Prediction of Surface Roughness in End-Milling with Multiple Regression Model

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Abstract

In this Paper, we propose statistical package for social sciences (SPSS), to predict surface roughness. Two independent data sets were obtained on the basis of measurement: training data set and testing data set. Spindle speed, feed rate, and depth of cut are used as independent input variables (parameters) while surface roughness as dependent output variable. The multiple regression model by using (SPSS) could predict the surface roughness (Ra) with average percentage deviation of 7.8%, or 92.2%, accuracy from training data, and from testing data set that was not included in the multiple regression analysis with average percentage deviation of 11.95%, or accuracy of 88%, for 4-Flute end mill.

الخلاصة

تم في هذا البحث استخدام النظام الاحصائي (SPSS) للتنبؤ بالخشونه السطحيه , كما تم اعداد بيانين مستقلين معتمدة على اساس القياسات : اعداد بيانات تدريبيه وبيانات اختباريه, أن السرعة الدورانيه (spindle speed) ومعدل التغذية وعمق القطع استخدمت كمتغيرات داخلة مستقلة بينما الخشونة السطحيه كمتغير تابع. ومن خلال استخدام نموذج الانحدار المتعدد في برنامج (SPSS)

يمكن التنبؤ بالخشونة السطحية مع معدل نسبة الانحراف 7.8% أو 92.2% الدقة من البيانات التدريبية , ومن خلال البيانات الأختبارية والتي من خلالها تم اختبار المعادلة فقد كان معدل نسبة الانحراف 11.95% أو 88% من الدقة لاداة القطع المستخدمة ومن النوع ذو الاربعة حزوز (Flute).

1. Introduction

Milling is one of the most important machining processes. As in other manufacturing technologies, milled surface roughness has a great influence on the functional properties of the product. It is well known that a high-quality milled surface significantly improves fatigue strength and corrosion resistance [1]. Roughness plays a significant role in determining and evaluating the surface quality of a product. Because surface roughness affects the functional characteristics of products such as resisting fatigue, friction, wearing, light reflection, heat transmission, and lubrication, the product quality is required to be at the high level. While surface roughness also decreases, the product quality increases [2].If the quality of the surface after milling is high, then further machining of the surface is frequently not necessary. In this way, the power consumption and the environment loading are decreased. These facts imply that good knowledge of the parameters determining the surface roughness and its precise prediction are very important. The influencing parameters can be divided into controlled and non-controlled parameters. The most important controlled cutting parameters are the spindle speed, feed rate, and depth of cut. However, there are many non-controlled cutting parameters (e.g., vibrations, tool wear, machine motion errors, material non-homogeneity of both the tool and workpiece, chip formation) which are hard to reach and whose interactions cannot be exactly determined. Most of the research

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$$yi=\alpha_i+\beta_1 x_{1i}+\beta_2 x_{2i}+\beta_3 x_{3i}+\beta_4 x_{1i}x_{2i}+\beta_5 x_{1i}x_{3i}+\beta_6 x_{2i}x_{3i}+\beta_7 x_{1i}x_{2i}x_{3i}$$

(3)Where *Yi*: surface roughness Ra (micro meter)
Xli: spindle speed (revolutions per minute)
X2i: feed rate (millimeter per minute)
X3i: depth of cut (millimeter)
αi: constant value
β: variable coefficients
In this model, the criterion variable is the surface roughness (Ra) and the predictor variables are spindle speed, feed rate, and depth of cut. Because these variables are controllable machining parameters, they can be used to predict the surface roughness in milling which will then enhance product quality.[1].
In order to judge the accuracy of the multiple regression prediction model, percentage deviation (φ_i) and average percentage deviation (Φ) were used and defined as:[7]

$$\varphi_i=\frac{\left|Ra_i'-Ra_i\right|}{Ra_i'}\times 100\% \quad (4)$$

Where φ_i: percentage deviation of single sample data
$Ra`_i$: actual Ra measured by a profilometer
Ra_i : predicted Ra generated by a multiple regression equation

$$\Phi=\frac{\sum_{i=1}^{m}\varphi\, i}{m} \quad (5)$$

Where Φ : average percentage deviation of all sample data
m: the size of sample data.

