JJMIE

Volume 3, Number 4, December 2009
ISSN 1995-6665
Pages 252 - 259

Jordan Journal of Mechanical and Industrial Engineering

Prediction of Surface Roughness in Turning Using Adaptive Neuro-Fuzzy Inference System

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Abstract

Due to the extensive use of highly automated machine tools in the industry, manufacturing requires reliable models for the prediction of output performance of machining processes. The prediction of surface roughness plays a very important role in the manufacturing industry. The present work deals with the development of surface roughness prediction model for machining of aluminum alloys, using adaptive neuro-fuzzy inference system (ANFIS). The experimentation has been carried out on CNC turning machine with carbide cutting tool for machining aluminum alloys covering a wide range of machining conditions. The ANFIS model has been developed in terms of machining parameters for the prediction of surface roughness using train data. The Experimental validation runs were conducted for validating the model. To judge the accuracy and ability of the model percentage deviation and average percentage deviation has been used. The Response Surface Methodology (RSM) is also applied to model the same data. The ANFIS results are compared with the RSM results. Comparison results showed that the ANFIS results are superior to the RSM results.

Keywords: Adaptive Neuro-Fuzzy; Surface Roughness Prediction; Turning.

1. Introduction

The aluminum alloys are used in various engineering applications like structural, cryogenic, food processing, oil and gas process industries etc. because of light weight and high tensile strength. The quality of the surface plays a very important role in the performance of the turning as a good quality turned 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, light reflection, heat transmission, 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 required quality [1]. To achieve the desired surface finish, a good predictive model is required for stable machining. The number of surface roughness prediction models available in literature is very limited [2]. Most surface prediction models are empirical and are generally based on experiments in the laboratory. In addition, it is very difficult in practice, to keep all factors under control as required to obtain reproducible results [3]. Taraman [4] used Response Surface Methodology for Prediction of surface roughness. Hasegawa et al., [5] conducted 3^4 factorial designs to conduct experiments for the surface roughness prediction model. They found that the surface roughness increased with an increase in cutting speed. Sundaram and Lambert [6-7] considered six variables i.e. speed, feed, depth of cut, time of cut, nose radius and type of tool to monitor surface roughness. Mital and Mehta [8] conducted a survey of surface roughness prediction models developed and factors influencing surface roughness. They found that most of the surface roughness prediction models developed for steels. Generally these models have a complex relation ship between surface roughness and operational parameters, work materials and chip breaker types. Salah Gasim Ahmed [9] developed an empirical surface roughness model for commercial aluminum, based on metal cutting results from factorial experiments. The model includes the feed, depth of cut and spindle speed. Dilbag Singh and P. Venkateswara Rao [10] conducted experiments to determine the effects of cutting conditions and tool geometry on the surface roughness in the finish hard turning of the bearing steel (AISI 52100) using mixed ceramic inserts made up of aluminum oxide and titanium carbide with different nose radius and different effective rake angles as cutting tools. They found that the feed is the most dominant factor determining the surface finish followed by nose radius and cutting velocity. Li Zhanjie [11] used Radial Basis Function network to predict surface roughness and compared with measured value 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). They found that the RBF networks have the advantage over Back Propagation Networks (BPN). In the present work

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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 alloys within the ranges of variables studied. The ANFIS results are compared with the RSM results. Comparison results showed that the ANFIS results are superior to the RSM results.

2. Aluminum Alloy Material

The work material used for the present investigation is aluminum alloy 6082 cylindrical work pieces. The chemical composition and physical properties of the material used in this work is given in Table 1 and Table 2.

3. Adaptive Neuro Fuzzy Inference Method

The fuzzy logic and fuzzy inference system (FIS) is an effective technique for the identification and control of complex non-linear systems. Fuzzy logic is particularly attractive due to its ability to solve problems in the absence of accurate mathematical models [13]. Surface roughness modeling in turning is considered complex process, so using the conventional techniques to model the surface roughness in turning results in significant discrepancies between simulation results and experimental data. Thus, this complex and highly time-variable process fits within the realm of neuro-fuzzy techniques. The application of a neuro-fuzzy inference system is used for prediction and overcomes the limitations of a fuzzy inference system such as the dependency on the expert for fuzzy rule generation and design of the non- adaptive fuzzy set.

