# Artificial Intelligence Based Surface Roughness Prediction Modeling for Three Dimensional End Milling

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***Abstract***

*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 varying cutter axis inclination angle (φ degree), spindle speed (S rpm), feed rate (*$f_y$ *mm/min), radial depth of cut (feed* $f_x$ *mm), 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 training data set and 16 testing data set. The training data set has been used to train different ANN and 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. Similarly better ANN model has been selected based on the minimum value of Root Mean Square Error (RMSE) and Mean Absolute Percentage of Error (MAPE). The Selected ANFIS model has been compared with theoretical equation output, ANN and Response Surface Methodology (RSM). This comparison is done based on RMSE and MAPE. The comparison shows that 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 three dimensional end milling operation.*

***Keywords:*** *Ball end mill, ANN, ANFIS, RSM, Roughness prediction*

## 1. 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 [1]. It is expected that the next decade machine tools will be intelligent machines with various capabilities such as prediction of self setup 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 [2]. Milling process is one of the common metal 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. 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 the advanced computing capability. Researchers have used various intelligent techniques, including neural network, fuzzy logic, neuro-fuzzy, 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 [4]. 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 ANN results, 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 three dimensional end milling of Aluminum, where ball end milling cutter is used.

## 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 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 [5] 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 ANNis used for face milling of Aluminum alloy by Bernardos et. al., [6], high chromium steel (AISI H11) by Rai et. al., [7] and AISI 420 B stainless steel by Bruni et. al., [8]. Bruni et al proposed analytical and artificial neural network models. Yazdi and Khorram [9] 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., [10] 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. Li Zhanjie [11] 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 [12] 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., [13] after end milling ofsteel C45 in order to obtain the roughness data of and modelANN 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., [14] 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. On the other hand Nabil and Ridha [15] developed an approach that combined the design of experiments (DOE) and the ANN methods. Luong and Spedding [16] 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., [17] for the prediction of flank wear and by Pal and Chakraborty [18] for predicting the surface roughness. In 2006, Zhong et. al., [19] 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., [20]. 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., [21] 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. In 2007, Lin et. al., [22] 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. In 2006, Basak et. al., [23] developed radial basis neural network models when turning AISI D2 cold-worked tool steel with ceramic tool. Tsai et. al., [24] used in process surface recognition system based on neural networks in end milling operation.

Mahdavinejad et. al., [25], Shibendu Shekhar Roy [26] and Jiao et. al., [27] used combination of adaptive neural fuzzy intelligent system to predict the surface roughness machined in turning process. Jiao et. al., [27] also used adaptive fuzzy-neural networks to model machining process especially for surface roughness. Shibendu Shekhar Roy [28] and Chen and Savage [29] designed Adaptive Network-based Fuzzy Inference System (ANFIS) for modeling and predicting the surface roughness in end milling operation. Shibendu Shekhar Roy [28] 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., [30] used neural-fuzzy system to model surface roughness of Alumic-79 workpiece in CNC down milling. Reddy et. al., [31] 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., [32] 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., [33] 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 [34] 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 of was developed by Alauddin et. al., [35] for 190 BHN steel and by Lou et. al., [3] for end milling of EN32. Many years ago Taramanand Lambert [36] also used Response Surface Methodology for Prediction of surface roughness. Ozcelik et. al., [37] present the development of a statistical model for surface roughness estimation in a high-speed flat end milling process under wet cutting conditions. Huang used multiple regression models to predict the surface roughness of machined parts in turning operation [38]. Feng et. al., [39] focused on developing an empirical model for the prediction of surface roughness in finish turning. Salah Gasim Ahmed [40] developed an empirical surface roughness model for commercial aluminum, based on metal cutting results from factorial experiments. Brezocnik et. al., [41] 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. But for three dimensional milling, ball end milling cutters are mostly used. 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, ANN and RSM model are developed in this research. This model will help the manufacturing industries in predicting the desired surface roughness selecting 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 Figure 1. The workpiece tested was an Aluminum plate of size 9cm×1cm×4cm. A two-flute carbide ball end mill cutter of 8 mm diameter is selected as the cutting tool. The cutter movement directions have been shown in Figure 2. 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 ($\theta$), spindle speed ($S$ rpm), the feed rate along $y$-axis ($f_y$ mm/min), feed along $x$-axis or radial depth of cut ($f_x$ mm) and the axial depth of cut ($t$). For each of the experiments, three sample readings were taken and their average value was considered.

Figure 1. Experimental Setup

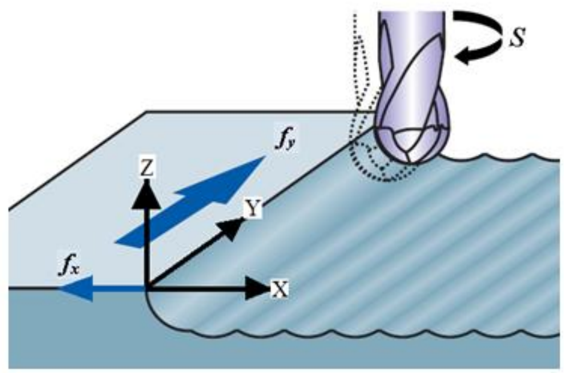


Figure 2. Ball End Mill Operation

## 3.2. 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 [6]. Surface roughness average parameter ($R_a$) is the most extended index of product quality and has been used 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 the equation (1).

$$R_a = \frac{1}{L}\int_0^L \left| Z(x)\,dx \right| \tag{1}$$

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.

