SURFACE ROUGHNESS PREDICTION IN END MILLING USING MULTIPLE REGRESSION AND ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM

Ibrahem Maher , M. E. H. Eltaib , R. M. El-Zahry
Mechanical Engineering Department, Faculty of Engineering, Assiut University, Assiut, Egypt.

ABSTRACT– *Multiple regression and adaptive neuro-fuzzy inference system (ANFIS) were used to predict the surface roughness in the end milling process. Spindle speed, feed rate and depth of cut were used as predictor variables. Generalized bell memberships function (gbellmf) was adopted during the training process of ANFIS in this study. The predicted surface roughness using multiple regression and ANFIS were compared with measured data, the achieved accuracy were 91.9% and 94% respectively. These results indicate that the training of ANFIS with the gbellmf is accurate than multiple regression in the prediction of surface roughness.*

KEYWORDS: *Multiple Regression -ANFIS – Surface Roughness- CNC –End milling*

1. INTRODUCTION

Surface roughness is one of the most important factors for evaluating surface quality during the finishing process. The quality of surface affects the functional characteristics of the workpiece such as fatigue and fracture resistance and surface friction. Furthermore, surface roughness in addition to tolerances imposes one of the most critical constraints for cutting parameter selection in manufacturing process planning.

Actual surface roughness monitoring can be achieved either through intensive post-process inspection, an in-process surface roughness measuring device, or surface roughness prediction system. While post process inspection is the easiest to implement it cannot prevent the parts from being processed before a defective batch is discovered. Measuring surface roughness in-process requires sensitive sensors added to a hostile environment. Eventually; surface roughness prediction system can be used to determine the surface roughness indirectly [1].

Several techniques including multiple regression, fuzzy, artificial neural network (ANN) and adaptive neuro-fuzzy inference system (ANFIS) have been used to predict surface roughness of different cutting process [1-12].

Multiple regression is used to determine the correlation between a certain variable and a combination of predictor variables. It was used to predict the surface roughness in different cutting operations [1-5]. The criterion variable is the surface roughness and the predictor variables are controllable machining parameters, such as spindle speed, feed rate, and depth of cut and their interactions. It was used in turning [1-3] and end milling [4, 5] with achieved accuracy up to 90%.

ANFIS is a fuzzy inference system implemented in the framework of an adaptive neural network. By using a hybrid learning procedure, ANFIS can be used to construct an input-output mapping based on both human-knowledge as fuzzy if-then rules and predetermined input-output data pairs for neural networks training. It provides a means for fuzzy modeling to learn information about the data set, in order to compute the membership function parameters that best allow the associated fuzzy inference system to track the given input-output data [13].

Recently, ANFIS was used to predict the work piece surface roughness in end milling operation, reaching accuracy as high as 96% [10]. It was also used to predict surface roughness in turning operation, reaching accuracy up to 93.4% [11]. Samhouri, and Surgenor [12] used ANFIS to monitor and identify the surface roughness of grinding operation online. Power spectral density (PSD) of signal related to grinding features and surface finish is used as an input to ANFIS, which in turn outputs a value for the on-line predicted surface roughness. The adoption of Bell-shaped membership function (gbellmf) in ANFIS gave a prediction accuracy of 91%.

Hence, the aim of the present work is to compare the effectiveness of multiple regression model and ANFIS model for prediction of surface roughness in end milling operation.

The next section introduces the experimental design followed by two sections for creating multiple regression model and ANFIS model respectively. The last section deals with the comparison of the effectiveness of the multiple regression model and ANFIS model in the prediction of surface roughness in end milling operation.

2. EXPERIMENTAL WORK

The experiments were performed using ProLight2000 CNC end milling machine **Figure 1(a)**. A high-speed steel four-flute end milling cutter with a diameter of 12.7 mm was used for machining blocks of Brass (60/40) under specific machining conditions (Speed *n*, feed *f* and depth of cut *t*). The surface roughness Ra, were measured by a stylus-based profilometer (Surtronic 3+, accuracy of 99%) as shown in **Fig. 1(b)**. Fifty four readings were used as training data set and twenty four readings were used as testing data set as listed in **Table 1** and **Table2** respectively.