3.1. Structure of The Adaptive Neuro-Fuzzy Inference System

Adaptive neuro-fuzzy inference system is a fuzzy inference system implemented in the framework of an adaptive neural network. By using a hybrid learning procedure, ANFIS can construct an input-output mapping based on both human-knowledge as fuzzy if-then rules and approximate membership functions from the stipulated input-output data pairs for neural network training. This procedure of developing a FIS using the framework of adaptive neural networks is called an adaptive neuro fuzzy inference system (ANFIS). There are two methods that ANFIS learning employs for updating membership function parameters: 1) backpropagation for all parameters (a steepest descent method), and 2) a hybrid method consisting of backpropagation for the parameters associated with the input membership and least squares estimation for the parameters associated with the output membership functions. As a result, the training error decreases, at least locally, throughout the learning process. Therefore, the more the initial membership functions resemble the optimal ones, the easier it will be for the model parameter training to converge. Human expertise about the target system to be modeled may aid in setting up these initial membership function parameters in the FIS structure [14-15]. The general ANFIS architecture is shown in Fig 1.

Five network layers are used by ANFIS to perform the following fuzzy inference steps. (i) Input fuzzification, (ii) Fuzzy set database construction, (iii) Fuzzy rule base construction, (iv) Decision making, and (v) Output defuzzification.

For instance assume that the FIS has two inputs x_1 and x_2 and one output y. For the first order Sugeno fuzzy model, a typical rule set with two fuzzy if-then rules can be expressed as:

Rule 1: IF $(x_1$ *is* $A_1)$ *AND* $(x_2$ *is* $B_1)$ *THEN* $f_1 = p_1x_1+q_1x_2+r_1$ (1)

Rule 2: IF $((x_1$ *is* $A_2)$ *AND* $(x_2$ *is* $B_2)$ *THEN* $f_2 = p_2x_1+q_2x_2+r_2$ (2)

Where A_1, A_2 and B_1, B_2 are the member ship functions for the input x_1 and x_2, respectively, p_1, q_1, r_1 and p_2, q_2, r_2 are the parameters of the output function. The functioning of the ANFIS is described as:

Layer 1: Calculate Membership Value for Premise Parameter

Every node in this layer produces membership grades of an input parameter. The node output

$$O_{l,i} = \mu_{Ai}(x_1) \text{ for } i=1,2, \text{ or} \quad (3)$$

$$O_{l,i} = \mu_{Bi-2}(x_2) \text{ for } i=3,4 \quad (4)$$

Where x_1 (or x_2) is the input to the node i; A_i (or B_{i-2}) is a linguistic fuzzy set associated with this node. $O_{1,i}$ is the membership functions (MFs) grade of a fuzzy set and it specifies the degree to which the given input x_1 (or x_2) satisfies the quantifier. MFs can be any functions that are Gaussian, generalized bell shaped, triangular and trapezoidal shaped functions. A generalized bell shaped function can be selected within this MFs and it is described as:

$$\mu_{Ai}(x_1) = \frac{1}{1+\left|\frac{x_1 - c_i}{a_i}\right|^{2b_i}} \quad (5)$$

Where a_i, b_i, c_i is the parameter set which changes the shapes of the membership function degree with maximum value equal to 1 and minimum value equal to 0.