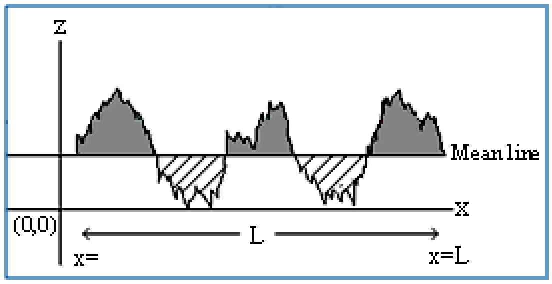


**Figure 3. Surface Roughness**

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 0.25mm to 25mm for selected instrument. In this study sampling length was 8 mm.

### 3.3. 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 network 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, 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.

### 3.4. 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 et al. and Mukherjee et. al., [6, 42]. In this study RSM was used to fit second order polynomial on experimental data with 95% confidence level by minitab software.

### 3.5. ANN

Artificial neural networks (ANNs) are one of the most powerful computer modeling techniques, currently being used in many fields of engineering for modeling complex relationships which are difficult to describe with physical models. The input/output dataset of the ANN model that is going to be formulated to predict surface roughness is illustrated schematically in Figure 4. The input parameters of the neural network are namely Cutter axis Inclination Angle $\varphi$, Spindle Speed $S$, Tool Diameter $d$, Feed rate $f_y$, Feed $f_x$ and Depth of Cut $t$. The output of the model is Surface Roughness $R_a$. Same practical data according to the design of experiment as used for ANFIS models was used for training and testing different ANN architectures and the better ANN model has been selected for comparing with ANFIS model. The four basic steps used in general application of neural network have been adopted in the development of the model: analysis and pre-processing of the data; design of the network object; training and testing of the network; and performing simulation with the trained network and post-processing of results. For developing the ANN models MATLAB code has been used.

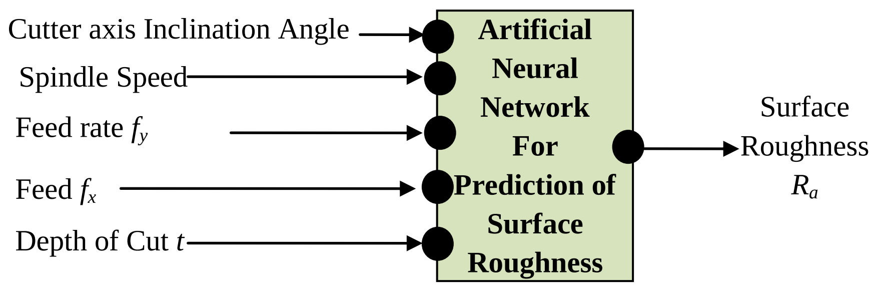


**Figure 4. Schematic Diagram of ANN for Surface Roughness Prediction**

### 3.6. Theoretical Equations

In Figure 5, a representative element of the ideal roughness profile after ball end milling operation has been shown. Using equation, (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.

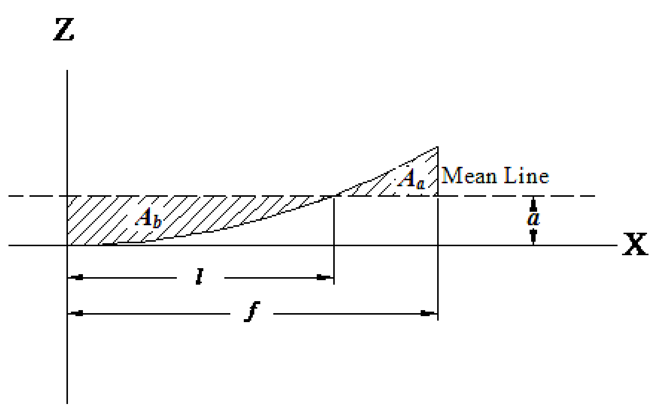


**Figure 5. Calculation of Mean Line and Roughness**

$$R_a = \frac{A_a + A_b}{f} \tag{2}$$

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

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

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

$$l = \sqrt{2Ra - a^2} \tag{6}$$

$$\theta_l = \sin^{-1}\frac{l}{R} \tag{7}$$

$$\theta_f = \sin^{-1}\frac{f}{R} \tag{8}$$

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.

### 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 $r$). 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).

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

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

# 4. Results and Discussion

## 4.1. ANFIS Output

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 7.6 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 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 $9.9854\times10^{-5}$ 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 6. 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 ($9.9845\times10^{-5}$) at $10^{th}$ iteration.

