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A Study of the Effects of Machining Parameters on the Surface Roughness in the End-Milling Process

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Abstract

A set of experiments designed to begin the characterization of surface quality for the end-milling process have been performed. The objective of this study is to develop a better understanding of the effects of spindle speed, cutting feed rate and depth of cut on the surface roughness and to build a multiple regression model. Such an understanding can provide insight into the problems of controlling the finish of machined surfaces when the process parameters are adjusted to obtain a certain surface finish. The model, which includes the effect of spindle speed, cutting feed rate and depth of cut, and any two-variable interactions, predicted the surface roughness values with an accuracy of about 12%.

Keywords: Surface Finish; ANOVA; Pareto Chart; Surface Roughness; End milling;

1. Introduction

Metal cutting is one of the most significant manufacturing processes in the area of material removal [1]. Black [2] 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 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 [3-5].

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 [6].

One may ask a logical question: do we really need to improve the methodology of metal cutting experimental study? The answer to this question is given in the recent CIRP working paper [7] the quote of which is as follows: "A recent survey by a leading tool manufacturer indicates that in the USA the correct cutting tool is selected less than 50% of the time, the tool is used at the rated cutting speed only 58% of the time, and only 38% of the tools are used up to their full tool life capability". The same has been found in an earlier survey of cutting regime selection on CNC machine tools in the American aircraft industry [8] showing that selected cutting speeds are far below the optimal economic speeds.

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 [9]. 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.

The accelerated application of computer aided manufacturing (CAM) to machining by the use of CNC machine tools has focused on developing reliable machinery data systems, to ensure optimum production using expensive equipment. These computerized machinability data systems have been classified into two

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general types [10], namely database system and mathematical model system. The database system uses the collection and storage of large quantities of data from experiments, and the mathematical models attempt to predict the optimum conditions [10].

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 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].

One should develop techniques to predict the surface roughness of a product before milling in order to evaluate the robustness of machining parameters such as feed rate or spindle speed for keeping a desired surface roughness and increasing product quality. It is also important that the prediction technique should be accurate and reliable.

Researchers in this area attempt to develop models which can predict surface finish of a metal for a variety of machining conditions such as speed, feed, depth of cut, etc. Reliable models would not only simplify manufacturing process planning and control, but would assist in optimizing machinability of materials. Therefore, the purpose of this study is (1) to study the effect of machining parameters on the surface quality of the machined surfaces, (2) to develop one surface prediction technique which is termed the multiple regression prediction model and (3) to evaluate prediction ability of model.

2. Experimental Setup and Procedure

2.1. Experiment Design

Experiments have been performed in order to investigate the effects of one or more factors of the process parameters (spindle speed, feed rate and depth of cut) on the surface finish of the machined surface. When an experiment involves two or more factors, the factors can affect the response individually or interactally. Often, the experimental design does not give an idea about the interaction effects of the factors as in the case of one factor at-a time experimentation, All possible factor level combinations experiments conducted in completely randomized designs are especially useful for testing the interaction effect of the factors. Completely randomized designs are appropriate when there are no restrictions on the order of the testing to avoid systematic biases error due to the wear of the cutting tool. The procedure to define a model of the process includes the following steps:

1. Selecting the factors to be involved in the process and choosing the levels of these factors.
2. Conducting the experimental at all possible factor level combinations randomly.
3. Analyzing the collected data using parametric analyses of variance (ANOVA).
4. Building the multiple regression model.
5. Validating of the model.

2.2. Experimental Procedure

This experiment employed a Bridgeport end-milling machine. Eight ¾-inch four-flute high-speed steel cutters were used. The experiment has been done under dry machining environment. The experimental setup is shown in figure. 1. The cutting parameters were set as: four levels of spindle speed (750, 1000, 1250, 1500 rpm), seven levels of feed rate (150, 225, 300, 375, 450, 525, 600 mm/min), and three levels of depth of cut (0.25, 0.75, 1.25 mm). The cutters used to execute the experiment were selected randomly. Surface roughness R_a measured in micro-meters was the response variable. 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), and the operator (the same operator machined all specimens). The surface roughness data were collected randomly for each of the 84 machining conditions defined by the levels of independent variables (4 spindle speeds ×7 cutting feeds × 3 depths of cut). The experiment was performed on aluminum workpieces.