(a) ProLight2000 CNC end milling machine

(b) Stylus-based profilometer (Surtronic 3+)

Fig. 1: Samples machining and Ra measurement.

Table 1: Measured Ra in microns (training data set).

n rpm	750			1000			1250			1500			1750			2000		
t mm / f mm/sec	0.2	0.4	0.6	0.2	0.4	0.6	0.2	0.4	0.6	0.2	0.4	0.6	0.2	0.4	0.6	0.2	0.4	0.6
2	2.21	2.39	2.15	1.88	1.98	1.69	1.78	1.79	1.72	1.85	1.99	1.91	1.83	1.93	1.89	1.63	1.85	1.7
4	3.37	3.43	3.3	3.04	3.11	3	3	3.12	3.11	1.98	2.21	2.15	2.23	2.29	2.18	1.91	2.42	2.12
6	3.77	3.99	3.85	3.63	3.8	3.27	3	3.59	3.51	3.1	3.13	3.33	2.42	2.48	2.6	2.47	2.48	2.12

Table 2: Measured Ra in microns (testing data set).

n rpm	750		1000		1250		1500		1750		2000	
t mm / f mm/sec	0.3	0.5	0.3	0.5	0.3	0.5	0.3	0.5	0.3	0.5	0.3	0.5
3 mm/s	2.85	3	2.55	2.44	2.41	2.43	1.57	1.81	2.2	2.27	2.31	2.24
5 mm/s	3.79	3.55	3.5	3.56	3.11	3.18	2.78	2.85	2.59	2.51	2.44	2.52

3. MULTIPLE REGRESSION PREDICTION MODEL

Multiple regression model is used in the current work. In this model, the criterion variable is the surface roughness *Ra* and the controller machining parameters used as predictor variables are spindle speed *n*, feed rate *f*, and depth of cut *t*. The full regression model containing all the main effects and interactions terms was listed in equation (1).

$$Ra = A + B1*n + B2*f + B3*t + B4*n*f + B5*n*t + B6*f*t + B7*n*f*t \tag{1}$$

Regression analysis was done through Microsoft Excel software. A stepwise solution was selected to further reduce the number of variables. Predictor variables were entered one at a time, but could be

deleted if they did not contribute significantly to the regression when considered in combination with newly entered predictors.
A statistical model was created by regression function based on the training data set listed in **table 1** is shown in **tables 3**, **4** and **5**.

Table 3: Regression Statistics.

Multiple R	0.946284792
R Square	0.895454907
Adjusted R Square	0.891355099
Standard Error	0.228922281
Observations	54

Table 4: ANOVA table.

	Df	SS	MS	F	Significance F
Regression	2	22.89213887	11.44606943	218.4138864	9.82298E-26
Residual	51	2.672675949	0.052405411		
Total	53	25.56481481			

Table 5: Variable included in the Multiple Regression Equation.

	Coefficients	Standard Error	t Stat	P-value
Intercept	1.32537037	0.082421441	16.08040759	1.29378E-21
f	0.61485941	0.030052151	20.45974696	3.04748E-26
$n*f$	-0.000221211	1.68879E-05	-13.0988178	6.05792E-18

From **table 3** The R Square was 0.8955 which showed that 89.55% of the observed variability in Ra could be explained by the independent variables. The Multiple R was 0.9463 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. The value of F was 218.4139 and the significance of F was 9.823E-26 ≈ 0 in the ANOVA table as shown in **Table 4**. The coefficients for the independent variables were listed in **table 5**. Using these coefficients, the multiple regression equation could be expressed as in equation (2).

$$Ra = 1.32537037 + 0.61485941*f - 0.000221211*n*f \tag{2}$$

It was apparent that feed rate f was the most significant machining parameter to influence surface roughness and depth of cut was not influence surface roughness.

4. ANFIS PREDICTION MODEL

ANFIS architecture is shown in **Figure 2**. Five network layers are used by ANFIS to perform the following fuzzy inference steps: (i) input fuzzification, (ii) fuzzy set database construction, (iii) fuzzy rule base construction, (iv) decision making, and (v) output defuzzification. ANFIS has been constructed through MATLAB.