3. Experimental Procedure

3.1 Machine

The experiment was performed by using a universal conventional milling machining, as shown in Fig. (1).

propose the multiple regression method to predict surface roughness [3]. in [4] a statistical model for surface roughness prediction in end-milling is introduced, while In [5], a commercial tool was used for surface roughness prediction. Some research applied neural network, fuzzy logic, and neural-fuzzy approaches for surface roughness prediction [6-7]. Optimization of surface roughness prediction model, developed by a multiple regression method, with (SPSS) is presented in [8-9].

2. Theoretical analysis

2.1 Surface Finish Parameters

Surface finish could be specified in many different parameters. Due to the need for different parameters in a wide variety of machining operations, a large number of newly developed surface roughness parameters were developed.
Some of the popular parameters of surface finish specification are described as follows: [1]

$$Ra=\frac{1}{L}\int_0^L\left|Y(x)\right|dx \quad (1)$$

Where Ra the arithmetic average deviation from the mean line, L the sampling length, Y the ordinate of the profile curve.

$$Rq=\sqrt{\left[\frac{1}{L}\int_0^L\left(Y(x)\right)^2 dx\right]} \quad (2)$$

Where *Rq* the root-mean-square parameter corresponding to *Ra*.

2.2 Multiple Regression Prediction Model

The proposed multiple regression model is a three-way interaction equation: [1]

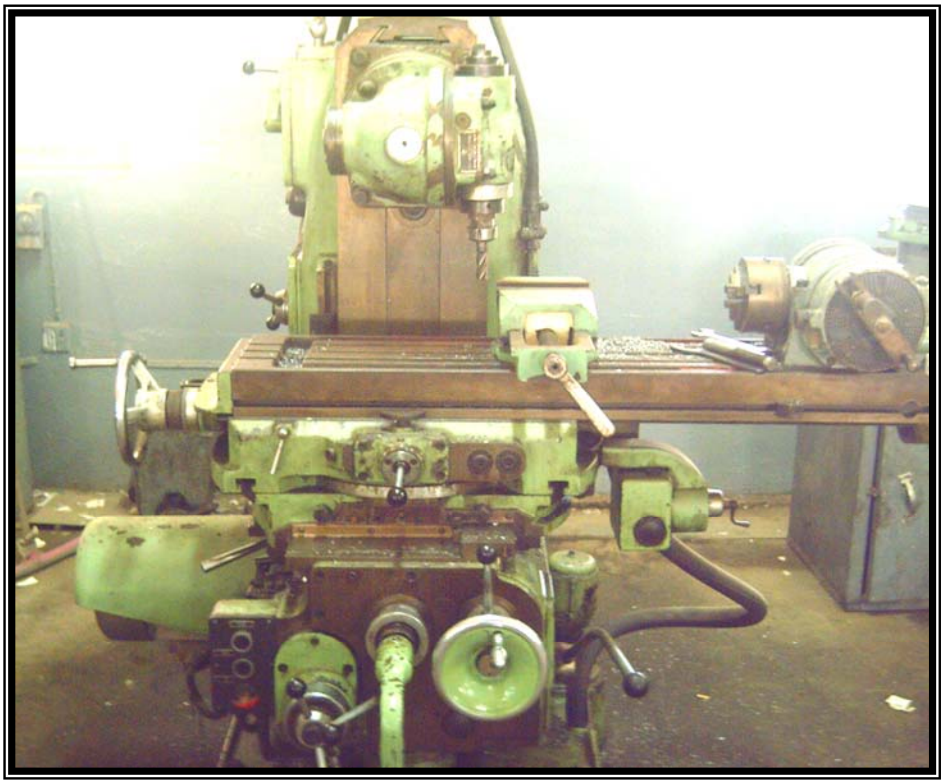

Fig. (1): Universal milling machine model (6H81)

3.2 workpiece material

The workpiece tested was (1020) carbon steel with a hardness of BHN 163 is used, the chemical composition and mechanical properties are given in table (1), and (2) respectively.