Layer 2: Firing Strength of Rule

Every node in this layer, labeled Π, whose output is the product of all incoming signals:

$$O_{2,i} = w_i = \mu_{Ai}(x_1)\,\mu_{Bi}(x_2) \text{ for } i = 1, 2 \quad (6)$$

Layer 3: Normalize Firing Strength

The i[th] node of this layer, labeled N, calculates the normalized firing strength as,

$$O_{3,i} = \vec{w}_i = \frac{w_i}{w_1 + w_2} \quad i = 1,2 \quad (7)$$

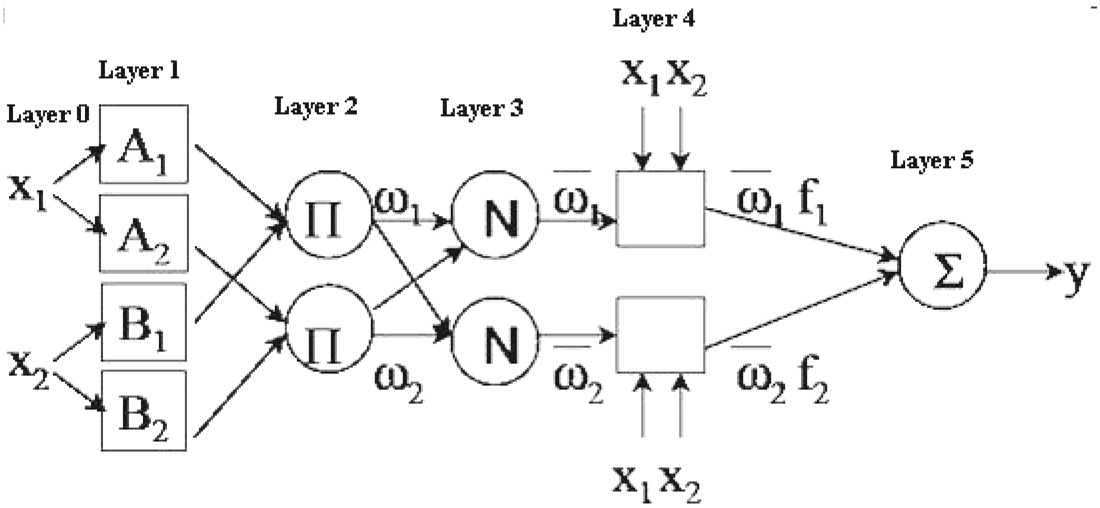

Figure 1. ANFIS architecture.

Table 1. Chemical composition of Aluminum Alloy 6082

Composition	weight (%)
Coper	0.1 (max)
Magnesium	0.4-1.2
Silicon	0.6-1.3
Iron	0.6
Manganese	0.4-1.0
Chromium	up to 0.25
Others	0.3
Aluminum	balance

Table 2. Physical properties of Aluminum alloy 6082.

Property	Value
Density	2.70 g/ cm^3
Melting point	555°C
Modulus of Elasticity	70 G Pa
Electrical Resistivity	$0.038x10^{-6}$ Ω .m
Thermal Conductivity	180 W/m K
Thermal Expansion	$24x10^{-6}$ /K

Layer 4: Consequent Parameters

Every node i in this layer is an adaptive node with a node function,

$$O_{4,i} = \vec{w}_i f_i = \vec{w}_i (p_i x_1 + q_i x_2 + r_i) \tag{8}$$

Where $\vec{w}_i$ is the normalized weighting factor of the i^{th} rule, f_i is the output of the i^{th} rule and p_i, q_i r_i is consequent parameter set of this node.

Layer 5: Overall Output

The single node in this layer is a fixed node labeled Σ, which computes the oveall output as the summation of all incoming signals:

$$\textit{Overall output} = O_{5,i} = \sum_i \vec{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{9}$$

ANFIS requires a training data set of desired input/output pair (x_1, $x_2 \ldots x_m$, y) depicting the target system to be modeled. ANFIS adaptively maps the inputs (x_1, $x_2 \ldots x_m$) to the outputs (y) through MFs, the rule base and the related parameters emulating the given training data set. It starts with initial MFs, in terms of type and number, and the rule base that can be designed intuitively. ANFIS applies a hybrid learning method for updating the FIS parameters. It utilizes the gradient descent approach to fine-tune the premise parameters that define MFs. 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. In addition to the training data, the validation data are also optionally used for checking the generalization capability of FIS.

