Effects of the Cutting Conditions and Vibration on the Surface Roughness of End Milling Process

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Abstract - *This study reported the investigation on the influence of cutting parameters and machining vibration on the surface quality of the milled workpieces. Regression analysis was used to establish a mathematical model to predict the surface accuracy under various cutting conditions (spindle speed, axial depth of cut and feed rate). According to the results, for regression model established by using cutting parameters, the correlation coefficient between the predicted values and the measured values is about 0.7, and the average prediction error is 16.9%. For regression model based on cutting parameters and machining vibration, the correlation coefficient between the predicted values and the measured values is more than 0.84, and the average error is about 13.6%. It shows that the tool vibration has a great influence on the cutting quality, which is also an important parameter for establishing a prediction model. This method can be combined with other optimization algorithms to optimize the cutting process. The results can provide the basis for the development of on-line cutting vibration monitoring system to predict the surface quality in milling process.*

Key Words: Cutting conditions, Machining vibration, Surface roughness, Regression analysis.

1. INTRODUCTION

The development of the machine tool industry is mainly motivated by the needs of the application side, especially, with high demand of processing efficiency and high quality. The basic characteristics of high precision and high surface quality are gradually widely used in aerospace industry, 3C industry and other industries. High performance machining actually is an integrated technology of machining process with high cutting speed, high feed rate and high material removal rate. Compared with traditional process, high performance machining technology not only achieves faster cutting speed, higher processing efficiency and lower processing costs, but also, shows new technical characteristics, which has become an important factor to promote the development of machinery manufacturing technology.

Another advantage of high performance machining technology is that it can produce better machined surface accuracy. This is based on the manufacturing process of mechanical components, and high-speed machining is an important method to obtain the final geometric size and shape. Nowadays, due to the high requirements for product quality, the surface roughness of high-precision products is an important indicator of workpiece quality. Poor surface accuracy will affect the frictional resistance of the combined interface, the lubricating interface layer and even the fatigue life [1-4]. Basically, the factors affecting the surface cutting accuracy include tool material geometry, workpiece material and cutting conditions, etc. [5,6]. Cutting parameters such as axial depth of cut, spindle speed, feed rate was shown to have great impacts on surface quality [7]. Therefore, monitoring the surface quality within the desired range is of importance and worthy of investigation. It follows that the optimization of cutting conditions is a perquisite for producing better surface accuracy [8-11].

Lou et al. [4] proposed a surface roughness prediction model for milling 6061 aluminum alloy, in which the dominant factors include cutting rate, feed rate, and depth of cut. Taguchi analysis based on the machining experiments shows that the cutting depth has a significant effect (40%), followed by tool material (30%) and rotational speed (20%), while the effect of feed rate is not significant. Finally, a multivariate regression analysis is used to establish a prediction model. This model provides a predicted surface roughness measure with 90% accuracy. Pinar et al. [12] also employed Taguchi method to investigate the influence of process parameters such as cutting rate, feed rate, cutting depth and cutting path on surface roughness. Their results confirmed that surface roughness has a significant positive correlation with feed rate and depth of cut, and a negative correlation with cutting rate, while there is no significant correlation with cutting path. Arokiadass et al. [8] reported the influence of cutting speed, feed rate, depth of cut and silicon content of silicon nitride hardened tools on the surface roughness. In their research, the response surface method was used to establish the correlation and mathematical model of surface roughness and cutting parameters. The results show that the second-order model can present such a relationship, and the regression analysis shows that the correlation coefficient is 99.85%, with a confidence level of 95%. This model also confirms that feed rate has a significant effect on surface roughness, followed by spindle speed. Nian et al.[13] applied Taguchi method to set cutting speed, feed rate and depth of cut as control factors, and considered multi-objective characteristics at the same time. Bhogal et al. [14] applied multivariable regression analysis to establish a prediction model of cutting parameters on surface roughness, tool wear and tool vibration, and found that feed rate is the main factor affecting surface accuracy, and spindle speed is the main factor affecting tool vibration in machining. These studies show that the influence extent of cutting parameters on the surface roughness is different, which is dependent on machine spindle tool system, geometry characteristics and material of the cutter, workpiece material and selected cutting parameters in the experimental conditions.

