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Surface Roughness Prediction Modeling for AISI 4340 after Ball End Mill Operation using Artificial Intelligence

Md. Shahriar Jahan Hossain and Dr. Nafis Ahmad

Abstract— Now a days a manufacturing system is oriented towards higher production rate, quality, and reduced cost. Surface roughness is an index for determining the quality of machined products and is influenced by the cutting parameters. In die manufacturing industries Surface roughness of dies are considered as a vital quality characteristic. For the complex shapes of a die, three dimensional machining is done by ball end mill in the most cases. In this study the average surface roughness value (R_a) for a die material AISI 4340 has been measured after ball end milling operation. Before conducting the experiments a design of experiment was done with Response Surface Methodology (RSM). 49 experiments have been conducted varying Cutter Axis Inclination Angle (*Ø* degree), Tool Diameter (*d* mm), Spindle Speed (*S* rpm), Feed Rate (f_y mm/min), Feed (f_x mm), Depth of Cut (*t* mm) in order to find R_a. This 49 data has been used for training purpose and more 25 data has been collected with random selection of input parameters and used as testing data set. The training data set has been used for train different ANFIS and RSM model for R_a prediction. And testing data set has been used for validate the models. Better ANFIS model has been selected for minimum value of mean square error (MSE) which is constructed with two double sided Gaussian membership functions (gauss2MF) for each input variables and a linear membership function for output. The Selected ANFIS model has been compared with theoretical model and RSM. This comparison was done based or Root Mean Square Error (RMSE) and Mean Absolute Percentage of Error (MAPE). The comparison shows that the selected ANFIS model gives better result for training and testing dataset. So, this ANFIS model can be used further for predicting surface roughness of a commercial die material (AISI 4340) for ball end milling operation. Correlation test shows that only cutter axis inclination angle and feed (f_x mm) have correlations with surface roughness.

Index Terms— Ball end mill, ANFIS, Roughness prediction, Artificial intelligence

1 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 [1]. 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 the best surface qualities. Typically, surface inspection is carried out through 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 [2]. 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. Particularly, in the manufacture of dies, surface roughness of which is crucial. Therefore the desired finish surface is usually specified and the appropriate processes are selected to reach the desired surface quality [3].

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, RSM, 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 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 three dimensional machining of AISI 4340 within the ranges of variables studied. The results are compared with the RSM results and results from theoretical equations. Comparison of results showed that the ANFIS results are supe-

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rior 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 a die material.

2 Literature Review

The quality of surface finish mainly depends on the interaction between the work-piece, 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. [4] and AISI 420 B stainless steel by Bruni et al. [5]. Bruni et al. proposed analytical and artificial neural network models. Yazdi and Khorram [6] 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-Escalon and Paul G. Maropoulos [7] 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. Li Zhanjie et al. [8] 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 [9] 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. [10] after end milling of steel C45 in order to obtain the roughness data of and model ANN for surface roughness predictions. Seref Aykut [2] had also used ANN to predict the surface roughness of cast-polyamide material after milling operation. Khorasani et al. [11] 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 on Al 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. [12]. For their research, they coupled a neural network and a genetic algorithm (GA) providing good results to solve the optimization of the problem. In 2007, Jesuthanam et al. [13] 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. [14] used in process surface recognition system based on neural networks in end milling operation.

Mahdavinejad et al. [15], Shibendu Shekhar Roy [16] and Jiao et al. [17] used combination of adaptive neural fuzzy intelligent system to predict the surface roughness machined in turning process. Shibendu Shekhar Roy [18] and Chen and Savage [19] designed Adaptive Network-based Fuzzy Inference System (ANFIS) for modeling and predicting the surface roughness in end milling operation. Shibendu Shekhar Roy [18] 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. [20] used neural-fuzzy system to model surface roughness of Alumic-79 workpiece in CNC down milling. Reddy et al. [21] 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. [22] 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. [23] 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 [24] 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 of was developed by Alauddin et al. [25] for 190 BHN steel and by Lou et al. [3] for end milling of EN32. Ozcelik and Bayramoglu [26] 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 AISI 4340 which is widely used as commercial die material, the ANFIS and RSM model are developed in this research. This helps the die manufacturing industry in predicting the desired surface roughness select-

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ing the right combination of cutting parameters.

