Mathematical Modeling to Predict Surface Roughness in CNC Milling

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***Abstract*—**Surface roughness (Ra) is one of the most important requirements in machining process. In order to obtain better surface roughness, the proper setting of cutting parameters is crucial before the process take place. This research presents the development of mathematical model for surface roughness prediction before milling process in order to evaluate the fitness of machining parameters; spindle speed, feed rate and depth of cut. 84 samples were run in this study by using FANUC CNC Milling α-T14ιE. Those samples were randomly divided into two data sets- the training sets (m=60) and testing sets(m=24). ANOVA analysis showed that at least one of the population regression coefficients was not zero. Multiple Regression Method was used to determine the correlation between a criterion variable and a combination of predictor variables. It was established that the surface roughness is most influenced by the feed rate. By using Multiple Regression Method equation, the average percentage deviation of the testing set was 9.8% and 9.7% for training data set. This showed that the statistical model could predict the surface roughness with about 90.2% accuracy of the testing data set and 90.3% accuracy of the training data set.

***Keywords*—**Surface roughness, regression analysis.

I. Introduction

To realize full automation in machining, computer numerically controlled (CNC) machine tools have been implemented during the past decades. CNC machine tools require less operator input, provide greater improvements in productivity, and increase the quality of the machined part. End milling is the most common metal removal operation encountered. It is widely used to mate with other part in die, aerospace, automotive, and machinery design as well as in manufacturing industries [1].

Surface roughness is an important measure of the technological quality of a product and a factor that greatly influences manufacturing cost. The quality of the surface plays a very important role in the performance of milling as a good-quality milled surface significantly improves fatigue strength, corrosion resistance, or creep life. [2] In addition, surface roughness also affects surface friction, light reflection, ability of holding a lubricant, electrical and thermal contact resistance. Consequently, the desired surface roughness value is usually specified for an individual part, and specific processes are selected in order to achieve the specified finish. Surface specification can also be a good reference point in determining the stability of a production process, because the stability of the machine is contingent on the quality of the operating part [3].

This research investigates to predicting surface roughness by using multiple regression prediction models. Three milling parameters have been selected, spindle speed, feed rate and depth of cut.

In manufacturing industries, manufacturers focused on the quality and productivity of the product. To increase the productivity of the product, computer numerically machine tools have been implemented during the past decades. Surface roughness is one of the most important parameters to determine the quality of product. The mechanism behind the formation of surface roughness is very dynamic, complicated, and process dependent. Several factors will influence the final surface roughness in a CNC milling operations such as controllable factors (spindle speed, feed rate and depth of cut) and uncontrollable factors (tool geometry and material properties of both tool and workiepce). Some of the machine operator using ‘trial and error’ method to set-up milling machine cutting conditions [1]. This method is not effective and efficient and the achievement of a desirable value is a repetitive and empirical process that can be very time consuming.

In order to solve the problem, a surface prediction technique which is termed the multiple regression prediction models to optimize the cutting conditions is developed. This method can find the best conditions required for the machining independent variables such as speed, feed and depth of cut that would result in the best machining response. Thus, manufacturers can improve the quality and productivity of the product with minimum cost and time.

II. Methodology

The experiment is performs by using a FANUC CNC Milling α-T14ιE. The workpiece tested is 6061 Aluminum 400mmx100mmx50mm. The end-milling and four-flute high speed steel is chooses as the machining operation and cutting tool. The diameter of the tool is D=16mm. 84 specimens are run in this experiment.60 specimens are used to build a prediction model and the testing set contain 24 specimens. Spindle speed, feed rate and depth of cut are selected as consider parameters. Four levels of spindle speed- 750, 1000,

This work was supported by the Faculty of Mechanical Engineering, Universiti Malaysia Pahang, Malaysia.

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1250, and 1500revolutions per minute (rpm), seven levels of feed rate- 152, 229, 305, 380, 457, 515, 588 millimeter per minute (mmpm), and three levels of depth of cut – 0.25, 0.76, 1.27 millimeter (mm) are determined. The parameter variables have shown in Table I.

