Experimental Study for Surface Roughness in End Milling Process by RSM

Dr. Abbas Fadhil Ibrahim
Production and Metallurgy Engineering Department, University of Technology/ Baghdad
Email:abbasfadhel-2006@yahoo.com

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ABSTRACT:

This research interesting to study effect of machine conditions end mill on the surface roughness for 1020 carbon steel. In this Paper, propose multiple regression model (MRM) by using response surface method (RSM) in Minitab program, to predict surface roughness and study the effect of the spindle speed, feed rate and depth of cut on the surface roughness. The R^2 (ability the Independent values to predict the dependent values) of the predictive model is 95.51%. From the applicant multiple regression model equation, the depth of cut (X_3) is the most significant machining parameter to influence on surface roughness (Ra).

دراسة عملية للخشونة السطحية في عملية التفريز العمودي باستخدام طريقة استجابة السطح

الخلاصة:

هذا البحث يهتم بدراسة تأثير ظروف تشغيل التفريز العمودي على ا لخشونة السطحية لعينة من الفولا ذ الكربوني(1020) . تم اقتراح نموذج الانحدار المتعدد باستخدام طريقة استجابة السطح في برنامج ميني تاب للتنبؤ بالخشونة السطحية ودراسة تأثير سرعة محور الدوران ، معدل التغذية وعمق القطع على الخشونة السطحية. R^2 ان قابلية القيم المستقلة للتنبؤ بالقيم المعتمدة كانت 95.51% .من خلال تطبيق معادلة نموذج الانحدار المتعدد تبين ان عمق القطع(X_3) هو كان اكثر تأثير من المتغيرات الاخرى على الخشونة السطحية .

INTRODUCTION

Human operators can select optimal operating conditions after learning the characteristics of the system through trial and error, but in modern industry, the goal is manufacturing low-cost and high-quality products in a short time. Surface roughness of a machined product plays a significant role in determining and evaluating the quality of the product because it could affect several functional attributes of the product, such as resisting fatigue, surface friction, wearing, light reflection, heat transmission, coating, and lubricant distribution. Moreover, surface roughness is an important factor in determining the machinability of materials [1]. The best logical

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2412-0758/University of Technology-Iraq, Baghdad, Iraq

surface finish is required to enhance the product's functional attributes. In other words, excessively better surface finish may involve more cost of manufacturing; therefore, more attention should be paid to the estimation of optimum surface roughness [2, 3]. Previously, Oktem et al. [4] proposed the genetic programming approach to predict surface roughness based on cutting parameters (spindle speed, feed rate and depth of cute) and on vibrations between cutting tool and workpiece. From this research, they conclude that the models that involve three cutting parameters and also vibrating, give the most accurate predictions of surface roughness by using genetic programming. Later on 2007, Chang et al. [5] were established a method to predict surface roughness in-process. In their research, roughness of machined surface was assumed to be generated by the relative motion between tool and workpiece and the geometric factors of a tool. The relative motion caused by the machining process could be measured in process using a cylindrical capacitive displacement sensor (CCDS). The CCDS was installed at the quill of a spindle and the sensing was not disturbed by the cutting. A simple linear regression model was developed to predict surface roughness using the measured signals of relative motion. Surface roughness was predicted from the displacement signal of spindle motion. The linear regression model was proposed and its effectiveness was verified from cutting tests. B. Sidda Reddy et al. [6] minimization of surface roughness has been investigated by integrating design of experiment method, Response surface methodology (RSM) and genetic algorithm. To achieve the minimum surface roughness optimal conditions are determined. K. Kadirgama et al. [7] concerned with the optimization of the surface roughness when milling aluminum alloys (AA6061-T6) with carbide coated inserts. Optimization of milling is very useful to reduce cost and time for machining mould. Potential support vector machine (PSVM) is used to develop surface roughness predicted model. Design of experiments method and response surface methodology techniques are implemented. The validity test of the fit and adequacy of the proposed models has been carried out through analysis of variance. The experiments results are compared with predictive model developed by PSVM.

