Digital Open Science Index, Mechanical and Industrial Engineering Vol:14, No:11, 2020 waset.org/publication/10011592

Development of Fuzzy Logic and Neuro-Fuzzy Surface Roughness Prediction Systems Coupled with Cutting Current in Milling Operation

Joseph C. Chen, Venkata Mohan Kudapa

Abstract—Development of two real-time surface roughness (Ra) prediction systems for milling operations was attempted. The systems used not only cutting parameters, such as feed rate and spindle speed, but also the cutting current generated and corrected by a clamp type energy sensor. Two different approaches were developed. First, a fuzzy inference system (FIS), in which the fuzzy logic rules are generated by experts in the milling processes, was used to conduct prediction modeling using current cutting data. Second, a neuro-fuzzy system (ANFIS) was explored. Neuro-fuzzy systems are adaptive techniques in which data are collected on the network, processed, and rules are generated by the system. The inference system then uses these rules to predict Ra as the output. Experimental results showed that the parameters of spindle speed, feed rate, depth of cut, and input current variation could predict Ra. These two systems enable the prediction of Ra during the milling operation with an average of 91.83% and 94.48% accuracy by FIS and ANFIS systems, respectively. Statistically, the ANFIS system provided better prediction accuracy than that of the FIS system.

Keywords—Surface roughness, input current, fuzzy logic, neuro-fuzzy, milling operations.

I. Introduction

THE goal of any manufacturing process is to transform raw materials into end products. End milling operation is one of the most commonly used operations in metal cutting industries. A manufacturing process is evaluated for its impact on efficiency of production methods, processing time, and quality of finished products. The quality of a finished milling product is defined by how closely the parts produced adhere to customer specifications, including surface finish and dimensions [1].

Surface roughness (Ra) is defined as the fine irregularities produced on a work piece by a cutting tool. Numerous attributes of a product such as appearance, cost, adhesion to another surface, assembly of the parts, light reflection, and other qualities are influenced by Ra. The number of defective items increases when the Ra of a machined part does not meet specifications.

Off-line methods were previously commonly applied to measure Ra: when the machining is ceased the part is taken out and is measured with conventional measuring gauges [2]. Since these methods are time consuming and the required down time for the inspection increases the production costs, competition between the corporations led to the development of in-process Ra recognition systems. With an in-process surface recognition system, the Ra of the part can be measured while the machining is being taken place. In this system there is no need to remove the machined part to obtain the Ra value. So, the time saved to do the inspection reduces processing time and thereby production costs. Application of in-process surface recognition systems can provide a competitive advantage over manufacturers still conducting Ra inspections off-line.

There are a variety of Ra measurement techniques. The techniques can be classified in several ways. Techniques can be described as using contact measurement or non-contact measurement. If there is a physical contact between the measuring device and the surface being tested, this would constitute a contact measurement technique. Stylus profilers are commonly used for this purpose. A Stylus profiler is a device incorporating a diamond stylus which detects vertical travel as it moves over the surface [3]. Contact measurement techniques do not lend themselves well to on-line surface recognition. As a result, research concerning non-contact dynamic measuring techniques has been pursued in recent years to obtain Ra in real time [2].

Optical measuring devices such as scanning electronic microscopes and optical microscope, which provide images of the test surface for the measurement of roughness, can be considered for on-line "Ra" data collection [3]. Unfortunately, optical devices also do not lend themselves well to on-line inspection. Sensor techniques are being explored to sense the parameters that contribute to Ra. The parameters could include cutting force, vibration, sound, motor current, light reflection, sound reflection, or others. [4]. Although these parameters cannot be controlled directly, variations in the Ra with the change in the monitored parameters could be captured and analyzed to aid in the development of a mathematical relation correlating the input factors and resulting Ra.

Many sensor techniques have been previously utilized. For example, an ultrasonic sensor has been used for the prediction of surface quality characteristics [4]. An accelerometer sensor has been used to detect the vibrations in the milling operation [5]. A dynamometer has been used to measure the cutting force in machining. Infra-red temperature sensors have been used to measure the temperature generated from the work piece while machining in a turning operation [6]. Attempts have been made by many researchers to optimize the Ra using the minimum input current for machining process. This research aims to find

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a correlation between the input current and the Ra and develop a prediction model by using the most suitable algorithm.

Computer numerical control (CNC) machines normally rely on current-electricity as the main power source. The input current drawn by the CNC milling machine is summation of the current drawn by all the sub systems of the machine. Once the machine is turned on, the controller interface, lights, computer fans, and coolant systems consume the current until the machine is switched off. This input current is almost constant when the machine is idle, i.e. if there is no machining taken place. While the machining is being started the system consumes more current since the spindle motor requires current to generate power for the milling operation. This input current for the spindle motor has variation, unlike the idle input current for the remaining sub-systems. The power generated is utilized to generate cutting force for the manufacturing operation. This input motor current is one of the key parameters that could affect the Ra [4]. According to the relative motion between the cutting tool and work piece, the amount of current required varies with the cutting parameters, namely speed, feed rate, depth of cut, and the type of material being machined. Presented is an in-process monitoring of Ra during machining operation using input motor current sensing.