After complete the data, all original 84 samples are randomly divided into two data sets- the training set and testing test. The training set contained 60 samples (Table II) which are used to build a prediction model and the testing set contained 24 (Table III) samples which are used to tes the flexibility of the prediction model. Each sample consisted of four elements: spindle speed, feed rate, depth of cut, and measured surface roughness (Ra). A commercial statistical package was used to do the regression anlysis. Stepwise method was selected to further reduce the number of variables.

A statistical model is created by regression function from the training data set. The proposed multiple regression model is three-way interaction equation:

$$Y_i = \alpha_i + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \beta_4 X_{1i} X_{2i} + \beta_5 X_{1i} X_{3i} + \beta_6 X_{2i} X_{3i} + \beta_7 X_{1i} X_{2i} X_{3i} \qquad --(Eq1)$$

Y_i : Surface roughness (Ra): micro inch (μ mm)

X_{1i} : Spindle speed(S): revolutions per minute (rpm)

X_{2i} : Feed rate (F): millimeter per minute (mmpm)

X_{3i} : Depth of cut (D): millimeter (mm)

Since the independent variables of this study were spindle speed, feed rate, and depth of cut, the dependent was the surface roughness, the full regression model containing all the main effects and interactions terms was listed in equation (2). To test the effects of spindle speed, feed rate, and depth of cut on the surface roughness, the general and alternative hypothesis are:

$$H_0 : \beta_j = 0, \qquad where\ j = 1,23,.....,7$$

$$H_1 = at\ least\ one\ of\ the\ \beta_j\ not\ equal\ to\ zero.$$

The general null hypothesis is describes as the effects of spindle speed, feed rate, and depth of cut on the surface roughness do not significantly differ from zero while the alternative hypothesis states that at least one of the β_j not equal to zero.

In order to judge the accuracy of the multiple regression prediction model, percentage deviation and average percentage deviation are used and defined as:

$$\phi_i = \frac{\left| Ra_i' - \hat{Ra}_i \right|}{Ra_i'} x100\%$$

Where ϕ_i : percentage deviation of single sample data

Ra_i' : actual Ra measured by a Perthometer S2

$\hat{Ra}_i$: predicted Ra generated by a multiple regression equation

$$\bar{\phi}_i = \frac{\sum_{i=1}^{m} \phi_i}{m}$$

This method tests the average percentage deviation of actual Ra (measured by a Perthometer S2) and predicted Ra (produced by the multiple regression models) as well as its ability to evaluate the prediction of this model.

TABLE I
DATA COLLECTED FROM MILLING PROCESS

F / D / S	152 mm/m			229mm/m			305mm/m			380mm/m			457mm/m			515mm/m			588mm/m		
	0.25 mm	0.76 mm	1.27 mm	0.25 mm	0.76 mm	1.27 mm	0.25 mm	0.76 mm	1.27 mm	0.25 mm	0.76 mm	1.27 mm	0.25 mm	0.76 mm	1.27 mm	0.25 mm	0.76 mm	1.27 mm	0.25 mm	0.76 mm	1.27 mm
750rpm	1.351	1.300	1.629	2.469	2.212	2.113	3.217	2.291	2.088	2.975	2.799	2.342	4.399	3.434	2.773	4.221	3.840	3.610	4.450	4.018	3.452
1000rpm	1.173	1.681	1.275	2.037	2.088	2.291	3.002	1.833	2.037	2.265	2.443	2.367	3.205	2.850	2.134	3.485	3.383	3.214	3.840	3.586	3.307
1250rpm	1.276	1.301	1.603	1.707	1.757	2.037	2.265	2.215	1.859	2.392	2.138	2.137	2.621	2.037	2.113	2.875	2.240	2.367	3.637	2.469	2.773
1500rpm	1.128	1.224	1.301	1.503	1.554	1.478	1.935	1.783	2.088	2.392	1.808	2.215	2.723	1.910	2.342	2.697	2.291	2.570	2.723	2.316	2.469

Note:

1. Feed rate (F), X_1 : millimeter per minute(mmpm)
2. Spindle speed(S), X_2 : revolutions per minute(rpm)
3. Depth of cut(D), X_3 : millimeter(mm)
4. Surface roughness(Ra): micro inch (μ mm)

III. Results and Discussion

The results of the experiment are shown in Table I. Three parameters, spindle speed, depth of cut and feed rate are considered in this experiment. 84 specimens were cut and measured by the Perthometer S2 to obtain the roughness average value, Ra. All the data were randomly divided into training data set (Table II) and testing data set (Table III).

