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Surface Roughness Prediction Model for Ball End Milling Operation Using Artificial Intelligence

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Abstract

Surface roughness is an index which determines the quality of machined products. In this study the average surface roughness value (R_a) for Aluminum after ball end milling operation has been measured. 84 experiments have been conducted varying cutter axis inclination angle (φ degree), spindle speed (S rpm), feed rate (f_y mm/min), radial depth of cut (f_x mm) and axial depth of cut (t mm) in order to find R_a. This data has been divided into two sets on a random basis. 68 data sets have been used for training different ANFIS model for R_a prediction. 16 test data sets have 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 inputs and a linear membership function for output. The Selected ANFIS model has been compared with theoretical model and Response Surface Methodology (RSM). This comparison is done based on RMSE and mean absolute percentage error (MAPE). The comparison shows that the selected ANFIS model gives better result for training and testing data. Here ANFIS model has been used further for predicting surface roughness of a typical die made by ball end milling operation. An algorithm was developed to determine the feasible solutions for the cutting parameters in order to obtain a desired surface roughness for the three dimensional die. This algorithm was used to show how a near optimal combination of machining parameters can be determined for a targeted level of surface finish.

Key words: Aluminium; Surface; Manufacturing; Quality; Milling; ANFIS; Machining; AI

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INTRODUCTION

The main objective of today's manufacturing industries is to produce 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 & 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 qualities. Typically, surface inspection is carried out by manually inspecting the machined surfaces. 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 metals cutting operations and 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 desired surface quality (Lou, *et al*., 1999).

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 their advanced computing capability. Researchers have used various intelligent techniques, including neural network, fuzzy logic, neuro-fuzzy, ANFIS, etc. for prediction of machining parameters and enhancing manufacturing automation. Artificial Neural Network (ANN) and Fuzzy Logic are two important tools 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 it creates a hybrid intelligent system.

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 shows 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 of Aluminium as a die material; and developing an algorithm to select the cutting parameters for a desired level of surface roughness.

1. LITERATURE REVIEW

The quality of surface finish mainly depends on the interaction between the workpiece, cutting tool and the machining system. Due to the above reasons, there have been a series of attempts by researchers to develop efficient prediction model 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.

For the prediction of surface roughness, a feed forward ANN was used for face milling of high chromium steel (AISI H11) by Rai *et al*. (2010) and AISI 420 B stainless steel by Bruni *et al.* (2008). Bruni *et al.* proposed analytical and artificial neural network models. Yazdi and Khorram (2010) worked for selection of optimal machining parameters (i.e., 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. In 2009, Patricia Munoz-Escalona *et al*. (2009) proposed the radial basisfeed 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. Chen Lu and Jean-Philippe Costes (Lu & Costes, 2008) considered three variables i.e., 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 ANN for surface roughness predictions. Seref Aykut (Aykut, 2011) had also used ANN to predict the surface roughness of cast-polyamide material after milling operation. Khorasani *et al*. (2011) have conducted 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. 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. Tsai, *et al*. (1999) used in process surface recognition system based on neural networks in end milling operation.

Mahdavinejad, *et al*. (2009), Shibendu Shekhar 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 surface roughness. Shibendu Shekhar Roy (2006) and Chen & Savage (2001) designed Adaptive Network-based Fuzzy Inference System (ANFIS) for modeling and predicting the surface roughness in end milling operation. Shibendu Shekhar 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. A neural fuzzy system was used to predict surface roughness in milling operations by. 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 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 when 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. 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.