Further, David et al. [15] demonstrated that workpiece topomorphy is affected by the vibration of cutter in machining. They found that an increased cutting force with an increasing cutting depth and feed rate leads to higher vibration, and it accordingly increases surface roughness. Zahoor [16] reported that surface roughness was greatly affected by the vibration amplitude of the machine tool and the axial cutting depth. The vibration levels are closely related to the cutting parameters and they increase with an increase in the cutting speed and feed rate [17-18].

Concluding from above mentioned studies, it is obvious that the influences of the cutting parameters and the induced vibration in machining are factors affecting machining performance. Therefore, this study was aimed to develop a mathematical model for predicting the surface roughness in end milling machining with consideration of the machining vibration. Then machining experiments using aluminum alloy were conducted under various combinations of cutting conditions. The surface roughness of the machined parts was examined by means of the white light interferometer. Multivariable linear regression analysis was employed to determine the correlation between the surface roughness and the machining parameters. Different mathematical models are proposed for comparing the effectiveness in roughness predictions. The models are expected to be applied for improve the machining quality with desired productivity.

2. Machining tests

In this study, machining experiments were conducted on the milling machine using a 4-tooth tungsten carbide end mill. The workpiece material is an aluminum alloy (Al6061) with a size of 150 mm × 150 mm × 80 mm. Machining processes performed by full immersion of slot milling, as shown in Figure 1. Each slot was milled in the X-direction under different cutting parameters. The axial cutting depth (Z) was 1、1.5、2.0、2.5、3.0、3.5 and 4.0mm. The spindle speed (S) was set from 3000 to 10000 rpm, increased by 1000 rpm, respectively. The linear feed rate (F) was set at 0.05 and 0.075 mm/tooth, corresponding to feed rate at 600 to 2400 mm/min, respectively. During milling process, a tri-axial accelerometer was mounted on the spindle housing to measure the vibrations in directions (X, Y, and Z) simultaneously. For each slot machining, the average value taken from the time domain root mean square (RMS) values of the accelerations were calculated and used to compare the vibration extent of milling under different cutting parameters. There are a total of 240 machining conditions defined by the different levels of cutting parameters, including 8 spindle speeds, 2 feed rates, and 7 cutting depths.

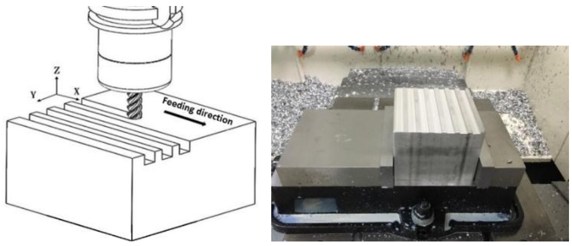

Fig -1: Machining test and workpiece.

After machining tests, the surface roughness (Ra) was measured using white light interferometer (Optical Surface Profiler, Zygo, NewView™ 8000 Series). For each machined slot, roughness values were measured at five equally spaced points along the feeding direction, and then, the average of these values was recorded for subsequent analysis. Figure 2 shows the morphologies of machined surfaces and the vibration spectrum of the milling spindle under specific machining conditions, which indicates that the cutting depth with a greater vibration level has a rougher surface. For example, for a cutting depth of 1.0 mm at a speed of 4000 rpm, Ra was measured as 0.478μm When the cutting depth was set at 1.3 mm, Ra =0.491 μm was generated under a spindle speed of 4000 rpm.