A statistical model was created by regression function in SPSS from the training data set. In Table IV, model 4 which included included X_1X_3 and this model showed the highest value of Adjusted R^2, 0.850 which meant that the correlation coefficient between the observed value of the dependent variable and the predicted value based on the regression model was high. Model 4 had the smallest value of standard error of the estimate which was 0.3009. Thus, model 4 had been chosen to construct the multiple regression equation.

Table V showed the summary of ANOVA test. The value of F was 84.746 and the significance of F was zero which is less than the critical value (α=0.05). The null hypothesis shows there is no linear relationship between R_a and the independent variables. Thus, the independent variables were rejected. At least one of the population regression coefficients was not zero.

In Table VI, the coefficients for the independent variables were listed in the column b. The b is a measure of how strongly each predictor variable influences the surface roughness. The higher the beta value the greater the impact of the predictor variable on surface roughness. By using these coefficients, the multiple regression equation could be expressed as:

$$Y_i = 0.260 + 0.01119x_{2i} - 0.000004357x_{1i}x_{2i} + 0.0006847x_{1i}x_{3i} - 0.002785x_{2i}x_{3i} \quad (4)$$

where Y_i was the predicted surface roughness, R_a .It was also apparent that feed rate (X_2) was the most significant machining parameters to influence surface roughness (R_a).

The average percentage deviation of the testing set (m=24) was 9.8% and the average percentage deviation of the training data set (m=60) was 9.7%. This showed that the statistical model could predict the surface roughness (Ra) with about 90.1% accuracy of the testing data(m=24) and 90.2% accuracy of the training data set(m=60).

TABLE II
Training Data Set

No	Spindle Speed X1 (rpm)	Feed Rate, X2 (mm/min)	Depth of Cut, X3 (mm)	Actual Ra
1	750	152	0.25	1.351
2	750	152	0.76	1.300
3	750	152	1.27	1.629
4	1000	152	0.25	1.173
5	1000	152	0.76	1.681
6	1000	152	1.27	1.275
7	1250	152	0.25	1.276
8	1250	152	0.76	1.301
9	1250	152	1.27	1.603
10	1500	152	0.25	1.128
11	750	229	0.25	2.469
12	750	229	0.76	2.212
13	750	229	1.27	2.113
14	1000	229	1.27	2.291
15	1250	229	0.25	1.707
16	1250	229	0.76	1.757
17	1250	229	1.27	2.037
18	1500	229	0.25	1.503
19	1500	229	0.76	1.554
20	750	305	0.76	2.291
21	750	305	1.27	2.088
22	1000	305	0.25	3.002
23	1000	305	0.76	1.833
24	1000	305	1.27	2.037
25	1250	305	0.25	2.265
26	1250	305	1.27	1.859
27	1500	305	0.25	1.935
28	750	380	0.76	2.799
29	750	380	1.27	2.342
30	1000	380	0.25	2.265
31	1000	380	0.76	2.443
32	1000	380	1.27	2.367
33	1250	380	1.27	2.137
34	1500	380	0.25	2.392
35	1500	380	1.27	2.215
36	750	457	0.25	4.339
37	750	457	1.27	2.773
38	1000	457	0.25	3.205
39	1250	457	0.25	2.621
40	1250	457	0.76	2.037
41	1250	457	1.27	2.113
42	1500	457	0.25	2.723
43	1500	457	1.27	2.342
44	750	515	0.76	3.84
45	750	515	1.27	3.61
46	1000	515	0.25	3.485
47	1000	515	0.76	3.383
48	1250	515	0.25	2.875
49	1250	515	0.76	2.24
50	1250	515	1.27	2.367
51	1500	515	0.25	2.697
52	1500	515	1.27	2.57
53	750	588	0.76	4.018
54	1000	588	0.25	3.84
55	1000	588	0.76	3.586
56	1250	588	0.25	3.637
57	1250	588	0.76	2.469
58	1500	588	0.25	2.723
59	1500	588	0.76	2.316
60	1500	588	1.27	2.469