4. Experimental Details

The experiments were conducted according to full factorial design. The cutting parameters selected for the present investigation is cutting speed (V), feed (f) and depth (d) of cut. Since the considered variables are multi-level variables and their outcome effects are not linearly related. It has been decided to use three level tests for each factor. The machining parameters used and their levels are given in Table 3. The machining parameters, actual setting values and average surface roughness values are presented in Table 4. All the experiments were conducted on CNC Turning Lathe with the following specifications: Swing Over the Bed: 150mm, Swing Over Cross Slide: 50mm, Distance Between Centers: 300mm, Spindle Power

Table 3. Machining Parameters and their Levels.

Control parameters	Unit	Symbol	Levels		
			Level 1	Level 2	Level 3
Cutting Speed	m/min	v	95	105	115
Feed rate	mm / rev	f	0.02	0.04	0.06
Depth of cut	mm	d	0.5	0.75	1.0

1 HP, Spindle Speed (step less):0-3000rpm, Spindle Bore: 21mm, Spindle Taper: MT3, Tailstock Taper: MT2, the Tool Holder used for Turning operation was a WIDAX tool holder SDJCR 1212 11F3 and the tool material used for the study was Carbide Cutting Tool.

The average surface roughness (R_a) which is mostly used in industrial environments is taken up for the present study. The roughness was measured number of times and averaged. The average surface roughness is the integral absolute value of the height of the roughness profile over the evaluation length and was represented by the following equation.

$$R_a = \frac{1}{L}\int_0^L \left|Y(x)dx\right| \quad (10)$$

Where L is the length taken for observation and Y is the ordinate of the profile curve. The surface roughness was measured by using Surtronic 3^+ stylus type instrument manufactured by Taylor Hobson with the following specifications. Traverse Speed: 1mm/sec, Cut-off values 0.25mm, 0.80mm and 2.50mm, Display LCD matrix, Battery Alcaline 600 measurements of 4 mm measurement length. The surfaces are cleaned and positioned using a V-block before each measurement. The actual setting values for the design matrix [16] and experimental results are shown in Table 4.

5. Results and Discussion

The ANFIS model has been developed as a function of machining parameters using twenty seven train data presented in Table 4. The fuzzy logic toolbox of MATLAB 7.0 was used to train the ANFIS and obtain the results. Different ANFIS parameters were tested as training parameters in order to achieve the perfect training and the maximum prediction accuracy. Fig 2 shows the fuzzy inference system (FIS) of ANFIS. The three inputs and one output and their final fuzzy membership functions are shown in Fig 2. A total of 78 network nodes and 27 fuzzy rules were used to build the fuzzy inference system. A triangular membership functions were used to train ANFIS because it achieved the lowest training error of (0.1666) at 10 epochs, as shown in the training curve of Fig 3. A perfect training is clear from Fig 3. Three triangular membership functions were used for inputs (V, f and d). Fig 4 shows the comparison between the experimental and predicted values by the ANFIS and RSM model for training data. The predicted values by ANFIS and RSM model for training data are presented in Table 4. The average percentage deviation for training data set in the prediction of Surface roughness using ANFIS and RSM model is found to be 9.75%, 15.57% respectively.

5.1. Validation Runs

The models developed by ANFIS and RSM are validated using the validation data presented in Table 5. The predicted results were presented in Table 5. The predicted surface roughness values with the actual experimental values of surface roughness were plotted and shown in Fig 5. The average percentage deviation in the prediction of Surface roughness using ANFIS and RSM is found to be 3.29% and 15.86% respectively.

6. Conclusions

An adaptive neuro-fuzzy system and RSM is applied to predict the surface roughness during the turning process. The machining parameters were used as inputs to the ANFIS and RSM to predict surface roughness. The following conclusions can be drawn from this study:

- The ANFIS model could predict the surface roughness for training data with an average percentage deviation of 9.75% when a triangular member ship function is applied or 90.25% accuracy, while RSM model could predict the surface roughness for training data with an average percentage deviation of 15.57% or 84.43% accuracy from training data set.
- The ANFIS model could predict the surface roughness for testing or validation data set with an average percentage deviation of 3.29% when a triangular member ship function is applied or 96.71% accuracy, while RSM model could predict the surface roughness for training data with an average percentage deviation of 15.86% or 84.14% from validation data set. The accuracy of the developed model can be improved by including more number of parameters.