Table (1): Chemical composition (1020) [AISI]

Metal	**C%**	**Mn%**	**P%**	**S%**	Fe%
Carbon steel (1020)	0.2	0.3	0.04	0.05	Remain

Table (2): Mechanical properties of carbon steel (1020) at 25ċ

Physical property	**values**
Density (kg/cm3)	7.7
Poisons ratio	0.27
Elastic modulus (Gpa)	200
Tensile strength (Mpa)	394.7
Yield strength (Mpa)	294.8

3.3 Cutting tool

The end-milling and type of cutter (4-Flute) high speed steel were selected as the machining operation and the cutting tool, respectively. The diameter of tool was D=20mm,as shown in Fig.(2).

Fig. (2): Type of cutting tool (4-Flute).

3.4 Roughness apparatus measurement

Roughness apparatus measurement for surface is used (Talysurf-4), it is produced by (Rank tayllor hobson) English company.[see Fig.(3)].

Fig. (3): Roughness apparatus measurement

4. Results and Discussions

A statistical model was created by regression function in (SPSS) from the training data set. The R square (ability the independent variables to predict dependent variable) was 0.742 which showed that 74.2%of the observed variability in Ra could be explained by the independent variables. The multiple R (correlation value between dependent and independent variables) was 0.862 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. The value of F(value represent signify R^2 to Ra) was 2.47 and the significance of F was 0.145 in the ANOVA table as shown in Table (6). In Table (7) the coefficients for the independent variables were listed in the column B. using these coefficients the multiple regression equation could be expressed as:

After 20 specimens were cut for experimental purposes, they were measured off-line with a (Talysurf-4) type profilometer to obtain the roughness average value Ra. All original 20 samples as shown in Tables (3) were randomly divided into two data sets - the training set and the testing set. The training set contained 14 samples which were used to build a prediction model as shown in Tables (4) and the testing set contained 6 samples which were used to test the flexibility of the prediction model as shown in Tables (5). Each sample consisted of four elements: spindle speed, feed rate, depth of cut, and measured surface roughness (Ra).

$$
\begin{aligned}
yi = {} & 0.03382 + 1.169*10^{-4}x_1 + 5.231*10^{-4}x_2 + 8.507*10^{-2}x_3 \\
& -2.567*10^{-6}x_1x_2 - 6.846*10^{-4}x_1x_3 - 1.925*10^{-3}x_2x_3 \\
& +9.686*10^{-6}x_1x_2x_3
\end{aligned} \tag{6}
$$

Where (yi) was the predicted surface roughness Ra. It was also apparent that depth of cut (x_3) was the most significant machining parameter to influence surface roughness (Ra) in equation (6).

The Scatterplot between the observed Ra and the predicted Ra of all 20 samples as shown in Figure (4) indicated that the relationship between the measured Ra and the Predicted Ra was linear.

The result of average percentage deviation (Φ) showed that the training data set (m=14) was 7.8% and the testing data set (m=6) was 11.95% .

This means that the statistical model could predict the surface roughness (Ra) with about 92.2% accuracy of the training data set and approximately 88% accuracy of the testing data set.

In Figure (5) shows that the predicted values are a close match of the measurement values for 4–Flute end mill using (SPSS), the error between the two is very small (1.8%), but there is a larger error between the predicted values and measurement values in (1, 7, 13, 18 and 20) testing data sets.

Table (3): Experimental Design for Prediction and Measured surface Roughness Model (4-Flute end mill)

No.	Spindle speed (rpm)	Feed rate (mm/min)	Depth of cut (mm)	Ra (µm) Measured	Ra (µm) Predicted
1	100	170	0.25	0.06	0.05739
2	160	170	0.25	0.055	0.05214
3	255	170	0.25	0.04	0.04382
4	255	170	0.25	0.04	0.04382
5	255	170	0.5	0.04	0.04354
6	255	170	0.75	0.045	0.04326
7	255	55	0.25	0.035	0.03993
8	255	65	0.25	0.04	0.04027
9	255	85	0.25	0.04	0.04094