TABLE III
TRAINING DATA SET

NO	Spindle Speed X_1 (rpm)	Feed Rate X_2 (mm/m)	Depth of Cut X_3 (mm)	Actual R_a (μm)
1	1500	152	0.76	1.224
2	1500	152	1.27	1.301
3	1000	229	0.25	2.037
4	1000	229	0.76	2.088
5	1500	229	1.27	1.478
6	750	305	0.25	3.217
7	1250	305	0.76	2.215
8	1500	305	0.76	1.783
9	1500	305	1.27	2.088
10	750	380	0.25	2.975
11	1250	380	0.25	2.392
12	1250	380	0.76	2.138
13	1500	380	0.76	1.808
14	750	457	0.76	3.434
15	1000	457	0.76	2.85
16	1000	457	1.27	2.134
17	1500	457	0.76	1.91
18	750	515	0.25	4.221
19	1000	515	1.27	3.214
20	1500	515	0.76	2.291
21	750	588	0.25	4.45
22	750	588	1.27	3.452
23	1000	588	1.27	3.307
24	1250	588	1.27	2.773

TABLE IV
MODEL SUMMARY BY STEPWISE METHOD

Model	R	R^2	Adjusted R^2	Std. Error of the Estimate
1	.781	.610	.603	.4899
2	.894	.799	.792	.3549
3	.913	.834	.825	.3252
4	.928	.860	.850	.3009

Model 1 Predictors: (Constant), X_2

Model 2 Predictors: (Constant), X_2 X_1X_2

Model 3 Predictors: (Constant), X_2, X_1X_2, X_2X_3

Model 4 Predictors: (Constant), X_2, X_1X_2, X_2X_3, X_1X_3

TABLE V
ANOVA TABLE

Model		Sum of Squares	df	Mean Square	F	Sig.
4	Regression	30.701	4	7.675	84.746	.000
	Residual	4.981	55	9.057E-02		
	Total	35.682	59			

(α=0.05).

TABLE VI
VARIABLE INCLUDED IN THE MULTIPLE REGRESSION METHOD

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
4	(Constant)	.260	.188		1.386	.171
	X_2	1.119E-02	.001	2.151	11.623	.000
	X_1X_2	-4.357E-06	.000	-1.204	-8.628	.000
	X_2X_3	-2.785E-03	.001	-.692	-4.376	.000
	X_1X_3	6.847E-04	.000	.456	3.224	.002

X_1: Spindle speed(S): revolutions per minute (rpm)

X_2: Feed rate (F): millimeter per minute (mmpm)

X_3 : Depth of cut (D): millimeter (mm)

IV. CONCLUSION

This research proposed the Multiple Regression Method approach to predict surface roughness based on cutting parameters by using FANUC CNC Milling in end-milling operations. Through experimentation, the system proved capable of predicting the surface roughness (Ra) with about 90% accuracy (average percentage of deviation less than 10%). The 10% of deviation cause by the uncontrollable variables like tool wear, chips loads and chips formations. Feed rate was the most significant machining parameter used to predict the surface roughness in the Multiple Regression model.The Ra could be predicted effectively by applying spindle speed, feed rate, depth of cut and their interactions in the Multiple Regression model.

V. RECOMMENDATIONS

The recommendations for improve this study are:

i. Consider more factors (tool geometry, tool wear, different materials, and different cutting tool) in the research to see how the factors would affect surface roughness.

ii. Analysis the data by using another method such as fuzzy logic system or neural networks technique to enhance the ability of the prediction system.

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