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APPLICATION OF ANFIS SYSTEM IN PREDICTION OF MACHINING PARAMETERS

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ABSTRACT

Since cutting conditions have an influence on reducing the production cost and time of machining process and also the quality of a final product the prediction of output machining parameters such as surface roughness and tool life criteria for different cutting speed, feed rate, depth of cut and tool geometry is one of vital modules in process planning of metal parts. In this study with use of experimental results on machining of ST-37 and subsequently, ANFIS system, importance of each parameter was studied. These parameters were considered as input in order to predict the surface finish and tool life criteria, two conflicting objectives, as the process performance. In this paper ANFIS system was applied to predict output parameters of machining. Results show that amount of input influence on the outputs parameters. By using ANFIS input parameters entered to ANFIS system then all training data was trained with 300 epochs. After training the value of error which is 1.039e−006 was calculated.

Keywords: *Cutting Parameters, Surface Roughness, Tool Life Criteria, ANFIS System, Fuzzy Logic, Intelligent System*

1. INTRODUCTION

Prediction of performance parameters include surface roughness and tool life criteria for different input machining parameters such as depth of cut, feed rate, cutting speed and rake angle is still challenging matter. It is found that neural networks have applications for prediction of cutting parameters in turning process. Four parameters were employed for surface roughness prediction by Azouzi and Guillot [1] using ANN model with sensor based fusion technology. Risbood et al. [2] used the feed, the depth of cut, the cutting speed and additional input parameters, the acceleration of radial vibration of the tool holder in their ANN model. The most likely values of surface roughness was predicted by Kohi and Dixit[3]. An adaptive neuro-fuzzy inference system for prediction of surface roughness was developed by Ho et al [4]. Jiao et al [5] used fuzzy adaptive network with only three parameters cutting speed feed rate and depth of cut.

Fuzzy logic was introduced by Zadeh in 1965 to represent and manipulate data and information in

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which there are various forms of uncertainty. Fuzzy rule-based systems use linguistic variables to reason using a series of logical rules that contain IF-THEN rules which connect antecedent(s) and consequent(s), respectively. An antecedent is a fuzzy clause with certain degree of membership. Fuzzy rules can have multiple antecedents connected with AND or OR operators, where all parts are calculated simultaneously and resolved into a single number.

Consequents can also be comprised of multiple parts, which are then aggregated into a single output of a fuzzy set [14].Fuzzy inference is a process of mapping from a given input to an output using the fuzzy set methods.

ANFIS is the implementation of fuzzy inference system (FIS) to adaptive networks for developing fuzzy rules with suitable membership functions to have required inputs and outputs. FIS is a popular and cardinal computing tool to which fuzzy if-then rules and fuzzy reasoning compose

bases that performs mapping from a given input know-ledge to desired output using fuzzy theory. This popular fuzzy set theory based tool have been successfully applied to many military and civilian areas of including decision analysis, forecasting, pattern recognition, system control, inventory management, logistic systems, operations management and so on. FIS basically consist of five subcomponents (Topçu and Saridemir, 2008), a rule base (covers fuzzy rules), a database (portrays the membership functions of the selected fuzzy rules in the rule base), a decision making unit (performs inference on selected fuzzy rules), fuzzification inference and defuzzification inference. The first two subcomponents generally referred knowledge base and the last three are referred to as reasoning mechanism (which derives the output or conclusion) [15].

An adaptive network is a feed-forward multi-layer Artificial Neural Network (ANN) with; partially or completely, adaptive nodes in which the outputs are predicated on the parameters of the adaptive nodes and the adjustment of parameters due to error term is specified by the learning rules. Generally learning type in adaptive ANFIS is hybrid learning (Jang, 1993). General structure of the ANFIS is illustrated in Figure 1 [15].

The ANFIS is a multilayer feed-forward network which uses neural network learning algorithms and fuzzy reasoning to map inputs into an output. Indeed, it is a fuzzy inference system (FIS) implemented in the framework of adaptive neural networks. For simplicity, a typical ANFIS architecture with only two inputs leading to four rules and one output for the first order Sugeno fuzzy model is expressed [7, 8, 9, 10, 11, 12, and 13].

The ANFIS architecture is shown in figure 2.

Using a given input/output data set, the ANFIS method constructs a fuzzy inference system (FIS) whose membership function parameters are tuned (adjusted) using either a backpropagation algorithm alone, or in combination with a least squares type of method. This allows fuzzy systems to learn from the data they are modeling. FIS Structure is a network-type structure similar to that of a neural network, which maps inputs through input membership functions and associated parameters, and then through output membership functions and associated parameters to outputs.

In our case ANFIS is a four-layer neural network that simulates the working principle of a fuzzy inference system. The linguistic nodes in layers one and four represent the input and output linguistic Variables, respectively. Nodes in layers two are term nodes acting as membership functions for input variables. Each neuron in the third layer represents one fuzzy rule, with input connections representing preconditions of the rule and the output connection representing consequences of the rules. Initially, all these layers are fully connected, representing all possible rules.