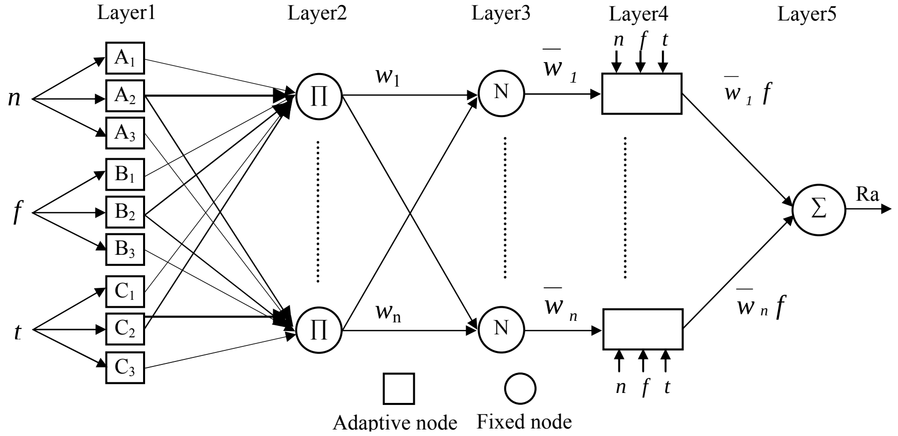


Fig.: 2 ANFIS architecture.

Different membership functions were used for training ANFIS to predict surface roughness. The Generalized bell memberships function (gbellmf) gives the lowest training error so it was adopted during the training process of ANFIS in this study. The fuzzy rule architecture of ANFIS when the gbellmf function is adopted consists of 27 fuzzy rules as shown in **Figure 3**. During the training the 54 Ra values (training data sets) were used to conduct 500 cycles of learning with average error of 0.1344.

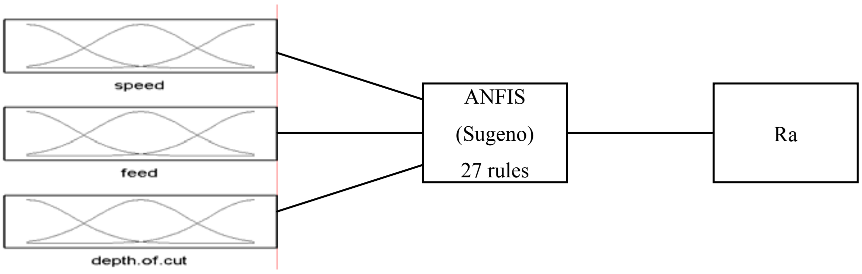


Fig. 3: Fuzzy role architecture of the generalized bell function.

The membership functions of every input parameter within the architecture can be divided into three areas, i.e. small, medium and large areas. **Figures 4–6** show the initial and final membership functions of the three end milling parameters derived by training via the gbellmf. In Figure 4 the initial membership function and the final membership function of the speed only experience small changes in the small and large areas and very large changes in the medium area. **Figure 5** shows the initial and final membership functions of the feed. It is indicated that the final membership function after training experiences smaller variation in the small and large areas, but slightly greater variation in the medium area. **Figure 6** shows the initial and final membership functions of the depth of cut. There is obviously a small change in the final membership function shape after training, regardless of the small, large or even medium area.

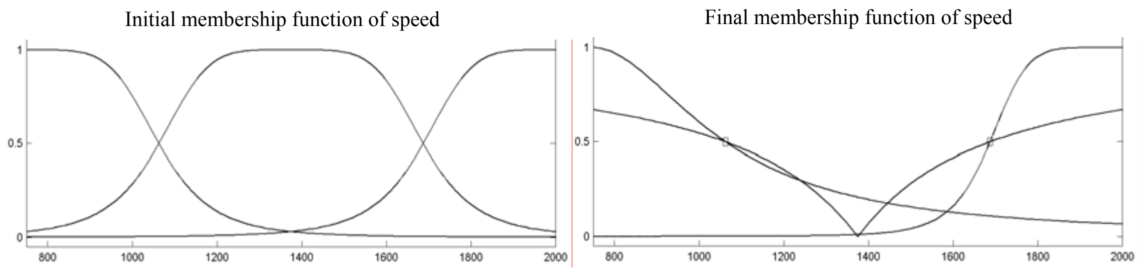


Fig. 4: Initial and final membership function of speed.

