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Error between predicted and measured surface roughness in the end-milling process

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ABSTRACT

The accusative of this field of study is to build up a more effective research to obtain and to understand the effects and the relation between/on the process parameters depth of cut, spindle speed and cutting feed rate on the surface roughness and to build a multiple regression model and predict the surface roughness values of machining parameters in the end-milling process. By the settling of experiments is to be designed and begin the enactment of surface quality and surface finish for the end-milling process have been performed. This set of experiments can provide brainstorm into the troubles of operating and controlling the finish of machined surfaces when the machining process parameters are aligned to obtain a certain surface finish. The set of experiments and the model, which includes the effect of depth of cut, spindle speed and cutting feed rate, and the interaction between any two-variable, which predict the surface roughness values with an accuracy of about 5.22 %.

Introduction

For a long time, manufacturing engineers and researchers have been realizing that in order to optimize the economic performance of metal cutting operations, efficient quantitative and predictive models that establish the relationship between a big group of input independent parameters and output variables are required for the wide spectrum of manufacturing processes, cutting tools and engineering materials currently used in the industry [1]. Furthermore, it has been observed that the improvement in the output variables, such as tool life, cutting forces, surface roughness, etc., through the optimization of the influencing parameters [2].

Metal cutting is one of the most significant manufacturing processes in the area of material removal [3]. Black [4] defined metal cutting as the removal of metal chips from a workpiece in order to obtain a finished product with desired attributes of size, shape, and surface roughness.

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 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 [5].

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 [6].

The imperative objective of the science of metal cutting is the solution of practical problems associated with the efficient and precise removal of metal from workpiece. It has been recognized that the reliable quantitative predictions of the various technological performance measures, preferably in the form of equations, are essential to develop optimization strategies for selecting cutting conditions in process planning [7-9].

The progress in the development of predictive models, based on cutting theory, has not yet met the objective; the most essential cutting performance measures, such as, tool life, cutting force, roughness of the machined surface, energy consumption etc., should be defined using experimental studies. Therefore, further improvement and optimization for the technological and economic performance of machining operations depend on a well- based experimental methodology. Unfortunately, there is a lack of information dealing with test methodology and data evaluation in metal cutting experiments [10].

The demand for high quality and fully automated production focuses attention on the surface condition of the product, especially the roughness of the machined surface, because of its effect on product appearance, function, and reliability. For these reasons it is important to maintain consistent tolerances and surface finish. Also, the quality of the machined surface is useful in diagnosing the stability of the machining process, where a deteriorating surface finish may indicate workpiece material non-homogeneity, progressive tool wear, cutting tool chatter, etc.

Among several industrial machining processes, milling is a fundamental machining operation. End milling is the most common metal removal operation encountered. It is widely used in a variety of manufacturing industries including the aerospace

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and automotive sectors, where quality is an important factor in the production of slots and dies. 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, and creep life. Surface roughness also affects several functional attributes of parts, such as wearing, heat transmission, ability of holding a lubricant, coating, or resisting fatigue. Therefore, the desired finish surface is usually specified and the appropriate processes are selected to reach the required quality. Several factors influence the final surface roughness in end milling operation [11]. Factors such as spindle speed, feed rate, and depth of cut that control the cutting operation can be setup in advance. However, factors such as tool geometry, tool wear, and chip formation, or the material properties of both tool and workpiece are uncontrolled [12].

This research is to develop the techniques and models for predict the surface roughness of a product before milling process and the machining parameters such as depth of cut, feed rate and spindle speed for keeping a desired surface roughness and increasing product quality. It is also important that the prediction technique should be accurate, reliable and the optimizing machinability of materials. Therefore, the purpose of this research as:

1. To recognize and visualize the effect of machining parameters on the surface quality of the machined surfaces.
2. To obtain one surface prediction technique which is termed the regression prediction model.
3. To evaluate the error between predicted and measured surface roughness in the end-milling process by prediction ability of model.

Experimental Setup

Experimental design

To build up a more effective research to obtain and to understand the effects and the relation between/on the process parameters depth of cut, spindle speed and cutting feed rate on the surface finish of the machined surface. Whenever an experiment requires two or more parameters, these parameters can affect the response individually. Frequently, the experimental design cannot give an idea about the interaction results of the parameters as in the case of one parameter, when all the possible parameters as to interaction with the certain level combinations thus the experiment is conducted in completely randomized designs are particularly utile for examining the interaction effect of the parameters. Experiments have been performed in arrange to designs are set aside when there are no limitations on the arrangement of the testing to avoid systematic biases error due to the wear of the cutting tool. The following steps as a procedure to define a model for the machining parameters:

1. Choosing the influencing parameters to be required in the end-milling process.
2. Choosing the different-different levels of these parameters.
3. Conducting the experiment at all possible parameters level combinations randomly.
4. Examining and analyzing the collected data using ANOVA (parametric Analyses of Variance) with the help of Microsoft office Excel 2007.
5. Formulating the MRM (Multiple Regression Models).
6. Formalizing of the model.