The suggested ANFIS has several properties:

- The output is zero the order Sugeno-type system.
- It has a single output, obtained using weighted average defuzzification. All output membership functions are constant.
- It has no rule sharing. Different rules do not share. The same output membership function, namely the number of output membership functions must be equal to the number of rules.
- It has unity weight for each rule.

2. EXPERIMENTAL WORK

The work material used for the present investigation is ST-37 steel with the diameter of 45

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mm and length of 400 mm. For machining operation a Russian lath machine was used and the tool material was HSS with clearance angle of 6°, back rake angle of 0°, side cutting edge angle of 90° and rake angle which was variable during machining process.

The machining parameters used and their levels were presented in Table1. The values of the levels were selected so that the standard values of parameters were included.

Cutting parameters	unit	symbol	Levels		
			1	2	3
Cutting speed	(m/min)	v	17	25	33
Feed rate	(mm/rev)	f	0.09	0.13	0.17
Depth of cut	(mm)	d	0.2	0.4	0.6
Rake angle	(degree)	z	0	14	-

Table 1. Machining parameters and their levels

Velocity of rotation for different diameters of workpiece and based on selected cutting speeds was calculated from equation1.

$$N = \frac{1000V}{\pi D} \quad (1)$$

Where diameter (D) is in mm, cutting speed (V) is in min/m and velocity of rotation (N) is in rev/min.

In this study tool life is defined by the volume of the material removed so that surface finish becomes 1.5 times higher than the initial surface roughness value at the beginning of machining operation.

$$1/v = \frac{1}{\pi \times D \times d \times L \times 10^3} \quad (2)$$

Were material removal volume (v) is in mm3, diameter (D) is in mm, depth of cut (d) is in mm and length of the workpiece (L) is in mm which reach the tool life criterion.

3. EXPERT ANFIS SYSTEM

The ANFIS system based on Expert knowledge contains 81 rules, 4 inputs and one single output for Outputs level. The structure of expert ANFIS is shown in figure 3.The fuzzy logic toolbox using the MATLAB software is employed to create the ANFIS model.

In fuzzy logic tool box, relevant FIS for trust model is created. In this model type of FIS is selected Sugeno type. In this study for space trust problem, the cross sectional areas of the structures are selected as ANFIS inputs and nodal displacements, element stresses and ultimate load factor can be separately considered as ANFIS output. For each input two Gaussian membership functions are adopted and the maximum number of epochs in training mode is set to 300.

4. MEMBERSHIP FUNCTION FOR EXPERT ANFIS

Gaussmf are used to build the expert ANFIS model. The shape of membership functions after training the AFNIS for 300 epochs is shown figure 4.

5. TRAINING DATA FOR SURFACE ROUGHNESS LEVEL

The entire data set of surface roughness level is 18 samples. They are referred to as training data, testing data and checking data. Upon training, the ANFIS shows the training error which reflects the how good the mapping function is. To validate the model, we further apply the testing data to see how the ANFIS behaves for known data. ANFIS maps the function onto the testing data as per the training.

Having created the data set the next step is to train the network. This means we create a new FIS to fit the data into membership functions. Using the grid partitioning method, the ANFIS automatically selects the membership function and also generates the new FIS.

Figure 5 shows training and testing data in ANFIS network that is loaded. In figure 6, the course of error during the training of adaptive network is shown.

At the end of 300 training epochs, the network error (mean square error) convergence course of each ANFIS was derived. From the curve, the final convergence value is 1.039e−006.The rule viewer for the 4 inputs and 1 output can be observed pictorially in the Figure 7.

6. DEVELOPMENT AND ANALYZING FUZZY SYSTEM

After discovering the rules related to trust level, relevant inputs and outputs for earning surface roughness level in fuzzy tool box to be organized and were created relevant membership for input and output figure 8 shows the fuzzy system that can be used to derive the Output level.

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7. ANALYSIS OF SURFACE ROUGHNESS VERSUS CUTTING SPEED

For complete understanding of participation needed in SURFACE ROUGHNESS level, it is necessary to separately test the participation of each factor. The Figure 9 shows contribution to Surface roughness from the cutting speed.

Figure 9 shows that in $V = 19$ m/min the surface roughness would be in the maximum level moreover by increasing of cutting speed better surface roughness will be obtained.

8. ANALYSIS OF SURFACE ROUGHNESS VERSUS RANK ANGLE FACTOR

Figure 10 shows how surface roughness is contributed from rank angle for constant values of 3 other factors. As it is shown by increasing of the rake angle until 8° the surface roughness will be decreased. After that it will be constant.

9. ANALYSIS OF SURFACE ROUGHNESS VERSUS DEPT OF CUT FACTOR

Figure 11 shows how surface roughness is contributed from depth of cut for constant values of 3 other factors. For depth of cut between (0.2-0.4) mm surface roughness increase but it seems that after that it starts to be decrease.

