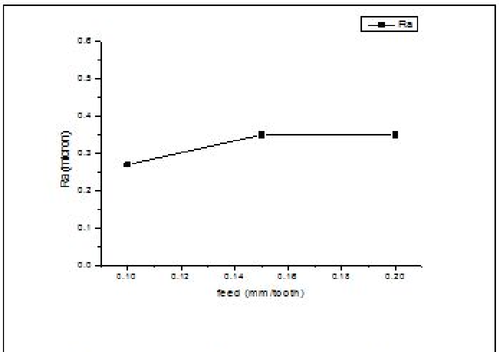

Figure 1(b): feed vs. surface roughness

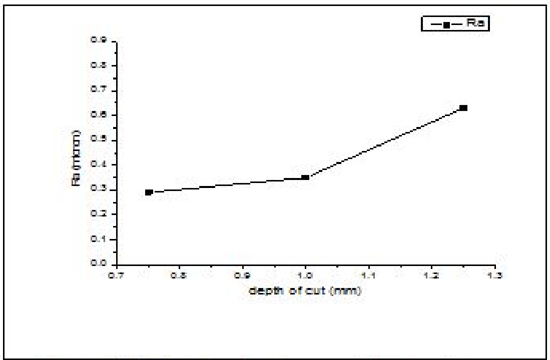

Figure 1(c): depth of cut vs. surface roughness

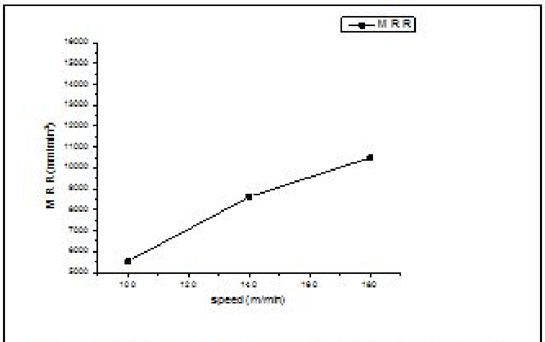

Figure 2(a): speed vs. material removal rate

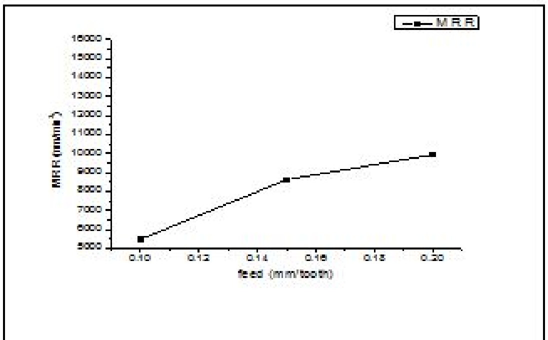

Figure 2(b): feed vs. material removal rate

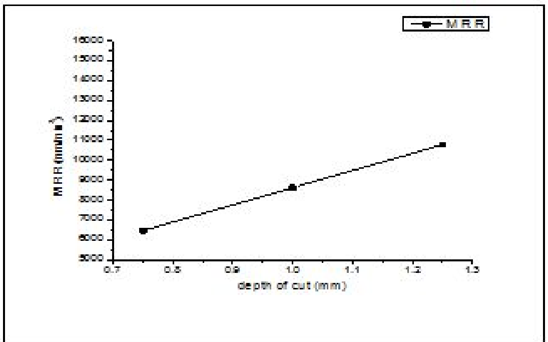

Figure 2(c): depth of cut vs. material removal rate

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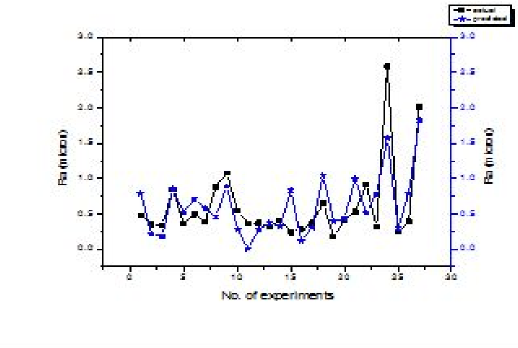

Figure 3: Actual vs. predicted values of Ra

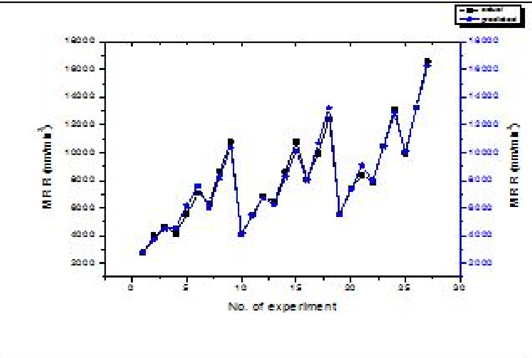

Figure 4: Actual vs. predicted values of MRR

V. CONCLUSION

The optimum cutting parameter for minimum surface roughness and maximum MRR has been found to be: cutting speed 177.72 m/min, feed=0.2 mm/ tooth and depth of cut=1.16 mm. The depth of cut and feed rate are dominant parameters for surface roughness as Ra increases with the increase of depth of cut & feed rate. Ra decreases as cutting speed increases from 100 to 140 m/min, but Ra increase as cutting speed further increases from 140 to 180m/min. In case of MRR, feed is a dominant factor, as feed increases MRR also increases. Comparison between experimental and predicted values validates the empirical model of responses.

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