Surface roughness

Regardless of the method of production, all surfaces have their own characteristics, indicated as surface texture [8]. Surface texture is the pattern of the surface which deviates from the nominal surface. The deviations may be repetitive or random and may result from roughness, flaws, and waviness [9]. Therefore, the actual surface profile is the superposition of errors of form, waviness and roughness.

Surface roughness definition

Surface roughness is defined as irregular deviations on a scale smaller than the scale of waviness. In other words, surface roughness is described as the inherent irregularities of work piece left by various machining processes. Figure (1) shows standard terminology and symbols for describing surface roughness. The profile (p) is the contour of any specific section through a machined surface on a plane perpendicular to the surface. Sampling length (l) is included in the measurement of average roughness height. The mean line (m) of the profile (p) is located so that the sum of areas above the mean line (within the sampling length (l)) is equal to the sum of areas below it. There are several ways to describe surface roughness. One of the most useful international parameters of surface roughness is average roughness, which is often quoted as Ra. Ra is defined as the arithmetic value of the departure of the profile from centerline along the sampling length. It is defined as:

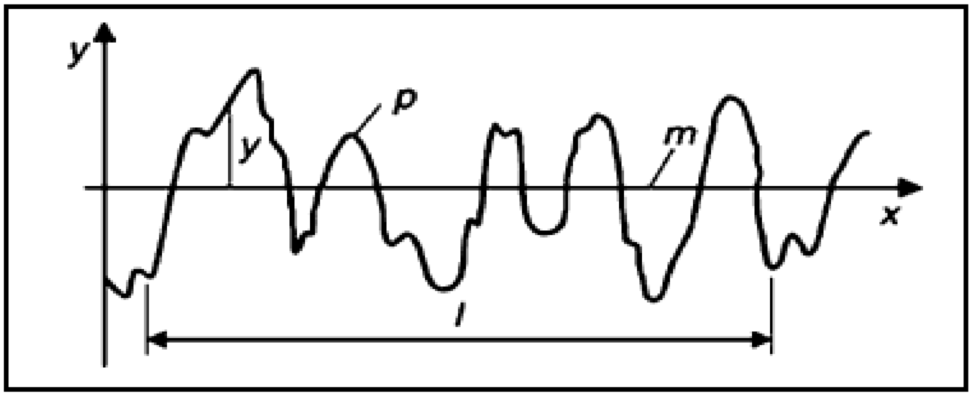

Figure 1: Surface Roughness Definition[11]

$$R_a = \frac{1}{l}\int_0^l |y(x)|dx \qquad \text{….. (1)}$$

Or

$$R_a = \frac{1}{n}\sum_{i=1}^{n} |y_i| \qquad \text{…… (2)}$$

Where

R_a is average surface roughness ,n number of sections, *l* is the sampling length and y is the ordinate of the profile curve.

Main factors affecting surface roughness[10]

Surface roughness is influenced by machining parameters, such as feed rate, spindle speed and depth of cut as well as non controlled factors, such as non-homogeneity of work-piece and tool, tool wear, machine motion errors, formation of chips and unpredictable random disturbances. It has been shown that both controlled and non-controlled parameters cause relative vibrations between the cutting tool and the work piece .

Multiple Regression Model[1]

The proposed multiple regression model is a three-way interaction and quadratic equation:

$$yi = \alpha_i + \beta_1 x_{1i} + \beta_2 x_{2i} + \beta_3 x_{3i} + \beta_4 x_{1i} x_{2i} + \beta_5 x_{1i} x_{3i} + \beta_6 x_{2i} x_{3i} + \beta_7 x^2{}_{1i} + \beta_8 x^2{}_{2i} + \beta_9 x^2{}_{3i} \quad ..(3)$$

Where;

yi= Surface Roughness (μm)

X_{1i}= Spindle Speed (RPM)

X_{2i} = Feed Rate (mm/min)

X_{3i} = Depth of Cut (mm)

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 controller machining parameters, they can be used to predict the surface roughness in milling which will then enhance product quality.

Experimental Work

To achieve the project objectives, multiple regression analysis is used for statistical method. The experiment is performs by using universal milling model (6H81) as shown in Figure (2). It has the following specification:

- Spindle speed (65-1800) RPM.
- Feed rate (35-1020) mm/min.
- Power spindle drive electric motor (4)Kw.
- Power feed drive electric motor (1.5)Kw.