10	255	115	0.25	0.05	0.04196
11	255	135	0.25	0.054	0.04264
12	255	170	0.25	0.04	0.04382
13	255	210	0.25	0.045	0.04518
14	160	65	0.5	0.04	0.03845
15	100	55	0.75	0.032	0.03385
16	100	85	0.5	0.046	0.0402
17	100	115	0.5	0.029	0.03206
18	255	55	0.5	0.025	0.02555
19	160	135	0.25	0.04	0.05269
20	100	210	0.25	0.054	0.0555

Table (4): 14 Training Data set (4-Flute end mill)

No.	Spindle speed (rpm)	Feed rate (mm/min)	Depth of cut (mm)	Measured Ra(μm)
1	100	170	0.25	0.06
2	255	170	0.25	0.04
3	255	170	0.5	0.04
4	255	170	0.75	0.045
5	255	65	0.25	0.04
6	255	85	0.25	0.04
7	255	135	0.25	0.054
8	255	170	0.25	0.04
9	160	65	0.5	0.04
10	100	55	0.75	0.032
11	100	115	0.5	0.029
12	255	55	0.5	0.025
13	160	135	0.25	0.04
14	100	210	0.25	0.054

Table (5): Testing Data set (4-Flute End mill)

No.	Spindle speed (rpm)	Feed rate (mm/min)	Depth of cut (mm)	Measured Ra(μm)
1	160	170	0.25	0.055
2	255	170	0.25	0.04
3	255	55	0.25	0.035
4	255	115	0.25	0.05
5	255	210	0.25	0.045
6	100	85	0.5	0.046

Table (6): ANOVA Table for 4-Flute end mill

Model	Sum of square	df	Mean square	F	Signify
Regression	8.918E-04	7	1.274E-04	2.470	0.145
Residual	3.095E-04	6	5.158E-05		
Total	1.201E-03	13			

Table (7): Variable included in the Multiple Regression Equation (4-Flute)

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig
	B	Std. Error	Beta		
Constant	3.382E-02	0.060		.565	.592
X_1	1.169E-04	.000	.875	.445	.672
X_2	5.231E-04	.000	2.872	1.574	.167
X_3	8.507E-02	.091	1.672	.933	.387
X_1X_2	-2.567E-06	.000	-3.707	-1.651	.150
X_1X_3	-6.846E-04	.000	-3.217	-1.436	.201
X_2X_3	-1.925E-03	.001	-5.746	-2.028	.089
$X_1X_2X_3$	9.686E-06	.000	8.183	2.238	.067