3 METHODOLOGY

3.1 EXPERIMENTAL SETUP AND DESIGN OF EXPERIMENT

The experiment was performed by using a vertical milling machine shown in Fig. 1. The work-piece tested was an AISI 4340 plate of size 7cm×1cm×4cm. Tungsten carbide coated ball end mill cutters of two-flutes were used as the cutting tool. The diameters of the tools were 6, 8 and 10 mm. Some surfaces of 1cm×1cm were produced on the work-piece by machining with various input parameters. In order to detect the average surface roughness (R_a) value, experiments were carried out by varying the cutter axis inclination angle (Ø) cpindle 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*). Here varying cutter axis inclination angle the scenario of three dimensional machining could be seen. For every input variable the allowable and possible maximum and minimum values were identified based on tool supplier specifications and commercial die manufacturers. For designing the experiments Fractional Box-Behnken Design of Experiment (DoE) was used as suggested by Box and Behnken [27], because it is very useful for observing the interaction effects. One sample point is the average. All other sample points are generated by setting a single spatial coordinate to its average value, and all other spatial coordinates to either the minimum or maximum. This DoE yields 49 sets of experiments. Few more experiments (25 sets of experiment) have been conducted using random sets of input parameters within the range. For each of the experiments, three sample readings were taken and their average value was considered. During the experiments movement directions of tool have been shown in Fig. 2.


Fig. 1: Experimental Setup

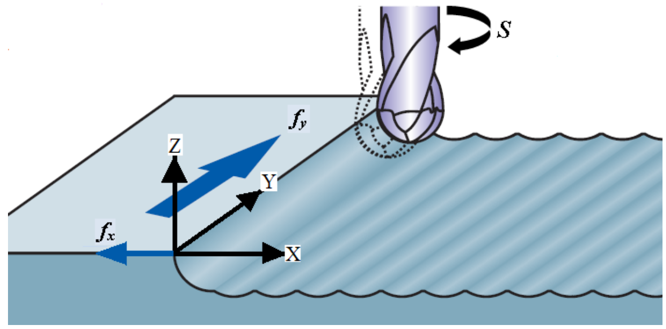

Fig. 2: Ball end mill operation

3.2 WORK MATERIAL

AISI 4340 is also known as EN24. EN24 is its commercial name. EN24 is a high quality, high tensile, alloy steel. It combines high tensile strength, shock resistance, good ductility and resistance to wear. Chemical composition of AISI 4340/EN24 is as,

C.	Si.	Mn	Ni.	Cr.	Mo.
0.40%	**0.30%**	**0.60%**	**1.50%**	**1.20%**	**0.25%**

3.3 SURFACE ROUGHNESS

There are various simple surface roughness amplitude parameters used in industries, such as roughness average (R_a), root-mean-square (RMS) roughness (R_q), and maximum peak-to-valley roughness (R_y or R_{max}), etc. [28]. Surface roughness average parameter (R_a) is the most extended index of product quality and it is used in this study. 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, it ranges from 0.25mm to 25mm for selected instrument. In this study sampling length was 8mm.

3.4 ANFIS

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. 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

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least locally, 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 (1000 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.

3.5 RSM

The Response Surface Methodology (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 [28] and also Mukherjee and Ray [29]. RSM is useful for dealing with nonlinear relationship. It provides different types of regression equations and hence shows multiple factor interaction effects on output. In this study RSM was used to fit second order polynomials on experimental data with 95% onfidence level by Minitab-16 software. The second order polynomial equation has been further used for prediction purpose.

3.6 Theoretical Equations

In the Fig. 3 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.

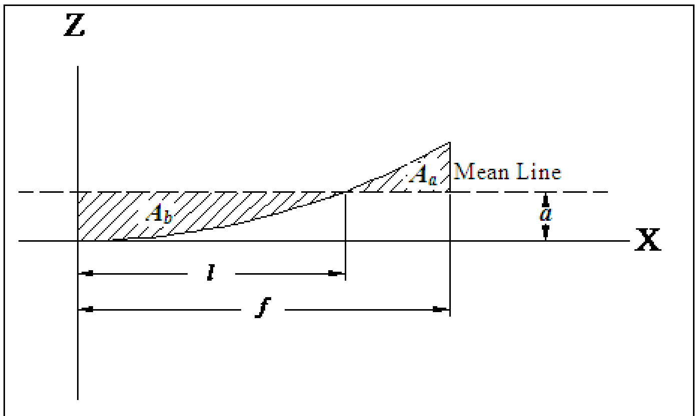

Fig. 3: Calculation of mean line and roughness

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

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

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

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

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

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

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

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_x=f×2 is repeated over the whole surface for gradual feed of f_x in each pass.