For developing an efficient prediction model a proper decision making algorithm is required. Since the complexity of the real world problems is higher, artificial intelligence techniques were selected. Previous studies have employed either artificial neural networks (ANN) [7], [8] or fuzzy logic [9], [10]. Fuzzy logic is initially used for many industrial and academic applications because of the ability to use linguistic variables to represent the uncertainties of human knowledge.

Negative aspects of fuzzy logic are the development of an efficient fuzzy interference system: a time and effort-consuming exercise. The main difficulty lies in finding proper membership functions and suitable IF-THEN rules, which are achieved through trial and error. The lack of ability to generalize and their difficulty to produce interference logical rules as their determination depends on knowledge of expert. Conversely, neural network methodology, which is a machine learning algorithm, has the ability to recognize patterns using machine learning capability. The key feature of a neural network is that it can learn a structure from training data. The input and the output patterns are recognized by adjusting the internal structure and artificial layer neurons and maps input/ output behavior for modeling the system with the level of acceptable error of the application. The monitoring application should be adaptable to change, eliminating the disadvantages and combining the advantages of both the fuzzy logic and ANN techniques; both have been combined and a hybrid of the two algorithms has been developed, variously known as neuro-fuzzy, neural fuzzy, or fuzzy nets [11]. For the research presented herein, the prediction models were generated by using both a FIS and adaptive neuro-fuzzy based inference system (ANFIS); evaluation was conducted to determine the superior model.

II. Overview of Fuzzy and Adaptive Neuro-Fuzzy Interference Systems

Before FIS or adaptive neuro-fuzzy inference system (ANFIS) can be developed, the experimental setup must be performed. Cutting parameters of the milling operations are considered key input variables and the research contained herein introduced a non-contact sensor to obtain additional cutting information for the prediction model; one machine current measurement device was set up to measure current while milling is taking place.

After experimental setup is completed, the system is ready for initial validation to further understand the cutting conditions and generate fuzzy rules to continue the development of the FIS system. The training data then can be used for neural network training to obtain the ANFIS system. Once two systems are developed and to be tested by the testing data to define their prediction accuracy. Finally, if the prediction accuracy is above the level of acceptance, the developed model shall be regarded as successful [12], [13].

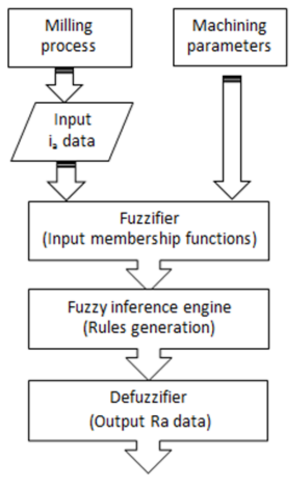

Fig. 1 Architecture of the work flow

The procedure for developing FIS systems is summarized as:

- Step 1: Determine a fuzzification inference. The fuzzification inference provides a way to deal with the vagueness and imprecision of information from the real world. The fuzzification inference maps the crisp input variables into a fuzzy set by dividing the space of each input factor and output factor into fuzzy regions. Each input domain interval could be divided into 2N+1 fuzzy region. The length of each region could be equal or unequal. A membership function needed to be employed. There are various types of membership functions; triangular is the most commonly used of all because of its effectiveness. The fuzzication inference converts these crisp values into linguistic terms through fuzzication.
- Step 2: Design a fuzzy rule bank. In the fuzzy control system, the fuzzy rule bank contains the linguistic control rules and fuzzy data manipulation. When several linguistic variables are involved in the antecedents and one variable in the consequent, a fuzzy IF-THEN rule is used for constructing a multi-input-single-output (MISO) fuzzy

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system.

- Step 3: If it is observed that two or more fuzzy rules having the same IF condition but different THEN condition after developing a rule base, then those fuzzy rules are categorized as conflicting rules. This conflicting condition for the rules could be resolved by calculating the degree of each fuzzy rule and selecting the rule with the maximum degree. A combined fuzzy rule bank is established from the fuzzy rule base. The entire fuzzy rule bank is developed in fuzzy interference system.
- Step 4: Determine a method of defuzzification. Defuzzification is a process to transfer fuzzy set into a value that best represents the possible distribution of an inferred fuzzy control action. There are many defuzzication techniques such as center of area method (COA), center of sums method, maxima method, middle of maxima method, Tsukomoto method, Sugeno method and so on. In this research, centroid of area (COA) method was used which is further explained in defuzzication stage of FIS model [14].