The work piece tested is 1020 carbon steel with a

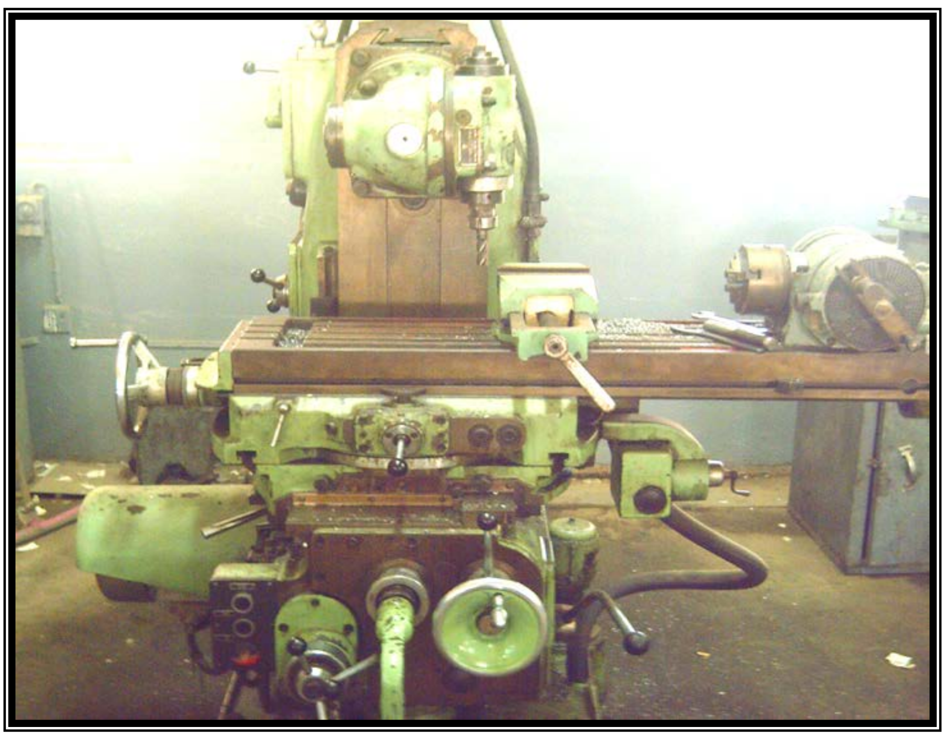

Figure (2): Universal milling machine model (6H81).

hardness of BHN 163 are used, the chemical composition and mechanical properties are given in Table (1), and (2) respectively. 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=20mm. Testing was done at the University of Technology.

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

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

Table (2): Mechanical properties of carbon steel (1020)

Physical property	**values**
Density (kg/cm^3)	7.7
Poisons ratio	0.27
Elastic modulus (Gpa)	200
Tensile strength (Mpa)	394.7
Yield strength (Mpa)	294.8

Three levels for each variable are used. For spindle speed 100, 160 and 255 rpm, for feed rate 135, 170 and 210 mm/min, and for depth of cut 0.25, 0.5 and 0.75 mm. These levels of parameters as shown in Table (3).

Table (3): The levels of parameters.

Independent variable	**Levels**		
	Low	**Medium**	**High**
Spindle Speed (rpm)	100	160	255
Feed Rate (mm/min)	135	170	210
Depth of Cut(mm)	0.25	0.5	0.75

Roughness measuring apparatus for machined holes is used (Talysurf-4), it is produced by (Rank Tayllor Hobson) company.
Figure (3) shows the roughness measurement apparatus for machined holes, the specifications of the apparatus is shown in Table (4)
The apparatus consists of the following main parts:-

- Transducer for electrical current (pick up).

- Gear box connected to the end of transducer.
- The base and probe.
- Electronic unit.

The electronic unit includes control unit amplifier and the demodulator which is used to separate the current, which is related to roughness.
The electronic unit also contains the filter which is used to separate the higher frequency from the lower frequency waves.

- Limiter for limitation of work piece length.

Recorder in order to draw the roughness and waviness.

Figure (3): Roughness measuring apparatus.

Table (4): Specification of the roughness apparatus measurement.