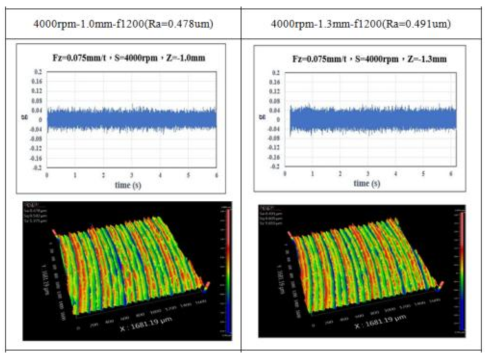

Fig -2: Surface morphologies and Vibration spectrum.

3. Multivariable regression analysis

The mathematical function of surface roughness (Ra) is proposed to be related the cutting depth (Z), spindle speed (S) and feed rate (F) by nonlinear model in the form as below:

1. Nonlinear polynomial model

$$R_a = \beta_0 + \beta_1 Z + \beta_2 S + \beta_3 F + \beta_4 \cdot Z \cdot S + \beta_5 \cdot S \cdot F + \beta_6 \cdot Z \cdot F + \beta_7 \cdot Z \cdot F \cdot S \quad (1)$$

2. Nonlinear power-law model

$$R_a = C \cdot Z^{\beta 1} \cdot S^{\beta 2} \cdot F^{\beta 3} \quad (2)$$

This model can be expressed in logarithmic transformation form, as follows

$$\ln R_a = \ln C + \beta_1 \cdot \ln Z + \beta_2 \cdot \ln S + \beta_3 \cdot \ln F \quad (3)$$

In above models, the regression coefficients βi (i=0,1,2) are to be estimated from experimental data by the method of least squares regression analysis.

The effectiveness of the regression models were evaluated based on root mean square errors (RMSE), determination coefficient (R), and mean absolute percentage error (MAPE). These values are determined by

$$RMSE = \left(\left(\sum_{i=1}^{N} |t_i - y_i|^2 \right) / N \right)^{1/2} \quad (4)$$

$$R^2 = 1 - \left(\sum_{i=1}^{N} (t_i - y_i)^2 / \sum_{1}^{N} (y_i)^2 \right) \quad (5)$$

$$MAPE = \sum_{i=1}^{N} ((t_i - y_i)/t_i) \times 100)/N \quad (6)$$

where t is the target value, y is the predicted value, and N is the number of samples in analysis.

3. Variation of surface roughness

Figure 3 (a) shows the distribution of surface roughness over different speeds and cutting depths. It is found that at specific speed, a larger cutting depth generates poor surface roughness. At a specific depth of cut, there is no specific trend in the effect of rotation speed on the surface thickness, but it is clearly shown that when the speed is between 6000 and 8000rpm and the depth of cut is above 3.0mm, the surface thickness increases significantly. Figure 3(b) shows the surface roughness distribution at different feed rates and speeds. It is clear that the surface finish produced by high feed rates (>2500 mm/min) and rotational speeds between 6000 and 8000 rpm is also significantly worse. Overall, as the depth of cut increases, the surface roughness also increases. When the feed rate is increased, the surface roughness will also increase relatively, which means that the feed rate has a certain influence on the surface roughness. From the data, it is known that the better or worse surface roughness is not at the same location, so the most suitable machining parameters can be found by using the surface roughness.

During machining, the best surface accuracy cannot be obtained in the steady cutting region. The most appropriate spindle speed, feed rate and depth of cut must be selected to improve the processing quality and achieve the effect of improving processing efficiency. Figure 4(a) and (b) show the distribution of the vibration amount with the adjustment of parameters such as spindle speed, depth of cut and feed. Its variation trend is similar to surface roughness. When the specific speed is 6000 to 8000 rpm and the depth of cut is above 3.0 mm, the vibration of the tool increases significantly, resulting in a significant increase in surface roughness. The same phenomenon, high feed rate (>2500 mm/min) and large depth of cut (above 2.5mm), the tool vibration increases significantly, which affects the machining quality, and hence the surface roughness value increases.

