Journal of Mechanical Engineering Research Vol. 4(3), pp. 112-129, March 2012
Available online at http://www.academicjournals.org/JMER
DOI: 10.5897/JMER10.079
ISSN 2141-2383 ©2012 Academic Journals

Full Length Research Paper

Adaptive neuro-fuzzy inference system (ANFIS) based surface roughness prediction model for ball end milling operation

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Accepted 17 January, 2012

Surface roughness is an index which determines the quality of machined products and is influenced by the cutting parameters. In this study, the average surface roughness R_a (value) for aluminum after ball end milling operation has been measured. 84 experiments have been conducted using varying cutter axis inclination angle (φ degree), spindle speed (S rpm), feed rate (f_y mm/min), feed (f_x mm), and depth of cut (t mm) in order to find R_a. This data has been divided into two sets on a random basis; 68 training data set and 16 testing data set. The training data set has been used to train different adaptive neuro-fuzzy inference system (ANFIS) models for R_a prediction. And testing data set has been used to validate the models. Better ANFIS model has been selected based on the minimum value of root mean square error (RMSE) which is constructed with three Gaussian membership functions (gaussmf) for each input variables and linear membership function for output. The selected ANFIS model has been compared with theoretical model and response surface model (RSM). This comparison is done based on RMSE and absolute average percentage error. The comparison shows that the selected ANFIS model gives better result for training and testing data. So, this ANFIS model can be used further for predicting surface roughness of aluminum for ball end milling operation.

Key words: Ball end mill, adaptive neuro-fuzzy inference system (ANFIS), roughness prediction.

INTRODUCTION

The main objective of modern industries is to manufacture low cost, high quality products in short time. The selection of optimal cutting parameters is a very important issue for every machining process in order to enhance the quality of machining products and reduce the machining costs (Cus and Zuperl, 2009). It is expected that the next decade machine tools will be intelligent machines with various capabilities such as prediction of self set up required parameters to reach to the best surface finishing qualities. Typically, surface inspection is carried out through manually inspecting the machined surfaces and using surface profilometers with a contact stylus. As it is a post-process operation, it becomes both time-consuming and-labor intensive. In addition, a number of defective parts can be found during the period of surface inspection, which leads to additional production cost (Aykut, 2011). Milling process is one of the common metal cutting operations and is especially used for making complex shapes and finishing of machined parts. The quality of the surface plays a very important role in the performance of the milling as a good quality milled surface significantly improves fatigue strength, corrosion resistance or creep life. Surface roughness also affects several functional attributes of parts, such as contact causing surface friction, wearing, heat transmission, light reflection, ability of distributing and holding a lubricant, load bearing capacity, coating or resisting fatigue. Therefore the desired finish surface is usually specified and the appropriate processes are selected to reach the desiredsurface quality (Lou et al., 1999).

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Unlike turning, face milling or flat end milling operations, predicting surface roughness for ball end milling by mathematical models is very difficult. In recent years, the trends are towards modeling of machining processes using artificial intelligence due to the advanced computing capability. Researchers have used various intelligent techniques, including neural network, fuzzy logic, neuro-fuzzy, adaptive neuro-fuzzy inference system (ANFIS), etc., for the prediction of machining parameters and to enhance manufacturing automation. Artificial neural network (ANN) and Fuzzy logic are two important methods of artificial intelligence in modeling nonlinear problems. A neural network can learn from data and feedback; however, understanding the knowledge or the pattern learned by it is difficult. But fuzzy logic models are easy to comprehend because they use linguistic terms in the form of if-then rules. A neural network with their learning capabilities can be used to learn the fuzzy decision rules, thus creating a hybrid intelligent system (John and Reza, 2003). A fuzzy inference system consists of three components. First, a rule base contains a selection of fuzzy rules; secondly, a database defines the membership functions used in the rules and, finally, a reasoning mechanism to carry out the inference procedure on the rules and given facts. This combination merges the advantages of fuzzy system and a neural network.

In the present work, the adaptive neuro-fuzzy model has been developed for the prediction of surface roughness. The predicted and measured values are fairly close to each other. The developed model can be effectively used to predict the surface roughness in the machining of aluminum within the ranges of variables studied. The ANFIS results are compared with the RSM results and results from theoretical equations. Comparison of results showed that the ANFIS results are superior to others. This study attempts to design adaptive network-based fuzzy interface system (ANFIS) for modeling and predicting surface roughness in ball end milling aluminum.

LITERATURE REVIEW

The quality of surface finish mainly depends on the interaction between the work piece, cutting tool and the machining system. Due to these reasons, there have been a series of attempts by researchers to develop efficient prediction systems for surface roughness before machining. Survey on previous surface roughness research reveals that most of the researches proposed multiple regression method to predict surface roughness. Some research applied neural network, fuzzy logic, and neural-fuzzy approaches. Optimization of surface roughness prediction model, developed by multiple regression method, with a genetic algorithm is presented in some journals. Among them, statistical (multiple regression analysis) and artificial neural network (ANN) based modeling are commonly used by researchers. Mital and Mehta (1988) conducted a survey of surface roughness prediction models developed and factors influencing surface roughness. They found that most of the surface roughness prediction models are developed for steels.

For the prediction of surface roughness, a feed forward ANN is used for face milling of aluminum alloy by Bernardos et al. (2003) high chromium steel (AISI H11) by Rai et al. (2010) and AISI 420 B stainless steel by Bruni et al. (2008). Bruni et al. (2008) proposed the analytical and artificial neural network models. Yazdi and Khorram (2010) worked for selection of optimal machining parameters (that is, spindle speed, depth of cut and feed rate) for face milling operations in order to minimize the surface roughness and to maximize the material removal rate using response surface methodology (RSM) and perceptron neural network. Munoz-Escalona and Maropoulos (2009) proposed the radial basis feed forward neural network model and generalized regression for surface roughness prediction for face milling of Al 7075-T735. The Pearson correlation coefficients were also calculated to analyze the correlation between the five inputs (cutting speed, feed per tooth, axial depth of cut, chip's width, and chip's thickness) with surface roughness. Zhanjie et al. (2007) used radial basis function network to predict surface roughness and compared with measured values and the result from regression analysis. Lu and Costes (2008) considered three variables, that is, cutting speed, depth of cut and feed rate to predict the surface profile in turning process using radial basis function (RBF). Experiments have been carried out by Brecher et al. (2011) after end milling of steel C45 in order to obtain the roughness data and model of ANN for surface roughness predictions. Aykut (2011) had also used ANN to predict the surface roughness of cast-polyamide material after milling operation. Khorasani et al. (2011) conducted a study to discover the role of machining parameters like cutting speed, feed rate and depth of cut in tool life prediction in end milling operations onAl 7075 by using multi layer perceptron neural networks and Taguchi design of experiment. On the other hand, Nabil and Ridha (2006) developed an approach that combined the design of experiments (DOE) and the ANN methods. Luong and Spedding (1995) also applied neural network technology for the prediction of machining performance in metal cutting. Back propagation neural network in turning operations was developed by Bisht et al. (2005) for the prediction of flank wear and by Pal and Chakraborty (2005) for predicting the surface roughness. Zhong et al. (2006) predicted roughness measures R_a and R_t of turned surfaces using a neural network. The determination of best cutting parameters leading to a minimum surface roughness in end milling mold surfaces used in biomedical applications was done by Oktem et al.

(2006). For their research, they coupled a neural network and a genetic algorithm (GA) providing good results to solve the optimization of the problem. Jesuthanam et al. (2007) proposed the development of a novel hybrid neural network trained with GA and particle swarm optimization for the prediction of surface roughness. The experiments were carried out for end milling operations. Lin et al. (2007) developed a surface prediction model for high-speed machining of 304L stainless steel, Al 6061-T6, SKD11 and Ti-4Al-4V. For this purpose, the finite element method and neural network were coupled. Basak et al. (2006) developed radial basis neural network models when turning AISI D2 cold-worked tool steel with ceramic tool. Tsai et al. (1999) used in-process surface recognition system based on neural networks in end milling operation.

Mahdavinejad et al. (2009), Roy (2005) and Jiao et al. (2004) used combination of adaptive neural fuzzy intelligent system to predict the surface roughness machined in turning process. Jiao et al. (2004) also used adaptive fuzzy-neural networks to model machining process especially for surface roughness. Roy (2006) and Chen and Savage (2001) designed adaptive network-based fuzzy inference system (ANFIS) for modeling and predicting the surface roughness in end milling operation. Roy (2006) used two different membership functions (triangular and bell shaped) during the hybrid-training process of ANFIS in order to compare the prediction accuracy of surface roughness by the two membership functions.

The predicted surface roughness values obtained from ANFIS were compared with experimental data and multiple regression analysis. The comparison indicated that the adoption of both membership functions in ANFIS achieved better accuracy than multiple regression models. Dweiri et al. (2003) used neural-fuzzy system to model surface roughness of Alumic-79 workpiece in CNC down milling. Reddy et al. (2009) also used ANFIS to prediction surface roughness of aluminum alloys but for turning operation. The response surface methodology (RSM) was also applied to model the same data. The ANFIS results are compared with the RSM results and comparison showed that the ANFIS results are superior to the RSM results. Kumanan et al. (2008) proposed the application of two different hybrid intelligent techniques, adaptive neuro fuzzy inference system (ANFIS) and radial basis function neural network- fuzzy logic (RBFNN-FL) for the prediction of surface roughness in end milling. Cabrera et al. (2011) investigated the process parameters including cutting speed, feed rate and depth of cut in order to develop a fuzzy rule-based model to predict the surface roughness in dry turning of reinforced PEEK with 30% of carbon fibers using TiN-coated cutting tools.

Some other prediction models like response surface methodology (RSM), statistical methods and multiple regression, etc., have been used in a wide range of literatures. Wang and Chang (2004) analyzed the influence of cutting condition and tool geometry on surface roughness using RSM during slot end milling AL2014-T6. Mathematical polynomial models using RSM for surface roughness prediction in terms of cutting speed, feed and axial depth of cut for end milling was developed by Alauddin et al. (1995) for 190 BHN steel and by Lou et al. (1999) for end milling of EN32. Many years ago, Taraman and Lambert (1974) also used response surface methodology for prediction of surface roughness.