10. ANALYSIS OF SURFACE ROUGHNESS VERSUS FEED RATE AND CUTTING SPEED FACTOR

In this section surface roughness level is depicted as a continuous function of its input parameters as cutting speed and feed rate. It is shown in figure 12.

11. CONCLUSION

The experiments were conducted on a lathe machine for the machining of ST-37 steel. The tool used for the machining operation is a HSS tool. In this study ANFIS system was exploited to predict two output machining parameters during machining of ST-37. Depth of cut, feed rate, cutting speed and rake angle were considered as input while surface roughness and tool life criteria were two process performances which were predicted between low and high levels. Base on training data, we able to obtain the proper outputs for each selected inputs. 81 rules were discovered by 300 epochs using ANFIS system which can be utilized for engineers in this area. The emphasis must be put on providing a preferred solution for the process engineer in the short period of the time and also the amount of influence of each parameter into outputs of the process. The choice of one solution over other ones is dependent on the requirements of process engineer.

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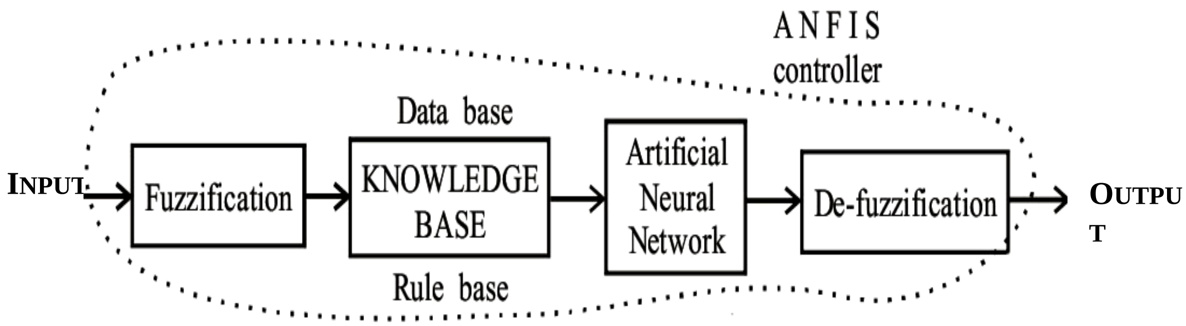


FIGURE 1 SCHEMATIC DIAGRAM OF FUZZY BUILDING BLOCKS

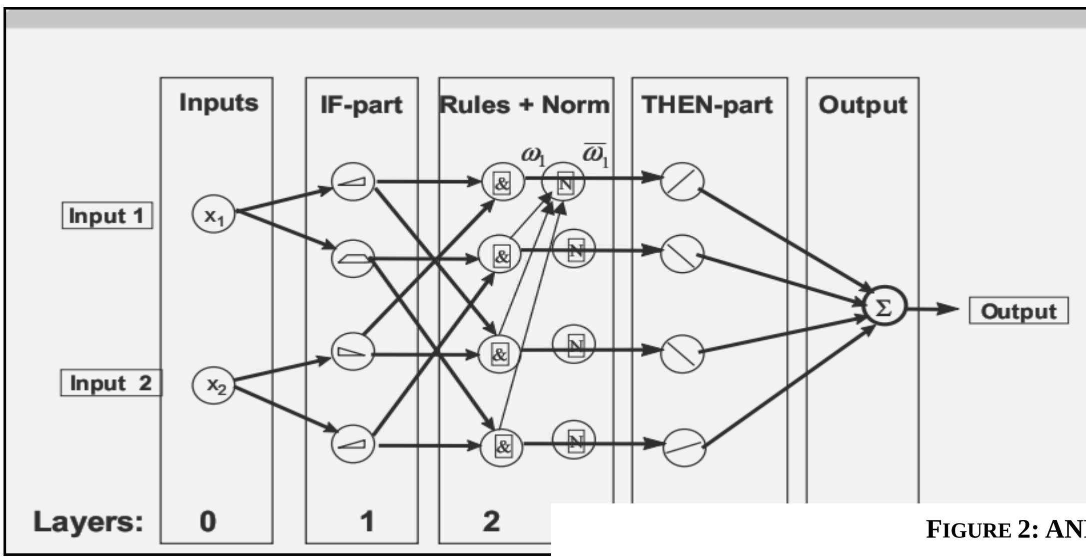
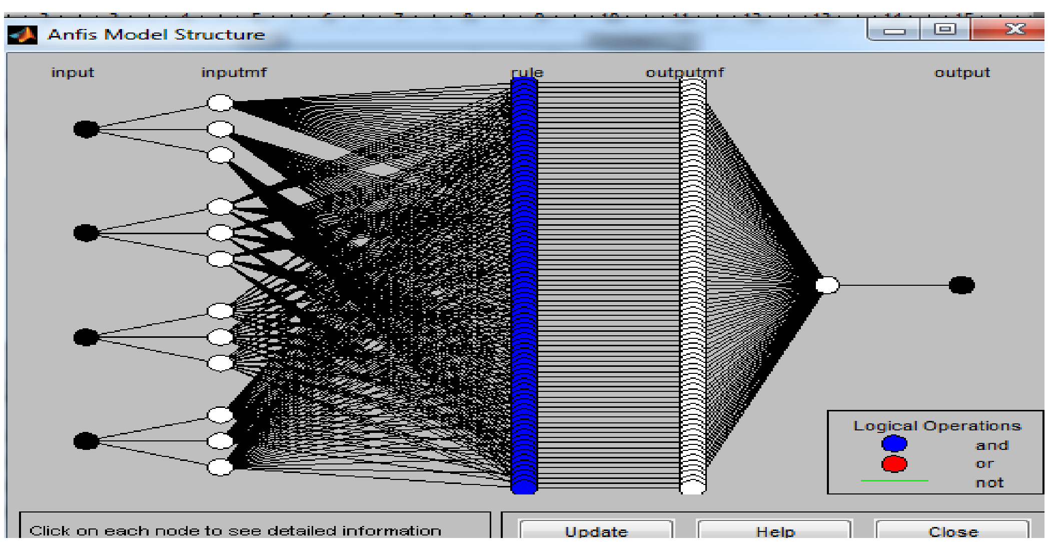


