Proceeding, 2nd International Conference on Radiation Sciences and Applications

28/3 – 1/4/2010 – Marsa Alam, Egypt

Comparative Study for Different Statistical Models to Optimize Cutting Parameters of CNC End Milling Machines

Amal El-Berry[1] and Afrah Al-Bossly[2]

1-Computer Science Department, Faculty of Education, El-Kharg University, El-Kharg, KSA and Mechanical Engineering Department, National Research Center, Cairo, Egypt

2-Mathmatics Department, Faculty of Education, El-Kharg University, El-Kharg, KSA

ABSTRACT

In machining operation, the quality of surface finish is an important requirement for many workpieces. Thus, that is very important to optimize cutting parameters for controlling the required manufacturing quality. Surface roughness parameter (Ra) in mechanical parts depends on turning parameters during the turning process. In the development of predictive models, cutting parameters of feed, cutting speed, depth of cut, are considered as model variables. For this purpose, this study focuses on comparing various machining experiments which using CNC vertical machining center, workpieces was aluminum 6061. Multiple regression models is used to predict the surface roughness at different experiments.

Keywords: Surface roughness; CNC end milling; Statistical Modeling

INTRODUCTION

Many factors are contributing to the surface roughness in manufacturing. When molding or forming a surface, the impression of the mold or die on the part is usually the principle factor in the surface roughness. In machining, and abrasive processes the interaction of the cutting edges and the microstructure of the material being cut both contribute to the roughness. A new surface roughness models in micro-end-milling process with four parameters, which are tool diameter, depth of cut, spindle speed and feed rate, were built by using the MBC toolbox. The statistical methods, such as ANOVA and RSM were applied to analyze the experimental data [1].

Ghani et al. [2] got optimum milling parameters; recently, Fredj et al. [3] developed surface roughness prediction model using design of experiment method and the neural network. Brezocnik, et al. [4] produced the genetic programming approach to predict surface roughness based on cutting parameters (spindle speed, feed rate, and depth of cut) and on vibrations between cutting tool and workpiece. The surface roughness values predicted by ANFIS are compared with the measurement values derived from a 24 data sets in order to determine the error of ANFIS. Besides, a 48 sets of experimental data are analyzed to verify the results obtained by ANFIS [5]. Çolak et al. [6] used GEP algorithm, surface roughness prediction from a few experimental data. GEP is coming from its ability to generate mathematical equations that can be easily programmed even into programming for use in monitoring of surface quality . Tansel et al. [7] proposed for selection of the optimal cutting conditions in specialized machining operations from the experimental data without developing any analytical or empirical models. Rashid et al. [8] used multiple regression method approach to predict surface roughness based on cutting parameters by using FANUC

CNC Milling in end-milling operations. neural network modeling approach is presented by P.G. Benardos, G.C. Vosniakos[9] for the prediction of surface roughness (R_a).

Most researchers have investigated the best cutting parameters for surface roughness. In this paper, a comparative study is performed to compare some previous studies under different machining parameters on surface roughness. A multiple regression method is used to determine surface roughness at different experiments.

MATERIALS AND METHODS

A statistical design consisting of a 3 previous experiments was adopted to collect the R_a average roughness height data. Models were compared to predict low surface roughness accurately within a wide range of cutting parameters based on design of experiments method. A genetic programming approach is used to predict surface roughness [4] and compared with the experiments [7], [9]. CNC milling machine and 6061 aluminum workpiece were used to obtain the previous testing data which classified in table 1.

Table 1: Testing data at different models

Model	Spindle Speed	Feed Rate	Depth of Cut
M4 Ref. [4]	750, 1000, 1250, and 1500 rpm.	228.6, 381.0, and 533.4 mm/min.	0.254, 0.762, and 1.27 mm.
M7 Ref. [7]	74–123 m/min.	0.07–0.12 mm/tooth.	0.1–0.3 mm.
M9 Ref. [9]	300,500,700 m/min.	0.08,0.14,20 mm/tooth.	0.25,0.75,1.2 mm.

For each combination of spindle speed, feed rate, and depth of cut, were recorded. The corresponding value of the dependent output variable, i.e., roughness average R_a was collected for each measurement. Multiple Regression Method was used to determine the correlation .The model was expressed as:

$R_a=\beta_0+ \beta_1 v+ \beta_2 f+ \beta_3 d_r$ (1)

R_a :Surface roughness (µm)

V :Spindle Speed (m/min)

f :Feed rate (mm/min)

d_r :Depth of cut (mm)

The independent variables of this study were spindle speed, feed rate, and depth of cut, the dependent was the surface roughness. On the surface roughness, the general and alternative hypothesis are:

H_o: $\beta_j=0$ *where* $j=1,2,3,\ldots\ldots$

H_1 at lest one not equal zero.