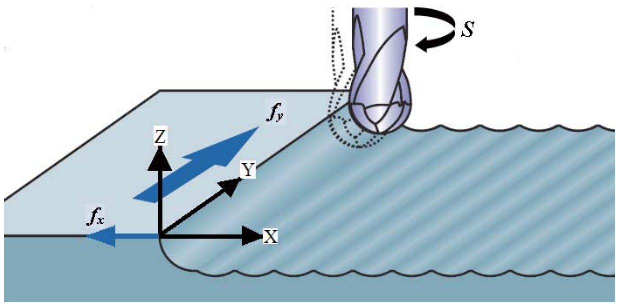
To achieve the desired surface finish, a good predictive model is required for stable machining. From the literature review, it was observed that majority of the work in the area of Artificial Intelligence application has been for turning and flat end or face milling operation. Due to this fact and also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

2. METHODOLOGY

2.1 Experimental Setup and Design of Experiment

The experiment was performed by using a vertical milling machine shown in Figure 1(a). The work-piece tested was an Aluminum plate of size 9cm×1cm×4cm. A two-flute tungsten carbide coated ball end mill cutter of 8mm diameter was selected as the cutting tool. Some samples were 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 were 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 measure the average surface roughness (R_a) value, experiments were carried out by varying the cutter axis inclination angle (φ) spindle speed (S rpm), the feed rate along y-axis (f_y mm/min), radial depth of cut namely feed along x-axis (f_x mm) and the depth of cut (t). The cutter movement directions have been shown in Figure 1(b). For each of the experiments, three sample readings were taken and their average value was considered.

(a) Vertical Milling Machine Used It the Study



(b) Cutting Tool Movement Direction

Figure 1
Experimental Setup

In this study, a Taylor Hobson Talysurf (Surtronic 25) was used for measuring average roughness (R_a). The distance that the stylus travels is sampling length; it ranges from 0.25 mm to 25 mm for selected instrument. In this study sampling length was 8 mm.

2.2 Prediction Models

Adaptive neuro-fuzzy inference system (ANFIS) 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. A hybrid method consists 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, throughout the learning process. 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. In this study a hybrid learning algorithm was used to identify premise and consequent parameters of first order Takagi-Sugeno type fuzzy system for predicting surface roughness in ball end milling.

In the Figure 2, a representative element of the ideal roughness profile after ball end milling operation has been shown. Using equation, (1) to (7) 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.

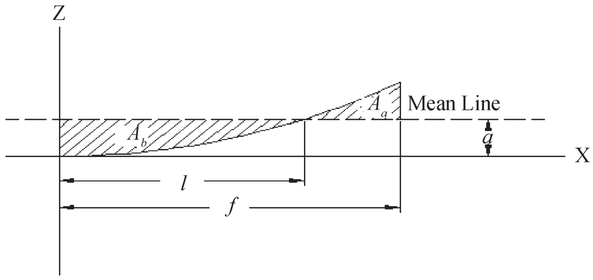


Figure 2
Calculation of Mean Line and Roughness

$$R_a = \frac{A_a + A_b}{f} -------------(1)$$

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

$$A_b = (a - R)l + \frac{R^2}{4}(2\theta_l + \sin 2\theta_l) ---------- (3)$$

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

$$l = \sqrt{2Ra - a^2} ------------ (5)$$

$$\theta_l = \sin^{-1}\frac{l}{R} --------------(6)$$

$$\theta_f = \sin^{-1}\frac{f}{R} ---------- (7)$$

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. In this study RSM was used to fit linear and second order polynomials on experimental data with 95% confidence level by minitab software.

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 (8).

$$r = \frac{1}{n-1}\sum_{i=1}^{n}\left(\frac{y_i - \overline{X}}{S_x}\right)\left(\frac{y_i - \overline{Y}}{S_y}\right) -------- (8)$$

Where n is the number of observations in the sample, x_i is the x value for observation i, $\overline{XX}$ is the sample mean of x, y_i is the y value for observation i, $\overline{YY}$ 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.

3. RESULTS AND DISCUSSION

The ANFIS models have been developed as a function of machining parameters using 68 training data presented in Table 1. The fuzzy logic toolbox of MATLAB 7.6 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 were those which have three Gaussian curve built-in membership functions (gaussMF) for each inputs and a linear output function. It can be observed 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 3(a). A total of 243 fuzzy rules were used to build the fuzzy inference system.