Ozcelik and Bayramoglu (2006) present the development of a statistical model for surface roughness estimation in a high-speed flat end milling process under wet cutting conditions. Huang and Chen (2001) used multiple regression models to predict the surface roughness of machined parts in turning operation. Feng and Wang (2002) focused on developing an empirical model for the prediction of surface roughness in finish turning. Ahmed (2006) developed an empirical surface roughness model for commercial aluminum, based on metal cutting results from factorial experiments. Brezocnik et al. (2004) proposed genetic programming to predict surface roughness in end milling of Al 6061.

To achieve the desired surface finish, a good predictive model is required for stable machining. From the literature review, it was observed that majority of the work in the area of artificial intelligence application has been for turning and flat end or face milling operation. Due to this fact and also considering the importance of ball end milling operation for machining of aluminum which is widely used in applications like structural, cryogenic, food processing, plastic molding, oil and gas process industries, etc., the ANFIS and RSM model are developed in this research. This model will help the manufacturing industries in predicting the desired surface roughness in selecting the right combination of cutting parameters.

METHODOLOGY

Experimental setup and design of experiment

The experiment was performed by using a vertical milling machine shown in Figure 1. The workpiece tested was an aluminum plate of size 9×1×4 cm. A two-flutecarbide ball end mill cutter of 8 mm diameter was selected as the cutting tool. The cutter linear movement direction has been shown in Figure 2. Some samples are machined with various input parameters and then the experimental data was used to create fuzzy rules and their processing via neural networks. Then the results of this model are compared with the real surface roughness. A total of 84 experiments were planned and carried out. The design of experiments was carried out considering parameter variations around the cutting tool provider recommendations and the machine tool capabilities. In order to detect the average surface roughness (R_a) value, experiments were carried out by varying the cutter axis inclination angle (θ) spindle speed (S rpm), the feed rate along y-axis (f_y mm/min), feed along x-axis (f_x mm) and the depth of cut (t). For each of the experiments, three sample readings were taken and their average value was considered.

Figure 1. Experimental setup.

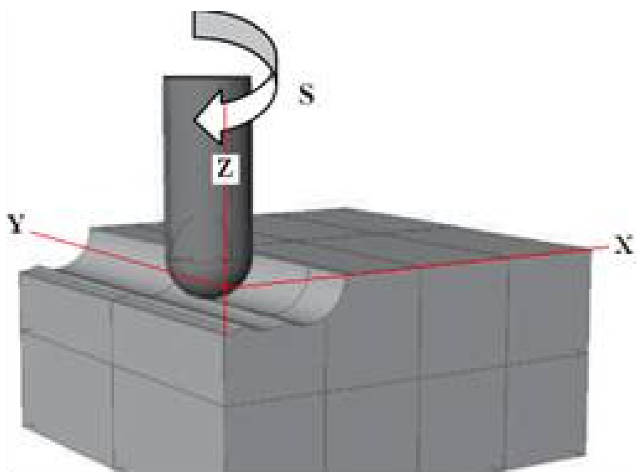


Figure 2. Ball end mill operation.

Surface roughness

There are various surface roughness amplitude parameters such as roughness average (R_a), root-mean-square (RMS) roughness (R_q), and maximum peak-to-valley roughness (R_y or R_{max}), which are used in industries (Bernardos and Vosniakos, 2003). Surface roughness average parameter (R_a) is the most extended index of product quality and has beenused in this study. The average roughness (R_a) can be defined as the area between the roughness profile and its mean line, or the integral of the absolute value of the roughness profile height over the evaluation length. Therefore, the R_a is specified by equation (1):

$$R_a = \frac{1}{L}\int_0^L |Z(x)|dx \quad (1)$$

Where R_a is the arithmetic average deviation from the mean line, L is the sampling length and Z the coordinate of the profile curve.

In this study, a Taylor Hobson Talysurf (Surtronic 25) has been used for measuring R_a. The distance that the stylus travels is sampling length L (Figure 3); it ranges from 0.25 to 25 mm for selected instrument. In this study, sampling length was 0.8 mm.

Adaptive neuro-fuzzy inference system (ANFIS)

Adaptive neuro-fuzzy inference system is a fuzzy inference system implemented in the framework of an adaptive neural network. By using a hybrid learning procedure, ANFIS can construct an input-output mapping based on both human-knowledge as fuzzy if-then rules and approximate membership functions from the stipulated input-output data pairs for neural network training. This procedure of developing a FIS using the framework of adaptive neural networks is called an adaptive neuro fuzzy inference system (ANFIS). There are two methods that ANFIS learning employs for updating membership function parameters: 1) backpropagation for all parameters (a steepest descent method), and 2) a hybrid method consisting of backpropagation for the parameters associated with the input membership and least squares estimation for the parameters associated with the output membership functions. As a result, the training error decreases, at least locally,

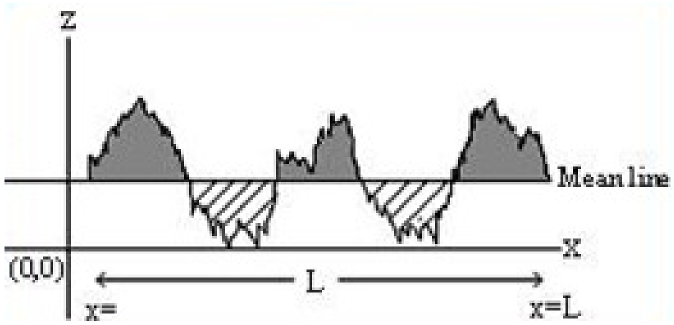


Figure 3. Surface roughness.

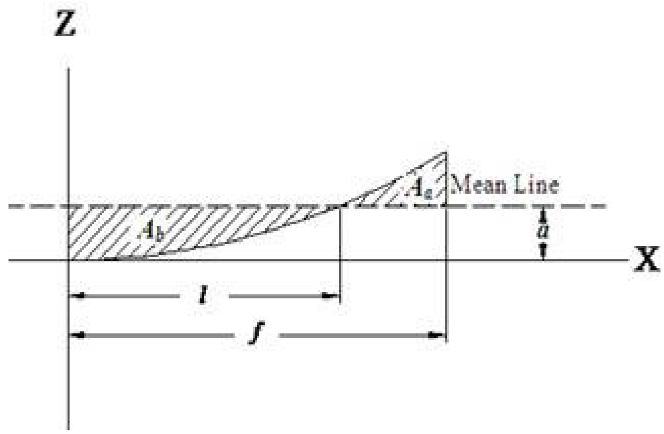


Figure 4. Calculation of mean line and roughness.

throughout the learning process. It applies the least-squares method to identify the consequent parameters that define the coefficients of each output equation in the Sugeno-type fuzzy rule base. The training process continues till the desired number of training steps (epochs) or the desired root mean square error (RMSE) between the desired and the generated output is achieved. This study uses a hybrid learning algorithm, to identify premise and consequent parameters of first order Takagi-Sugeno type fuzzy system for predicting surface roughness in ball end milling.

Response surface method (RSM)

The response surface method (RSM) is a dynamic and foremost important tool of design of experiment (DOE). RSM was successfully applied for prediction and optimization of cutting parameters by Bernardos and Vosniakos (2003) Mukherjee and Ray (2006). In this study, RSM was used to fit linear and second order polynomials on experimental data with 95% confidence level by minitab software.

Theoretical equations

In Figure 4, a representative element of the ideal roughness profile after ball end milling operation has been shown. Using equations (2) to (8), the theoretical values of R_a can be calculated. The theoretical R_a depends on feed f_x and tool nose radius R. Here, *"a"* is the mean line height. A_b area below mean line and A_a is the area above mean line.

$$R_a = \frac{A_a + A_b}{f} \quad (2)$$

$$A_a = (f - l)(R - a) - \frac{R^2}{4}\{(2\theta_f + \sin 2\theta_f) - (2\theta_l + \sin 2\theta_l)\} \quad (3)$$

$$A_b = (a - R)\, l + \frac{R^2}{4}(2\theta_l + \sin 2\theta_l) \quad (4)$$

$$a = R - \frac{R^2}{4f}(2\theta_f + \sin 2\theta_f) \quad (5)$$

$$l = \sqrt{2Ra - a^2} \quad (6)$$

$$\theta_l = \sin^{-1}\frac{l}{R} \quad (7)$$

$$\theta_f = \sin^{-1}\frac{f}{R} \quad (8)$$

The representative element with length "*f*" of the curve or surface profile is symmetric with respect to z-axis and surface profile with length $f=f_x/2$ is repeated over the whole surface for gradual feed of f_x in each pass.

Pearson correlation coefficient

A correlation is a statistical technique which can show if, and how strongly, pairs of variables are related. The main result of a correlation is called correlation coefficient (or *r*). Correlation coefficients measure the strength of association between two variables. There are several correlation techniques but the most common one is the Pearson product-moment correlation coefficient. The correlation *r* between two variables is expressed as equation (9):

$$r = \frac{1}{n-1}\sum_{i=1}^{n}\left(\frac{y_i - \bar{X}}{S_x}\right)\left(\frac{y_i - \bar{Y}}{S_y}\right) \quad 9$$

Where n is the number of observations in the sample, x_i is the x value for observation i, $\bar{X}$ is the sample mean of x, y_i is the y value for observation i, $\bar{Y}$ is the sample mean of y, S_x is the sample standard deviation of x, and S_y is the sample standard deviation of y.

Significance of Pearson's correlation coefficient r with P-value

The correlation coefficient is a number between -1 and 1. In general, the correlation expresses the degree that, on an average, two variables change correspondingly. If one variable increases when the second one increases, then there is a positive correlation. In this case the correlation coefficient will be closer to 1. If one variable decreases when the other variable increases, then there is a negative correlation and the correlation coefficient will be closer to -1. The *P*-value is the probability, if this probability is lower than the conventional 5% ($P<0.05$), the correlation coefficient is called statistically significant. Both *r* and *P*-value have been calculated using the software Minitab-16.