The procedure of developing ANFIS systems is summarized as follows: A hybrid (combination of gradient descent and least squares) neuro-fuzzy technique that tunes learning capabilities of neural networks to FIS is proposed in this research for developing the adaptive ANFIS. The learning algorithm of neural networks tunes the membership functions of a Sugeno-type FIS using the training input/output data. The architecture of ANFIS consists of five layers. Among those layers both first and fourth layers consist of adaptive neurons and the second, third & fifth layers consist of fixed neurons [15]. The if-then rules of typical Sugeno-fuzzy model are expressed as:

- Rule 1: If (Y is A_1) and (Z is B_1) then ($f_1 = p_1Y + q_1Z + r_1$)

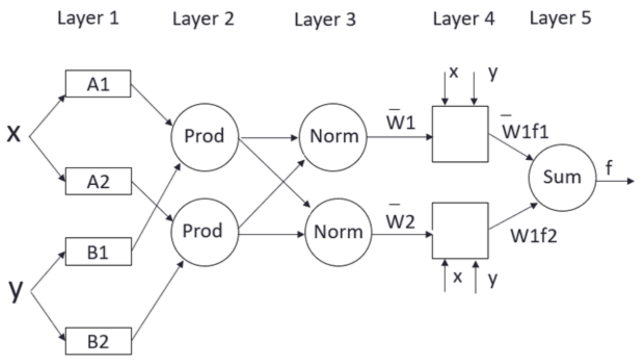

Fig. 2 Architecture of ANFIS

Layer1: The nodes in this layer are called adaptive nodes. The output of every node in this layer takes the form of a function. This is also called as fuzzication layer.

$$O_{1,i} = \mu Ai\ (x) \qquad \text{for } i = 1, 2 \tag{1}$$

$$O_{1,i} = \mu_{B_{i-2}}(x) \qquad \text{for } i = 3, 4 \tag{2}$$

where, A_i or B_{i-2} is the linguistic label associated with i_{th} neuron, and they are defined as:

$$\mu A(x) = \frac{1}{1+\left|\frac{x-c_i}{a_i}\right|2b_i} \tag{3}$$

Layer 2: The nodes in this layer are called as fixed nodes which are labelled "Prod", in the ANFIS architecture shown in Fig. 2. The function of every i_{th} node in this layer is to multiply the input signals from layer 1. The output follows as given below. This is called a rule layer.

$$O_{2,i} = w_i = \mu_{A_i}(x) \times \mu_{B_i}(y) \qquad \text{for } i = 1, 2 \tag{4}$$

Layer 3: Every neuron in this layer is a fixed neuron which is represented as circle named 'Norm' in Fig. 2. The nodes in this layer determine the normalized firing strength of i_{th} rule by the ratio of i_{th} rule firing strength to sum of all firing strengths. This is normalized layer.

$$O_{3,i} = w_i = \frac{w_i}{w_1+w_2} \qquad \text{for } i = 1, 2 \tag{5}$$

Layer 4: The nodes or neurons are adaptive in this layer. The output is in the form of a node function given below, where P_i, q_i, r_i are called consequent parameters which will get updated duly for each iteration.

- Rule 2: If (Y is A_2) and (Z is B_2) then ($f_2 = p_2Y + q_2Z + r_2$)

The architecture of ANFIS is shown in Fig. 2 in which the circle indicates a fixed neuron and the square indicates an adaptive neuron.

$$O_{4,1} = w_i f_i = w_i\,(\,p_x + q_i\,y + r_i\,) \tag{6}$$

$$O_{5,i} = \sum_i w_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{7}$$

Layer 5: This layer consists of only a single node in which the output is the weighted average of all incoming signal from previous layer.

III. Development of FIS and ANFIS Systems

To develop a Ra model, the experiments examined the impact of the following parameters on the Ra in end milling: (1) feed rate, (2) spindle speed, (3) depth of cut, (4) Input current. The data needed for the training must derive from experiments rather than handbooks for a more realistic depiction of the phenomenon under investigation. Then, in view of the number of factors and continuous range of values that most of them take, a strategy for reduction of the number of experiments (measured values) should be devised. The design of experiments was performed based on the levels of interest for each factor.

The levels of interest for each factor are presented in Table I which determines the need for 27 runs of experiments. These experiments were conducted for the acquisition of training data. Training data are used to find the patterns of the changes in the output with the changes in the input parameters and to develop a predictive model.

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TABLE I
FACTORS & LEVELS OF INTEREST FOR DESIGN OF EXPERIMENTS

S(R.P.M)	F.R(Inch/min)	Doc(Inches)
700	6	0.02
900	8	0.03
1100	10	0.04

The order of the 27 experiments is randomized first. Then these experiments are conducted on HAAS CNC machine and the material used for the experimentation was 1045 AISI steel. The average input current (µa) associated with the each run of experiments was collected using a clamp type energy meter evaluated in two ways 1) for the machine to operate which is considered constant for all the input parameter settings; 2) motor spindle current which varies with the changes in speed (S), feed rate (FR) and depth of cut (DOC).