FIGURE 2: ANFIS STRUCTURE FOR RE

FIGURE 2: A TYPICAL ANFIS ARCHITECTURE FOR A TWO-INPUT SUGENO MODEL WITH FOUR RULES



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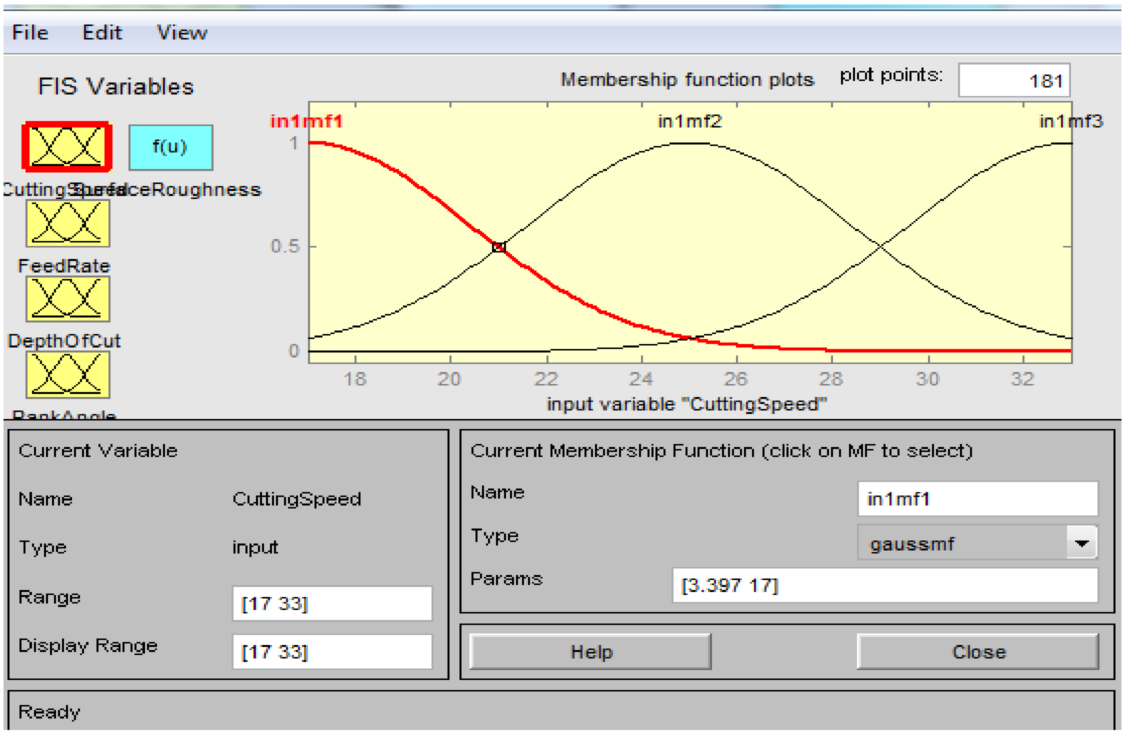