Table 4. Experimental Conditions, results (Experimental and Predicted).

v	f	d	Experimental Ra	Predicted Ra (RSM)	%Deviation (RSM)	Predicted Ra (ANFIS)	%Deviation (ANFIS)
95	0.02	0.50	1.706	2.38069	39.5481	2.0651	21.040
95	0.02	0.75	2.286	2.74749	20.1877	2.6736	16.950
95	0.02	1.00	5.393	5.14752	4.5518	6.5284	21.050
95	0.04	0.50	2.720	2.56557	5.6776	3.2926	21.050
95	0.04	0.75	2.366	2.33230	1.4243	2.8010	18.380
95	0.04	1.00	4.460	4.13224	7.3489	5.3989	21.050
95	0.06	0.50	2.546	2.09469	17.7262	3.0820	21.050
95	0.06	0.75	1.640	1.26132	23.0902	1.9742	20.370
95	0.06	1.00	2.006	2.46119	22.6914	2.4283	21.050
105	0.02	0.50	3.613	2.19788	39.1675	3.9571	9.520
105	0.02	0.75	2.540	2.76319	8.7870	2.6973	6.190
105	0.02	1.00	5.773	5.36171	7.1244	5.7739	0.015
105	0.04	0.50	2.113	2.60985	23.5140	2.3143	9.520
105	0.04	0.75	2.080	2.57507	23.8014	2.2046	5.990
105	0.04	1.00	4.890	4.57352	6.4720	5.3565	9.530
105	0.06	0.50	1.753	2.36605	34.9715	1.9200	9.520
105	0.06	0.75	2.213	1.73119	21.7718	2.4206	9.380
105	0.06	1.00	2.333	3.12955	34.1427	2.5552	9.520
115	0.02	0.50	2.200	2.47596	12.5436	2.2232	1.050
115	0.02	0.75	3.080	3.23977	5.1873	3.0902	0.330
115	0.02	1.00	5.760	6.03680	4.8056	5.9086	2.570
115	0.04	0.50	3.413	3.11502	8.7307	3.4490	1.050
115	0.04	0.75	3.660	3.27874	10.4169	3.6871	0.740
115	0.04	1.00	4.956	5.47569	10.4861	5.0818	2.530
115	0.06	0.50	2.840	3.09830	9.0951	2.8699	1.050
115	0.06	0.75	2.726	2.66194	2.3500	2.7357	0.350
115	0.06	1.00	5.006	4.25880	14.9261	5.1351	2.570
				Average % Deviation:	15.5756%		9.750%