Necessary requirement for experimental procedure

In this research the necessary requirements and conditions for performing the experiment as follows:

1. Bridgeport vertical end-milling machine.
2. Eight 3/4 inch four-flute high-speed steel cutters.
3. The cutting parameters were set as:

a. Four levels of spindle speed (850, 1050, 1150, 1300 rpm)
b. Seven levels of feed rate (125, 200, 250, 400, 470, 525, 575 mm/min)
c. Three levels of depth of cut (0.5, 0.95, 1.75 mm)

4. The experiment has been done under dry machining environment.
5. The cutters used to execute the experiment were selected randomly.
6. Surface roughness Ra measured in micro-meters was the response variable.
7. Several variables were put under close control including the machine on which milling operation was performed (the same machine was used for all experimental work)
8. The operator (the same operator machined all specimens).
9. The surface roughness data were collected randomly for each of the 45 machining conditions defined by the levels of independent variables (4 spindle speeds, 7 cutting feeds, 3 depths of cut).
10. The experiment was performed on aluminum workpieces and the experimental setup is shown in figure. 1.
11. Profilometer which is a measuring instrument used to measure a surface's profile, in order to quantify its roughness.

The details of the end milling cutter are given below:

1. Cutter diameter =98 mm
2. Overall length = 150 mm
3. Fluted length = 50 mm
4. Helix angle = 25^0
5. Hardness = 1605 HV
6. Density = 15.5 g/cc
7. Transverse rupture strength =4700 N/mm^2

The test work pieces are made of Aluminum of size 100 mm x 80 mm x 15mm rectangular plate. Different plates of same dimension and material are used for each experimental run. Material properties are given below:

1. Density: 2200-2600 kg/m3
2. Melting Point: 670 °C
3. Elastic Modulus: 80-90 GPa
4. Tensile Strength: 200-520 MPa
5. Yield Strength: 205-550 MPa

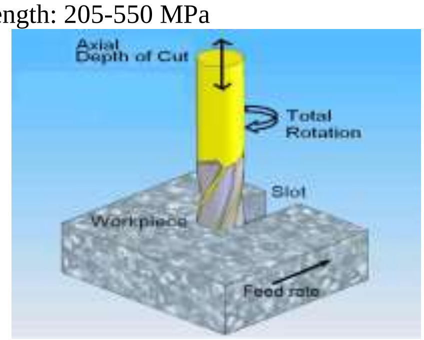

Figure 1: End milling operation

Formulating the MRM (Multiple Regression Models)

The suggested MRM is a two-way interaction equation:

$$Y = A + B_1X_1 + B_2X_2 + B_3X_3 + B_{12}\,X_1X_2 + B_{13}X_1X_2 + B_{23}X_2X_3 \quad \ldots\ldots\ldots\ldots\ldots\ldots\ (1)$$

Where;

Y: surface roughness in µm
X1: spindle speed in rpm
X2: cutting feed in m/min
X3: depth of cut in mm

In this MRM, a commercial statistical package of Microsoft office Excel 2007was used to do the regression analysis and the measure variable is the predictor variables are depth of cut, spindle speed and feed rate and the surface roughness (Ra).

Table 1: The training set contained 30 specimens

No.	Cutting parameters			Mesaured	Predicted	δi	δbar
	N	F	D	Ram	Rap		
	rpm	mm/min	mm	µm	µm		
1	850	575	1.75	3.70	2.98	19.34	
2	1150	250	1.75	2.40	2.36	1.54	
3	1050	400	0.5	2.60	3.01	15.70	
4	850	525	1.75	4.40	2.88	34.53	
5	850	250	0.95	2.60	2.36	9.20	
6	1300	400	1.75	2.50	2.50	0.06	
7	1150	470	1.75	2.30	2.62	13.99	
8	1050	250	1.75	2.30	2.35	1.97	
9	850	125	1.75	1.90	2.05	7.91	
10	1300	525	0.95	2.60	3.01	15.80	
11	1300	470	0.5	3.20	3.00	6.22	
12	1050	470	0.5	4.00	3.38	15.62	
13	850	400	0.95	3.10	3.03	2.14	
14	1150	525	0.5	3.80	3.50	7.97	
15	1150	200	0.95	2.10	2.04	2.86	
16	1050	125	1.75	1.60	2.16	35.04	
17	1050	250	0.95	2.10	2.27	7.92	
18	850	470	1.75	3.30	2.77	16.17	
19	1300	525	0.5	3.20	3.25	1.50	
20	1150	575	0.95	2.50	3.38	35.38	
21	1300	470	1.75	2.60	2.55	1.95	
22	850	525	0.95	4.50	3.59	20.13	
23	1050	575	0.5	3.80	3.93	3.30	
24	850	250	1.75	2.40	2.31	3.76	
25	1300	200	0.95	1.90	1.99	4.83	
26	1150	125	0.5	1.20	1.52	26.73	
27	1150	575	1.75	2.50	2.75	9.81	
28	1150	400	1.75	2.50	2.54	1.57	
29	1050	200	0.5	2.30	1.96	14.78	
30	1050	470	0.95	3.00	3.12	4.04	
					Sum:	341.77	11.39