Table 1
Training Data Set

SL	Inclination angle φ	Speed S rpm	Feed rate 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

To be continued

Continued

SL	Inclination angle φ	Speed S rpm	Feed rate 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)
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
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

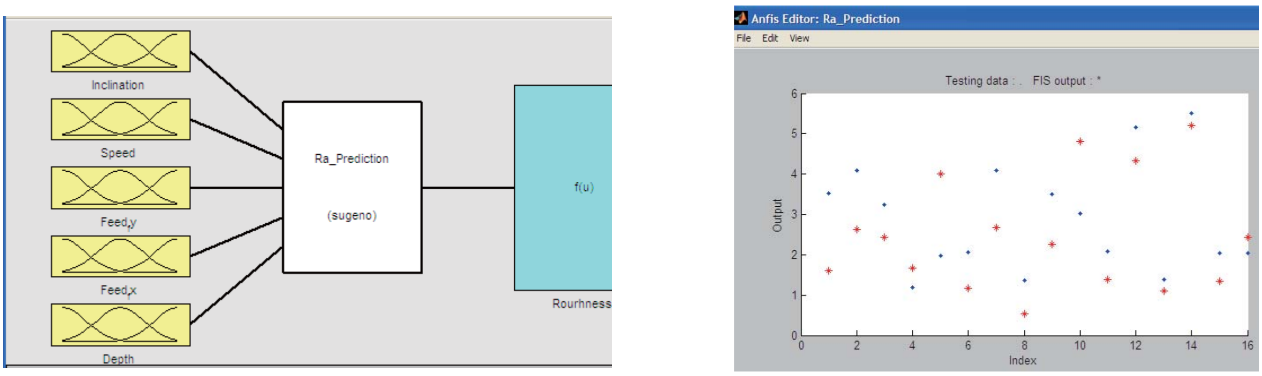
Table 2
Different ANFIS Architecture

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	9.9845×10^{-5}	1.146
25		gauss2MF	Constant	0.058802	3.9327
26			Linear	1.7924×10^{-4}	1.5134
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

To be continued

Continued

No.	No. of membership function	Function type	Output function	Error (RMSE)	
				Training error	Test error
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



(a) (b)

Figure 3
(a) Final ANFIS Model with 5 Inputs and Loutput
(b) Comparison Between the Experimental and Predicted Values by the ANFIS for Testing Data Set

Three *Gaussian* membership functions (gaussMF) were used for each input. The model developed by ANFIS was tested using the testing data and the predicted results were 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 compared in Figure 3(b).

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 (R_a)	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