RESULTS AND DISCUSSION

The ANFIS models have been developed as a function of machining parameters using 68 train data presented in Table 1. The fuzzy logic toolbox of MATLAB 7.0 was used to train the ANFIS and obtain the results. Different ANFIS parameters were tested as training parameters in order to achieve the perfect training and the maximum prediction accuracy. Table 2 shows 48 different architectures of ANFIS. From Table 2, the best-responding model of neuro-fuzzy system was found that have three Gaussian curve built-in membership functions (gaussMF) in input functions and linear output functions. It is shown that the predicted error (RMSE) for the training data is 9.9854×10^{-5} and for the test data it is 1.146. The 5 inputs and 1 output and their final fuzzy membership functions are shown in Figure 5. A total of 243 fuzzy rules were used to build the fuzzy inference system. Gaussian membership functions (*gaussmf*) were used to train ANFIS because it achieved the lowest training error of 9.9845×10^{-5} at 10 epochs, as shown in the training curve in Figure 6.

Three Gaussian membership functions (gaussmf) were used for each input. Figure 7 shows the comparison between the experimental and predicted values by the ANFIS training data. The model developed by ANFIS is tested using the testing data and the predicted results are presented in Table 3. 16 sets of data were used for test the model. The predicted surface roughness values with the actual experimental values of surface roughness were plotted and shown in Figure 8.

Equation 10 is the response surface equation developed by RSM. It can be used for predicting surface roughness. Test data set has been used for verifying this equation and predicted results have been summarized in Table 3. The results using the theoretical equations (2) to (8) for 16 test data sets also have been listed in Table 3:

$$R_a = 1.35355 + 0.0874799\,\varphi + 0.000887986\,S - 0.101501\,f_y + 7.92503\,f_x - 6.14303\,t - 0.00320667\,\varphi^2 - 1.20701 \times 10^{-07}\,s^2 + 0.00122325\,f_y^2 + 9.91836\,f_x^2 + 10.5552\,t^2 + 8.53234\times10^{-06}\varphi S - 9.68995 \times 10^{-04}\varphi f_y + 0.1357\,\varphi f_x + 0.00848098\,\varphi t + 3.41726 \times 10^{-05} S f_y - 0.00576076\,S f_x - 2.94529 \times 10^{-04} S t - 0.101860\,f_y f_x + 0.0719970\,f_y t - 12.5766\,f_x t \quad 10.$$

It has been mentioned earlier that in this study, an ANFIS, RSM and theoretical equations have been used for predicting surface roughness. The root mean squired errors and absolute mean percentage of errors have been calculated for each of the aforementioned models and summarized in Table 4. It can be observed from Table 4 that the prediction results for surface roughness are more accurate in ANFIS model if both training and testing data are considered. So, finally, the ANFIS model can be suggested as the best prediction model and can be used further for surface roughness prediction using ball end milling operation on aluminum.

The results listed in Table 3 are found to be within acceptable limits for the ANFIS model. Larger deviation in prediction for surface roughness that occurred in few of the cases may be due to inhomogeneity in work piece composition, small discrepancy in tool setting/work piece setting and tool or machining condition. Figure 9 show the relationship between ANFIS predicted roughness and different input parameters. In Figure 9a and b, it can be observed that low spindle speed S and low feed rate f_y near 0° inclination angle of the spindle axis gives better surface finish. Feed f_x leads to deteriorate surface quality at low inclination angle. Figure 9c suggests f_x is kept at a medium level cutter axis vertical to the machining surface. At low depth of cut, surface quality seems worse in Figure 9d. Figure 9e and f shows that for medium level of speed feed rate f_y and feed f_x has low impact on surface finish. Graph in shows Figure 9g abnormality at lower depth and higher speed. On the other hand, from Figure 9h, it is observed that higher feed rate in both direction results in increased surface roughness. Figure

Table 1. Training data set.

SL	Inclination angle (*φ*)	Speed *S* (rpm)	Feed f_y (mm/min)	Feed f_x (mm)	Depth of Cut *t* (mm)	Avg. R_a (experimental)	R_a (theoretical equations)	R_a (ANFIS)	R_a (RSM)
1	0	380	22	0.4	0.2	1.36	1.28	1.3601	1.785
2	0	380	34	0.6	0.2	2.11	2.89	2.1098	3.164
3	0	380	22	0.4	0.4	1.95	1.28	1.9500	1.111
4	0	380	34	0.6	0.4	3.55	2.89	3.5500	2.160
5	0	380	22	0.4	0.6	0.56	1.28	0.5601	1.282
6	0	380	34	0.6	0.6	1.33	2.89	1.3301	2.000
7	0	520	34	0.5	0.3	2.46	2.01	2.4600	1.472
8	0	520	44	0.6	0.3	2.84	2.89	2.8400	2.054
9	0	520	68	0.7	0.3	3.9	3.94	3.8997	3.096
10	0	520	44	0.6	0.5	0.73	2.89	0.7300	1.608
11	0	520	68	0.7	0.5	1.36	3.94	1.3599	2.744
12	0	520	34	0.5	0.6	1.43	2.01	1.4301	1.280
13	0	520	44	0.6	0.6	2.66	2.89	2.6599	1.701
14	0	520	68	0.7	0.6	3.62	3.94	3.6200	2.885
15	0	715	34	0.4	0.4	0.49	1.28	0.4898	0.559
16	0	715	68	0.8	0.4	3.01	5.14	3.0104	3.275
17	0	715	34	0.4	0.5	0.44	1.28	0.4400	0.615
18	0	715	44	0.6	0.5	0.85	2.89	0.8499	1.342
19	0	715	68	0.8	0.5	1.98	5.14	1.9801	3.073
20	0	715	34	0.4	0.6	1.33	1.28	1.3300	0.883
21	0	715	44	0.6	0.6	1.59	2.89	1.5898	1.430
22	0	1020	22	0.4	0.6	0.98	1.28	0.9799	0.636
23	0	715	34	0.8	0.4	3.07	5.14	3.0699	3.445
24	15	380	34	0.4	0.3	1.35	1.28	1.3500	1.870
25	15	380	68	0.8	0.3	5.11	5.14	5.1100	5.547
26	15	380	34	0.4	0.5	1.65	1.28	1.6500	1.817
27	15	380	44	0.6	0.5	3.71	2.89	3.7100	3.077
28	15	380	34	0.4	0.6	1.61	1.28	1.6100	2.107
29	15	380	44	0.6	0.6	3.71	2.89	3.7100	3.188
30	15	380	68	0.8	0.6	4.43	5.14	4.4300	5.009
31	15	520	34	0.4	0.4	1.61	1.28	1.6100	1.689
32	15	520	68	0.8	0.4	5.23	5.14	5.2299	4.948
33	15	520	34	0.4	0.5	1.27	1.28	1.2700	1.764
34	15	520	44	0.6	0.5	3.05	2.89	3.0500	2.910
35	15	520	68	0.8	0.5	5.18	5.14	5.1800	4.764
36	15	520	34	0.4	0.6	1.39	1.28	1.3900	2.049
37	15	520	44	0.6	0.6	3.99	2.89	3.9900	3.017
38	15	715	34	0.4	0.3	1.79	1.28	1.7900	1.754
39	15	715	44	0.6	0.3	2.07	2.89	2.0701	3.102
40	15	715	68	0.8	0.3	5.69	5.14	5.6900	5.049
41	15	715	34	0.4	0.4	1.25	1.28	1.2500	1.612
42	15	715	68	0.8	0.4	5.49	5.14	5.4900	4.648
43	15	715	34	0.4	0.6	1.53	1.28	1.5300	1.961
44	15	715	68	0.8	0.6	5.07	5.14	5.0700	4.481
45	15	520	34	0.6	0.4	3.55	2.89	3.5500	3.367
46	30	380	34	0.4	0.3	1.81	1.28	1.8100	1.425
47	30	380	44	0.6	0.3	3.37	2.89	3.3701	3.306
48	30	380	68	0.8	0.3	5.19	5.14	5.1901	5.422
49	30	380	34	0.4	0.5	1.45	1.28	1.4500	1.397
50	30	380	44	0.5	0.5	1.5	2.01	1.5000	1.924

Table 1 contd.

51	30	380	34	0.3	0.6	1.37	0.72	1.3700	1.126
52	30	380	44	0.5	0.6	2.06	2.01	2.0600	2.173
53	30	380	68	0.6	0.6	3.67	2.89	3.6703	3.078
54	30	520	34	0.4	0.4	1.61	1.28	1.6100	1.274
55	30	520	68	0.8	0.4	4.74	5.14	4.7402	4.853
56	30	520	34	0.4	0.5	1.85	1.28	1.8500	1.361
57	30	520	68	0.7	0.5	2.53	3.94	2.5301	3.616
58	30	520	34	0.3	0.6	1.39	0.72	1.3900	1.167
59	30	520	44	0.5	0.6	1.42	2.01	1.4200	2.101
60	30	520	68	0.6	0.6	3.41	2.89	3.4100	3.040
61	30	715	34	0.4	0.3	1.41	1.28	1.4100	1.351
62	30	715	68	0.8	0.3	5.88	5.14	5.8799	4.966
63	30	715	34	0.4	0.4	1.46	1.28	1.4600	1.222
64	30	715	44	0.5	0.4	1.92	2.01	1.9199	1.725
65	30	715	68	0.7	0.4	1.96	3.94	1.9601	3.499
66	30	715	34	0.3	0.6	1.44	0.72	1.4400	1.216
67	30	715	44	0.5	0.6	1.26	2.01	1.2600	1.992
68	30	715	68	0.6	0.6	3.51	2.89	3.5100	2.978

Table 2. Different ANFIS architecture.

No.	No. of membership function	Function type	Output function	Error (RMSE)	
				Training error	Test error
1	2	triMF	Constant	0.52621	1.1201
2			Linear	0.0015313	8.6738
3		trapMF	Constant	0.67267	1.8066
4			Linear	0.062238	32.5008
5		gbellMF	Constant	0.44127	2.6083
6			Linear	0.0017631	4.1674
7		gaussMF	Constant	0.47684	2.4983
8			Linear	0.0010401	11.4902
9		gauss2MF	Constant	0.44438	14.6782
10			Linear	0.0040477	15.409
11		piMF	Constant	0.67038	2.7691
12			Linear	0.062238	225.4342
13		dsigMF	Constant	0.66458	3.4325
14			Linear	0.0087274	65.9564
15		psigMF	Constant	0.66458	3.4325
16			Linear	0.0093929	63.1275
17	3	triMF	Constant	0.0044346	1.5592
18			Linear	9.246×10^{-5}	1.5502
19		trapMF	Constant	0.055762	4.1632
20			Linear	6.8203×10^{-5}	1.7523
21		gbellMF	Constant	0.0019349	1.4268
22			Linear	1.9238×10^{-4}	1.1749
23		gaussMF	Constant	0.00063287	1.5905
24			Linear	$\mathbf{9.9845\times10^{-5}}$	**1.146**
25		gauss2MF	Constant	0.058802	3.9327
26			Linear	1.7924×10^{-4}	1.5134

Table 2 cont.