TABLE II
TRAINING DATA FOR PREDICTION MODEL

No	S (R.P.M)	F.R (Inch/min)	DOC (Inches)	C (ma)	Ra(µm)
1	700	6	0.04	5.5	3.871
2	700	6	0.02	3.8	1.965
3	700	6	0.03	4.5	3.179
4	900	6	0.03	4.25	2.275
5	900	6	0.02	3.95	1.341
6	900	6	0.04	5.75	2.703
7	1100	6	0.03	4.9	1.064
8	1100	6	0.04	5.35	1.288
9	1100	6	0.02	4.3	1.94
10	700	8	0.03	4.7	3.722
11	700	8	0.04	6.3	4.123
12	700	8	0.02	3.85	2.77
13	900	8	0.02	4.05	2
14	900	8	0.03	7.8	3.312
15	900	8	0.04	6.55	4.11
16	1100	8	0.02	4.15	1.124
17	1100	8	0.03	8	1.721
18	1100	8	0.04	6.7	2.113
19	700	10	0.04	6.8	4.186
20	700	10	0.02	4.45	3.955
21	700	10	0.03	5.4	3.989
22	900	10	0.02	4.4	3.121
23	900	10	0.04	6.9	3.878
24	900	10	0.03	6.15	3.449
25	1100	10	0.02	4.6	2.594
26	1100	10	0.04	7	2.893
27	1100	10	0.03	3.8	3.17

Here the current associated with the motor spindle is measured for the model development. The Ra data were collected using zy-gauge. Five measurements were taken for each sample. The average "Ra" values of the five measurements from each sample and the corresponding current data are presented in Table II.

Step 1. Design of Experiment Analysis

A three factorial DOE (Design of experiments) was performed for evaluate the whether any cutting parameter is significantly affecting the Ra, as well as current (ma) value during the cuts. Table III presents the ANOVA, showing the dependent variables related to the Ra. The result concludes that FR, cutting speed and DOC had a significant effect over the surface roughness. Table IV presents the ANOVA, showing the dependent variables related to the current (ma). The result concludes that FR and DOC are the significant factors for the current value received during the machining process is taken place.

TABLE III
ANOVA FOR RA (µM)

Source	df	SS	MS	F	P
Speed (S)	2	10.7997	5.3999	30.83	0.000
FR	2	7.501	3.7505	21.41	0.001
DOC	2	3.9349	1.9675	11.23	0.005
S*F.R	4	0.8839	0.221	1.26	0.36
F.R*DOC	4	0.8905	0.2226	1.27	0.357
DOC*S	4	1.2335	0.3084	1.76	0.23
Errors	8	1.4012	0.1752		
Total	26	26.6447			

TABLE IV
ANOVA FOR CURRENT (MA)

Source	df	SS	MS	F	P
Speed (S)	2	1.2407	0.6204	0.96	0.422
FR	2	5.7274	2.8637	4.45	0.049
DOC	2	21.0857	10.5429	16.38	0.001
S*F.R	4	2.7765	0.6941	1.08	0.428
F.R*DOC	4	6.1715	1.5429	2.4	0.136
DOC*S	4	1.1615	0.2904	0.45	0.77
Errors	8	5.148	0.6435		
Total	26	43.3113			

Step 2: Development of FIS

The architecture of the Mamdani FIS is shown in Fig. 3. The ranges of input parameters and the range of the measured Ra output of milling operation were used to construct fuzzy regions and membership functions. The fuzzy domains are defined as the range between the maximum and minimum values of the parameters and then adding a safety factor such as 100.1% of the maximum and 99.9% of the minimum values. Then it was established that the domain intervals of speed (S), FR, DOC and Current (C) are [S^-,S^+], [Fr^-, Fr^+], [Doc^-, Doc^+] and [C^-, C^+] respectively; here the space interim implies that there is a decent likelihood that an estimation of a variable will lie in this interim. For instance the scope of speed [S] of machining operation is [700,1100], so it has a fuzzy area of [S-, S+] = [699.3, 1101]. These areas are later separated into 2N+1 covered triangular regions. N can be partitioned into various factors, and the lengths of these regions can be equivalent or unequal indicated by (Low N), L1, L2… Medium, L1 (Large1), L2….LN (Large N), and for every area a fuzzy membership capacity is assigned.

A case of the fuzzy membership work for various levels of information parameters appears in Figs. 4 & 5, where VS, S, M, L and VL are very little, little, medium, large and very large respectively. It is demonstrated that the area interim is separated into three regions by considering the estimation of N = 1 (2N + 1 = 2*1 + 1 = 3) for the factors speed, feed and DOC whereas for the factors surface roughness and the input current,

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it is observed that the space interim is isolated into five regions by considering the estimation of N = 2 (2N + 1 = 2*2 + 1 = 5). The state of the membership function considered in this work is triangular with the vertex lying at the inside.