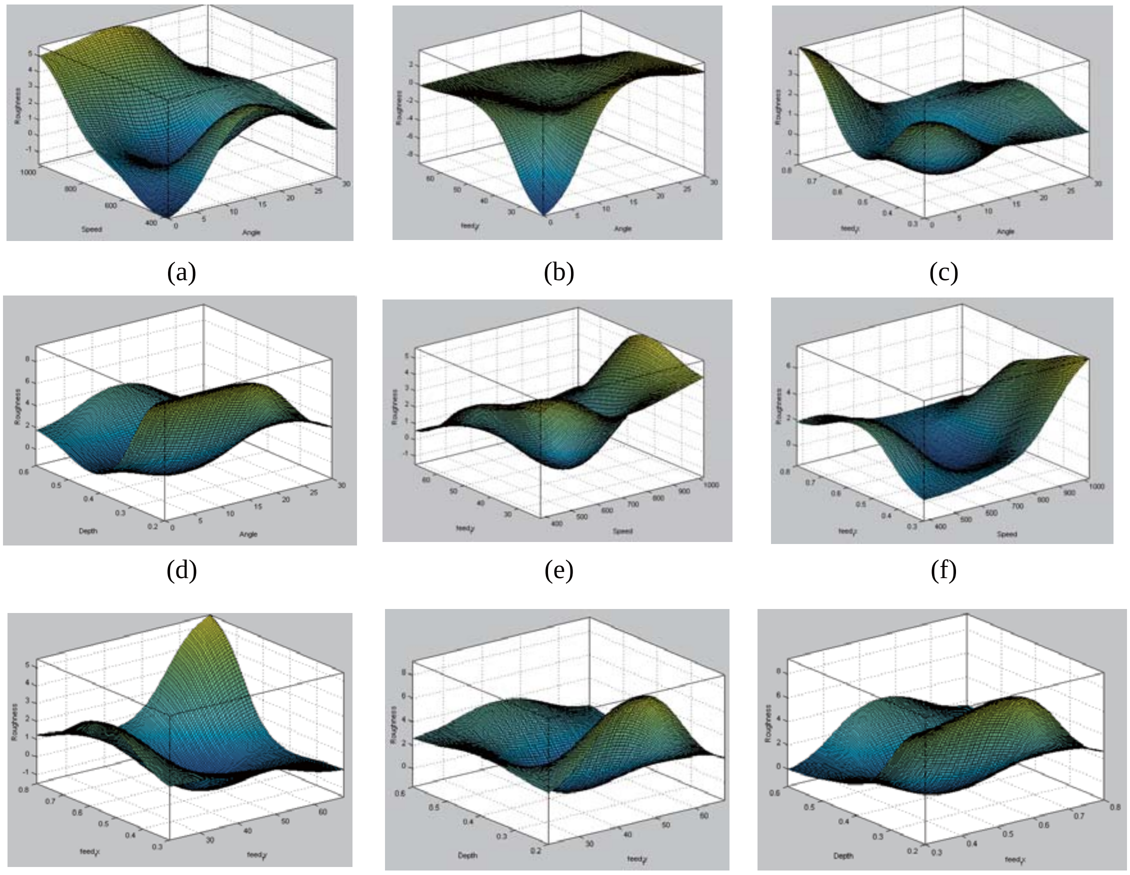
Equation (9) is the response surface equation developed by RSM. It can be used for predicting surface roughness. Test data set has been used for verifying this equation and predicted results have been summarized in Table 3. The results using the theoretical equations (1) to (7) for 16 test data sets also have been listed in Table 3.

$$R_a = 1.35355 + 0.0874799\ \varphi + 0.000887986\ S - 0.101501\ f_y + 7.92503\ f_x - 6.14303\ t - 0.00320667\ \varphi^2 - 1.20701\times10^{-07} s^2 + 0.00122325\ f_y^2 + 9.91836\ f_x^2 + 10.5552\ t^2 + 8.53234\times10^{-06}\varphi S - 9.68995\times10^{-04}\varphi f_y + 0.1357\ \varphi f_x + 0.00848098\ \varphi t + 3.41726\times10^{-05} S f_y - 0.00576076\ S f_x - 2.94529\times10^{-04} St - 0.101860\ f_y f_x + 0.0719970\ f_y t - 12.5766\ f_x t \quad (9)$$

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 (RMSE) and Mean Absolute Percentage Errors (MAPE) have been calculated for each of the above mentioned models and summarized in Table 4. It can be observed from the 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 in few of the cases occurs may be due to heterogeneity in work piece composition, small discrepancy in tool or work piece setting and tool or machining condition.

Table 4
Errors in Different Models

Model	For Training Data Set		For Testing Data Set	
	RMSE	MAPE	RMSE	MAPE
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



(a) (b) (c)

(d) (e) (f)

(g) (h) (i)

Figure 4
Surface Plot of Roughness R_a µm vs
(a) Inclination Angle φ and Spindle Speed S rpm, (b) Inclination Angle φ and Feed Rate f_y mm/min, (c) Inclination Angle φ and Feed f_x mm, (d) Inclination Angle φ and Depth of Cut t mm, (e) Spindle Speed S rpm and Feed Rate f_y mm/min, (f) Spindle Speed S rpm and Feed f_x mm, (g) Feed Rate f_y mm/min and Feed f_x mm, (h) Feed Rate f_y mm/min and Depth of Cut t mm, (i) Feed f_x mm and Depth of Cut t mm.