27		piMF	Constant	0.062843	2.5633
28			Linear	9.2752×10^{-5}	1.8044
29		dsigMF	Constant	0.030196	4.168
30			Linear	0.0021019	2.7252
31		psigMF	Constant	0.030196	4.168
32			Linear	6.6216×10^{-4}	2.6197
33	4	triMF	Constant	9.5473×10^{-6}	1.9769
34			Linear	2.2411×10^{-5}	1.8897
35		trapMF	Constant	7.4861×10^{-6}	2.5756
36			Linear	3.8743×10^{-5}	2.6091
37		gbellMF	Constant	1.1209×10^{-5}	1.8921
38			Linear	5.5699×10^{-4}	1.8935
39		gaussMF	Constant	1.0605×10^{-5}	1.8773
40			Linear	1.3647×10^{-4}	1.8018
41		gauss2MF	Constant	7.4889×10^{-6}	2.5885
42			Linear	1.0873×10^{-4}	2.6164
43		piMF	Constant	7.9488×10^{-6}	2.7837
44			Linear	5.3625×10^{-5}	2.8038
45		dsigMF	Constant	7.5323×10^{-6}	2.5586
46			Linear	1.4076×10^{-4}	2.5763
47		psigMF	Constant	7.5323×10^{-6}	2.5586
48			Linear	1.4611×10^{-4}	2.5695

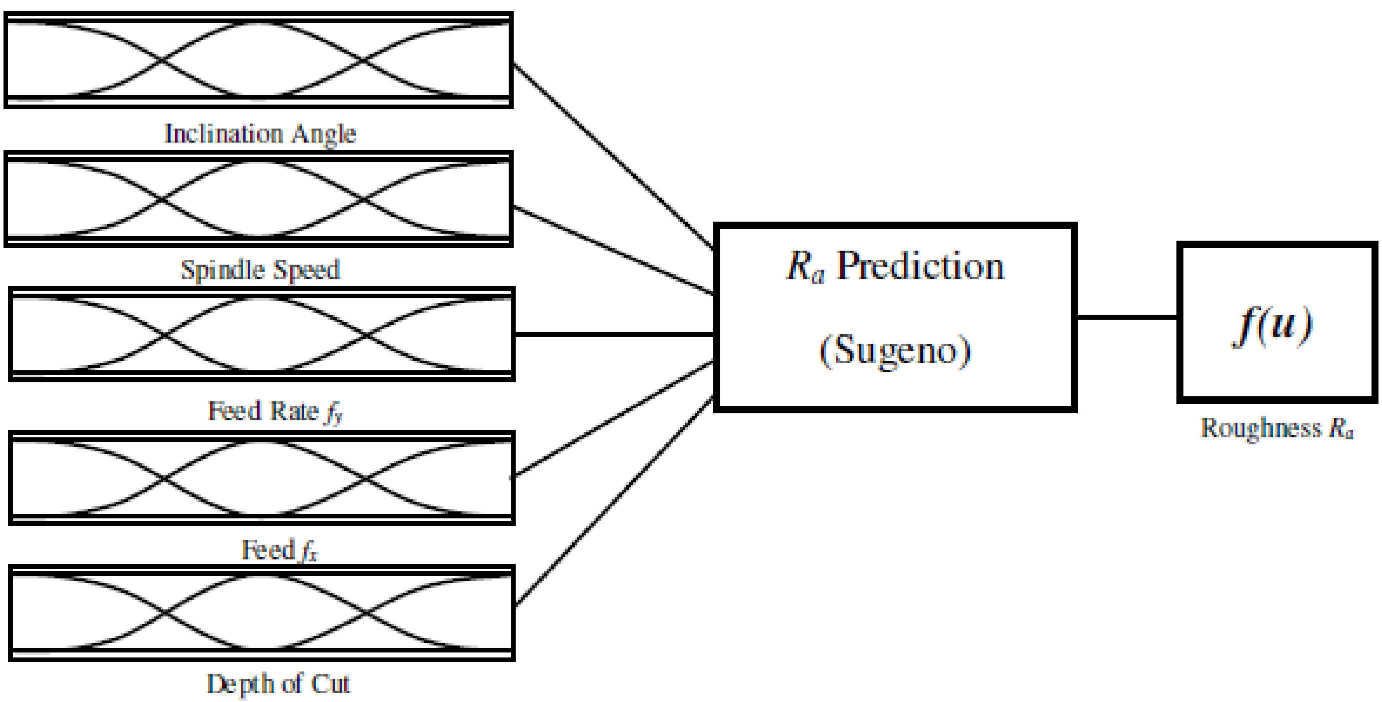


Figure 5. Final ANFIS model with 5 inputs and 1output.

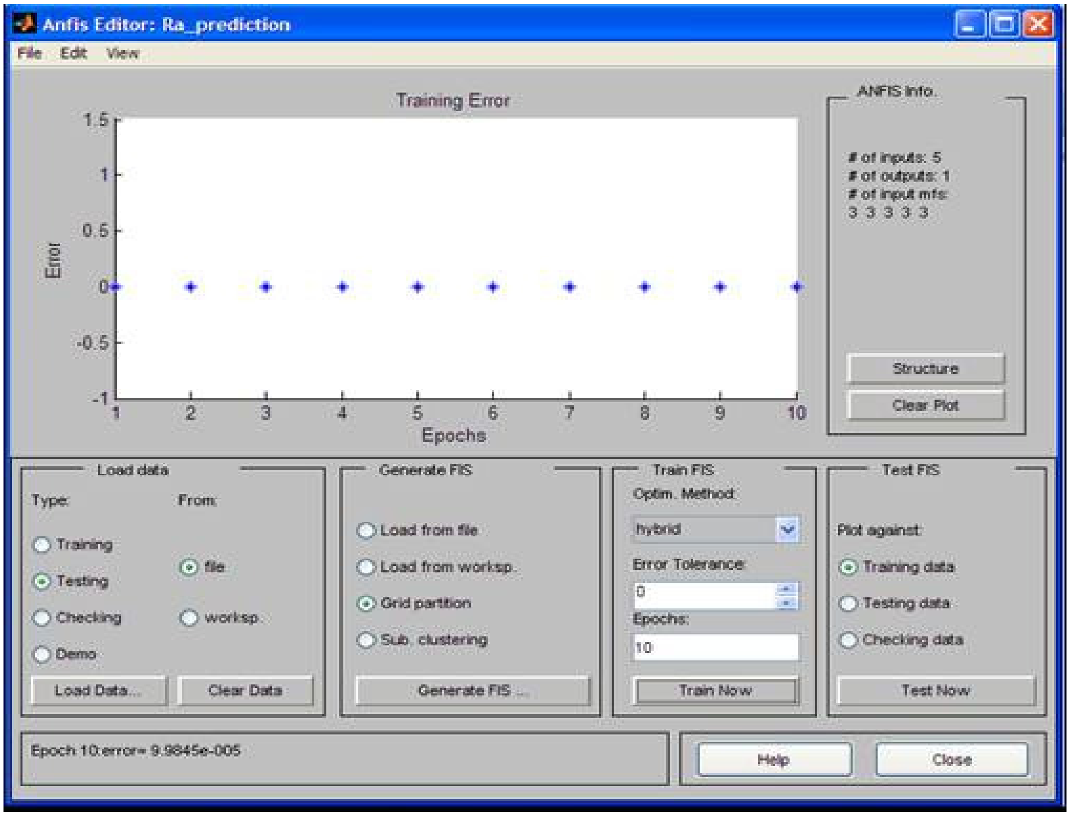


Figure 6. Train of ANFIS up to 10 epochs.

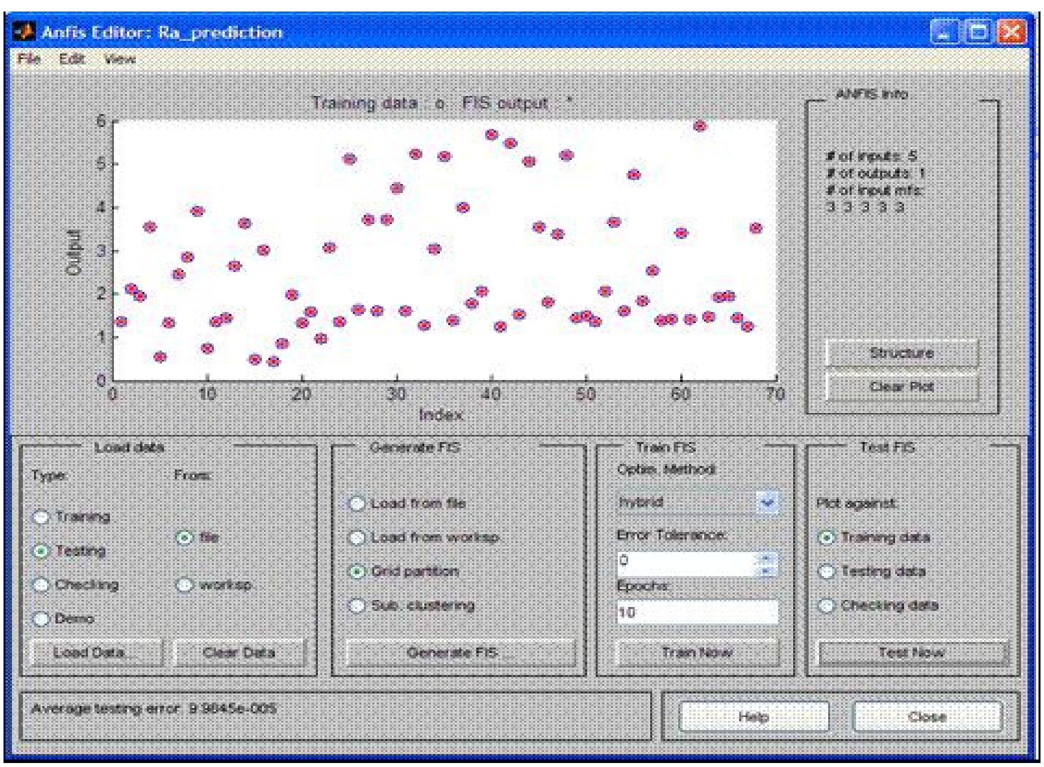


Figure 7. Comparison between the experimental and predicted values by the ANFIS training data.