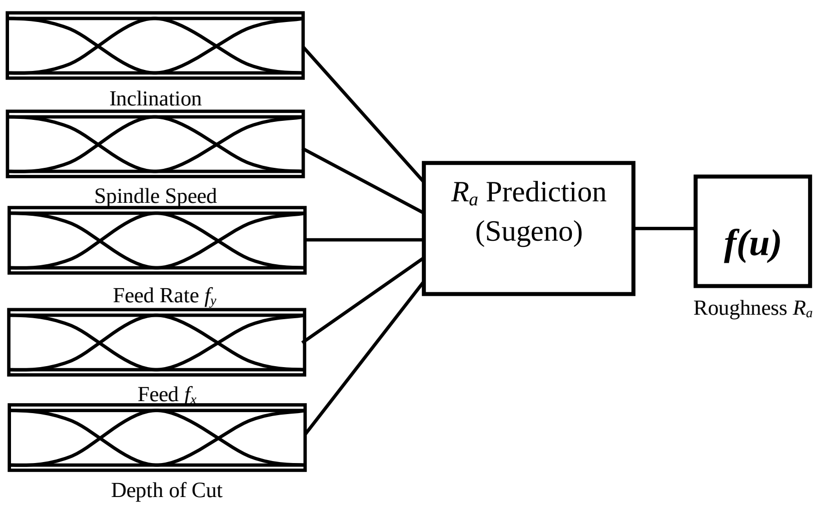


**Figure 6. Final ANFIS Model with 5 Inputs and 1Output**

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 were presented in Table 4. 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.