FIGURE 4. MEMBERSHIP FUNCTION EDITOR

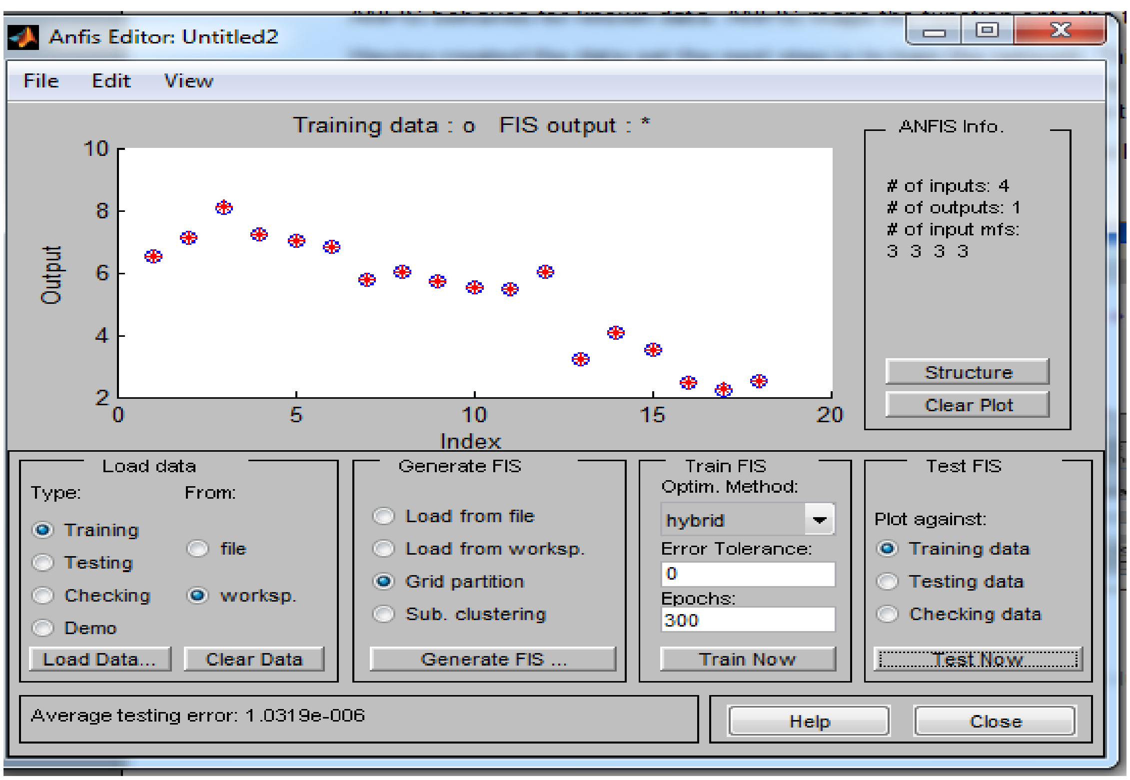

FIGURE 5. ANFIS EDITOR: TRAINING THE RULES

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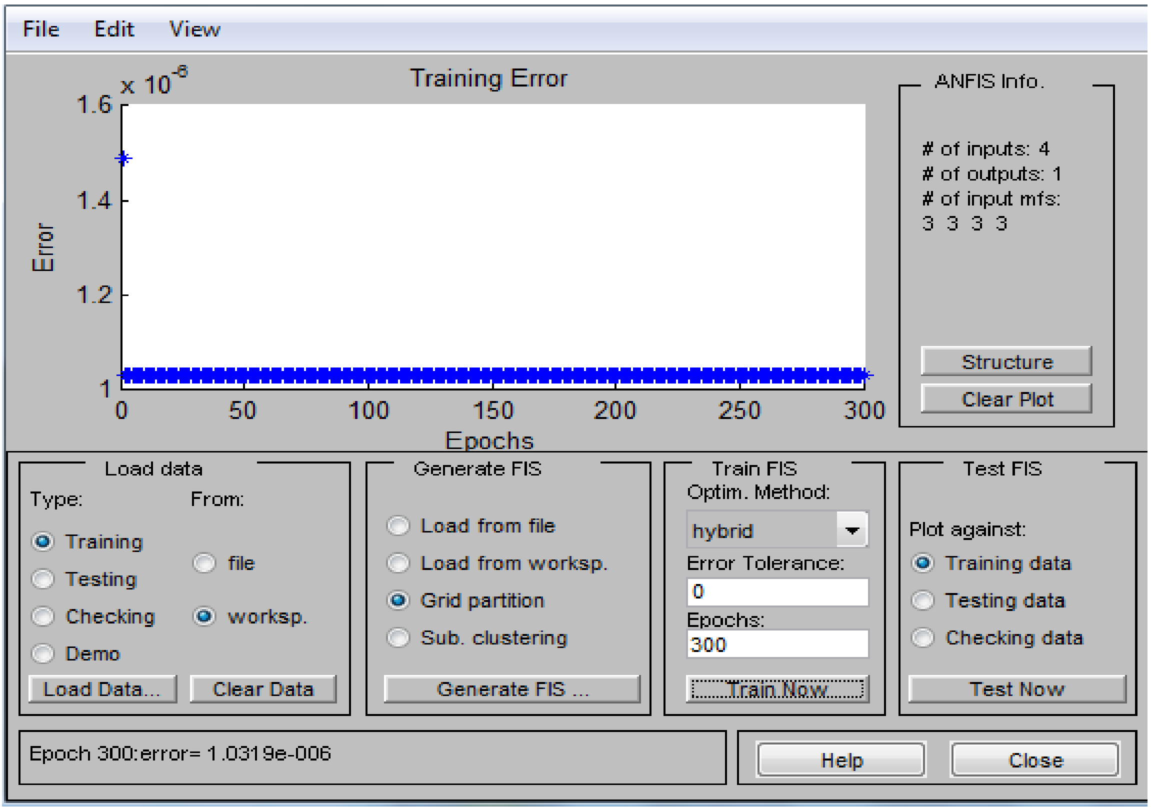