An independent T test and a one-way ANOVA for two or more independent samples test is used to compare. A univariate test used with only one dependent variable R_a . There can be one or more independent variable or factors and/or variables. A one-way ANOVA is a univariate with exactly one independent variable

RESUITS AND DISCUSSION

The general null hypothesis, that describes the effects of spindle speed, feed rate, and depth of cut on the surface roughness, do not significantly differ from zero while the alternative hypothesis states that at least one of the β_j not equal to zero. A statistical software program, SPSS was used. Figure 1 shows normal p-p plots of Regression Standardized Residual which supported strong linear relationships in the different models. The result of analysis of ANOVA at table 2 indicates F values of regression 10.683, 13.431, 10.141 and great significance $\alpha=0.003^a$ for M4, $\alpha=0.000$ for both M7 and M9. So for M7 and M9 models in rejecting, the null hypothesis (H_o) give indication that the variable in the models M7 and M9 was zero. Instead the alternative at least one of these coefficients did not equal to zero. The coefficient for all model's variables and constants are given in Table 3, the multiple regression equations constructed as shown:

M4 equation: $R_a=1.249+0.001v+0.004f-0.466d_r$ (2)

M7 equation: $R_a=-0.138+0.004v+5.350E\text{-}05f-1.219d_r$ (3)

M9 equation: $R_a=-0.353+1.556f-0.083d_r$ (4)

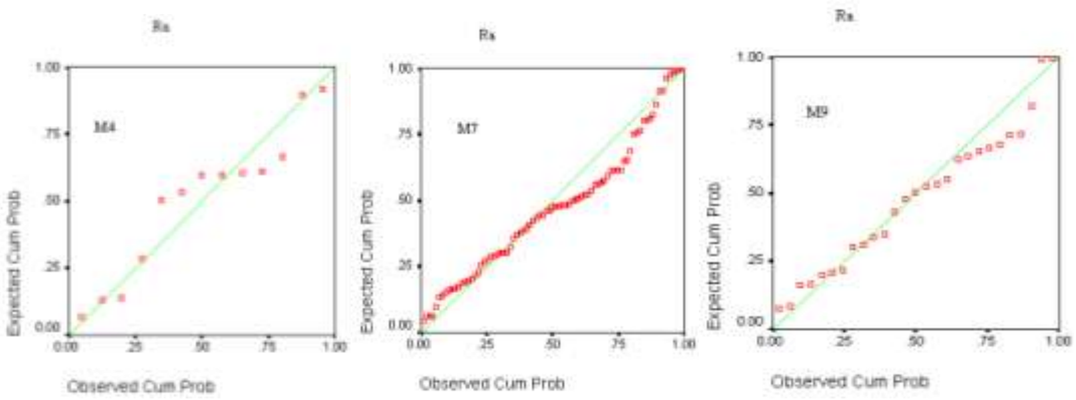

Figure 1: Normal p-p plots of Regression Standardized Residua

Table 2: ANOVA for different models

Model	Item	Sum of Squares	dF	Mean Square	F	**Sig.**
M4	Regression Residual Total	6.629 1.862 8.490	3 9 12	2.210 0.207	10.683	0.003^a
M7	Regression Residual Total	1.845 3.526 5.372	3 77 80	0.615 0.046	13.431	**.000**
M9	Regression Residual Total	2.584 2.953 4.537	3 23 26	0.861 0.85	10.141	**.000**

Table 3: Coefficients of Models

Variables	Coefficients		
	M4	M7	M9
Constant	1.249	-.138	-.353
v	0.001	0.004	0.000
f	0.004	5.350E-05	1.556
d_r	-.466	1.219	0.083

To test the null hypothesis that several population means are equal, based on the results of several independent samples. The test variable is measured on an interval or ratio scale for the experiments and is grouped by a variable which can be measured on a nominal or discrete ordinal scale**.** Table 4 shows 'Test of Homogeneity of Variances' the result of Levene's Test for Equality of Variances. It tests the condition that the variances of both samples are equal, indicated by the Levene Statistic. In this statistic, a high value results normally in a significant difference as *Sig*. = 0.000, H_o is rejected as it assumes equal variances.