Table 3. Summary of different models output with testing data set.

SL	Inclination angle (φ)	Speed S (rpm)	Feed f_y (mm/min)	Feed f_x (mm)	Depth of cut t (mm)	Avg. R_a (experimental)	R_a (from equations)	MSE	% error	R_a (from ANFIS)	RMSE	% error	RSM (Ra)	MSE	% error
1	30	520	44	0.6	0.4	3.53	2.890	0.410	18.130	1.603	3.714	54.598	2.862	0.447	18.930
2	30	380	68	0.7	0.5	4.09	3.940	0.023	3.667	2.637	2.112	35.531	3.731	0.129	8.785
3	15	520	44	0.6	0.4	3.25	2.890	0.130	11.077	2.423	0.683	25.434	3.015	0.055	7.234
4	30	380	68	0.4	0.6	1.19	1.280	0.008	7.563	1.661	0.221	39.538	2.028	0.701	70.378
5	15	715	44	0.6	0.6	1.97	2.890	0.846	46.701	4.005	4.139	103.274	2.770	0.640	40.624
6	0	380	44	0.8	0.6	2.06	5.140	9.486	149.515	1.178	0.778	42.811	3.409	1.820	65.484
7	0	380	44	0.8	0.4	4.09	5.140	1.103	25.672	2.669	2.019	34.743	3.928	0.026	3.970
8	0	715	44	0.6	0.4	1.37	2.890	2.310	110.949	0.543	0.684	60.372	1.465	0.009	6.956
9	30	715	44	0.6	0.3	3.5	2.890	0.372	17.429	2.268	1.519	35.211	2.961	0.291	15.404
10	0	380	44	0.8	0.2	3.03	5.140	4.452	69.637	4.822	3.209	59.125	5.291	5.111	74.609
11	0	715	68	0.8	0.6	2.08	5.140	9.364	147.115	1.376	0.496	33.856	3.082	1.005	48.188
12	15	380	68	0.8	0.5	5.15	5.140	0.000	0.194	4.330	0.672	15.920	4.978	0.030	3.346
13	0	520	34	0.5	0.5	0.38	2.010	0.397	45.652	1.113	0.072	19.377	1.133	0.061	17.893
14	15	520	68	0.8	0.6	5.52	5.140	0.144	6.884	5.215	0.093	5.534	4.792	0.530	13.191
15	30	520	44	0.5	0.5	2.03	2.010	0.000	0.985	1.349	0.463	33.527	1.856	0.030	8.585
16	15	380	44	0.6	0.3	2.05	2.890	0.706	40.976	2.436	0.149	18.824	3.489	2.072	70.218

9i and j shows the interaction effect of depth of cut with feed rate f_y and feed f_x on R_a. At low feed rate (f_y), depth of cut is more or less consistent. For low feed, f_x depth of cut should be higher for getting better surface quality.

Table 5 presents the summary of correlation test between R_a (experimental) and different input parameters for training data set. It shows that feed rate f_y (mm/min) and feed f_x (mm) have a great positive correlation with R_a, and depth of cut t (mm) has a weak negative correlation with R_a.

Conclusion

In this research, an adaptive neuro-fuzzy system and RSM is applied to predict the surface roughness during ball end milling operation. The machining parameters were used as inputs to the ANFIS and RSM to predict surface roughness. The ANFIS model could predict the surface roughness for training data with an average percentage deviation of 0.003014% when Gaussian membership function is applied, while RSM model could predict the surface roughness for training data with an average percentage deviation 27.72% from training data set. The ANFIS model could predict the surface roughness for testing or validation data set with an average percentage deviation of 38.605%, while RSM model could predict the surface roughness for testing data with an average percentage deviation of 29.612%. But prediction results for surface roughness are more accurate in ANFIS model if training data are considered. For train data set, average percentage deviation from practical data is only 0.003014% for ANFIS model, while RSM model could predict the surface roughness for training data with an average percentage deviation of 27.722%.

Engineered components must satisfy surface texture requirements and, traditionally, surface roughness (arithmetic average, R_a) has been used as one of the principal methods to assess quality. It is quite obvious from the results of the predictive models that the predicted accuracy was good and the predicted results matched well with the experimental values. As the correlation between the machining and the surface roughness is strongly dependent on the material being machined, there is an impending need to develop a generic predictive platform to predict surface roughness. The present investigation is a step in this regard. The proposed model is helpful in the

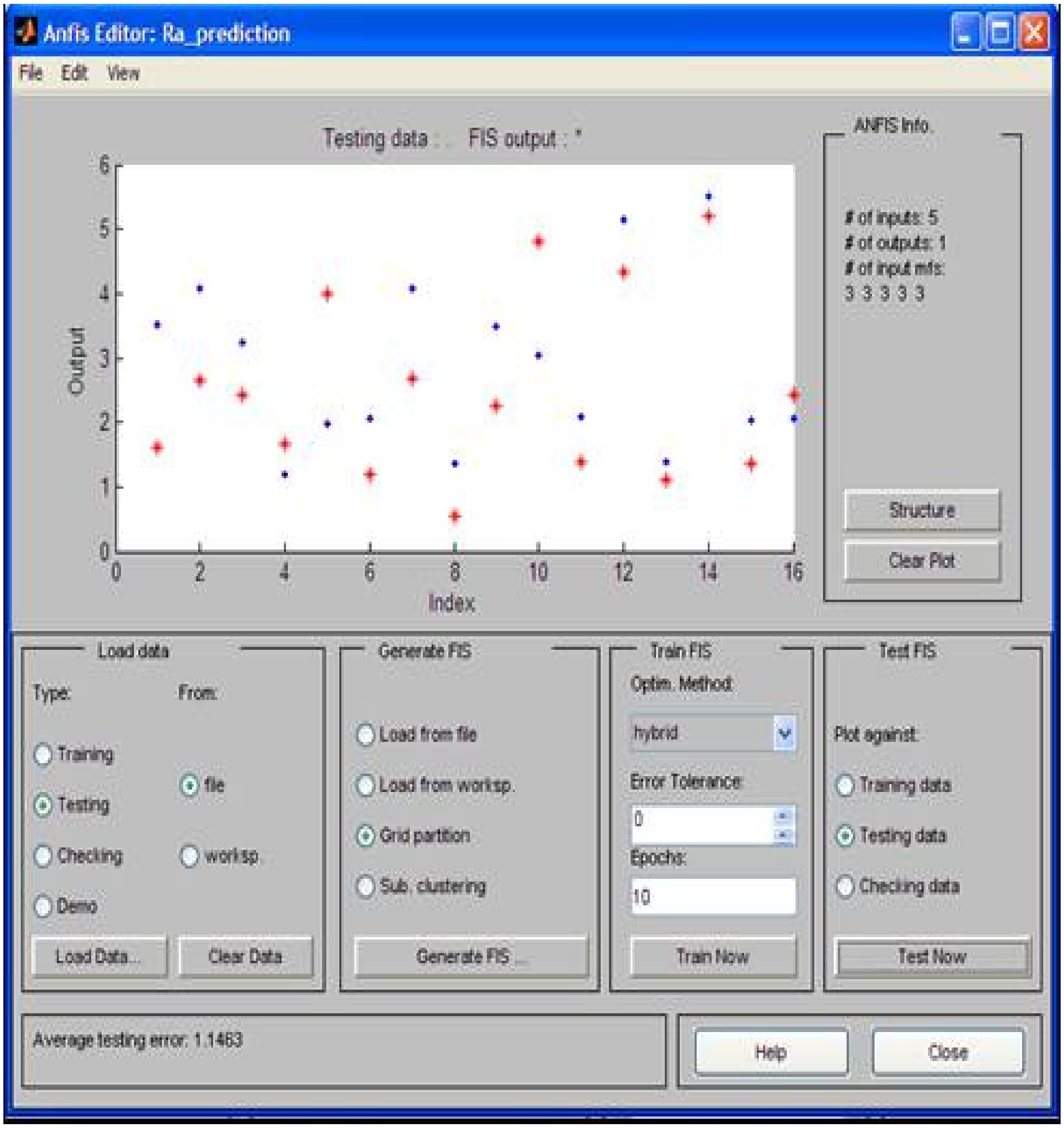


Figure 8. Comparison between the experimental and predicted values by the ANFIS testing data.

Table 4. Errors in different models.