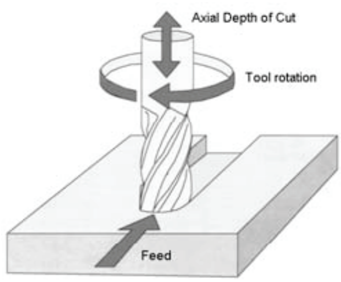

Figure 1: End milling operation

2.3. Building the multiple Regression model

The proposed multiple regression model is a two-way interaction equation:

$$Y = C + B_1X_1 + B_2X_2 + B_3X_3 + B_{12}X_1X_2 + B_{13}X_1X_2 + B_{23}X_2X_3 \qquad (1)$$

where

Y: surface roughness in μm

X_1: spindle speed in rpm

X_2: cutting feed in m/min

X_3: depth of cut in mm

In this model, the criterion variable is the surface roughness (R_a) 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. A commercial statistical package STATISTICA 6.0 was used to do the regression analysis. In order to judge the accuracy of the multiple regression prediction model, percentage deviation ϕ_i and average percentage deviation $\bar{\phi}$ were used and defined as

$$\phi_i = \frac{|R_{aim} - R_{aip}|}{R_{aim}} \times 100\% \quad (2)$$

where ϕ_i: percentage deviation of single sample data.

R_{aim}: measured R_a .

R_{aip}: predicted R_a generated by a multiple regression equation.

$$\bar{\phi} = \frac{\sum_{i=1}^{n} \phi_i}{n} \quad (3)$$

where $\bar{\phi}$: average percentage deviation of all sample data

n: the size of sample data

This method would test the average percentage deviation of actual R_a (measured by an off-line stylus type profilometer) and predicted R_a (produced by the multiple regression model).

3. Results and Discussion

After 84 specimens were cut for experimental purposes, they were measured off-line with a stylus type profilometer to obtain the roughness average value R_a. All original 84 samples were randomly divided into two data sets, training set and testing set. The training set contained 60 samples which were used to build the model and the testing set contained 24 samples which were used to test the flexibility and the validity of the regression model as shown in Tables 1 and 2, respectively. The collected data were analyzed using parametric analyses of variance (ANOVA) with surface finish as the dependent variable and spindle speed N, Cutting feed F and depth of cut D as independent variables. The ANOVA model was modified to include the main effects of the independent variables and up to two-variable interactions only. The significance level was based on the P-value from ANOVA [13] as

$$\begin{aligned} &\textit{Insignificant if } P > 0.10 \\ &\textit{Mildly significant if } 0.05 < P < 0.10 \\ &\text{and} \\ &\textit{Significant if } P < 0.05 \end{aligned} \quad (4)$$

A statistical model was created by regression function in STATISTICA 6.0 from the training data set. The R Square was 0.83879, which showed that 83.879 % of the observed variability in R_a 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.

Table 1 Effect of cutting parameters on the surface finish of the machined surfaces (training data set)