3.7 Pearson Correlation Coefficient

A correlation is a statistical technique which can show whether and how strongly pairs of variables are related. The main result of a correlation is called correlation coefficient (or r). There are several correlation techniques but the most common one is the Pearson product-moment correlation coefficient measures the strength of the linear association between variables and this is the one which has been adopted in our work. The correlation coefficient is a number between -1 and 1. 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 which indicates the level of significence of the correlation coefficient; if this probability is lower than the conventional 5% (P<0.05) the correlation coefficient is called statistically significant.

4 Results And Discussion

The ANFIS models have been developed as a function of machining parameters using 49 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 examined as training parameters in order to achieve the perfect training and the maximum prediction accuracy.

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TABLE 1

Training Data Set

SL	Cutter axis Inclination Angle φ	Spindle Speed *S* rpm	Tool Dia *d* mm	Feed rate f_y mm/min	Feed f_x mm	Depth of Cut *t* mm	Avg. R_a (Experimental)	R_a (From Equations)	R_a (From ANFIS)	R_a (From RSM)
1	30	520	10	34	0.3	0.3	1.005	0.58	1.0049	0.964595
2	30	316	8	44	0.3	0.2	1.81	0.72	1.81	1.642788
3	15	520	6	44	0.3	0.1	1.02	0.96	1.0199	1.039454
4	15	520	6	44	0.3	0.3	1.03	0.96	1.03	0.980076
5	30	715	8	44	0.3	0.2	1.74	0.72	1.7399	1.468776
6	30	316	8	22	0.3	0.2	1.795	0.72	1.795	1.606223
7	30	520	10	34	0.3	0.1	0.64	0.58	0.64	0.744389
8	15	316	8	34	0.2	0.3	0.875	0.32	0.875	1.093271
9	15	520	10	22	0.3	0.3	0.955	0.58	0.955	0.906225
10	15	316	8	34	0.4	0.3	1.325	1.28	1.325	1.316547
11	15	520	8	34	0.3	0.2	0.91	0.72	0.91	0.90996
12	15	715	8	34	0.2	0.3	1.21	0.32	1.21	1.374592
13	30	520	8	44	0.4	0.2	1.525	1.28	1.525	1.693338
14	15	715	8	34	0.4	0.3	1.82	1.28	1.82	1.859192
15	0	316	8	22	0.3	0.2	0.395	0.72	0.395	0.620694
16	0	520	8	22	0.4	0.2	0.68	1.28	0.68	0.76514
17	15	520	10	44	0.3	0.1	0.665	0.58	0.665	0.803441
18	15	715	10	34	0.2	0.2	0.485	0.26	0.4851	0.60542
19	0	715	8	22	0.3	0.2	0.915	0.72	0.9149	1.055446
20	15	316	10	34	0.4	0.2	0.955	1.03	0.955	1.01822
21	15	316	10	34	0.2	0.2	0.52	0.26	0.5201	0.611195
22	30	520	8	22	0.4	0.2	1.575	1.28	1.575	1.694079
23	15	715	6	34	0.2	0.2	0.49	0.43	0.4901	0.577216
24	30	715	8	22	0.3	0.2	1.635	0.72	1.635	1.526891
25	15	520	10	22	0.3	0.1	0.69	0.58	0.69	0.757269
26	30	520	8	44	0.2	0.2	0.9	0.32	0.9001	0.803861
27	0	520	6	34	0.3	0.3	0.405	0.96	0.405	0.267405
28	15	715	6	34	0.4	0.2	1.76	1.71	1.76	1.510565
29	30	520	6	34	0.3	0.1	0.69	0.96	0.69	0.983158
30	15	520	10	44	0.3	0.3	0.975	0.58	0.975	0.947814
31	0	520	10	34	0.3	0.1	0.5	0.58	0.5	0.227181
32	15	715	8	34	0.2	0.1	0.88	0.32	0.88	0.734294
33	0	520	8	44	0.4	0.2	0.88	1.28	0.8801	0.944032
34	15	316	6	34	0.2	0.2	0.795	0.43	0.7951	0.580633
35	0	715	8	44	0.3	0.2	0.945	0.72	0.945	1.176963
36	0	520	6	34	0.3	0.1	0.325	0.96	0.325	0.39845
37	15	316	8	34	0.2	0.1	0.91	0.32	0.91	1.024806
38	15	520	6	22	0.3	0.1	0.935	0.96	0.935	0.925095
39	0	316	8	44	0.3	0.2	0.7	0.72	0.7	0.836892
40	15	316	6	34	0.4	0.2	1.215	1.71	1.215	1.252658
41	15	715	8	34	0.4	0.1	1.925	1.28	1.925	1.851393
42	0	520	8	22	0.2	0.2	0.45	0.32	0.45	0.310366
43	15	520	6	22	0.3	0.3	0.96	0.96	0.96	0.870301
44	0	520	10	34	0.3	0.3	0.56	0.58	0.56	0.299887
45	30	520	6	34	0.3	0.3	0.76	0.96	0.76	0.999613
46	0	520	8	44	0.2	0.2	0.615	0.32	0.6151	0.467054
47	15	715	10	34	0.4	0.2	1.21	1.03	1.21	1.273769
48	30	520	8	22	0.2	0.2	0.88	0.32	0.88	0.826806
49	15	316	8	34	0.4	0.1	2.19	1.28	2.19	1.880582