## Table 1. Training Data Set

| SL | Inclination Angle $\varphi$ | 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) | $R_a$ (ANN) |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 380 | 22 | 0.4 | 0.2 | **1.36** | 1.28 | 1.3601 | 1.785 | 1.3596 |
| 2 | 0 | 380 | 34 | 0.6 | 0.2 | **2.11** | 2.89 | 2.1098 | 3.164 | 2.1098 |
| 3 | 0 | 380 | 22 | 0.4 | 0.4 | **1.95** | 1.28 | 1.9500 | 1.111 | 1.9494 |
| 4 | 0 | 380 | 34 | 0.6 | 0.4 | **3.55** | 2.89 | 3.5500 | 2.160 | 3.5497 |
| 5 | 0 | 380 | 22 | 0.4 | 0.6 | **0.56** | 1.28 | 0.5601 | 1.282 | 0.5599 |
| 6 | 0 | 380 | 34 | 0.6 | 0.6 | **1.33** | 2.89 | 1.3301 | 2.000 | 1.3304 |
| 7 | 0 | 520 | 34 | 0.5 | 0.3 | **2.46** | 2.01 | 2.4600 | 1.472 | 2.4596 |
| 8 | 0 | 520 | 44 | 0.6 | 0.3 | **2.84** | 2.89 | 2.8400 | 2.054 | 2.8398 |
| 9 | 0 | 520 | 68 | 0.7 | 0.3 | **3.9** | 3.94 | 3.8997 | 3.096 | 3.8999 |
| 10 | 0 | 520 | 44 | 0.6 | 0.5 | **0.73** | 2.89 | 0.7300 | 1.608 | 0.7301 |
| 11 | 0 | 520 | 68 | 0.7 | 0.5 | **1.36** | 3.94 | 1.3599 | 2.744 | 1.3601 |
| 12 | 0 | 520 | 34 | 0.5 | 0.6 | **1.43** | 2.01 | 1.4301 | 1.280 | 1.43 |
| 13 | 0 | 520 | 44 | 0.6 | 0.6 | **2.66** | 2.89 | 2.6599 | 1.701 | 2.6597 |
| 14 | 0 | 520 | 68 | 0.7 | 0.6 | **3.62** | 3.94 | 3.6200 | 2.885 | 3.6197 |
| 15 | 0 | 715 | 34 | 0.4 | 0.4 | **0.49** | 1.28 | 0.4898 | 0.559 | 0.4897 |
| 16 | 0 | 715 | 68 | 0.8 | 0.4 | **3.01** | 5.14 | 3.0104 | 3.275 | 3.01 |
| 17 | 0 | 715 | 34 | 0.4 | 0.5 | **0.44** | 1.28 | 0.4400 | 0.615 | 0.4401 |
| 18 | 0 | 715 | 44 | 0.6 | 0.5 | **0.85** | 2.89 | 0.8499 | 1.342 | 0.8499 |
| 19 | 0 | 715 | 68 | 0.8 | 0.5 | **1.98** | 5.14 | 1.9801 | 3.073 | 1.9803 |
| 20 | 0 | 715 | 34 | 0.4 | 0.6 | **1.33** | 1.28 | 1.3300 | 0.883 | 1.3302 |
| 21 | 0 | 715 | 44 | 0.6 | 0.6 | **1.59** | 2.89 | 1.5898 | 1.430 | 1.5901 |
| 22 | 0 | 1020 | 22 | 0.4 | 0.6 | **0.98** | 1.28 | 0.9799 | 0.636 | 0.9792 |
| 23 | 0 | 715 | 34 | 0.8 | 0.4 | **3.07** | 5.14 | 3.0699 | 3.445 | 3.0698 |
| 24 | 15 | 380 | 34 | 0.4 | 0.3 | **1.35** | 1.28 | 1.3500 | 1.870 | 1.3496 |
| 25 | 15 | 380 | 68 | 0.8 | 0.3 | **5.11** | 5.14 | 5.1100 | 5.547 | 5.11 |
| 26 | 15 | 380 | 34 | 0.4 | 0.5 | **1.65** | 1.28 | 1.6500 | 1.817 | 1.6502 |
| 27 | 15 | 380 | 44 | 0.6 | 0.5 | **3.71** | 2.89 | 3.7100 | 3.077 | 3.7096 |
| 28 | 15 | 380 | 34 | 0.4 | 0.6 | **1.61** | 1.28 | 1.6100 | 2.107 | 1.6102 |
| 29 | 15 | 380 | 44 | 0.6 | 0.6 | **3.71** | 2.89 | 3.7100 | 3.188 | 3.7095 |
| 30 | 15 | 380 | 68 | 0.8 | 0.6 | **4.43** | 5.14 | 4.4300 | 5.009 | 4.4298 |
| 31 | 15 | 520 | 34 | 0.4 | 0.4 | **1.61** | 1.28 | 1.6100 | 1.689 | 1.6095 |
| 32 | 15 | 520 | 68 | 0.8 | 0.4 | **5.23** | 5.14 | 5.2299 | 4.948 | 5.23 |
| 33 | 15 | 520 | 34 | 0.4 | 0.5 | **1.27** | 1.28 | 1.2700 | 1.764 | 1.2694 |
| 34 | 15 | 520 | 44 | 0.6 | 0.5 | **3.05** | 2.89 | 3.0500 | 2.910 | 3.0498 |
| 35 | 15 | 520 | 68 | 0.8 | 0.5 | **5.18** | 5.14 | 5.1800 | 4.764 | 5.1799 |
| 36 | 15 | 520 | 34 | 0.4 | 0.6 | **1.39** | 1.28 | 1.3900 | 2.049 | 1.3898 |
| 37 | 15 | 520 | 44 | 0.6 | 0.6 | **3.99** | 2.89 | 3.9900 | 3.017 | 3.9899 |
| 38 | 15 | 715 | 34 | 0.4 | 0.3 | **1.79** | 1.28 | 1.7900 | 1.754 | 1.7888 |
| 39 | 15 | 715 | 44 | 0.6 | 0.3 | **2.07** | 2.89 | 2.0701 | 3.102 | 2.0694 |
| 40 | 15 | 715 | 68 | 0.8 | 0.3 | **5.69** | 5.14 | 5.6900 | 5.049 | 5.6901 |
| 41 | 15 | 715 | 34 | 0.4 | 0.4 | **1.25** | 1.28 | 1.2500 | 1.612 | 1.2483 |
| 42 | 15 | 715 | 68 | 0.8 | 0.4 | **5.49** | 5.14 | 5.4900 | 4.648 | 5.49 |
| 43 | 15 | 715 | 34 | 0.4 | 0.6 | **1.53** | 1.28 | 1.5300 | 1.961 | 1.5279 |
| 44 | 15 | 715 | 68 | 0.8 | 0.6 | **5.07** | 5.14 | 5.0700 | 4.481 | 5.07 |
| 45 | 15 | 520 | 34 | 0.6 | 0.4 | **3.55** | 2.89 | 3.5500 | 3.367 | 3.5493 |
| 46 | 30 | 380 | 34 | 0.4 | 0.3 | **1.81** | 1.28 | 1.8100 | 1.425 | 1.8098 |
| 47 | 30 | 380 | 44 | 0.6 | 0.3 | **3.37** | 2.89 | 3.3701 | 3.306 | 3.3698 |
| 48 | 30 | 380 | 68 | 0.8 | 0.3 | **5.19** | 5.14 | 5.1901 | 5.422 | 5.1899 |
| 49 | 30 | 380 | 34 | 0.4 | 0.5 | **1.45** | 1.28 | 1.4500 | 1.397 | 1.449 |
| 50 | 30 | 380 | 44 | 0.5 | 0.5 | **1.5** | 2.01 | 1.5000 | 1.924 | 1.4988 |
| 51 | 30 | 380 | 34 | 0.3 | 0.6 | **1.37** | 0.72 | 1.3700 | 1.126 | 1.3696 |
| 52 | 30 | 380 | 44 | 0.5 | 0.6 | **2.06** | 2.01 | 2.0600 | 2.173 | 2.0586 |
| 53 | 30 | 380 | 68 | 0.6 | 0.6 | **3.67** | 2.89 | 3.6703 | 3.078 | 3.6693 |
| 54 | 30 | 520 | 34 | 0.4 | 0.4 | **1.61** | 1.28 | 1.6100 | 1.274 | 1.6095 |
| 55 | 30 | 520 | 68 | 0.8 | 0.4 | **4.74** | 5.14 | 4.7402 | 4.853 | 4.7398 |
| 56 | 30 | 520 | 34 | 0.4 | 0.5 | **1.85** | 1.28 | 1.8500 | 1.361 | 1.8486 |
| 57 | 30 | 520 | 68 | 0.7 | 0.5 | **2.53** | 3.94 | 2.5301 | 3.616 | 2.5293 |
| 58 | 30 | 520 | 34 | 0.3 | 0.6 | **1.39** | 0.72 | 1.3900 | 1.167 | 1.3885 |
| 59 | 30 | 520 | 44 | 0.5 | 0.6 | **1.42** | 2.01 | 1.4200 | 2.101 | 1.4187 |
| 60 | 30 | 520 | 68 | 0.6 | 0.6 | **3.41** | 2.89 | 3.4100 | 3.040 | 3.409 |
| 61 | 30 | 715 | 34 | 0.4 | 0.3 | **1.41** | 1.28 | 1.4100 | 1.351 | 1.4093 |
| 62 | 30 | 715 | 68 | 0.8 | 0.3 | **5.88** | 5.14 | 5.8799 | 4.966 | 5.8798 |
| 63 | 30 | 715 | 34 | 0.4 | 0.4 | **1.46** | 1.28 | 1.4600 | 1.222 | 1.4588 |
| 64 | 30 | 715 | 44 | 0.5 | 0.4 | **1.92** | 2.01 | 1.9199 | 1.725 | 1.9188 |
| 65 | 30 | 715 | 68 | 0.7 | 0.4 | **1.96** | 3.94 | 1.9601 | 3.499 | 1.9595 |
| 66 | 30 | 715 | 34 | 0.3 | 0.6 | **1.44** | 0.72 | 1.4400 | 1.216 | 1.4382 |
| 67 | 30 | 715 | 44 | 0.5 | 0.6 | **1.26** | 2.01 | 1.2600 | 1.992 | 1.2586 |
| 68 | 30 | 715 | 68 | 0.6 | 0.6 | **3.51** | 2.89 | 3.5100 | 2.978 | 3.5091 |