Model	For training data		For testing data	
	RMSE	Absolute mean % of error	RMSE	Absolute mean % of error
Theoretical equation	0.934292	42.02314	1.364	43.884
ANFIS	9.9845×10^{-5}	0.003014	1.146	38.605
RSM	0.630641	27.72202	0.900	29.612

judicious selection of the various machining parameters to minimize surface roughness. Vibrations are unavoidable during the machiningoperation. Vibrations may result from the variation of cutting forces generated during the machining process. It can be caused due to sources inside or outside the machine tool. It is important to know the effects of vibrations on the characteristics of surface profile as vibration is responsible for degrading the surface finish. Further work can be done considering vibration as an input factor for developing a prediction

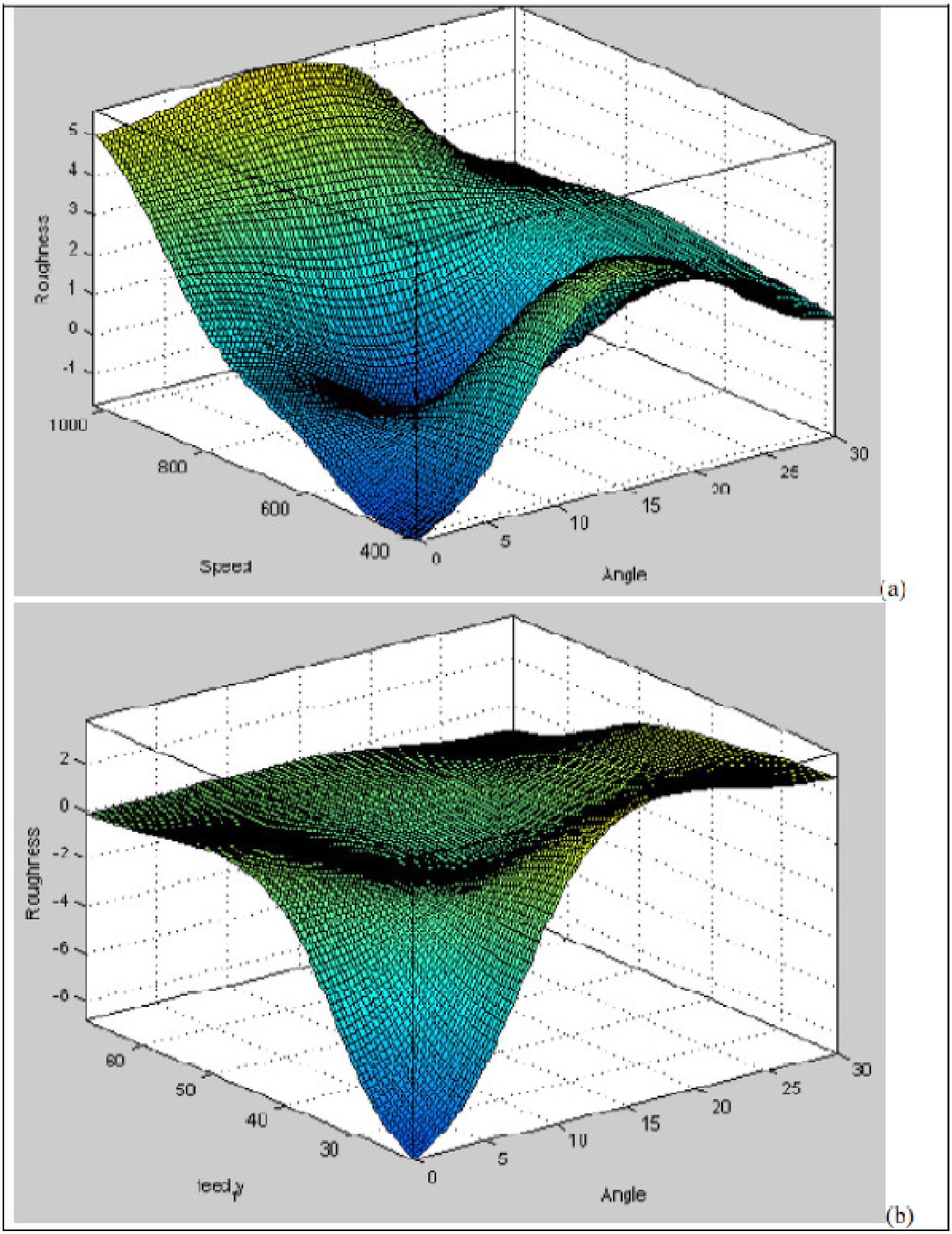


Figure 9. (A)Surface plot of roughness R_a µm vs. Inclination angle φ and Spindle Speed S rpm; (B); Inclination angle φ and Feed rate f_y mm/min.

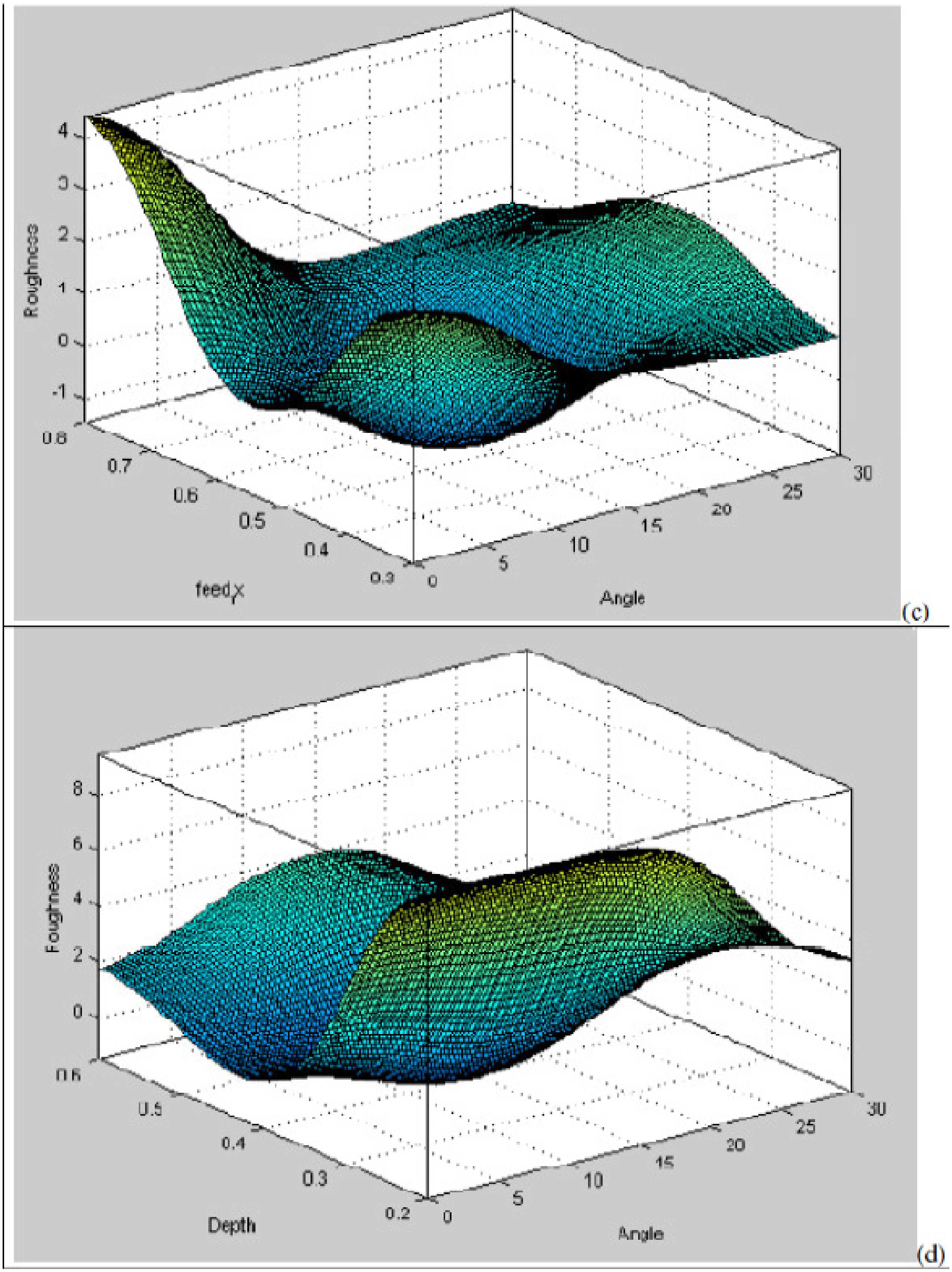


Figure 9. (C) Inclination angle φ and Feed f_x mm; (D) Inclination angle φ and Depth of Cut t mm;