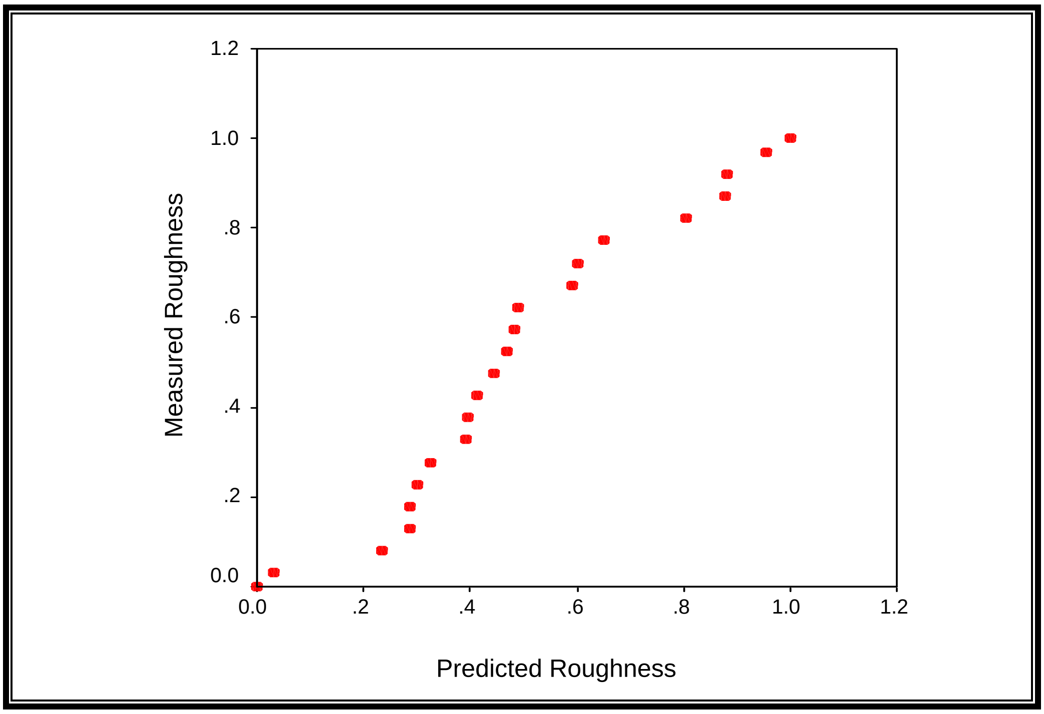

Fig. (4): Scatterplot of the Measured Ra and the Predicted Ra of the Multiple Regression Prediction Model for 4-Flute end mill using (SPSS)

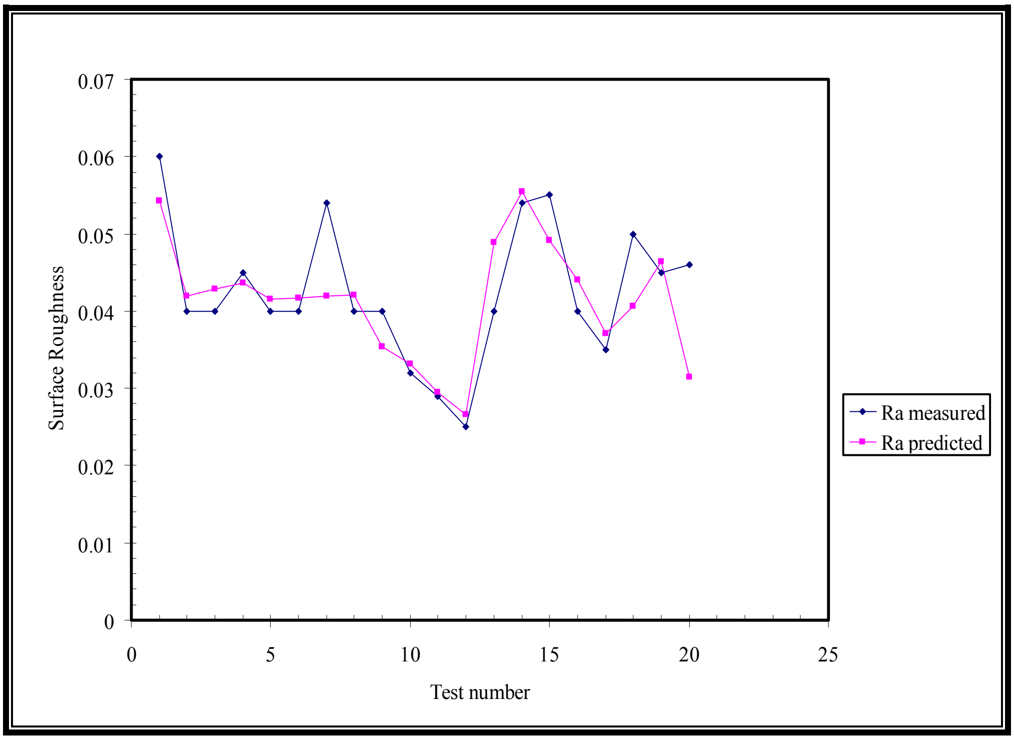

Fig. (5): The diagram of the measured and predicted surface roughness for the experimental data using the commercial statistical package (SPSS) for 4-Flute end mill

5. Conclusions

The present work has reached to the following conclusions

1. The surface roughness (Ra) could be predicted effectively by applying spindle speed, feed rate, depth of cut, and their interactions in the multiple regression model.

2. The multiple regression model by using (SPSS) could predict the surface roughness (Ra) with average percentage deviation of 7.8%, or 92.2% accuracy from training data set .

3. The multiple regression model (SPSS) could predict the surface roughness from testing data set that was not included in the multiple roughness from testing data set that was not included in the multiple regression analysis with average percentage deviation of 11.95%, or accuracy of 88% .

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