**Table 2. Different ANFIS Architecture**

| No. | No. of Membership Function | Function Type | Output Function | Error (RMSE) Training Error | Error (RMSE) 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 | $9.246\times10^{-5}$ | 1.5502 |
| 19 | | trapMF | Constant | 0.055762 | 4.1632 |
| 20 | | | Linear | $6.8203\times10^{-5}$ | 1.7523 |
| 21 | | gbellMF | Constant | 0.0019349 | 1.4268 |
| 22 | | | Linear | $1.9238\times10^{-4}$ | 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 | $1.7924\times10^{-4}$ | 1.5134 |
| 27 | | piMF | Constant | 0.062843 | 2.5633 |
| 28 | | | Linear | $9.2752\times10^{-5}$ | 1.8044 |
| 29 | | dsigMF | Constant | 0.030196 | 4.168 |
| 30 | | | Linear | 0.0021019 | 2.7252 |
| 31 | | psigMF | Constant | 0.030196 | 4.168 |
| 32 | | | Linear | $6.6216\times10^{-4}$ | 2.6197 |
| 33 | 4 | triMF | Constant | $9.5473\times10^{-6}$ | 1.9769 |
| 34 | | | Linear | $2.2411\times10^{-5}$ | 1.8897 |
| 35 | | trapMF | Constant | $7.4861\times10^{-6}$ | 2.5756 |
| 36 | | | Linear | $3.8743\times10^{-5}$ | 2.6091 |
| 37 | | gbellMF | Constant | $1.1209\times10^{-5}$ | 1.8921 |
| 38 | | | Linear | $5.5699\times10^{-4}$ | 1.8935 |
| 39 | | gaussMF | Constant | $1.0605\times10^{-5}$ | 1.8773 |
| 40 | | | Linear | $1.3647\times10^{-4}$ | 1.8018 |
| 41 | | gauss2MF | Constant | $7.4889\times10^{-6}$ | 2.5885 |
| 42 | | | Linear | $1.0873\times10^{-4}$ | 2.6164 |
| 43 | | piMF | Constant | $7.9488\times10^{-6}$ | 2.7837 |
| 44 | | | Linear | $5.3625\times10^{-5}$ | 2.8038 |
| 45 | | dsigMF | Constant | $7.5323\times10^{-6}$ | 2.5586 |
| 46 | | | Linear | $1.4076\times10^{-4}$ | 2.5763 |
| 47 | | psigMF | Constant | $7.5323\times10^{-6}$ | 2.5586 |
| 48 | | | Linear | $1.4611\times10^{-4}$ | 2.5695 |