Table 2 shows 32 different architectures of ANFIS. From table 2 the best-responding model of neuro-fuzzy system was found, that have two double Gaussian curve (a two-sided composite of two different Gaussian curves) built-in membership functions (gauss2MF) for each input and a linear output function. It is shown that the predicted error (RMSE) for the training data is 4.2392×10^{-5} and for the test data it is 0.17024. The 6 inputs and 1 output and their final fuzzy membership functions are shown in Fig. 4. A total of 64 fuzzy rules were used to build the final fuzzy inference system.

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TABLE 2

Different ANFIS Architecture

No.	No. of Membership Function	Function Type	Output Function	Error (RMSE)	
				Training Error	Test Error
1	2 (Number of nodes: 161 Number of fuzzy rules: 64)	triMF	Constant	0.23099	0.35903
2			Linear	5.3339×10^{-5}	0.23714
3		trapMF	Constant	0.24046	0.32059
4			Linear	4.2482×10^{-5}	0.19737
5		gbellMF	Constant	0.24037	0.3750
6			Linear	4.7944×10^{-5}	0.17702
7		gaussMF	Constant	0.2404	0.32185
8			Linear	5.1378×10^{-5}	0.21889
9		gauss2MF	Constant	0.24051	0.35244
10			Linear	**4.2392×10^{-5}**	**0.17024**
11		piMF	Constant	0.23938	0.35074
12			Linear	4.054×10^{-5}	0.23541
13		dsigMF	Constant	0.23919	0.35727
14			Linear	3.9943×10^{-5}	0.26027
15		psigMF	Constant	0.23919	0.35727
16			Linear	3.6989×10^{-5}	0.35499
17	3 (Number of nodes: 1503 Number of fuzzy rules: 729)	triMF	Constant	1.2312×10^{-6}	1.0926
18			Linear	4.6399×10^{-5}	1.0926
19		trapMF	Constant	1.1003×10^{-6}	1.1004
20			Linear	2.9322×10^{-5}	1.1004
21		gbellMF	Constant	1.8552×10^{-6}	1.06
22			Linear	3.6996×10^{-4}	1.0069
23		gaussMF	Constant	1.2832×10^{-6}	1.0924
24			Linear	2.5907×10^{-4}	1.0057
25		gauss2MF	Constant	1.1034×10^{-6}	1.1002
26			Linear	1.3823×10^{-4}	1.1001
27		piMF	Constant	1.1003×10^{-6}	1.1004
28			Linear	2.9322×10^{-5}	1.1004
29		dsigMF	Constant	1.1031×10^{-6}	1.1002
30			Linear	1.3011×10^{-4}	1.0999
31		psigMF	Constant	1.1061×10^{-6}	1.1001
32			Linear	1.742×10^{-4}	1.0999

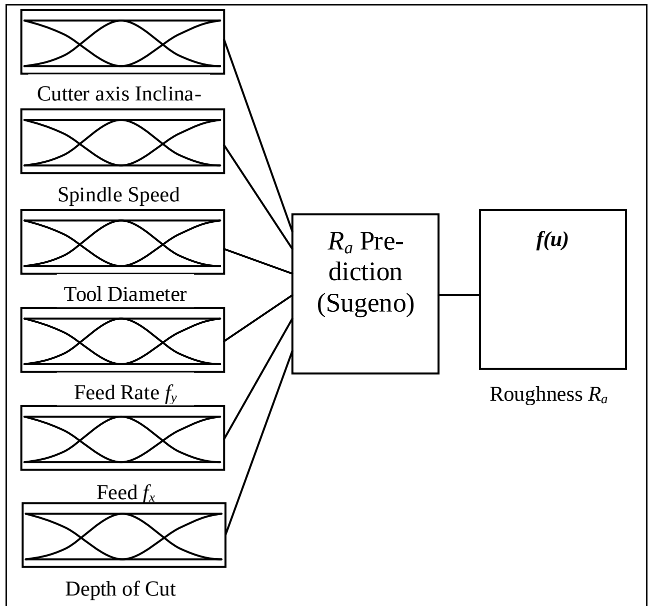

Fig. 4. Final ANFIS Model With 6 Inputs And 1 Output

The model developed by ANFIS was tested using the 25 testing dataset measured from randomly selected input parameters (Table 3) and the predicted results were presented in Table 4. The predicted surface roughness values with the actual experimental values of surface roughness were plotted and shown in Fig. 5. This plot slows that the proposed ANFIS model can predict surface roughness very well; which are quite close to practical results.