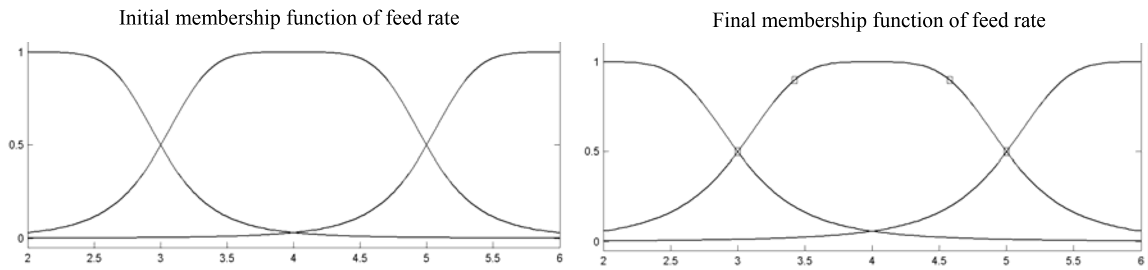


Fig. 5: Initial and final membership function of feed rate.

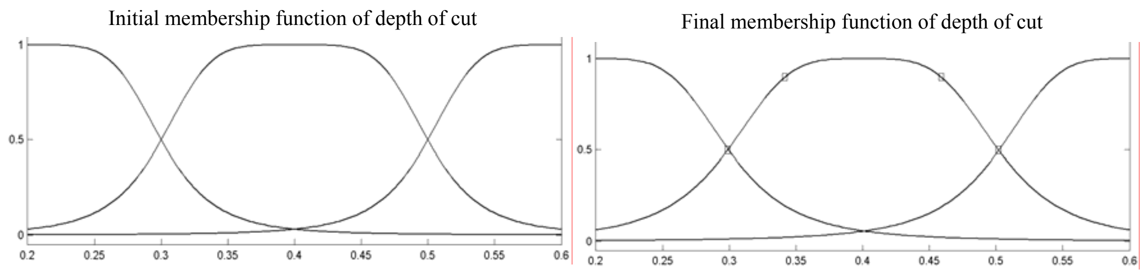


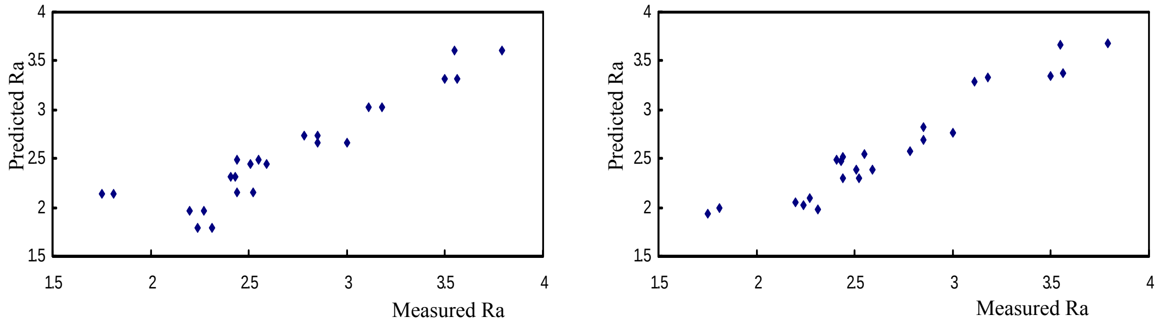
Fig. 6: Initial and final membership function of depth of cut.

The above analysis indicates that among the three end-milling parameters studied, speed has the most impact on surface roughness, followed by feed rate and finally by depth of cut, which was the least significant factor of all.

5. MODELS VERIFICATION

The plots of measured Ra data versus predicted Ra using multiple regression model and ANFIS model are shown in **Figure 7**.