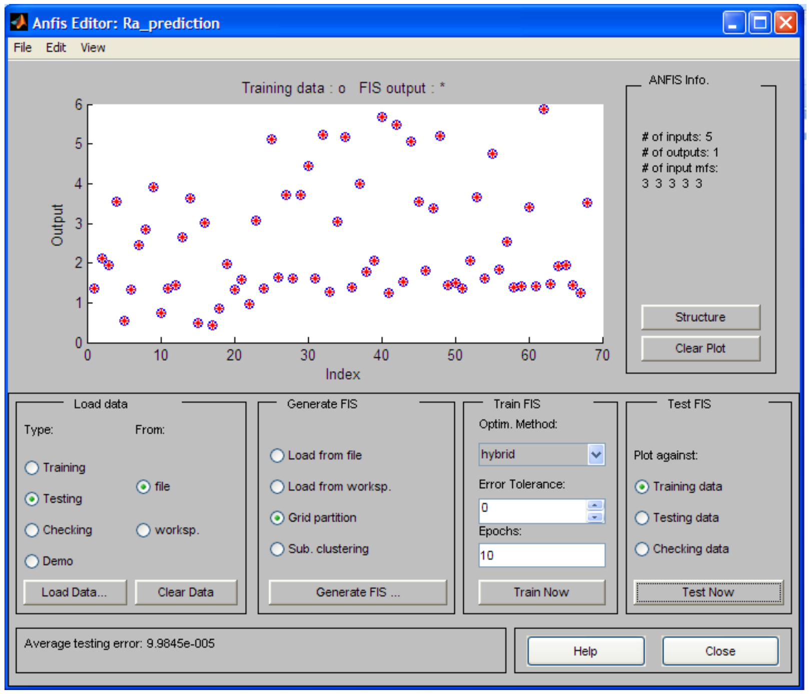


**Figure 7. Comparison between the Experimental and Predicted Values by the ANFIS Training Data**

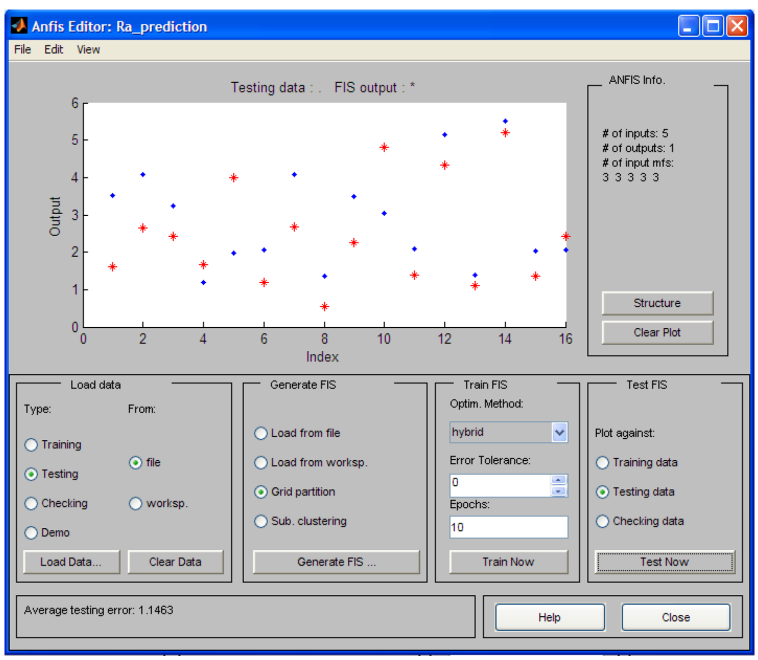


**Figure 8. Comparison between the Experimental and Predicted Values by the ANFIS Testing Data**

### 4.2. ANN Output

In order to find out the best neural network architecture different networks with different number of layers and neurons in the hidden layer were designed and tested; transfer function in the hidden layer and output layer were changed and finally the optimal network was selected. For the obtain optimal network architecture, logarithmic transfer function 'logsig' and tangent sigmoid transfer function 'tansig' have been used in the hidden layer and logarithmic transfer function 'logsig', tangent sigmoid transfer function 'tansig', linear transfer function 'purelin' have been used in the output layer. For this study, number of hidden neuron chosen was 10, 20 and 30. The performance of the network was evaluated by mean sum of squared error (MSE) between the measured and the predicted values for every output nodes in respect of training the network. The feedback from that processing is called the "average error" or "performance". Once the average error is below the required goal or reaches the required goal, the neural network stops training and is, therefore, ready to be verified.

MATLAB 7.6 has been used for training the network architecture. A computer program was performed under this MATLAB version. In this study, 68 experimental data which have been listed in Table 1, were utilized for training different ANN models. The algorithm used for the neural network learning is 'the backward propagation algorithm' with Levenberg-Marquardt (LM) version. The momentum constant and learning rate used in this model is 0.5 and 0.5 respectively. The maximum number of training epochs set was 1,000 and the training error goal was 0.000001.