No.	Cutting parameters N rpm	F mm/min	D mm	R_a, μm	No.	Cutting parameters N rpm	F mm/min	D mm	R_a, μm	No.	Cutting parameters N rpm	F mm/min	D mm	R_a, μm
1	750	525	1.25	3.7	21	1500	450	1.25	2.6	41	1000	600	0.75	4.0
2	1250	300	1.25	2.4	22	750	600	0.75	4.5	42	1250	150	1.25	1.7
3	1000	375	0.25	2.6	23	1000	525	0.25	3.8	43	1000	375	0.75	2.6
4	750	600	1.25	4.4	24	750	300	1.25	2.4	44	1250	300	0.75	2.5
5	750	300	0.75	2.6	25	1500	225	0.75	1.9	45	1000	225	0.75	2.4
6	1500	375	1.25	2.5	26	1250	150	0.25	1.2	46	1500	300	0.75	2.1
7	1250	450	1.25	2.3	27	1250	525	1.25	2.5	47	1000	525	0.75	3.9
8	1000	300	1.25	2.3	28	1250	375	1.25	2.5	48	1250	225	0.25	2.1
9	750	150	1.25	1.9	29	1000	225	0.25	2.3	49	1000	150	0.75	1.9
10	1500	600	0.75	2.6	30	1000	450	0.75	3.0	50	1250	375	0.75	2.5
11	1500	450	0.25	3.2	31	1000	600	0.25	4.1	51	1000	150	0.25	1.6
12	1000	450	0.25	4.0	32	1500	150	0.25	1.3	52	1000	225	1.25	2.7
13	750	375	0.75	3.1	33	750	375	1.25	2.6	53	750	225	1.25	2.5
14	1250	600	0.25	3.8	34	1500	525	1.25	3.0	54	1250	450	0.75	2.2
15	1250	225	0.75	2.1	35	1250	300	0.25	2.6	55	1500	300	0.25	2.3
16	1000	150	1.25	1.6	36	1000	300	0.25	3.1	56	750	450	0.25	4.8
17	1000	300	0.75	2.1	37	1500	225	0.25	1.4	56	1250	600	0.75	2.6
18	750	450	1.25	3.3	38	750	225	0.75	2.6	58	750	525	0.25	4.5
19	1500	600	0.25	3.2	39	750	150	0.75	1.7	59	1250	225	1.25	2.4
20	1250	525	0.75	2.5	40	750	525	0.75	4.0	60	1250	150	0.75	1.7

Table 2 Effect of cutting parameters on the surface finish of the machined surfaces (testing data set)

No.	Cutting parameters N rpm	F mm/min	D mm	R_a, μm	No.	Cutting parameters N rpm	F mm/min	D mm	R_a, μm	No.	Cutting parameters N rpm	F mm/min	D mm	R_a, μm
1	1000	450	1.25	2.1	9	1500	450	0.75	2.3	17	1500	525	0.75	2.6
2	1500	150	1.25	1.5	10	750	600	0.25	4.7	18	1500	525	0.25	3.1
3	750	300	0.25	3.0	11	1500	375	0.75	2.1	19	1500	600	1.25	3.2
4	750	450	0.75	3.7	12	750	375	0.25	3.2	20	750	150	0.25	1.6
5	1000	375	1.25	2.6	13	1250	600	1.25	3.1	21	1250	450	0.25	2.5
6	750	225	0.25	2.1	14	1250	375	0.25	2.7	22	1500	150	0.75	1.4
7	1500	375	0.25	2.7	15	1000	600	1.25	2.1	23	1000	525	1.25	1.5
8	1250	525	0.25	3.1	16	1500	300	1.25	2.4	24	1500	225	1.25	1.8

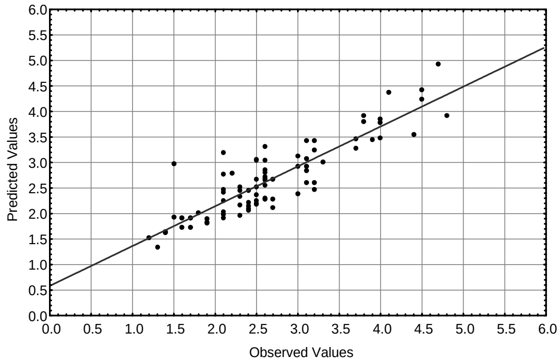

Figure 2:Observed vs. predicted values of surface roughness

In Table 3, the coefficients for the independent variables were listed in the column B. Using these coefficients, the multiple regression equation could be expressed as:

$$R_a = 1.178854 - 0.000492N + 0.009897F - 0.17625D$$
$$- 0.000003N \times F + 0.000811N \times D - 0.003012F \times D \quad (5)$$

The scatterplot between the observed R_a and the predicted R_a of all 84 samples as shown in Figure 2 indicated that the relationship between the actual R_a and the predicted R_a was linear.