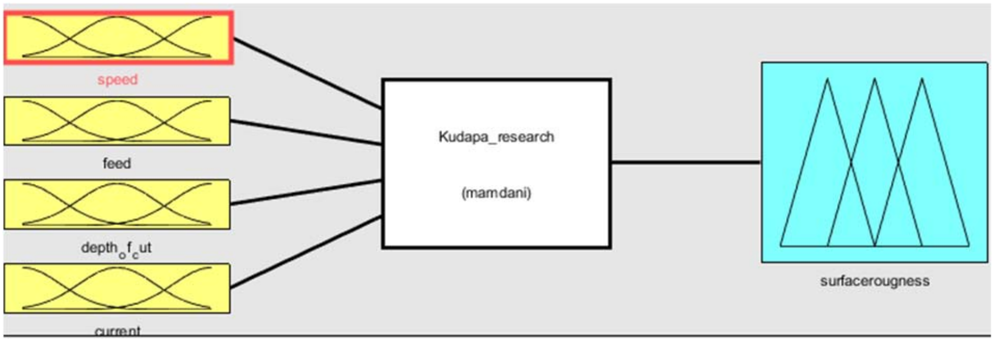
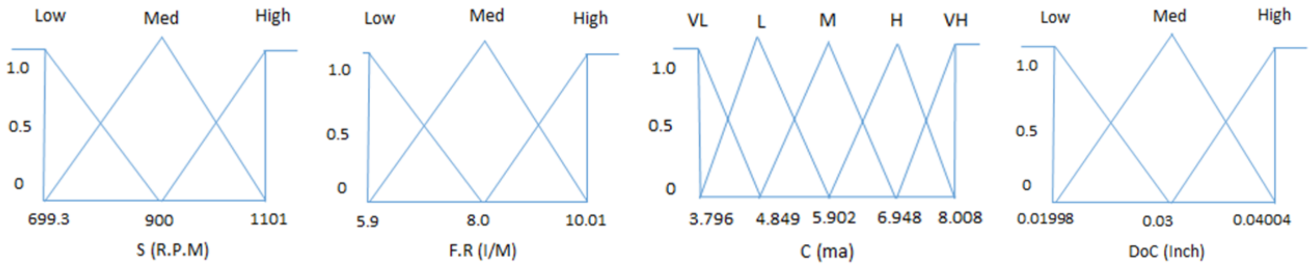


Fig. 3 Mamdani FIS



(a) (b) (c) (d)

Fig. 4 Input fuzzy membership functions: (a) FR, (b) Speed, (c) Current, (d) DOC

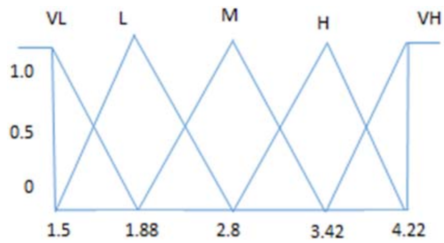


Fig. 5 Output (Ra) fuzzy membership functions (unit: Ra)

Fuzzy degrees for training data depend upon the membership function of each region in each domain. The fuzzy degree of every fuzzy region for every single parameter was then determined using the fuzzy membership functions in (8):

$$f_A(x) = \begin{cases} 1 - \frac{x - C_A}{W}, & x \in [\,C_A,\, C_A + W] \\ 1 - \frac{C_A - x}{W}, & x \in [\,C_A - W, C_A] \\ 1, & x \in [-\infty\,, D^-] \\ & or\ x \in [D^+, \infty] \\ 0, & Elsewhere \end{cases} \tag{8}$$

where, x – Value if input or output parameter, A – Region in a membership function, W – Region width = $(D^+ - D^-)/2N$, D^+ & D^- are the maximum and minimum values of the fuzzy domain.C_A – center point of region.

Generation of Fuzzy Rule Bank

Degrees of S, F.R, DOC and C in different regions were determined. Overlapping membership functions will cause an input or output value to produce two fuzzy degrees, one for each of the two overlapping membership functions. Fuzzy rules will be generated based on various parameters. Depending upon the number of regions, the number of fuzzy rules varies. There is also a chance for overlapping as the number of factors increases. To avoid such complexities in the data set, fuzzy rules are generated as a membership function with the largest fuzzy degree.

The calculation of degree of fuzzy membership function is shown as an example below. The input current value "7ma" belongs to the region high, very high. After finding the degrees, the following was determined:

- The degree of "High" is defined as 1-((7-6.955)/2.106) = 0.978632479
- The degree of "Very high" is defined: 1-((8.008-7)/2.106) = 0.521368.

Since the region "High" is the winner of the rule bank for the set of training data because it possess higher fuzzy degree compared that of "Very high" region, it was assigned to the fuzzy region "High". By this training process, a total of 135 fuzzy rules are generated for the FIS system to be tested.

Defuzzification

After the rule bank, the output obtained is still fuzzy, so it has to be taken through a process of defuzzification to make it useful. Defuzzification is performed through the following method:

For inputs (x1, x2) using product operation, we combine the

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antecedents of the i^{th} fuzzy rule to find the degree, f^i_{Oi}, of the output control that is

$$f^i_{Oi} = f^i_{I\,1}(x1)\ f^i_{I\,2}(x2) \tag{9}$$

where, O_i, - Output region of rule i, f^i_j - Input region of rule i for the j^{th} component.

A minimal value has to be determined for each combination of degree of the input functions, which will be the fuzzy degree of the output for each combination. This is obtained in the form of f^i_{Oi}. The following centroid defuzzification formula is used to determine the output:

$$y = \frac{\Sigma\left(f^i_{outputj}\right)\left(C_{outputj}\right)}{\Sigma\left(f^i_{outputj}\right)} \tag{10}$$

where, "y" is the crisp output value, $C_{outputj}$ – Center point of the output fuzzy region.

The FIS system was tested using the same training data and the accuracy of each test is shown in Table V with a 95.22% accuracy for predicting the Ra using current and cutting parameters.

Step 3: Development of ANFIS

A Sugeno-FIS is shown in Fig. 6. This ANFIS configuration was used.