**Table 3. Summary of the ANN Model for 5-20-20-1 ANN Architecture for $R_a$ Prediction of Al**

<table>
<tr><td rowspan="14">Architecture</td><td colspan="3">Multi layer feed-forward back-propagation neural networks</td></tr>
<tr><td colspan="3">Input Neurons: Cutter axis inclination angle ($\varphi$ degree), Spindle Speed ($S$</td></tr>
<tr><td colspan="3">Output Neurons: average surface roughness $R_a$</td></tr>
<tr><td colspan="3">Hidden Layer: 2</td></tr>
<tr><td colspan="3">Hidden Neurons: 20 (First layer) and 20 (Second layer)</td></tr>
<tr><td colspan="3">Learning Algorithm: Levenberg- Marquardt Optimization</td></tr>
<tr><td colspan="3">Learning scheme: Supervised learning</td></tr>
<tr><td colspan="3">Learning rule: Gradient descent rule</td></tr>
<tr><td rowspan="2">Transfer Function:</td><td>Input layer</td><td>tangent sigmoid (tansig), logarithmic sigmoid (logsig)</td></tr>
<tr><td>Output layer</td><td>linear transfer function (purelin)</td></tr>
<tr><td colspan="3">Sample pattern vector: 68 (for training), 16 (for testing)</td></tr>
<tr><td colspan="3">Learning rate/coefficient: 0.5</td></tr>
<tr><td colspan="3">Momentum rate: 0.5</td></tr>
<tr><td colspan="3">All input data normalized between -1 and +1</td></tr>
<tr><td rowspan="4">Computation/ Termination</td><td colspan="3">Performance goal/Error goal: $7.08 \times 10^{-8}$</td></tr>
<tr><td colspan="3">Maximum epochs (cycles) set: 1,000</td></tr>
<tr><td colspan="3">Number of epochs required for: 6</td></tr>
<tr><td colspan="3">Gradient: $9.96 \times 10^{-4}$</td></tr>
</table>

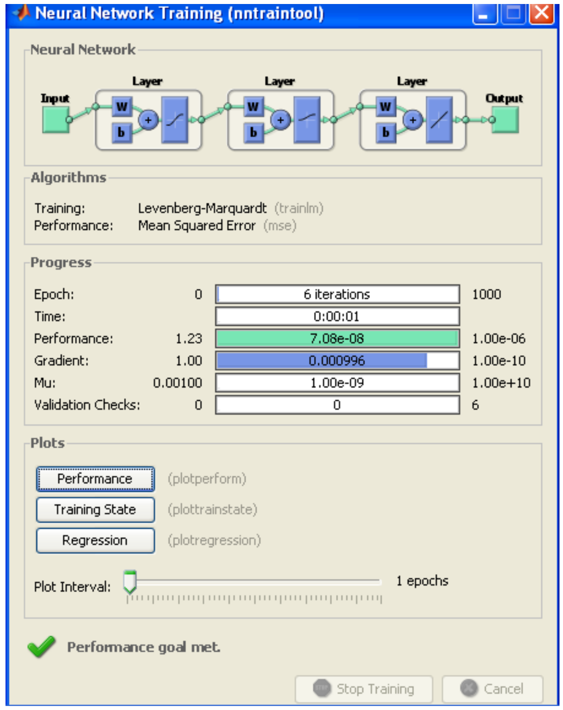


**Figure 9. Final ANN Model Developed with MATLAB 7.6 for Prediction of Surface Roughness**

After the training is completed, the actual weight values were stored in a separate file. To find out the optimal model, 102 different neural network architecture models have been constructed. Network with 2 hidden layer and 20 neurons in the first hidden layer with tangent sigmoid transfer function 'tansig', and 20 neurons in the second hidden layer with logarithmic sigmoid transfer function 'logsig' and linear transfer function 'purelin' in the output layer respectively and trained with Levenberg-Marquardt algorithm provides the best result. The architecture of the final ANN model for has been summarized in Table 3. The final ANN model developed with MATLAB 7.6 for prediction of surface roughness has been presented in Figure 9. So, 5-20-20-1 network architecture was selected as the optimum ANN model.

### 4.3. RSM Output and Output from Theoretical Equations

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 4.The results using the theoretical equations (2) to (8) for 16 test data sets also have been listed in Table 4.