Figure 4 shows the relationship between ANFIS predicted roughness with different input parameters. In Figure 4(a) and 4(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 4(c) suggests to keep f_x at a medium level if cutter axis is vertical to the machining surface. At low depth of cut surface quality seems worse in Figure 4(d). Figure 4(e) and 4(f) shows that for medium level of speed feed rate f_y and feed f_x has low impact on surface finish. On the other hand from Figure 4(g) it is observed that higher feed rate in both direction results increased surface roughness. Figure 4(h) and 4(i) 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.

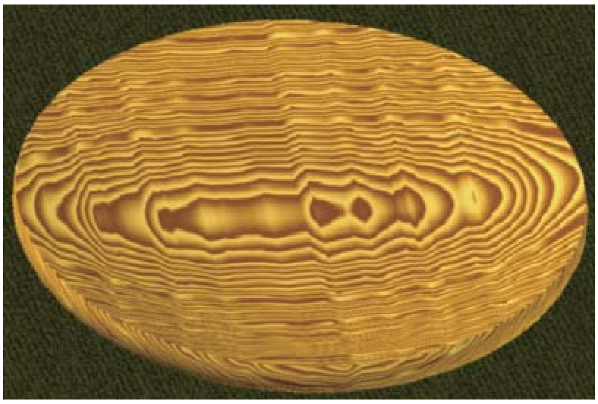
Correlation test has been done between R_a (Experimental) and different input parameters for training data set. It shows that feed rate f_y (mm/min) and feed f_x (mm) have a great positive correlation with R_a; Pearson correlation coefficient was r = 0.722 for f_y (mm/min) and r = 0.788 for f_x (mm) with P-value approximately zero for both direction of feed. And depth of cut t (mm) has a weak negative correlation with R_a; in this case r = -0.209 with p-value 0.088. Cutter axis inclination angle and spindle speed have very poor correlation with $R_{a.}$

4. APPLICATION OF PROPOSED PREDICTION MODEL

Surface roughness is one of the main quality characteristics of commercial dies. The model developed for the prediction of surface roughness of dies made of Aluminium can be used for setting the cutting parameters to obtain a predetermined surface roughness. Let us implement the ANFIS model for a practical example of manufacturing a commercial die with a particular level of surface roughness. Here the die selected as an example is made of Aluminium used in ceramic plate production. The surface quality of the die will affect the surface of the final ceramic product. The post processing of a machined surface will cost higher if the machined surface is too much rough. As a result it is important that the die surface should be of low surface roughness.

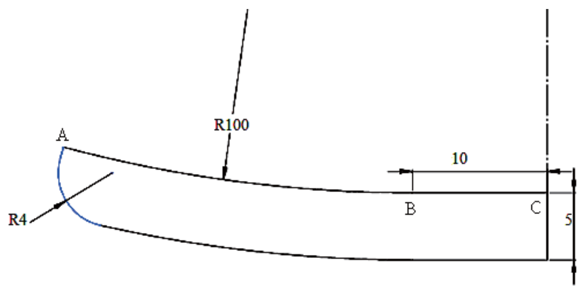
In this example the surface roughness of the die is targeted to be smooth which is defined a triangular membership function, where the desired R_a should have smallest possible value of 0μm, most promising value of 2.0 μm and largest possible value 2.2 μm respectively. Only a ball end mill cutter of 8 mm diameter was being used for the machining. It was previously machined with rough cut for removing the maximum material and already given a near to desired shape. Now it is needed to machine for finishing and obtaining the final die. For the final machining operation with ball end mill, the average depth of cut is needed only 0.2 mm. The shape of final die is shown in Figure 5 (a). It is round shaped plate of 71.8 mm diameter. The center portion of the die is flat. The diameter of the center of the die (flat part BC) is 20 mm and outer round part (AB) of the die is as an internal shape of a sphere of radius 100 mm. This spherical portion AB forms 15° angle at its center. The cross section view and dimension of this die is shown in Figure 5 (b) and (c) respectively. Our focus is on the surface roughness of the upper face (ABC) of the die as shown in Figure 5 (c). The possible cutting parameters are as follows,