FIGURE 6. COURSE OF ERROR DURING THE TRAINING OF ADAPTIVE NETWORK

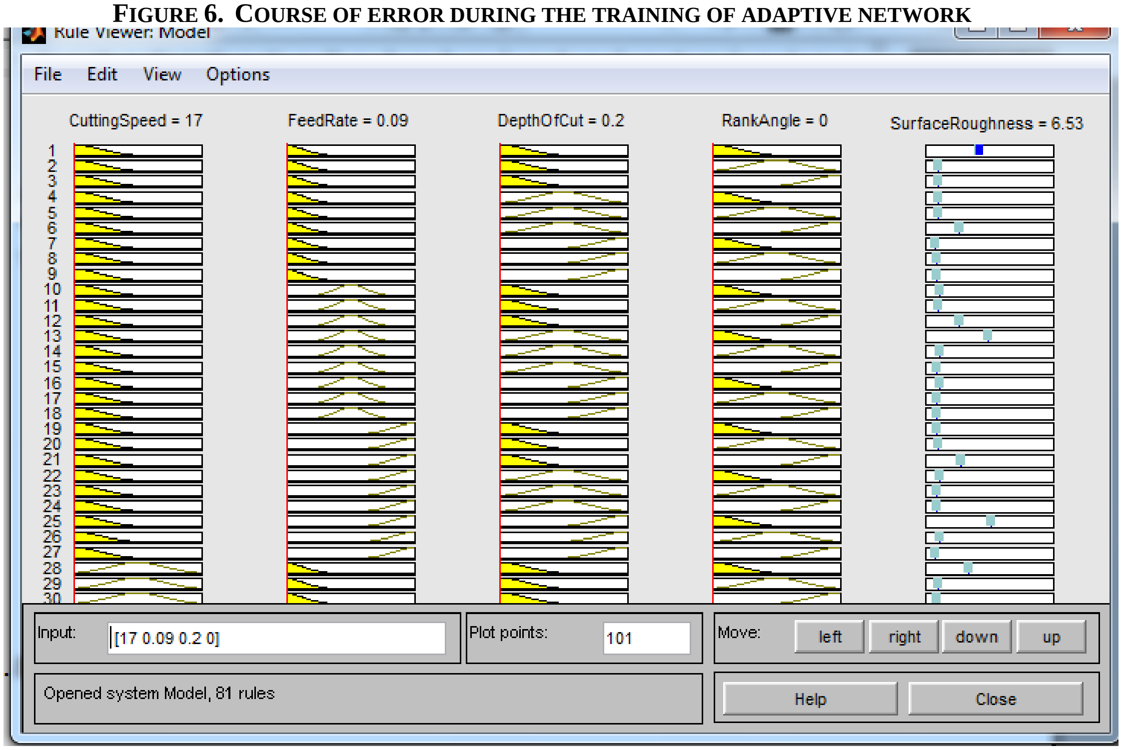

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FIGURE 7. RULE VIEWER WINDOW