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

**Table 4. Summary of Different Models Output with Testing Data Set**

| SL | Inclin-ation Angle φ | Speed S rpm | Feed $f_y$ mm/min | Feed $f_x$ mm | Depth of Cut t mm | Avg. $R_a$ (Exp.) | From Equations | | | From ANFIS | | | From RSM | | | From ANN | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | $R_a$ | MSE | % error | $R_a$ | MSE | % error | ($R_a$) | MSE | % of error | $R_a$ | MSE | % of error |
| 1 | 30 | 520 | 44 | 0.6 | 0.4 | **3.53** | 2.89 | 0.41 | 18.13 | 1.6 | 3.71 | 54.6 | 2.86 | 0.45 | 18.9 | 2.39 | 1.3 | 32.4 |
| 2 | 30 | 380 | 68 | 0.7 | 0.5 | **4.09** | 3.94 | 0.02 | 3.67 | 2.64 | 2.11 | 35.5 | 3.73 | 0.13 | 8.8 | 3.27 | 0.67 | 20 |
| 3 | 15 | 520 | 44 | 0.6 | 0.4 | **3.25** | 2.89 | 0.13 | 11. | 2.4 | 0.68 | 25.4 | 3.02 | 0.06 | 7.23 | 3.12 | 0.02 | 3.9 |
| 4 | 30 | 380 | 68 | 0.4 | 0.6 | **1.19** | 1.28 | 0.01 | 7.56 | 1.66 | 0.22 | 39.5 | 2.03 | 0.7 | 70.4 | 2.54 | 1.83 | 113 |
| 5 | 15 | 715 | 44 | 0.6 | 0.6 | **1.97** | 2.89 | 0.85 | 46.7 | 4.01 | 4.14 | 103 | 2.77 | 0.64 | 40.6 | 2.47 | 0.25 | 25.3 |
| 6 | 0 | 380 | 44 | 0.8 | 0.6 | **2.06** | 5.14 | 9.49 | 149 | 1.18 | 0.78 | 42.8 | 3.41 | 1.82 | 65.5 | 1.76 | 0.09 | 14.7 |
| 7 | 0 | 380 | 44 | 0.8 | 0.4 | **4.09** | 5.14 | 1.1 | 25.7 | 2.67 | 2.02 | 34.7 | 3.93 | 0.03 | 3.97 | 4.6 | 0.28 | 12.9 |
| 8 | 0 | 715 | 44 | 0.6 | 0.4 | **1.37** | 2.89 | 2.3 | 111 | 0.54 | 0.68 | 60.4 | 1.46 | 0.01 | 6.96 | 1.27 | 0.01 | 7.2 |
| 9 | 30 | 715 | 44 | 0.6 | 0.3 | **3.5** | 2.89 | 0.37 | 17.4 | 2.27 | 1.52 | 35.2 | 2.96 | 0.29 | 15.4 | 2.88 | 0.38 | 17.7 |
| 10 | 0 | 380 | 44 | 0.8 | 0.2 | **3.03** | 5.14 | 4.45 | 69.6 | 4.8 | 3.21 | 59.1 | 5.29 | 5.1 | 74.6 | 3.57 | 0.29 | 17.8 |
| 11 | 0 | 715 | 68 | 0.8 | 0.6 | **2.08** | 5.14 | 9.36 | 147 | 1.38 | 0.5 | 33.9 | 3.08 | 1.01 | 48.2 | 3.93 | 3.4 | 88.7 |
| 12 | 15 | 380 | 68 | 0.8 | 0.5 | **5.15** | 5.14 | 0 | 0.19 | 4.3 | 0.67 | 15.9 | 4.98 | 0.03 | 3.35 | 4.27 | 0.77 | 17 |
| 13 | 0 | 520 | 34 | 0.5 | 0.5 | **0.38** | 2.01 | 0.4 | 45.7 | 1.1 | 0.07 | 19.4 | 1.13 | 0.06 | 17.9 | 0.53 | 0.71 | 61.4 |
| 14 | 15 | 520 | 68 | 0.8 | 0.6 | **5.52** | 5.14 | 0.14 | 6.88 | 5.2 | 0.09 | 5.5 | 4.79 | 0.53 | 13.2 | 5.84 | 0.1 | 5.8 |
| 15 | 30 | 520 | 44 | 0.5 | 0.5 | **2.03** | 2.01 | 0 | 0.98 | 1.35 | 0.46 | 33.5 | 1.86 | 0.03 | 8.6 | 1.4 | 0.4 | 31 |
| 16 | 15 | 380 | 44 | 0.6 | 0.3 | **2.05** | 2.89 | 0.71 | 41 | 2.44 | 0.15 | 18.8 | 3.49 | 2.07 | 70.2 | 3.75 | 2.9 | 83 |

It has been mentioned earlier that in this study ANFIS, ANN, RSM and theoretical equations have been developed and used for predicting surface roughness. The RMSE and MAPE have been calculated for each of the above mentioned models and summarized in Table 5. 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 after ball end milling operation during three dimensional machining on Aluminum.

**Table 5. Errors in Different Models**

| Model | For Training Data | | For Testing Data | |
|---|---|---|---|---|
| | RMSE | MAPE | RMSE | MAPE |
| Theoretical equation | 0.934292 | 42.02314 | 1.364 | 43.884 |
| **ANFIS** | **$9.9845 \times 10^{-5}$** | **0.003014** | **1.146** | **38.605** |
| RSM | 0.630641 | 27.72202 | 0.900 | 29.612 |
| ANN | $7.2355 \times 10^{-4}$ | 0.0314 | 0.9158 | 34.5351 |

Table 6 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 $R_a$.

**Table 6. Pearson Correlation for Different Inputs with Experimental $R_a$**

| | $r$ | $P$-value |
|---|---|---|
| Inclination Angle $\varphi$ | 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 |

## 5. Conclusion

In this research an Adaptive Neuro-Fuzzy Inference System, Artificial Neural Network and Response Surface Methodology were applied to predict the surface roughness during ball end milling operation. The machining parameters were used as inputs to the ANN ANFIS and RSM to predict surface roughness. The ANFIS model could predict the surface roughness for training data with MAPE of 0.003014% when Gaussian membership function is applied, whereas ANN model could predict the surface roughness for training data with 0.0314% error and RSM could predict with MAPE of 27.72%. In case of test dataset it seems that ANFIS model is worse than ANN and even RSM model. But prediction results for surface roughness are more accurate in ANFIS model if training data are considered. It should be mentioned that size of test dataset was only 16, while size of train dataset was 64. On the other hand, errors in ANN model are very close to ANFIS model errors, but ANN provides different results every time its MATLAB code is run.

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 judicious selection of the various machining parameters to minimize surface roughness.

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