Figure 8 shows a comparison of the measured Ra and predicted Ra of the twenty four set of testing data following the training using multiple regression and ANFIS. It is shown that the predicted values using ANFIS model are closer to the measured values than predicted values using multiple regression model.



Multiple regression model **ANFIS model**

Fig. 7: Plot of the Measured Ra versus Predicted Ra

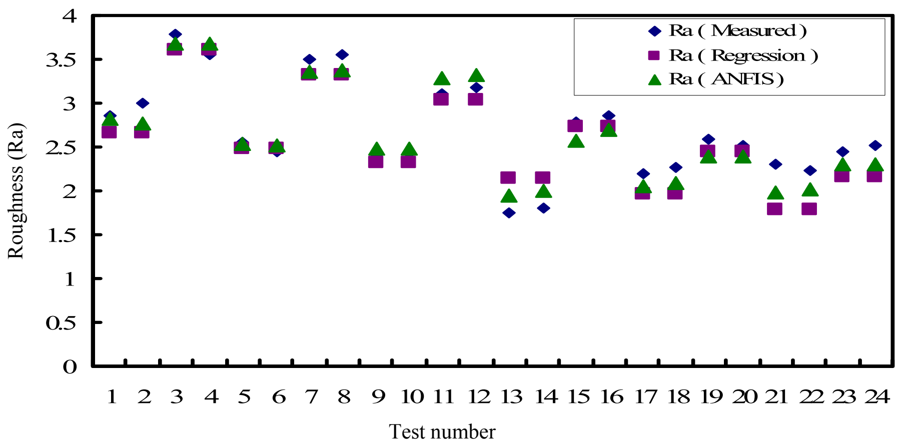


Fig. 8: Comparison of measured Ra and predicted Ra for the testing data set using regression and ANFIS models.

To evaluate the multiple regression prediction model and ANFIS model, the percentage error E_i and the average percentage error E_{av} defined in equations 3, 4 respectively were used.

$$E_i = \frac{\left|Ra_i - \hat{R}a_i\right|}{Ra_i} \times 100 \tag{3}$$

Where E_i : percentage error of sample number *i*.

Ra_i : measured Ra of sample number. *i*.

$\hat{R}a_i$: predicted Ra generated by a multiple regression model or ANFIS model

$i = 1,2,3\ldots\ldots m$

where m is the number of samples

$$E_{av} = \frac{\sum_{i=1}^{m} E_i}{m} \tag{4}$$

Where E_{av} is the average percentage error of m sample data

Table 6 shows that the average error of the prediction of surface roughness is 8.1% when multiple regression model is used. That is, the accuracy is 91.9%. When the ANFIS model is used, the average error is 6%, i.e. the accuracy is 94%. These results indicate that ANFIS model with the gbellmf is accurate than multiple regression model in prediction of surface roughness.

Table 6: Comparison of measured Ra and predicted Ra from regression and ANFIS.

Test No.	Parameter			Measured Ra	Regression model		ANFIS model	
	n *rpm*	f *mm/sec*	t *mm*		Predicted	Error (%)	Predicted	Error (%)
1	750	3	0.3	2.85	2.66	6.24	2.82	1.05
2			0.5	3	2.66	10.93	2.76	8
3		5	0.3	3.79	3.61	5.8	3.68	2.90
4			0.5	3.55	3.61	0.57	3.67	3.38
5	1000	3	0.3	2.55	2.49	1.71	2.54	0.39
6			0.5	2.44	2.49	2.72	2.52	3.28
7		5	0.3	3.5	3.32	5.9	3.35	4.29
8			0.5	3.56	3.32	7.48	3.38	5.06
9	1250	3	0.3	2.41	2.31	2.89	2.49	3.32
10			0.5	2.43	2.31	3.69	2.48	2.06
11		5	0.3	3.11	3.03	2.99	3.29	5.79
12			0.5	3.18	3.03	5.12	3.33	4.72
13	1500	3	0.3	1.75	2.14	24.26	1.94	10.86
14			0.5	1.81	2.14	20.14	2	10.5
15		5	0.3	2.78	2.74	01.42	2.58	7.19
16			0.5	2.85	2.74	3.84	2.69	5.61
17	1750	3	0.3	2.2	1.96	8.70	2.05	6.82
18			0.5	2.27	1.96	11.52	2.09	7.93
19		5	0.3	2.59	2.44	4.86	2.39	7.72
20			0.5	2.51	2.44	1.83	2.39	4.78
21	2000	3	0.3	2.31	1.79	20.23	1.98	14.29
22			0.5	2.24	1.79	17.74	2.02	9.82
23		5	0.3	2.44	2.15	10.35	2.3	5.74
24			0.5	2.52	2.15	13.19	2.3	8.73
					Average error	8.1	Average error	6