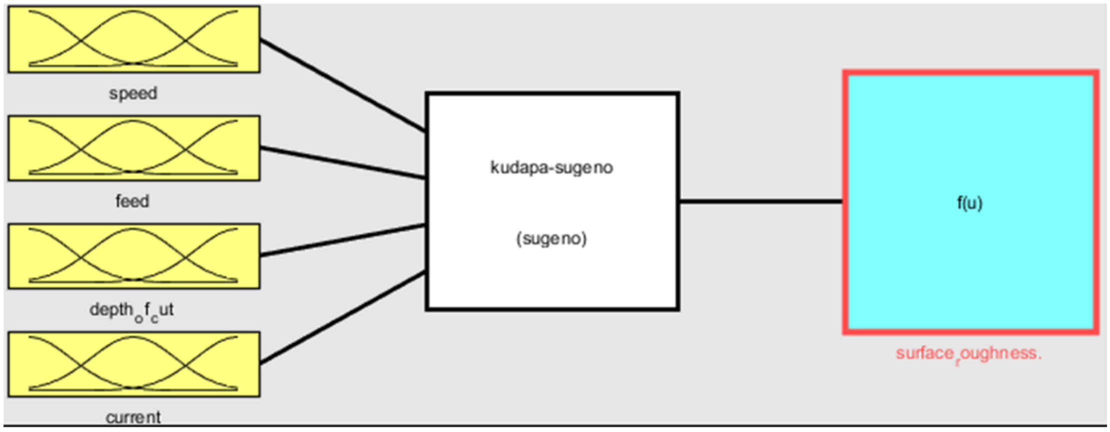

Fig. 6 Sugeno-FIS

A total of 27 sample training data used in FIS were also used in this system. Hybrid and back propagations are only two options to be implemented in the proposed ANFIS system, while the research uses hybrid method. A user defined thread hold value is defined and used to end the training process once the error is less than it. The 3 x 3 x 3 x 5 = 135 rules generated after training the model are shown in Fig. 8, and the five layers ANFIS system is shown in Fig. 9.

Training data are evaluated for training prediction accuracy as completed for FIS model in Step 3. The prediction accuracy is shown in Table VI.

Step 4: Accuracy Evaluation for FIS and ANFIS Systems

The developed prediction models were evaluated by running the testing data with different cutting parameters from those of training data. Table VII lists the observed Ra, the actual measured Ra, and the accuracy percentages for all 10 testing data via FIS model. Similarly, Table VIII lists the observed Ra, the predicted Ra, and the accuracy percentages for same testing data via ANFIS model. A t-test analysis is conducted to provide further information to whether which of these two systems enables to performance a better prediction for Ra with cutting parameters and current data obtained while the machine process is taken place. The hypothesis of the t-test is defined as:

$$H_0: \mu_{FIS} \geq \mu_{ANFIS}$$
$$H_1: \mu_{FIS} < \mu_{ANFIS}$$

where, μ_{FIS} = Mean of the accuracy percentage from Table VII and μ_{ANFIS} = Mean of the accuracy percentage from Table VIII. The t value is defined in:

$$t = \frac{\bar{\mu}_{FIS} - \bar{\mu}_{ANFIS}}{\sqrt{\frac{S^2_{FIS} + S^2_{ANFIS}}{n_1 + n_2}}} \tag{11}$$

where, S^2_{FIS} is the variance of 10 testing data points in Table VII, and S^2_{ANFIS} is the variance of 10 testing data points in Table VIII.

The t value was defined as -2.36. The critical t value was defined based on 97.5% confidence interval ($\alpha = 0.025$) with 18 degrees of freedom (n_1 -1 + n_2-1, while $n_1 = n_2 = 10$); one tailed analysis was -2.101. Since the t value fell outside of the critical t values, the null hypothesis was rejected. This concludes that the FIS system has less accuracy than the ANFIS system.

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TABLE V
PREDICTION ACCURACY FOR TRAINING DATA

S (RPM)	FR (Inch/m)	DOC (Inch)	C (ma)	Observed (Ra) (μm)	Predicted (Ra) (μm)	Accuracy (%)
700	6	0.02	3.8	1.965	1.87	95.17
700	6	0.03	4.5	3.179	3.3	96.19
900	6	0.03	4.25	2.275	2.7	81.32
900	6	0.02	3.95	1.341	1.33	99.18
900	6	0.04	5.75	2.703	2.63	97.30
1100	6	0.03	4.9	1.064	1.23	84.40
1100	6	0.04	5.35	1.288	1.32	97.52
1100	6	0.02	4.3	1.94	1.83	94.33
700	8	0.03	4.7	3.722	3.45	92.69
700	8	0.04	6.3	4.123	3.96	96.05
700	8	0.02	3.85	2.7722	2.68	96.67
900	8	0.02	4.05	2	1.89	94.50
900	8	0.03	7.8	3.312	3.42	96.74
900	8	0.04	6.55	4.11	3.89	94.65
1100	8	0.02	4.15	1.3	1.34	96.92
1100	8	0.03	8	1.7214	1.8	95.43
1100	8	0.04	6.7	2.113	1.91	90.39
700	10	0.04	6.8	4.186	3.95	94.36
700	10	0.02	4.45	3.955	3.85	97.35
700	10	0.03	5.4	3.989	3.9	97.77
900	10	0.02	4.4	3.121	3.23	96.51
900	10	0.04	6.9	3.878	3.9	99.43
900	10	0.03	6.15	3.449	3.54	97.36
1100	10	0.02	4.6	2.594	2.67	97.07
1100	10	0.04	7	2.893	2.69	92.98
1100	10	0.03	3.8	3.17	3.83	79.18
					Average Accuracy	94.29