Table 2: The testing set contained 15 specimens which were used to test the flexibility and the validity of the regression model

No.	Cutting parameters			Mesaured	Predicted	δi	δbar
	N	F	D	Ram	Rap		
	rpm	mm/min	mm	µm	µm		
1	1050	470	1.75	2.10	2.67	27.14	
2	1300	125	1.75	1.50	2.30	53.25	
3	850	250	0.5	3.00	2.39	20.36	
4	850	470	0.95	3.70	3.35	9.53	
5	1050	400	1.75	2.60	2.57	1.28	
6	850	200	0.5	2.10	2.10	0.13	
7	1300	400	0.5	2.70	2.69	0.50	
8	1150	575	0.5	3.10	3.74	20.78	
9	1300	470	0.95	2.30	2.84	23.41	
10	850	525	0.5	4.70	4.00	14.99	
11	1300	400	0.95	2.10	2.62	24.71	
12	850	400	0.5	3.20	3.27	2.05	
13	1150	525	1.75	3.10	2.69	13.34	
14	1150	400	0.5	2.70	2.88	6.65	
15	1050	525	1.75	2.10	2.75	31.01	
					Sum:	249.11	16.61

Because these variables are controllable machining parameters, they can be used to predict the surface roughness in milling which will then raise product quality.

In systematic to estimate the accuracy of the MRPM (Multiple Regression Prediction Model), percentage deviation δ_i and average percentage deviation ($\overline{\delta}$) were used and defined as:

$$\delta_i = \frac{|R_{am} - R_{ap}|}{R_{am}} \times 100\ \% \qquad \text{…………..} (2)$$

Where;

δ_i Percentage deviation of single sample data.

R_{am}: measured Ra .

R_{ap}: predicted Ra generated by a multiple regression equation.

$$\overline{\delta} = \sum_{i=1}^{n} \delta_i \qquad \dots\dots\dots\dots\dots (3)$$

Where;

($\overline{\delta}$) average percentage deviation of all sample data

n: the size of sample data

This method would examine as follows:

1. The average percentage deviation of actual Ra is measured by a contact profilometer's stylus
2. The predicted Ra is produced by the MRM.

Results and Discussion

After performing the experiments on 45 specimens were examined, they were measured contact profilometer's stylus to obtain the surface roughness average value Ra. All original 45 specimens were randomly divided into two data sets, training set and testing set. The training set contained 30 specimens which were used to build up the model and the testing set contained 15 specimens which were used to test the flexibility and the validity of the regression model as shown in Tables 1 and 2, respectively.

A statistical model was created by regression function in Microsoft office Excel 2007 from the training data set. The R Square was 0.644, which showed that 64.40 % of the observed variability in Ra could be explained by the independent variables. The Multiple R was 0.9158, 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.

Using these coefficients, the multiple regression equation could be expressed as:

$$R_a = 1.178854 - 0.000492N + 0.009897F - 0.17625 - 0.000003N \times F + 0.000811N \times D - 0.003012F \times D \qquad \text{………………} (5)$$

The scatter plot between the observed Ra and the predicted Ra of all 45 samples as shown in Figure 2 indicated that the relationship between the measured Ra and the predicted Ra was linear.

The result of average percentage deviation ($\overline{\phi}$) showed that the training data set (n=30) was 11.39% and the testing data set (n=15) was 16.61%. This means that the statistical model could predict the surface roughness (Ra) with about 88.61% accuracy of the training data set and approximately 83.39% accuracy of the testing data set.

Conclusions

A series of experiments has been conducted in order to begin to characterize the factors affecting surface roughness for the end-milling process. The effect of spindle speed, feed rate, depth of cut on surface roughness of aluminum samples was studied.

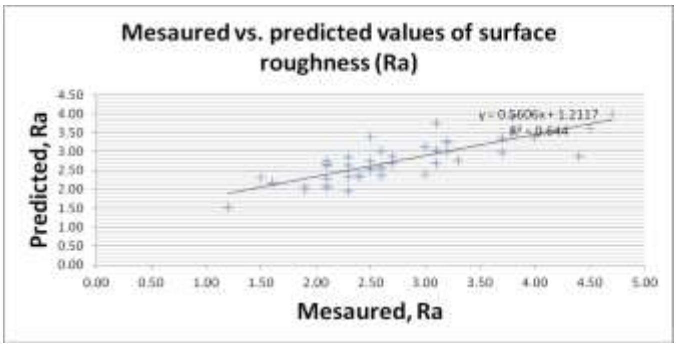

Figure 2: Measured vs. predicted values of surface roughness

The model generated, which includes the effect of spindle speed, feed rate, depth of cut, and the any two-variable interactions, predicts surface roughness reasonably well. The deviation between predicted and measured surface roughness values was within an error band of about 5.22 %. The machining parameters investigated influenced the surface finish of the machined workpiece significantly. In general, the study shows that cutting feed is by far the most dominant factor of those studied. The most important interactions, that effect surface roughness of machined surfaces, were between the cutting feed and depth of cut, and between cutting feed and spindle speed.

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