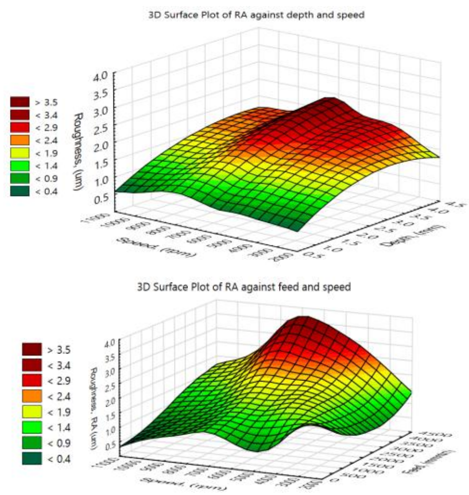

Fig -3: Distributions of surface roughness under different cutting conditions.

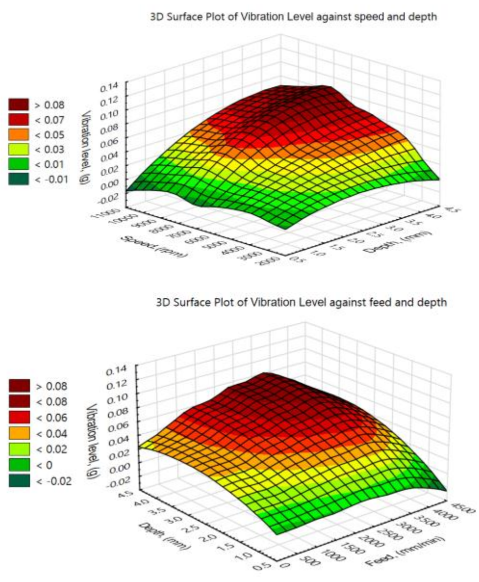

Fig -4 Distributions of machining vibration under different cutting conditions.

4. Regression Analysis - Surface Roughness Model

In this study, regression analysis was used to examine relationship between the independent variable and the dependent variable, and predict the dependent variable based on the change in the value of the independent variable. From the experimental results, the influence of cutting parameters and spindle tool vibration on the surface roughness or machining quality of the workpiece was examined. Therefore, when establishing the prediction model of surface roughness, the effects of tool vibration was also be considered, and it was included as one of the independent variables. Through regression analysis, the influence of each parameter and their interaction as well as the machining vibration on surface roughness can be observed. Two multivariable nonlinear functions in different form were used to establish a rough prediction models, respectively. Statistical coefficients of regression analysis are shown in Tables 1 to 2, and various surface roughness prediction mathematical models are as follows:

(a) RA Model - I

$$R_a = 0.953 - 0.0804 \times Z - 5.6 \times 10^{-5} \times S \;\; 7.68 \times 10^{-5} \times F - 5.30 \times 10^{-5} \times Z \times S + 7.00 \times 10^{-9} \times Z \times F + 2.83 \times 10^{-4} \times S \times F + 2.83 \times 10^{-4} \times Z \times S \times F \quad (7)$$

(b) RA Model - II

$$R_a = 0.9916 + 0.0987 \times Z - 0.0987 \times S - 8.8 \times 10^{-5} \times F - 4.80 \times 10^{-5} \times Z \times S + 1.49 \times 10^{-8} \times Z \times F + 3.0 \times 10^{-4} \times S \times F - 1.80 \times 10^{-8} \times Z \times S \times F + 10.8 \times Vb \quad (8)$$

The roughness values predicted by regression model are compared with the measured values, as shown in Figure5. For regression model I without including the vibration feature, the correlation coefficient between the measured and predicted values is above 0.75, and the average prediction error is 16.9%.

For regression model II established with inclusion of the vibration feature, the correlation coefficient between the measured and predicted values is around 0.84 and the average prediction error is 13.6%. The results show that the roughness models (RA II) constructed by using cutting parameters (speed, depth of cut and feed rate) and machining vibration have excellent accuracy in predicting surface roughness, which is superior than the model based only on the cutting parameters. This also verifies that surface quality can be substantially affected by tool vibration induced in machining process.