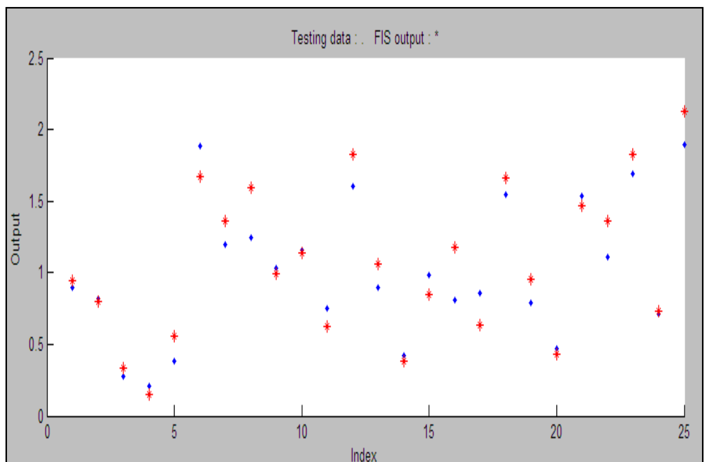

Fig. 5. comparison between the experimental and predicted values by the ANFIS testing data

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TABLE 3
RANDOMLY SELECTED INPUT PARAMETERS FOR OBTAINING TEST DATA SET

SL	Cutter axis Inclination Angle φ	Spindle Speed S rpm	Tool Dia d mm	Feed rate f_y mm/min	Feed f_x mm	Depth of Cut t mm
1	0	715	8	34	0.4	0.2
2	0	520	10	44	0.4	0.2
3	0	316	10	22	0.2	0.3
4	0	316	6	22	0.2	0.2
5	0	316	6	44	0.2	0.1
6	15	715	8	44	0.4	0.2
7	30	316	10	22	0.4	0.2
8	30	316	6	22	0.2	0.2
9	15	520	8	22	0.3	0.2
10	15	520	8	44	0.3	0.2
11	0	520	8	34	0.3	0.2
12	30	316	6	34	0.4	0.1
13	30	520	6	22	0.2	0.3
14	0	520	8	34	0.2	0.2
15	0	520	8	34	0.4	0.2
16	15	316	6	44	0.2	0.3
17	15	520	6	34	0.3	0.2
18	15	316	10	44	0.4	0.1
19	15	520	10	22	0.3	0.3
20	20	520	6	34	0.2	0.15
21	25	316	8	22	0.4	0.25
22	30	715	6	44	0.3	0.1
23	30	316	6	34	0.4	0.1
24	15	520	10	22	0.3	0.2
25	15	316	6	44	0.4	0.1

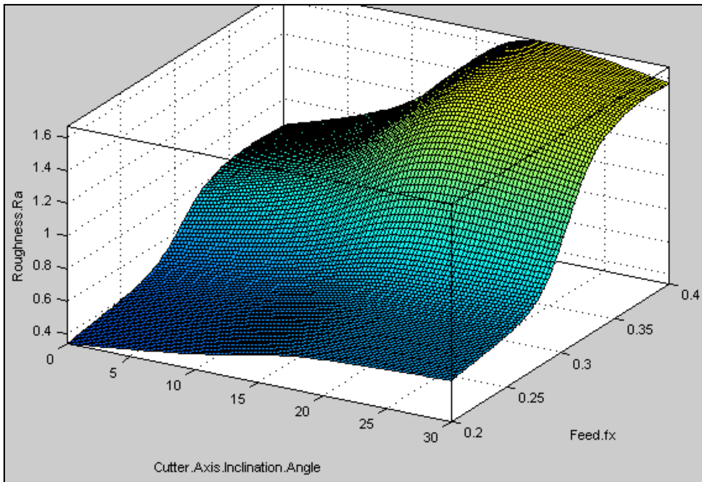
Equation (8) is the response surface equation developed by RSM. It can be used for predicting surface roughness. Test dataset has been used for verifying this equation and predicted results have been summarized in Table 4. The results using the equations (1) to (7) for 25 test data sets also have been listed in Table 4.