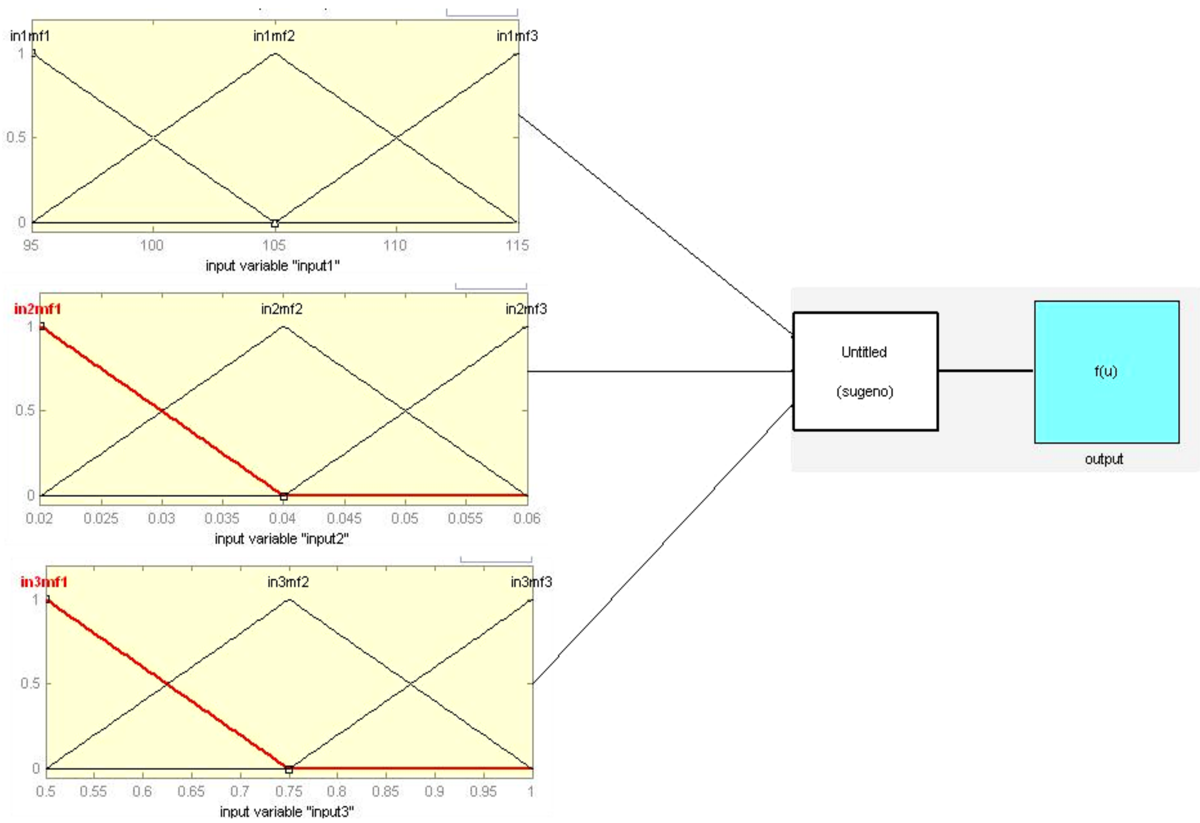

Figure 2. Fuzzy inference system for surface roughness prediction

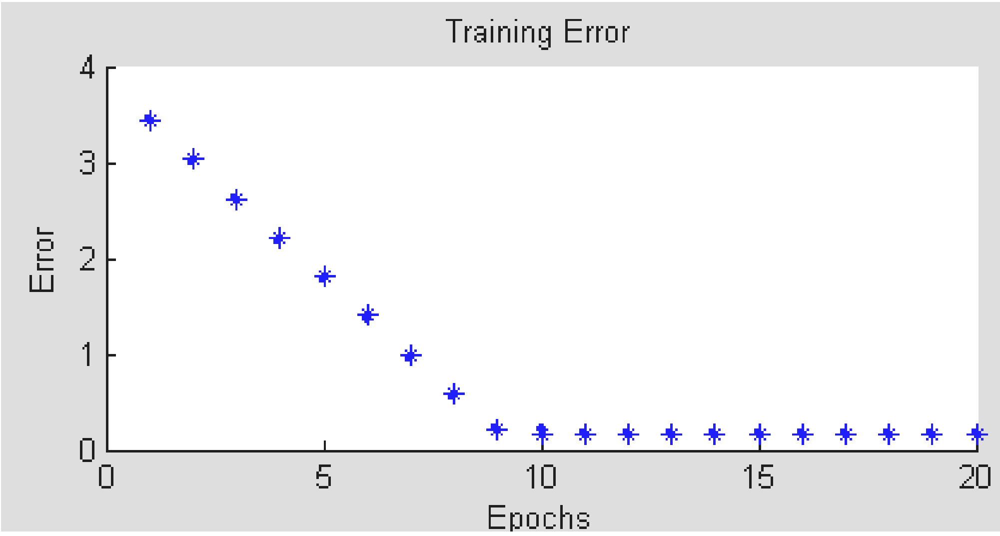

Figure 3. ANFIS Training Curve.