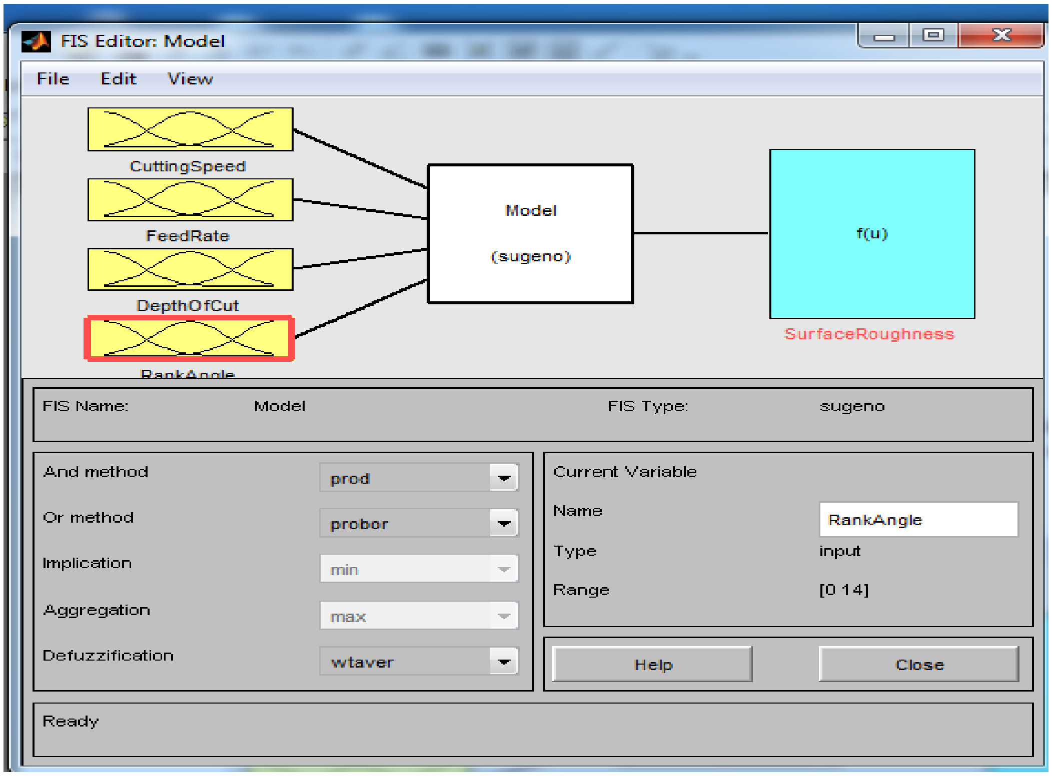

FIGURE 8. THE RESEARCH MODEL

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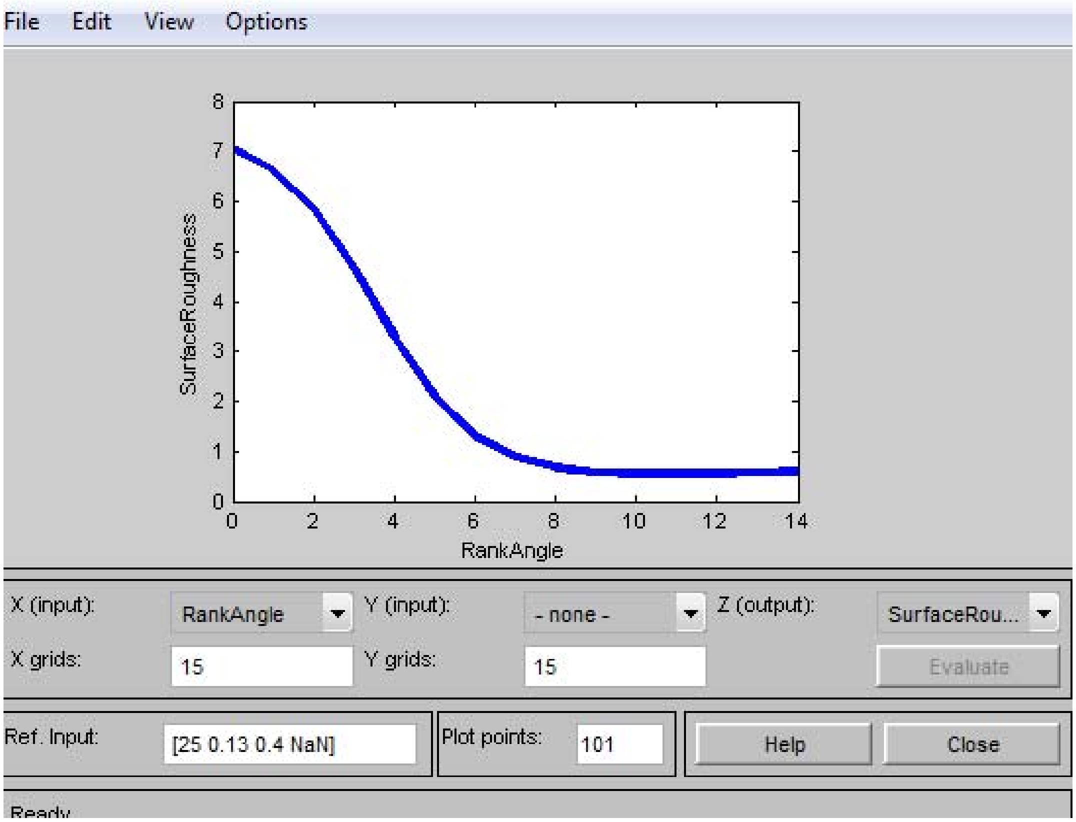