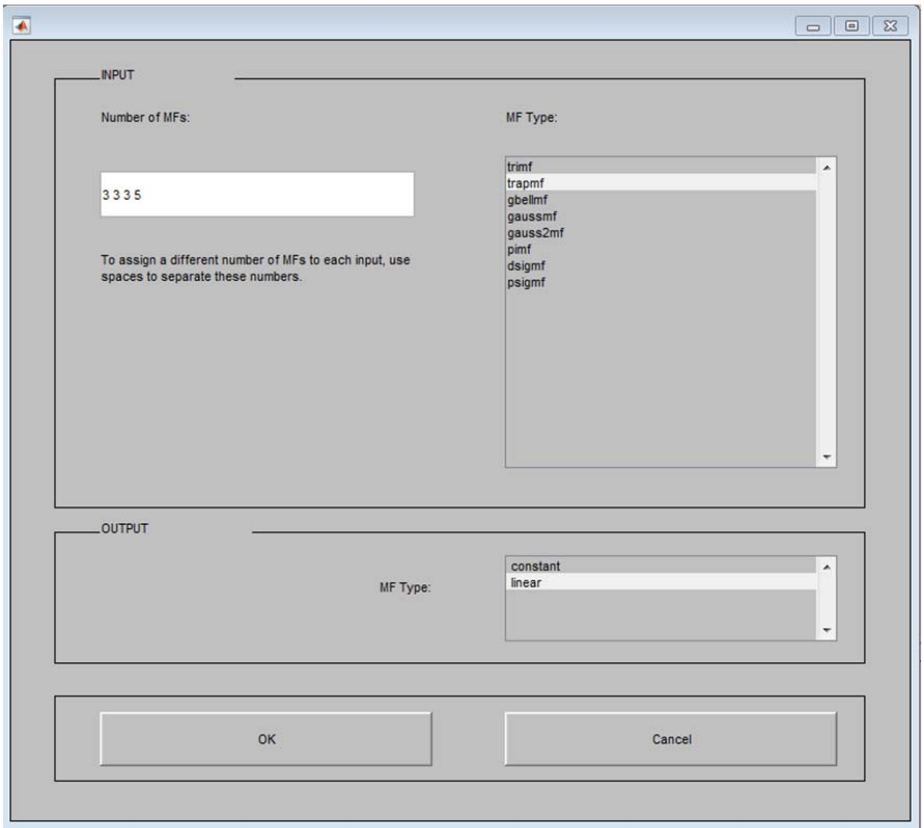

Fig. 7 Membership function selection

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TABLE VI
MODEL EVALUATIONS WITH TRAINING DATA OF ANFIS

S (RPM)	FR (Inch/min)	DOC (Inch)	C (ma)	Observed (Ra) (µm)	Predicted (Ra) (µm)	Accuracy (%)
700	6	0.04	5.5	3.871	3.88	99.45
700	6	0.02	3.8	1.965	1.96	99.74
700	6	0.03	4.5	3.179	3.18	99.96
900	6	0.03	4.25	2.275	2.26	99.34
900	6	0.02	3.95	1.341	1.38	97.01
900	6	0.04	5.75	2.703	2.7	99.88
1100	6	0.03	4.9	1.064	1.07	99.43
1100	6	0.04	5.35	1.288	1.29	99.21
1100	6	0.02	4.3	1.94	1.95	99.48
700	8	0.03	4.7	3.722	3.67	98.65
700	8	0.04	6.3	4.123	4.1	99.44
700	8	0.02	3.85	2.77	2.8	98.18
900	8	0.02	4.05	2	1.98	99.99
900	8	0.03	7.8	3.312	3.3	99.98
900	8	0.04	6.55	4.11	4.09	99.99
1100	8	0.02	4.15	1.124	1.13	99.01
1100	8	0.03	8	1.721	1.71	99.40
1100	8	0.04	6.7	2.113	2.1	99.38
700	10	0.04	6.8	4.186	4.17	99.61
700	10	0.02	4.45	3.955	3.98	99.36
700	10	0.03	5.4	3.989	4.1	97.21
900	10	0.02	4.4	3.121	3.9	75.04
900	10	0.04	6.9	3.878	3.85	99.27
900	10	0.03	6.15	3.449	3.46	99.42
1100	10	0.02	4.6	2.594	2.62	98.84
1100	10	0.04	7	2.893	2.92	98.96
1100	10	0.03	3.8	3.17	3.2	99.05
					Average Accuracy	98.30