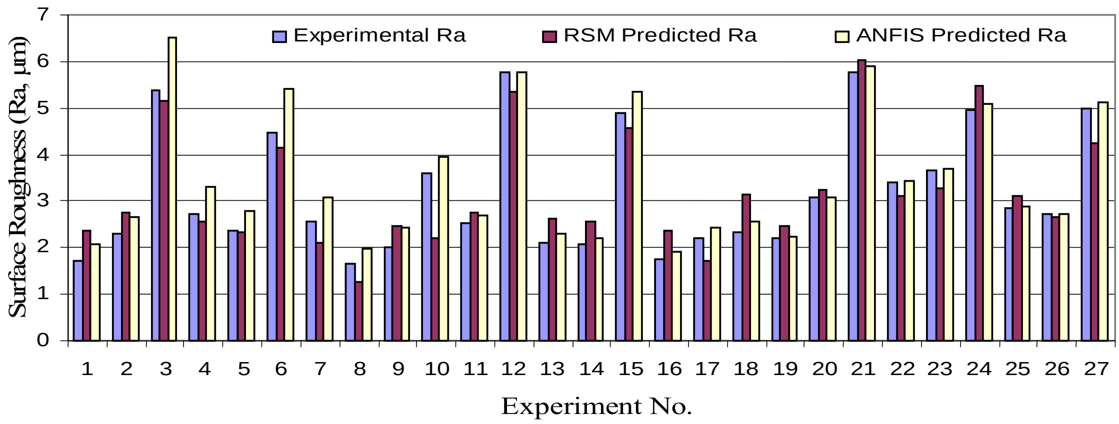

Figure 4. comparison between experimental and predicted values for training data.

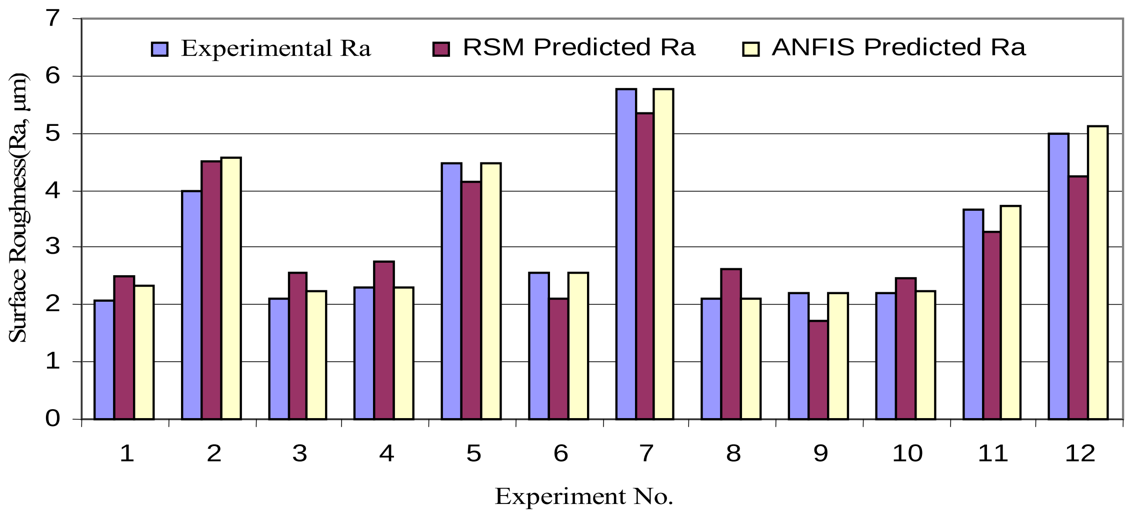

Figure 5. ANFIS Validation diagram.

Acknowledgement

The Authors are thankful to the Hon'ble Chairman Dr. M.Santhi Ramudu, Managing Director Mr. M. Sivaram, Principal Dr. T. Jaya Chandra Prasad and H.O.D of M.E, Rajeev Gandhi memorial College of Engg& Technology, Nandyal for providing the facilities to carry out the research work.

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