Specification	Value
Magnification range	500-100,000 times
Switch position	1-8
Full scale represents	0.5-100µm
Small division represents	0.02-4µm
Pick-up traverse speeds	50Hz supply: 3,0-15,2-76,2mm/min 60Hz supply:3,6-18,3-91,4mm/min
Max. traversing length	11mm
Probe material	Diamond (tip width 0,0025mm)
Voltage range	From 95V to 130V and from 190V to 260V a.c.
Accuracy	Better than 3% of full scale for any magnification

Results and Discussion

The results depicted in Figure.3 show the generalization capabilities of prediction of the proposed multiple regression models. Surface roughness for each experiment is measured using portable surface finish tester. All the data taken from the experiment are shown in Table 5. Each sample consisted of four elements: spindle speed, feed rate, depth of cut and measured surface roughness (Ra). A statistical model was created by regression function in (RSM) from the Minitab program .The surface roughness from the experiment has been established, to obtain regression coefficients (β_0,β_1,…..etc.) from applied RSM in minitab program which entered in equation (3) . By using this equation to predict surface roughness, the following prediction function was derived to represent the predictive surface roughness R_a as a function of the tested control factors:

$$y_i = -0.3067 + 0.472*10^{-3}\,X_1 + 0.355*10^{-2}\,X_2 + 0.01951\,X_3 - 2.587*10^{-6}\,X_1X_2 - 2.0192*10^{-5}X_1X_3 - 2.996*10^{-5}X_2X_3 + 3.679*10^{-8}X_1^2 - 8.670*10^{-6}X_2^2 + 0.312*10^{-2}X_3^2 \quad .... \quad (4)$$

Where (y_i) was the predicted surface roughness R_a. It was also apparent that depth of cut (x_3) was the most significant machining parameter and influence surface roughness (Ra) in equation (4).

The R^2 (ability the Independent values to predict the dependent values) of the predictive model is 95.51%. The error between measured and predicted surface roughness was ± 4.5%. The relation between measured and predicted surface roughness as shown in Figure 4, it is clear there are agree in more points between two curves , this shows that the efficiency response surface method to predict the variables by multiple regression model. In Figure5, show the normal probability plots of the residuals response for surface roughness, a check on this plot in Figure reveal that the residuals generally fall on a straight line implying that errors are distributed normally.

Table (5): Surface roughness obtained from the experiments

No.	Spindle speed (RPM)	Feed rate (mm/min)	Depth of cut (mm)	Surface Roughness Measured (µm)	Surface Roughness Predicted (µm)
1	100	210	0.5	0.057	0.05642
2	100	210	0.75	0.06	0.06019
3	100	170	0.5	0.06	0.05708
4	100	170	0.75	0.062	0.06116
5	100	135	0.25	0.03	0.03096
6	100	135	0.5	0.033	0.03491
7	100	135	0.75	0.038	0.03924
8	160	210	0.25	0.05	0.04903
9	160	210	0.5	0.051	0.05211
10	160	210	0.75	0.054	0.05558
11	160	170	0.5	0.057	0.05898
12	160	170	0.75	0.061	0.06275
13	160	135	0.5	0.044	0.04224
14	160	135	0.75	0.05	0.04627
15	255	210	0.5	0.044	0.04583
16	255	210	0.75	0.052	0.04882
17	255	135	0.5	0.056	0.05439
18	255	135	0.75	0.055	0.05794