$$R_a = -1.98118 + 0.0499226\times\phi - 0.00933244\times S + 1.30489\times d - 0.0685035\times f_y + 5.47377\times f_x - 7.18853\times t - 6.18471\times10^{-04}\times\phi^2 + 8.00734\times10^{-06}\times S^2 - 0.0779180\times d^2 + 0.00131261\times f_y^2 + 1.33118\times f_x^2 + 15.1453\times t^2 - 4.29476\times10^{-05}\times\phi\times S - 5.62500\times10^{-04}\times\phi\times d - 2.72170\times10^{-04}\times\phi\times f_y + 0.0687500\times\phi\times f_x + 0.0245833\times\phi\times t - 1.47734\times10^{-06}\times S\times d - 1.07861\times10^{-05}\times S\times f_y + 0.00327474\times S\times f_x + 0.00716583\times S\times t - 7.74847\times10^{-04}\times d\times f_y - 0.331250\times d\times f_x + 0.254688\times d\times t + 0.00504650\times f_y\times f_x - 0.00104179\times f_y\times t - 15.8125\times f_x\times t \quad (8)$$

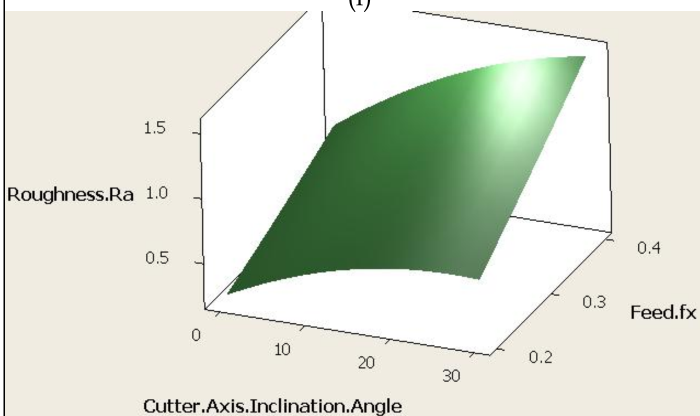
It has been mentioned earlier that in this study an ANFIS, RSM and theoretical equation have been used for predicting surface roughness. For the test datasets, the Root Mean Squired Errors (RMSE) and Absolute Mean Percentage of Errors (MAPE) have been calculated for each of the above mentioned models and summarized in Table 5. It can be observed from the Table 5 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 a better prediction model and can be used further for surface roughness prediction using ball end milling operation on EN 24.