The result of average percentage deviation ($\bar{\phi}$) showed that the training data set (n=60) was 11.645% and the testing data set (n=24) was 12.134%. This means that the statistical model could predict the surface roughness (R_a) with about 88.355% accuracy of the training data set and approximately 87.866% accuracy of the testing data set.

Table 3: included in the multiple regression model (α=0.05)

Factor	Effect (Beta)	Standard error of effect (SE Beta)	Regression Coefficient (B)	P-value
Intercept			1.178854	0.0000*
N	-0.166194	0.173971	-0.000492	0.0000*
F	1.792732	0.242093	0.009897	0.0000*
D	-0.086891	0.258455	-0.176250	0.0002*
N×F	-0.803242	0.258455	-0.000003	0.0017*
N×D	0.507176	0.242093	0.000811	0.0585**
F×D	-0.726007	0.173971	-0.003012	0.0000*

* : Strongly significant
**: Mildly significant

The analysis indicated that all main factors and their interactions were highly significant (P<0.05). The individual effects of various factors as well as their interactions can be discussed from the Pareto chart illustrated by Figure 3. The length of each bar in the Pareto chart is proportional to the absolute value of its associated regression coefficient or estimated effect. The effects of all parameters and interactions terms, are standardized (each effect is divided by its standard error). The order in which the bars are displayed corresponds to the order of the size of the effect. The chart includes a vertical line that corresponds to the 95% limit indicating statistical significance. An effect is, therefore, significant if its corresponding bar crosses this vertical line.

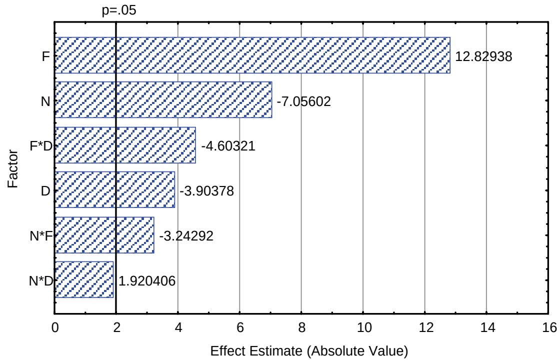

Figure 3: Pareto Chart of Standardized Effects for surface roughness R_a showing significant factors and interactions

The numerical estimates of the effects indicate that the effect of feed is the largest (12.82) and has positive direction. The positive direction means that the surface finish deteriorated with increasing the cutting feed. This is due to the increase in distance between the successive grooves made by the tool during the cutting action, as the cutting feed increases.

Figure 3 shows the effect of spindle speed (-7.05). The negative direction means that increasing the spindle speed improves the surface finish. It is generally well known that an increase in cutting speed improves machineability. This may be due to the continuous reduction in the build up edge formation as the cutting speed increases.

The interaction between the cutting feed and depth of cut significantly affects the surface roughness (-4.6). The interaction also suggests that to get a certain surface finish and maximum metal removal it is preferable to use a high cutting feed associated with depth of cut.

The depth of cut also has negative value (-3.9), which indicates that increasing the depth of cut improves the surface finish. The effect of the depth of cut is less significant on the surface finish.

The interaction between the cutting feed and spindle speed is significantly affecting the surface roughness as shown in Figure 3. The figure shows that increasing the spindle speed improves the surface finish as the cutting feed decreases. This supports the earlier discussion about the effect of decreasing cutting speed on the surface roughness of the machined workpieces.

The interaction between the depth of cut and spindle speed is less significant as shown in Figure 3. The interaction reveals that increasing the spindle speed and increasing the depth of cut deteriorates the surface finish.

4. 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. 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 12%. 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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