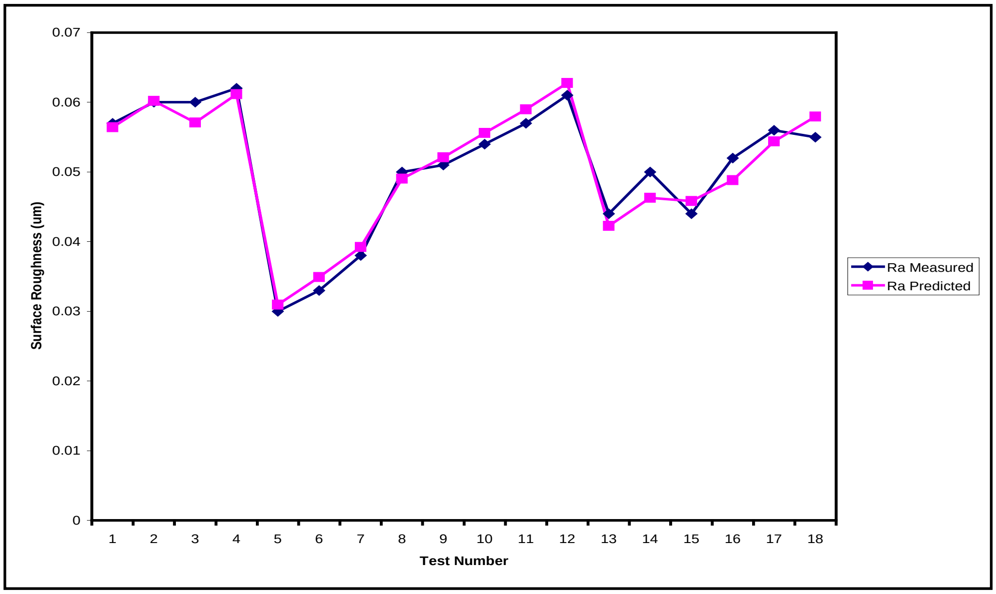

Figure (4): the diagram of the measured and predicted surface roughness for the experimental data.

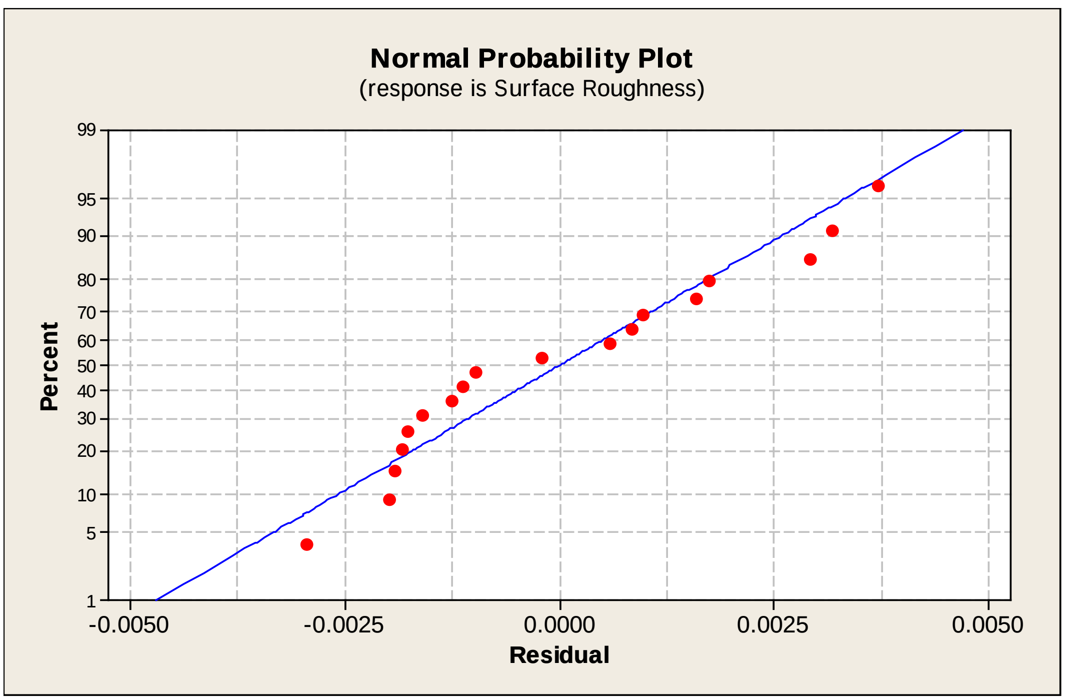

Figure (5): Normal Probability Plot response for improvement of average surface roughness

CONCLUSION:

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 and quadratic in the multiple regression model, by using (RSM) in Minitab program.
2- The R^2 (ability the Independent values to predict the dependent values) of the predictive model is 95.51%.
3- From equation 4.the depth of cut (X_3) is the most significant machining parameter and influence surface roughness (Ra), then the feed rate (X_2) and spindle speed (X_1).

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