Table 4: Test of Homogeneity of Variances

R_a

Levene Statistic	df1	df2	Sig.
15.010	2	118	0.000

In table 5 'ANOVA', the variation (*Sum Of Squares*), the degrees of freedom (*df*), and the variance (*Mean Square*) are given for the within and the between groups, as well as the F value (*F*) and the significance of the F (*Sig*.). *Sig.* indicates null hypothesis so population means are all equal. There is much difference between the Mean Squares resulting in a significant difference (*F* , *Sig*. = 0,000). Thus the average R_a are equals.

Table 5: ANOVA

R_a

	Sum of Squares	df	Mean Square	F	Sig.
Between groups With Groups Total	45.581 33.581 20.512 25.096 18.399 63.981	2 1 1 1 118 120	22.791 33.581 20.512 25.06 0.156	146.163 215.367 131.553 160.774	0.000 0.000 0.000 0.000

Use Post Hoc Tests to evaluate differences among specific means is required. To pinpoint differences between all possible pairs of values of a factor variable, select the factors to be tested. The 'Post Hoc Tests' is suitable. Additionally, select one of the multiple comparison procedures. Table 6 'Multiple Comparisons' shows the out of three groups vary:

1 _ Sig. = 0.0 which is lower than the Sig. level of 0.05 this group vary. 2 _ Sig. = 0,0.929 which is higher than the Sig. level of 0.05. These groups not vary. 3 _ Sig. = 0, 0,0.929 which is higher than the Sig. level of 0.05. These groups vary

Post Hoc Tests

Table 6: Multiple Comparison

R_a

Scheffe

(i)MI (J)MI	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
				Lower Bound	Upper Bound
1.00 2.00	1.9899*	0.11798	0.000	1.6974	2.2824
3.00	1.9563*	0.13330	0.000	1.6258	2.2867
2.00 1.00	-1.9899*	0.11798	0.000	-2.2824	-1.6974
3.00	-0.0337	0.08775	0.929	-.2512	0.1839
3.00 1.00	-1.9563*	0.13330	0.000	-2.2867	-1.6258
2.00	0.0337	0.08775	0.929	-.1839	0.2512

CONCLUSION

A comparison between the proposed models using surface roughness data measured from the experiments within a wide range of cutting parameters were done. Three multiple regression models has been developed to predict the surface roughness. The results showed that Regression Standardized Residual supported has a strong linear relationships in the different models. The surface quality can be produced when machined with a higher cutting speed, small depth of cut a feed rate also have significant impact on surface roughness. An independent T-test and a one-way ANOVA for two or more independent samples test is used to comparison.

REFERENCES

[1] W. Wang, S.H. Kweon, S.H. Yang, A study on roughness of the micro-end-milled surface produced by a miniatured machine tool, W. Wang et al., Journal of Materials Processing Technology 162–163 (2005) 702–708

[2] J.A. Ghani, L.A. Choudhury, H.H. Hassan, Application of Taguchi method in the optimaization of end milling parameters, J. Mater. Process. Technol. 145 (1) (2004) 84–92.

[3] N.B. Fredj, R. Amamou, M.A. Rezgui, Surface roughness prediction based upon experimental design and neural network models, SMC IEEE 5 (2002).

[4] M. Brezocnik, M. Kovacic, M. Ficko, Prediction of surface roughness with genetic Programming, Journal of Materials Processing Technology 157–158 (2004) 28–36

[5] Ship-Peng Lo, An adaptive-network based fuzzy inference system for prediction of workpiece surface roughness in end milling, Journal of Materials Processing Technology 142 (2003) 665–675

[6] Oğuz Çolak, Cahit Kurbanoğlu, M. Cengiz Kayacan , Milling surface roughness prediction using evolutionary programming methods, Materials and Design 28 (2007) 657–666.

[7] I.N. Tansel, B. Ozcelik, W.Y. Bao, P. Chena, D. Rincon, S.Y. Yang, A. Yenilme, Selection of optimal cutting conditions by using GONNS, International Journal of Machine Tools & Manufacture 46 (2006) 26–35

[8] Ab. Rashid M.F.F., Gan S.Y., and Muhammad N.Y., Mathematical Modeling to Predict Surface

Roughness in CNC Milling, World Academy of Science, Engineering and Technology 53 2009.

[9] P.G. Benardos, G.C. Vosniakos, Prediction of surface roughness in CNC face milling using neural networks and Taguchi's design of experiments, Robotics and Computer Integrated Manufacturing 18 (2002) 343–354