TABLE 4
SUMMARY OF DIFFERENT MODELS OUTPUT WITH TESTING DATA SET

SL	Avg. R_a (Experimental)	R_a (From Equations)	RMSE	Absolute % error	R_a (From ANFIS)	RMSE	Absolute % error	RSM (R_a)	RMSE	Absolute % error
1	**0.892**	1.28	0.150544	43.49776	0.9403	0.00233289	5.414798206	1.274826	0.146556	42.91774
2	**0.815**	1.03	0.046225	26.38037	0.7948	0.00040804	2.478527607	0.515916	0.089451	36.69745
3	**0.28**	0.26	0.0004	7.142857	0.3334	0.00285156	19.07142857	0.413503	0.017823	47.67953
4	**0.21**	0.43	0.0484	104.7619	0.1497	0.00363609	28.71428571	0.111	0.009801	47.14291
5	**0.38**	0.43	0.0025	13.15789	0.5605	0.03258025	47.5	0.556263	0.031069	46.38511
6	**1.88**	1.28	0.36	31.91489	1.6752	0.04194304	10.89361702	1.880809	6.54E-07	0.043022
7	**1.198**	1.03	0.028224	14.02337	1.3619	0.02686321	13.68113523	1.559197	0.130463	30.14997
8	**1.25**	0.43	0.6724	65.6	1.5986	0.12152196	27.888	0.924028	0.106258	26.07773
9	**1.03**	0.72	0.0961	30.09709	0.9963	0.00113569	3.27184466	1.024942	2.56E-05	0.491096
10	**1.155**	0.72	0.189225	37.66234	1.1367	0.00033489	1.584415584	1.102915	0.002713	4.509498
11	**0.75**	0.72	0.0009	4	0.6248	0.01567504	16.69333333	0.45845	0.085002	38.87338
12	**1.6**	1.71	0.0121	6.875	1.8293	0.05257849	14.33125	2.124809	0.275424	32.80056
13	**0.895**	0.43	0.216225	51.95531	1.0657	0.02913849	19.0726257	0.81779	0.005961	8.626821
14	**0.421**	0.32	0.010201	23.9905	0.3792	0.00174724	9.928741093	0.238319	0.033372	43.39215
15	**0.98**	1.28	0.09	30.61224	0.8435	0.01863225	13.92857143	0.705204	0.075513	28.04043
16	**0.812**	0.43	0.145924	47.04433	1.1811	0.13623481	45.45566502	0.939749	0.01632	15.73261
17	**0.86**	0.96	0.01	11.62791	0.6394	0.04866436	25.65116279	0.649859	0.044159	24.43495
18	**1.546**	1.03	0.266256	33.37646	1.6636	0.01382976	7.606727038	1.606304	0.003637	3.900627
19	**0.786**	0.58	0.042436	26.20865	0.955	0.028561	21.50127226	0.906225	0.014454	15.29585
20	**0.468**	0.43	0.001444	8.119658	0.4275	0.00164025	8.653846154	0.287239	0.032675	38.62424
21	**1.54**	1.28	0.0676	16.88312	1.4696	0.00495616	4.571428571	1.774817	0.055139	15.24784
22	**1.106**	0.96	0.021316	13.20072	1.359	0.064009	22.87522604	1.246158	0.019644	12.67249
23	**1.687**	1.71	0.000529	1.363367	1.8293	0.02024929	8.435091879	2.124809	0.191677	25.95193
24	**0.712**	0.58	0.017424	18.53933	0.7355	0.00055225	3.300561798	0.680294	0.001005	4.45306
25	**1.89**	1.71	0.0324	9.52381	2.1234	0.05447556	12.34920635	1.973611	0.006991	4.423858
Average			**0.318**	**27.1**		**0.17024119**	**15.7941**		**0.236**	**23.78**

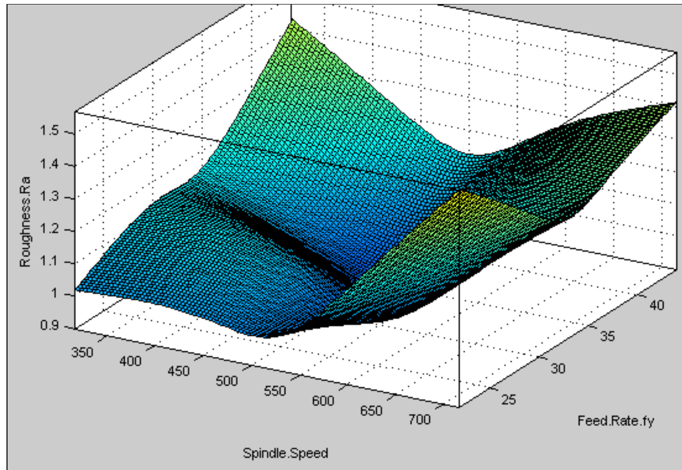


(i)

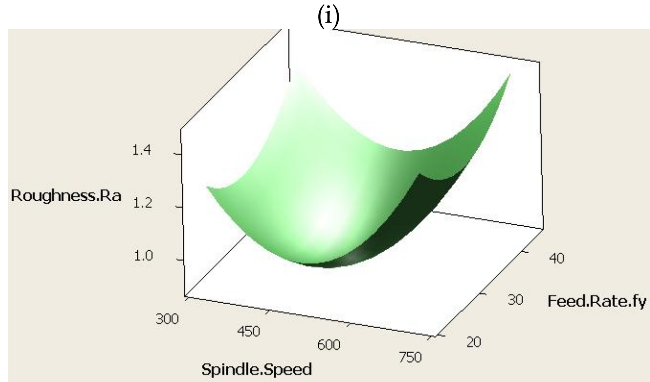


(ii)

Fig. 6. Surface plot of Roughness R_a µm vs. Feed f_x mm and Cutter Axis Inclination angle φ from (i) ANFIS and (ii) RSM



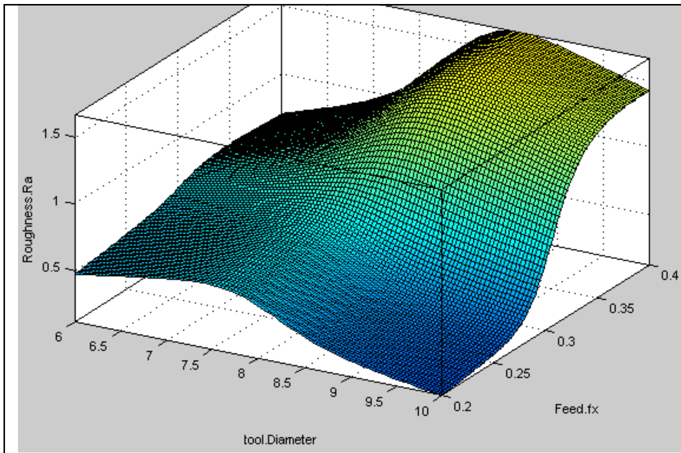
(i)