CONCLUSIONS

Multiple regression analysis and ANFIS were used to develop empirical models for predicting the surface roughness in end milling. Spindle speed, feed rate and depth of cut were used as predictor variables. Fifty four measured Ra values, under different cutting conditions, were used as training data set and twenty four values were used as testing data set. The models were verified with test data where the average errors were 8.1% and 6% for multiple regression model and ANFIS respectively. The accuracy achieved by multiple regression model was 91.9% while the accuracy was 94% when using ANFIS model. These results indicate that ANFIS model with the gbellmf is accurate than multiple regression model in prediction of surface roughness.

REFERENCES

[1] E. D. Kirby, Z. Zhang, J. C. Chen, "Development of an accelerometer–based surface roughness predication system in turning operations using multiple regression techniques", J. Ind. Technol. Vol. 20 (4), pp 1-8, 2004.

[2] L. Huang, J. C. Chen, "A multiple regression model to predict in-process surface roughness in turning operation via accelerometer", J. Ind. Technol. Vol. 17 (2), pp 1-8, 2001.

[3] C. Feng, "An experimental study of the impact of turning parameters on surface roughness", proceeding of the Industrial Engineering Research Conference, 2001, No. 2036.

[4] M. S. Lou, J. C. Chen, C. M. Li, "Surface roughness prediction technique for CNC end-milling", J. Ind. Technol. Vol. 15 (1), pp 1-6, 1999.

[5] M. D. Savage, J. C. Chen, "Effects of tool diameter variations in on-line Surface roughness recognition system", J. Ind. Technol. Vol. 15 (4), pp 1-7, 1999.

[6] F. Dweiri, M. Al-Jarrah, H. Al-Wedyan, "Fuzzy surface roughness of CNC down milling of Alumic-79", J. Mater. Process. Technol. Vol. 133, pp 266-275, 2003.

[7] A. M. Abd El-Raaouf, M. S. Osman, M. H. El-Axir, A. A. Elshanawani, "Applicability of fuzzy approach for the optimization and analysis of surface roughness in orthogonal cutting", Seventh international conference on production engineering, design, and control, Alexandria-Egypt, pp 1261-1272, 2001.

[8] C. X. Feng, X. F. Wang, "Surface roughness predictive modeling: Neural network versus regression", IIE Transactions on Design and Manufacturing, 2002.

[9] T. Ozel and Y. Karpat," Predictive modeling of surface roughness and tool wear in hard turning using regression and neural networks", International Journal of Machine Tools & Manufacture Vol. 45, pp 467–479, 2005.

[10] S. P. Lo, "An adaptive-network based fuzzy inference system for prediction of workpiece surface roughness in end milling", J. Mater. Process. Technol. Vol. 142, pp 665-675, 2003.

[11] S.-Y. Ho, K.-C. Lee, S.-S. Chen, S.-J. Ho, "Accurate modeling and prediction of surface roughness by computer vision in turning operations using an adaptive neuro-fuzzy inference system", Int. J. of machine tool and manufacture Vol. 42, pp 1441-1446, 2002.

[12] M. S. Samhouri, B. W. Surgenor, "Surface roughness in grinding: on-line prediction with adaptive neuro-fuzzy inference system", Proceeding of thirty-third Annual North American Manufacturing Research Conference, (NAMRC 33), 2005.

[13] J.-S. R. Jang, E. Mizutani, C.-T. Sun, Neuro-Fuzzy and Soft Computing, Prentic Hall Upper Saddle River, NJ 07458, 1997.