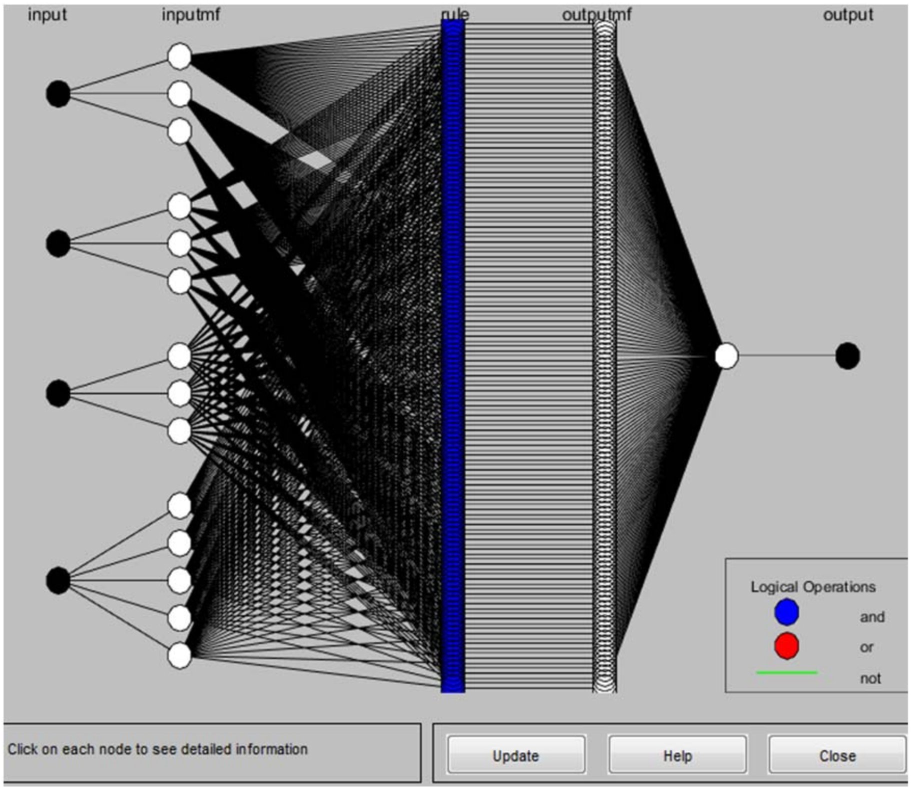

Fig. 8 ANFIS model

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TABLE VII
MODEL ACCURACY EVALUATION OF MAMDANI FIS

NO	S (RPM)	FR (I/m)	DOC (I)	C (ma)	Observed (Ra) (µm)	Predicted (Ra) (µm)	Accuracy (%)
1	800	7	0.025	4.75	3.41	3.14	92.08
2	800	8	0.04	6.55	4.15	3.82	92.05
3	800	9	0.035	6.7	3.77	3.54	93.90
4	950	7	0.02	4.35	1.7	1.75	97.06
5	710	6.5	0.03	5.1	3.28	3.48	93.94
6	810	9.2	0.04	7.1	3.9	3.77	94.87
7	1050	6.4	0.035	5.7	2.69	2.42	88.48
8	701	9.7	0.04	7.3	3.88	3.26	85.06
9	750	7.8	0.035	6.1	3.8	3.53	91.32
10	850	6.1	0.025	3.8	2.49	2.23	89.56
						Average Accuracy	91.83

TABLE VIII
MODEL ACCURACY EVALUATION OF ANFIS

No	S (RPM)	FR (I/m)	DOC (I)	C (ma)	Observed (Ra) (µm)	Predicted (Ra) (µm)	Accuracy (%)
1	850	6.1	0.025	3.8	2.49	2.4	96.39
2	800	8	0.04	6.55	4.15	3.98	96.14
3	800	9	0.035	6.7	3.77	3.45	91.51
4	950	7	0.02	4.35	1.7	1.67	97.06
5	710	6.5	0.03	5.1	3.28	3.17	96.64
6	810	9.2	0.04	7.1	3.9	3.6	92.31
7	1050	6.4	0.035	5.7	2.69	2.72	98.88
8	701	9.7	0.04	7.3	3.88	3.43	90.26
9	750	7.8	0.035	6.1	3.8	3.61	95.00
10	800	7	0.025	4.75	3.2	2.9	90.63
						Average Accuracy	94.19

IV. CONCLUSION

The purpose of this research was to develop an input current based in-process Ra prediction model, providing real-time Ra values during milling operations. This system aids in the decision making process during milling operations by utilizing the input current data collected. A fuzzy model of 135 rules was developed for predicting the Ra for a given set of inputs. The obtained fuzzy model was shown to be capable of predicting the Ra for a given set of inputs with more accuracy than with a regression model utilizing current. With this system, the operator can choose the optimal input parameters for minimum Ra. The model was evaluated by comparing the output of the FIS with the ANFIS output which are trained for 135 fuzzy rules and 135 neuro-fuzzy rules, respectively. The average accuracy values for both systems were 92.21% and 94.39%, respectively. This research could be further extended as following:

1. Different machining operations could be considered for further research under different parameter settings on various materials.
2. A completely different methodology such as neural networks (ANN) or gene expression programming (GEP) could be used for building a model and the prediction accuracy could be estimated.

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