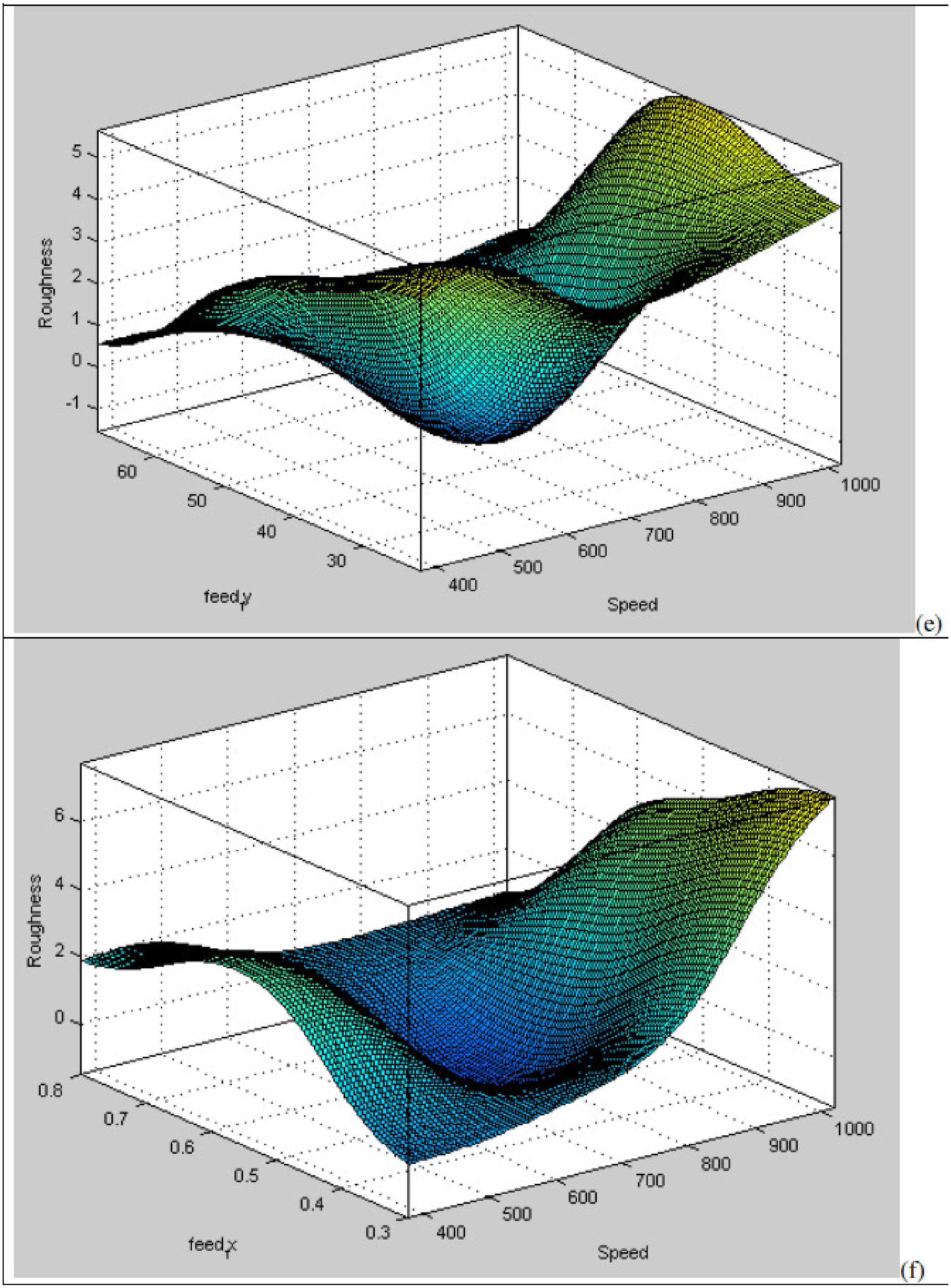
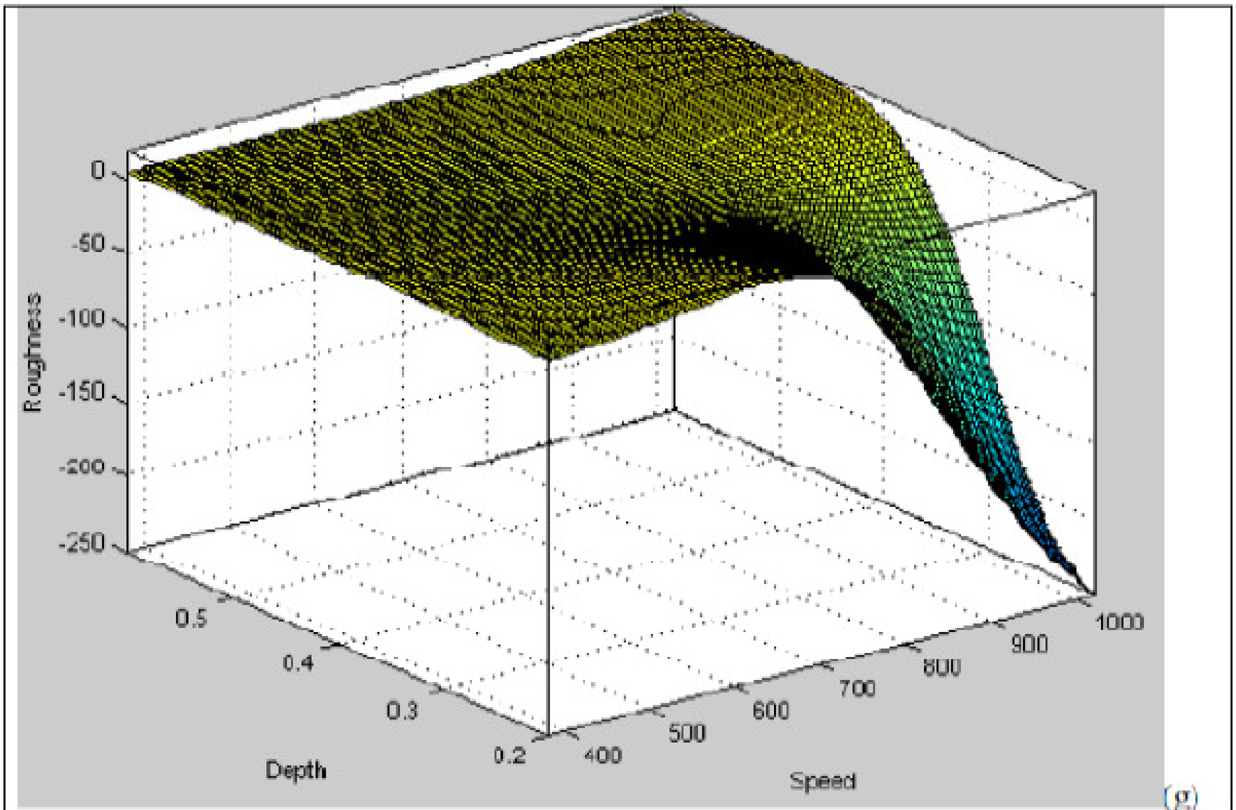
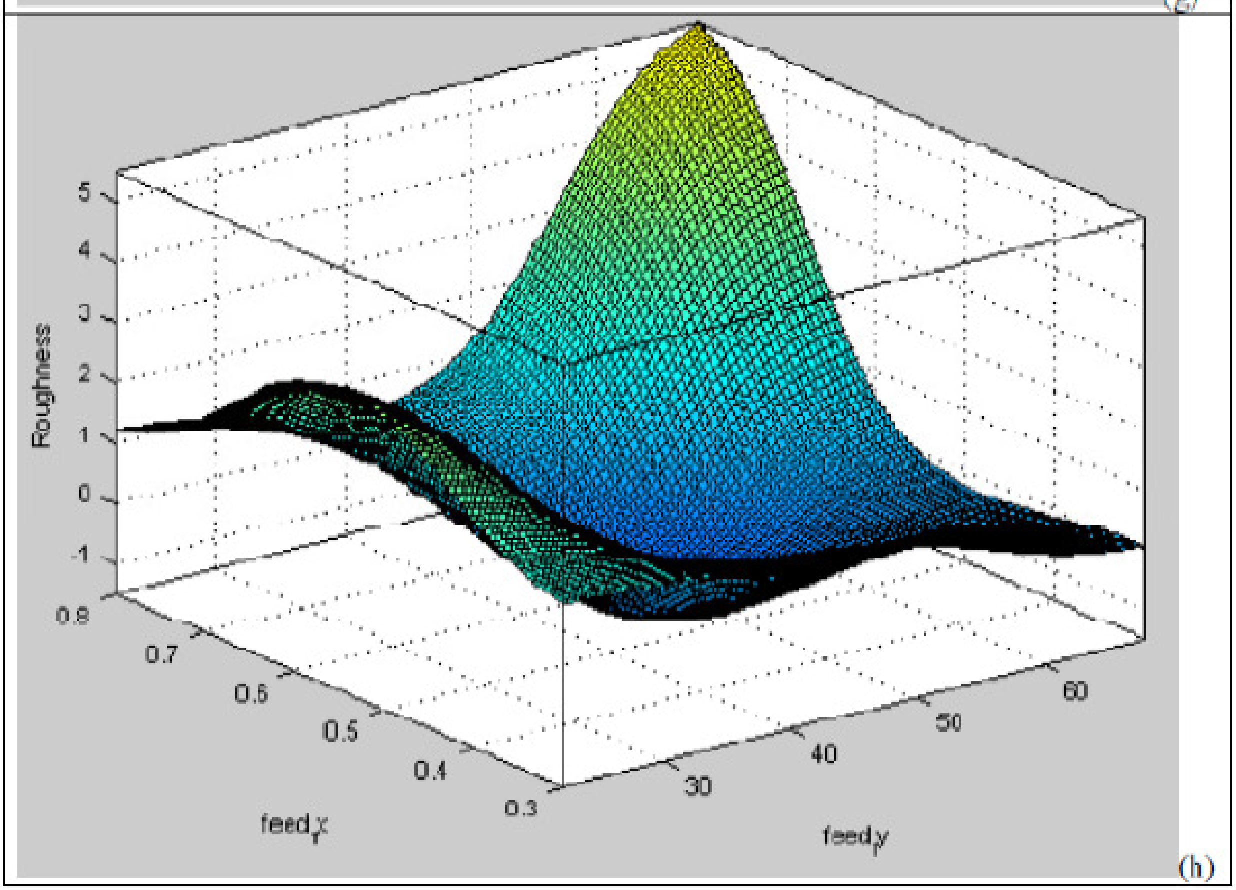


Figure 9. (E)Spindle Speed *S* rpm and Feed rate f_y mm/min; (F)Spindle Speed *S* rpm and Feed f_x mm;





(G) Speed S rpm and Depth of Cut t mm Feed; (H)rate f_y mm/min and Feed f_x mm;