Table-1: Regression parameters of nonlinear polynomial RA model -I

Parameters	Coefficients	Standard deviations	P-value
Intercept	9.53E-01	5.36E-01	7.71E-02
Cutting depth (Z)	8.04E-02	1.99E-01	6.87E-01
Spindle speed (S)	-5.60E-05	8.45E-05	5.06E-01
Feed rate (F)	7.68E-05	3.72E-04	8.37E-01
Depth × speed (Z·S)	-5.30E-06	3.14E-05	8.67E-01
Depth × feed (Z·F)	7.00E-09	4.36E-08	8.73E-01
Feed × speed (F·S)	2.83E-04	1.38E-04	4.20E-02
Feed × speed×Depth (F·S·Z)	-2.10E-08	1.62E-08	2.06E-01

Table-2: Regression parameters of nonlinear polynomial RA model -II

Parameters	Coefficients	Standard deviations	P-value
Intercept	9.16E-01	4.39E-01	3.86E-02
Cutting depth (Z)	9.87E-02	1.63E-01	5.46E-01
Spindle speed (S)	-2.60E-05	6.93E-05	7.07E-01
Feed rate (F)	-8.80E-05	3.05E-04	7.74E-01
Depth × speed (Z·S)	-4.80E-05	2.62E-05	7.05E-02
Depth × feed (Z·F)	1.49E-08	3.58E-08	6.78E-01
Feed × speed (F·S)	3.08E-04	1.13E-04	7.17E-03
Feed × speed×Depth (F·S·Z)	-1.80E-08	1.33E-08	1.79E-01
Vibration （VB）	1.08E+01	1.21E+00	1.22E-15

3. CONCLUSIONS

This research was aimed to establish a mathematical prediction model for the surface roughness of workpieces. The constructed algorithm can feed back vibration signal detected in machining process to the model to predict the roughness of the machined surface and determine whether it meets the required quality without off line measurements. The roughness prediction model can be served as a reference for optimizing the processing parameters of the process.

Based on the current research results, the following conclusions are drawn:

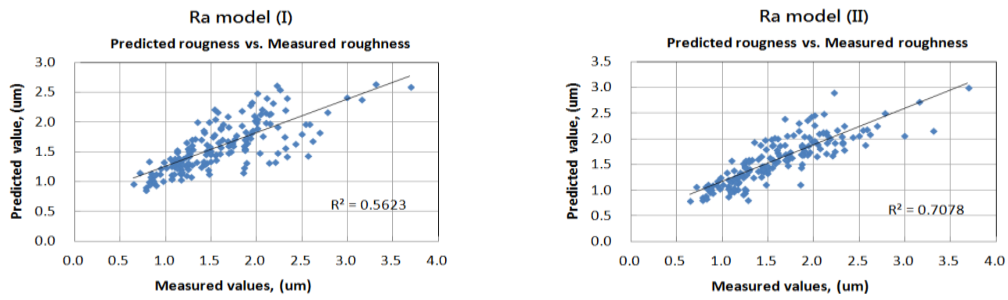

Fig-5: Comparisons of the surface roughness between measurements and predictions.

1. Within the experimental parameters, as the depth of cut increases, the surface roughness also increases gradually. When the feed rate is increased, the surface roughness will also increase relatively, which means that the depth of cut and the feed rate have a certain influence on the surface roughness. There is no specific trend in the effect of spindle speed on the surface roughness, but it clearly shows that the surface roughness increases significantly when the spindle speed is between 6000 and 8000rpm and the depth of cut is above 3.0 mm.

2. The results show that the roughness model (Ra II) based on cutting parameters and machining vibration have excellent prediction performance as compared with model based only on the cutting parameters. This clearly verifies that tool vibration induced in machining process have influential effects on the surface quality.

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