FIGURE 10. SURFACE ROUGHNESS VERSUS RANK ANGLE FACTOR

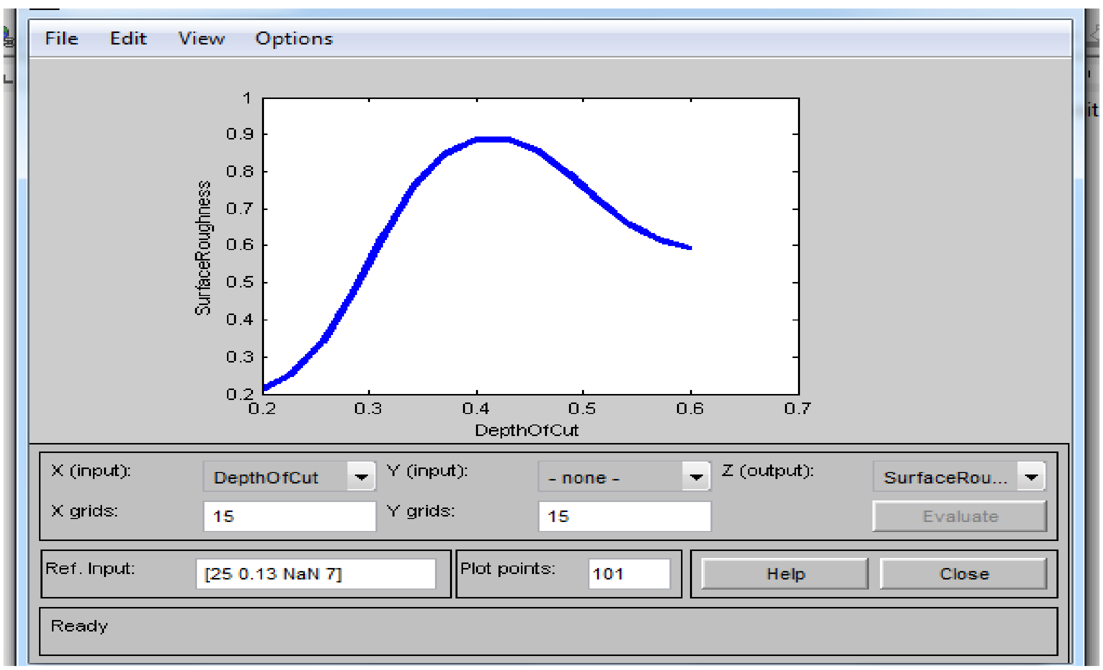

FIGURE 11. PLOT OF SURFACE VS. DEPTH OF CUT

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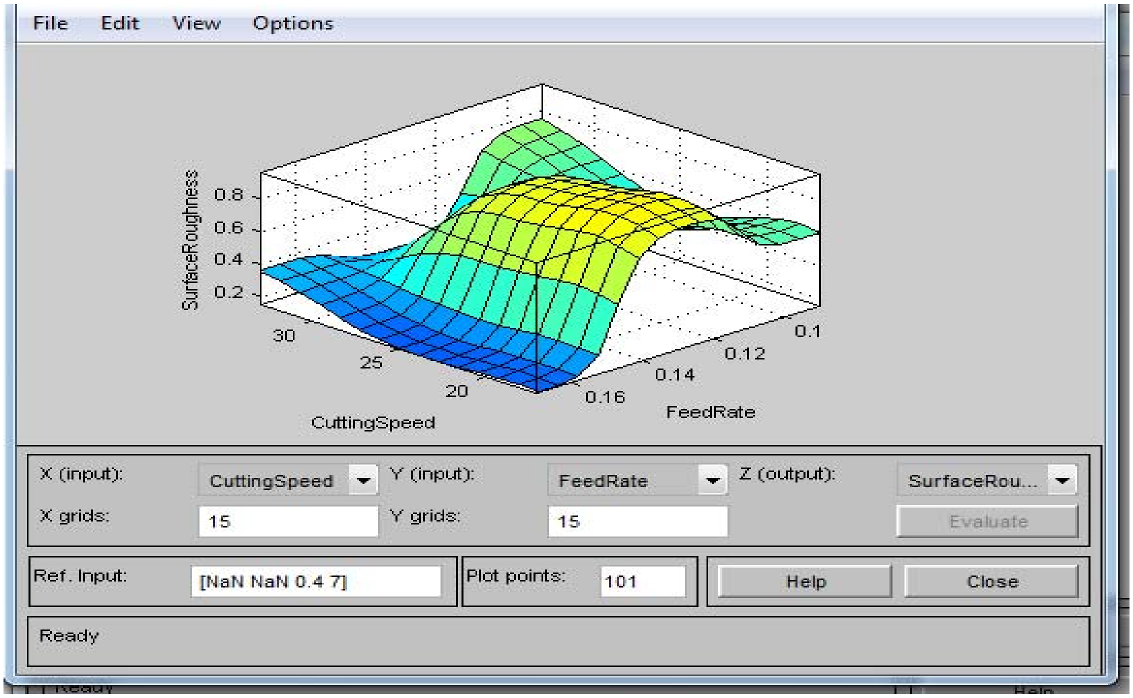

FIGURE 12.SURFACE ROUGHNESS LEVEL IS RELATED TO LEVELS OF FEED RATE AND CUTTING SPEED