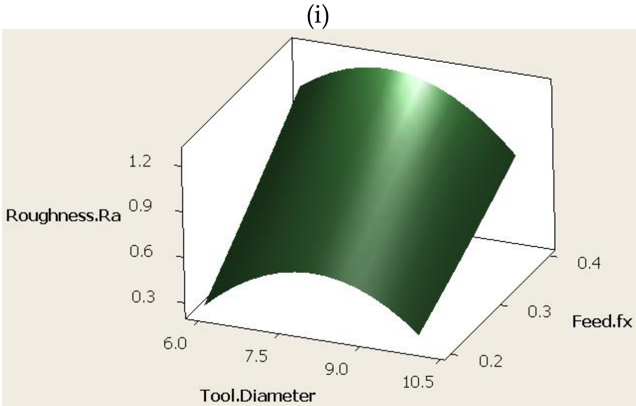
(ii)

Fig. 7. Surface plot of Roughness R_a µm vs. Feed rate f_y mm/min and Spindle Speed S rpm from (i) ANFIS and (ii) RSM

Most of the results listed in Table 4 are found to be within acceptable limits for the ANFIS model. Larger deviation in prediction for surface roughness in few of the cases cited above may be due to in homogeneity in work piece composition, small discrepancy in tool setting or work piece setting and tool or machining condition. Fig. 6, 7 and 8 show few interaction effects of input parameters on roughness R_a predicted by ANFIS and RSM. From these figures we can note that, RSM produces smooth and simple surfaces but the actual relationships and interaction effects of input parameters on R_a are clearer from ANFIS generated surfaces. More 12 sets of such three dimensional graphs for different interaction effects can be possible, but there is no significantly noticeable 'interaction effects' other than these three relationships, that is why these are not mentioned in this paper.



(i)



(ii)

Fig. 8. Surface plot of Roughness R_a µm vs. Feed f_x mm and Tool Diameter d from (i) ANFIS and (ii) RSM

TABLE 5

ERRORS IN DIFFERENT MODELS

Model	For Training Data		For Testing Data	
	RMSE	MAPE (%)	RMSE	MAPE (%)
Equations	0.475	39.73	0.318	27.1
ANFIS	**4.2392×10^{-5}**	**0.00302**	**0.17024119**	**15.7941**
RSM	0.151	15.94	0.236	23.78

Table 6 presents the summary of correlation test between R_a (Experimental) and different input parameters for training data set. It shows that Cutter axis Inclination Angle φ and feed f_x (mm) have a positive correlation with R_a. And other input parameters have low level of correlation with low reliability.

TABLE 6

PEARSON CORRELATION FOR DIFFERENT INPUTS WITH AVG. R_A (EXPERIMENTAL)

	r	*P-value*
Cutter axis Inclination Angle ϕ	**0.483**	**0.000**
Spindle Speed *S* rpm	0.091	0.534
Tool Dia *d* mm	-0.078	0.594
Feed rate f_y mm/min	0.056	0.702
Feed f_x mm	**0.513**	**0.000**
Depth of Cut *t* mm	0.032	0.825

5 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.

In this study an adaptive neuro-fuzzy system and RSM is applied to predict the surface roughness of die material EN 24, during ball end milling operation. Six 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 MAPE of 0.00302%, while RSM model could predict the surface roughness for training data with MAPE of 15.94% from training data set. The ANFIS model could predict the surface roughness for testing or validation data set with MAPE of 15.7941%, while RSM model could predict the surface roughness for training data with an average percentage deviation of 23.78%. This fact leads the authors to conclude that the ANFIS model for prediction of Surface Roughness R_a of commercial dies made of EN24 after three dimensional machining with ball end milling is more appropriate.

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 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 the various machining parameters to minimize surface roughness.

Vibrations are unavoidable during the machining operation. Vibrations may result from the variation of cutting forces generated during the machining process or due to sources outside the machine tool. Vibrations degrade the surface finish. So it is important to know the effects of vibrations on the characteristics of surface profile. Further work can be done considering vibration as an input factor for developing a prediction model for surface roughness.

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