- (Cutter Axis Inclination Angle or Inclination Angle of machining surface) φ = 0° to 15°
- Spindle Speed S = [380, 433, 520, 596, 715] rpm
- Tool Diameter d = 8 mm
- Feed Rate fy= [22, 34, 44, 68] mm/min
- Radial Depth of Cut or Feed along x-axis fx = 0.3 mm
- Axial Depth of Cut t = 0.2 mm



(a) Isometric view of the die

(b) Cross sectional view of the die



(c) Dimension of the die (Arc AB forms 15o angle at its center)

Figure 5
Die for a Ceramic Plate Manufacturing

All of the possible combinations of input parameters would be used to find corresponding R_a using already developed ANFIS model for Aluminium, which is constructed with three Gaussian membership functions (gauss2MF) for each of five inputs and a linear membership function for output R_a. This ANFIS model was developed and saved with the name of 'anfis' using MATLAB 7.6 FIS toolbox and exported to workspace of MATLAB. As the target is to obtain a surface roughness less than 2.20 μm, there may be a lot of combinations of the input parameters which result the required roughness value. But it can be observed from the correlation analysis that low values of feed f_x (redial depth of cut) will produce smoother surface. As a result the f_x has been set to its minimum value (0.3) within its range of training dataset. The value of φ will change after every round pass of the cutter at a rate θ which is a function of radial depth of cut f_x, tool diameter d and radius R of the spherical portion (AB) of the die, as shown in Eq. (10).

$$\theta = 2\sin^{-1}\frac{f_x}{2\left(R-\frac{d}{2}\right)} \qquad (10)$$

So, after every round pass, the cutting tool will move to both vertical and horizontal direction whose resultant vector sum is equal to the radial depth of cut f_x. As φ will increment by θ = 1.79°, the curved surface can be divided into 10 machining points namely 10 round pass. An important note should be mentioned; here φ is not the tilt angle of the cutter axis rather inclination angle of the machining surface at the particular point of machining. But this φ represents the same meaning as the cutter axis inclination angle. For each value of φ, all possible combinations of other input parameters are used for simulating the 'anfis' model. To conduct this simulation MATLAB code was written as, "evalfis ([input dataset], anfis)". Now among the simulated results, outputs $R_a \leqslant 2.2$ are stored along with corresponding input parameters. Again among these stored dataset the R_a nearest to the most promising value 2.0 and its corresponding machining parameters are finally considered and presented in Table 5. The average of the 'R_a' value 1.68186 µm presented in Table 5 would be the final roughness of round part AB of the die which was targeted. The process described above has been summarized in a flowchart shown in Figure 6.