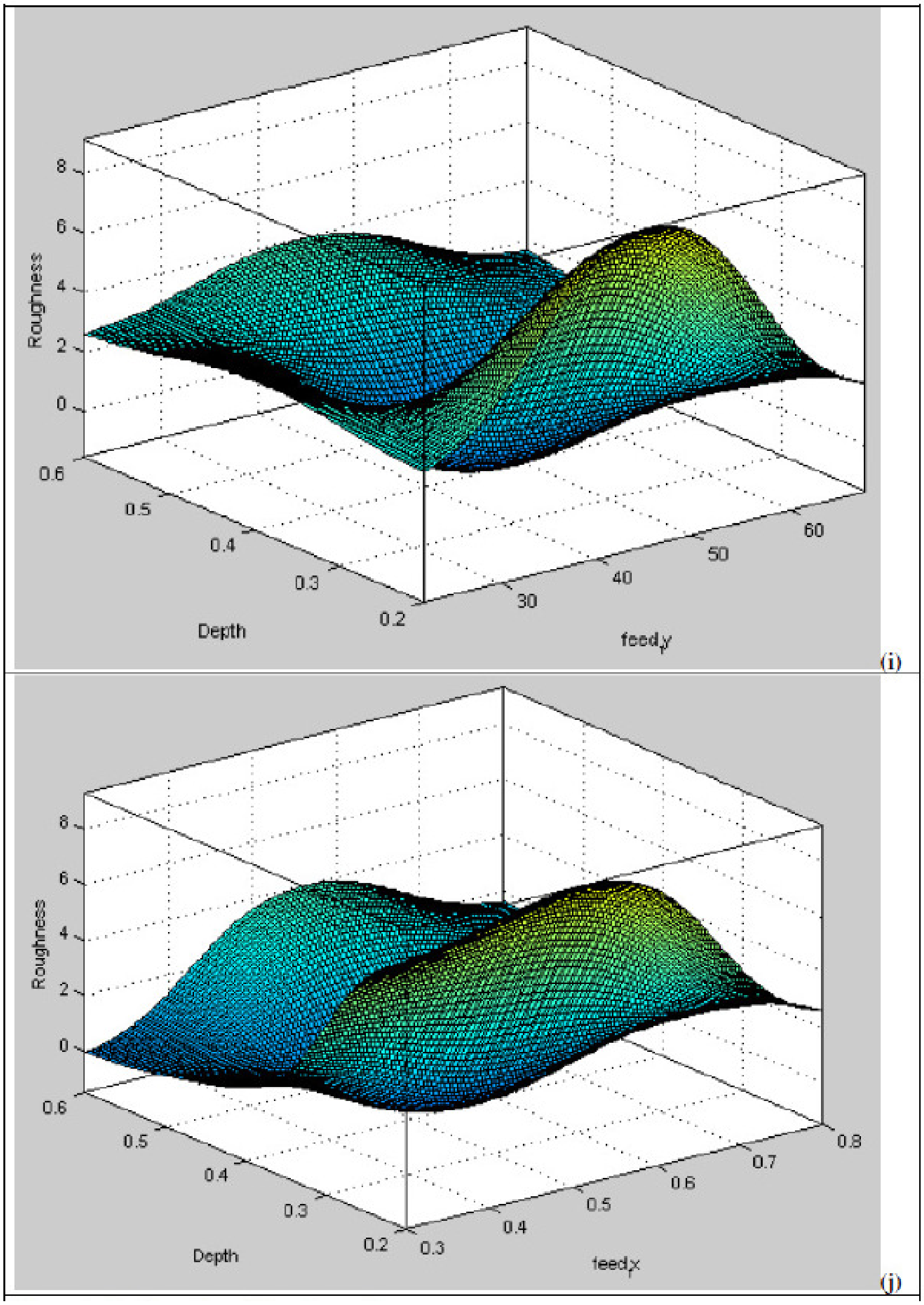


Figure 9. (I)Feed rate f_y mm/min and (J)Depth of Cut t mm; Feed f_x mm and Depth of Cut t mm.

Table 5. Pearson correlation for different inputs with experimental R_a.

Variable	*r*	*P*-value
Inclination angle (φ)	0.156	0.203
Speed S (rpm)	0.096	0.437
Feed f_y (mm/min)	0.722	0.000
Feed f_x (mm	0.788	0.000
Depth of cut t (mm)	-0.209	0.088

model for surface roughness.

REFERENCES

Ahmed SG (2006). “Development of a prediction model for surface roughness in finish turning of aluminum”. J. Sudan Eng. Soc., 52(45): 1-5.

Alauddin A, Baradie MAE, Hashimi MSJ (1995). “Computer Aided Analysis of a Surface Roughness Model for End Milling”. J. Mater. Prod. Technol., 55(2): 123-127.

Aykut S (2011) “Surface Roughness Prediction in Machining Castamide Material Using ANN”, Acta Polytechnica Hungarica, 8(2): 21-32.

Basak S, Dixit US, Davim JP (2007). “Application of Radial Basis Function Neural Networks in Optimization of Hard Turning of AISI D2Cold-Worked Tool Steel with Ceramic Tool”, Proceedings of the Institution of Mechanical Engineers, Part B. J. Eng. Manufacture, 221(6): 987-998.

Bernardos PG, Vosniakos GC (2003). “Predicting Surface Roughness in Machining: a Review”, Int. J. Machine Tools Manufacture, 43:833-844.

Bisht H, Gupta J, Pal SK, Chakraborty D (2005). “Artificial Neural Network Based Prediction of Flank Wear in Turning”, International J.Materials and P Ciurana Prod. Technol., 22(4): 328-338.

Brecher C, Quintana G, Rudolf T, Ciurana J (2011). “Use of NC Kernel Data for Surface Roughness Monitoring in Milling Operations”, Int. J. Adv. Manufacturing Technol., 53: 953–962.

Brezocnik M, Kovacic M, Ficko M (2004). “Prediction of surface roughness with genetic programming”. J. Mater. Proc. Technol., 157(158): 28–36.

Bruni C,d’Apolito L, Forcellese A, Gabrielli F, Simoncini M, (2008). “Surface Roughness Modelling in Finish Face Milling Under MQL and Dry Cutting Conditions”, Int. J. Mater. Formation, Suppl., 1: 503–506.

Cabrera FM, Beamud E, Hanafi Z, Khamlichi A, Jabbouri (2011). “Fuzzy Logic-Based Modeling of Surface Roughness Parameters for CNC Turning of PEEK CF30 by TiN-Coated Cutting Tools”, J. Thermoplastic Composite Mater., 24(3): 399-413.

Chen JC, Savage M (2001). “A Fuzzy-Net Based Multi Level In-process Surface Roughness Recognition System in Milling Operation”, International J. Advanced Manufacturing Technol., 17: 670–676.

Cus F, Zuperl U (2009). “Particle Swarm Intelligence Based Optimization of High Speed End-Milling”, Archives of Computational Mater. Sci. Surface Eng., 1(3): 148-154.

Dweiri F, Al-Jarrah M, Al-Wedyan H. (2003) “Fuzzy Surface Roughness modeling of CNC Down Milling of Alumic-79”, J. Mater. Prod. Technol., 133: 266-275.

Feng C.X, Wang X. (2002) “Development of Empirical Models for Surface Roughness Prediction in Finish Turning”, Int. J. Adv. Manufacturing Technol., 20: 348–356.

Huang L, Chen JC. (2001). “A Multiple Regression Model to Predict In-process Surface Roughness in Turning Operation via Accelerometer”, J. Ind. Technol., 17: 1-8.

Jesuthanam CP, Kumanan S, Asokan P (2007). “Surface Roughness Prediction Using Hybrid Neural Networks”, Machining Sci. Technol., 11(2): 271-286.

Jiao Y, Lei S, Pei ZJ, Lee ES (2004). “Fuzzy adaptive networks in machining process modeling: surface roughness prediction for turning operations”,International J. Machine Tools Manufacture, 44: 1643–1651.

John Y, Reza L (2003). “Fuzzy Logic Intelligence Control and Information”, Pearson Education, Delhi.

Khorasani AM, Yazdi MRS, Safizadeh MS (2011). “Tool Life Prediction in Face Milling Machining of 7075 Al by Using Artificial Neural Networks (ANN) and Taguchi Design of Experiment (DOE)”, IACSIT International J. Eng. Technol., 3(1): 30-35.

Kumanan S, Jesuthanam CP, Kumar RA (2008). “Application of multiple regression and adaptive neuro fuzzy inference system for the prediction of surface roughness”, International J. Advanced Manufacturing Technol., 35: 778–788.

Lin SY, Cheng SH, Chang CK (2007). “Construction of a Surface Roughness Prediction Model for High Speed Machining”. J. Mechanical Sci.Technol., 21: 1622-1629.

Lou MS, Chen JC, Li CM (1999). “Surface roughness prediction technique for CNC end-milling”, J. Industrial Technol., 15(1): 1-6.

Lu C, Costes J (2008). “Surface profile prediction and analysis applied to turning process”, International J. Machining Machinability Mat., 4(2-3): 158-180.

Luong LHS, Spedding TA (1995). “A Neural Network System for Predicting Machining Behavior”, J. Mater. Processing Technol., 52: 585-591.

Mahdavinejad RA, Bidgoli HS (2009). “Optimization of Surface Roughness Parameters in Dry Turning”, J. Achievements Mater. Manufacturing Eng., 37(2): 571-577.

Mital A, Mehta M (1988). “Surface Roughness Prediction Models for Fine Turning”. Int. J. Prod. Res., 26: 1861-1876.

Mukherjee I, Ray PK (2006). "A Review of Optimization Techniques in Metal Cutting Processes", Comp. Ind. Engr., 50(2006): 15–34.

Nabil BF, Ridha A (2006). “Ground Surface Roughness Prediction Based upon Experimental Design and Neural Network Models”, Int. J. Adv. Manufacturing Technol., 31: 24-36.

Oktem H, Erzurumlu T, Erzincanli F. (2006). “Prediction of Minimum Surface Roughness in End Milling Mold Parts Using Neural Network and Genetic Algorithm”, Mater. Des., 27: 735-744.

Ozcelik B, Bayramoglu M. (2006). “The Statistical Modeling of Surface Roughness in High-Speed Flat End Milling”, International J. Machine Tools Manuf., 46: 1395-1402.

Pal S, Chakraborty D. (2005). “Surface Roughness Prediction in Turning Using Artificial Neural Network”. Neural Comp. Appl., 14: 319-324.

Rai R, Kumar A, Rao S, Shriram S (November 2010). “Development of a Surface Roughness Prediction System for Machining of Hot Chromium Steel (Aisi H11) Based on Artificial Neural Network”, ARPN J. Engr. Appl. Sci., 5(11): 53-59.

Reddy BS, Kumar JS, Reddy KVK (2009). “Prediction of Surface Roughness in Turning Using Adaptive Neuro-Fuzzy Inference System”, Jordan J. Mech. Ind. Engr., 3(4):252-259

Roy SS. (2005). “Design of adaptive Neuro-Fuzzy Interface System for Predicting Surface Roughness in Turning Operation”, J. Sci. Ind. Res., 64: 653-659.

Roy SS (April 2006). “An Adaptive Network-based Approach for Prediction of Surface Roughness in CNC End Milling”, J. Sci. Ind. Res., 65: 329-334.

Taraman K, Lambert B. (1974). “A surface roughness model for a turning operation”. International J. Prod. Res., 12(6): 691-703.

Tsai YH, Chen JC, Lou SJ. (1999). “An In-process Surface Recognition System Based on Neural Networks in End Milling Cutting Operations”, Int. J. Machine Tools Manufacture, 39: 583-605.

Wang MY, Chang HY (2004). “Experimental Study of Surface Roughness in Slot End Milling AL2014-T6”, Int. J. Machine Tools Manufacture, 44: 51-57.

Yazdi MRS, Khorram A. (2010). “Modeling and Optimization of Milling Process by using RSM and ANN Methods”, IACSIT Int. J. Engr. Technol., 2(5): 474-480.

Zhanjie L, Bing Y, Meili T. (2007).“Prediction of surface roughness of difficult-to-cut material by HSM based on RBF neural network”, 6th International conference on Instrumentation, measurement, circuits and systems, Hangzhou, China.

Zhong ZW, Khoo LP, Han ST (2006). “Prediction of Surface Roughness of Turned Surfaces Using Neural Networks”, Int. J. Adv. Manuf. Technol., 28: 688-693.