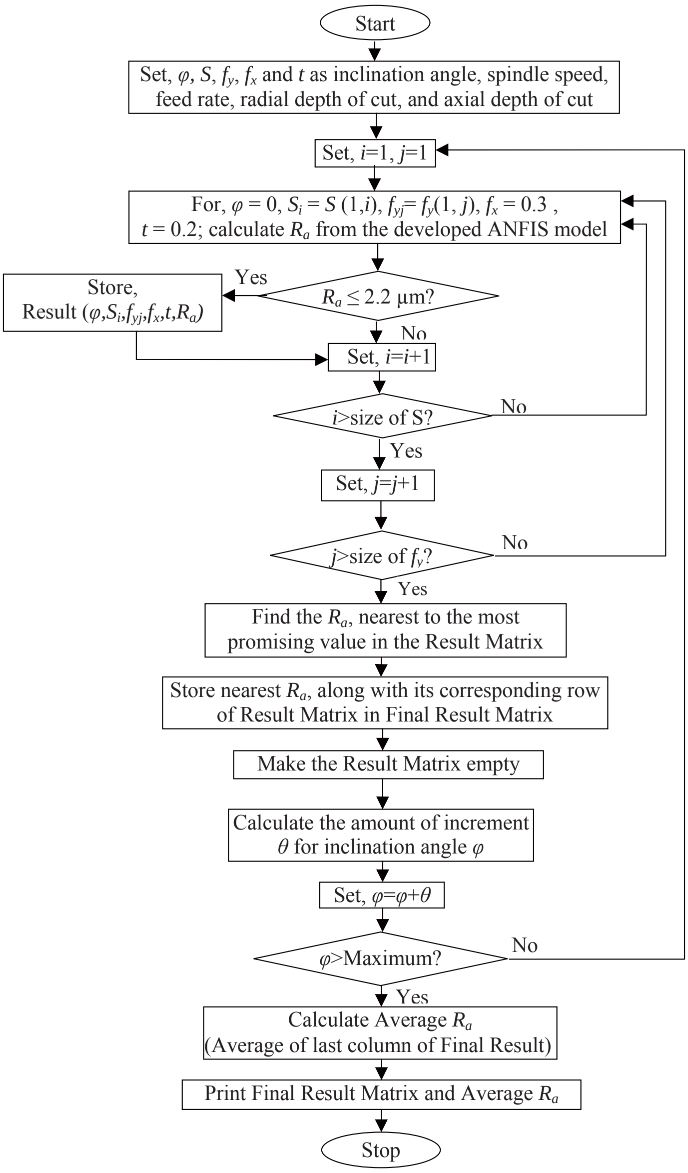


Figure 6
Flow Chart for Obtaining Desired R_a of a Spherical Surface of a Die

Table 5
Final Machining Parameters for Manufacturing Round Surface of a Ceramic Plate Die

Machining points	φ	S	f_y	f_x	t	R_a
1	0	715	68	0.3	0.2	1.9486
2	1.79	715	68	0.3	0.2	1.8602
3	3.58	715	68	0.3	0.2	1.7129
4	5.37	715	68	0.3	0.2	1.4932
5	7.16	596	68	0.3	0.2	1.3827
6	8.95	433	44	0.3	0.2	1.4677
7	10.74	433	44	0.3	0.2	1.5390
8	12.53	433	44	0.3	0.2	1.5322
9	14.32	715	34	0.3	0.2	2.1152
10	15	715	34	0.3	0.2	1.7669
	Average Roughness of the round surface of the die					1.68186

5. DISCUSSION AND CONCLUSION

Engineered components especially commercial dies 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. In this research an adaptive neuro-fuzzy system, theoretical equation and RSM were 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 testing or validation data set with an MAPE of 38.605%, while RSM model could predict the surface roughness for training data with an MAPE of 29.612%. But, ANFIS model could predict the surface roughness for training data with mean *absolute percentage error* (MAPE) of 0.003014%, while RSM model could predict the surface roughness for training data with an MAPE 27.72% from training data set.

From Table 5, it can be observed that as the value of φ increases, feed rate f_y and speed cannot be maintained at a consistent value, rather these have to be changed to meet the desired surface roughness. The solution may be obtained in a different way and that may result different combination of cutting parameters. The process described above is producing one of many feasible solutions. Moreover here many other constraints have not been considered. As low value of f_x causes higher machining time, higher values of f_x can be taken for further calculations till R_a at any point of the curved surface remains below desired level, to obtain more economic solutions.

The ball end mill can be set on a spindle of a CNC milling machine. And CNC code can be written easily for a desired surface finish, for dies similar to the example. As cutting parameters can be preselected for a particular level of surface finish, the values of cutting parameters can be changed during production phase of the die. Thus Artificial Intelligence can be implemented in a CNC machining center. It is not only an application of Artificial Intelligence but also a framework for the commercial die manufacturers in order to implement the Computer-Aided Tools and Methodologies for achieving the desired surface finish of the dies. The model developed in the research will help the die manufacturing industries to reduce their production lead time through predicting the desired surface roughness and selecting the right combination of cutting parameters. As the correlation between the machining parameters and the surface roughness is strongly dependent on the material being machined, there is an imminent 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 judicious selection of few machining parameters, to minimize surface roughness. Vibrations are unavoidable during the machining operation. Vibrations may result variation of cutting forces 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 model for surface roughness.

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