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Design of adaptive neuro-fuzzy inference system for predicting surface roughness in turning operation

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This paper proposes an Adaptive Neuro-Fuzzy Inference System (ANFIS) for predicting the surface roughness in turning operation for set of given cutting parameters, namely cutting speed, feed rate and depth of cut. Two different membership functions, triangular and bell shaped, were adopted during the training process of ANFIS in order to compare the prediction accuracy of surface roughness by the two membership functions. The comparison of ANFIS values with experimental data indicates that the adoption of both triangular and bell shaped membership functions in proposed system achieved satisfactory accuracy. The bell-shaped membership function in ANFIS achieves slightly higher prediction accuracy than triangular membership function.

Keywords: Adaptive, Neuro-fuzzy system, Surface roughness, Turning

IPC Code: G 05 B 13/04

Introduction

A good-quality turned surface significantly improves fatigue strength, corrosion resistance, or creep life in manufacturing industry. Surface roughness (SR) also affects several functional attributes of parts, such as contact causing surface friction, wearing, light reflection, heat transmission, ability to distributing and holding a lubricant, and coating. Baradie[1], Bhattacharya[2] and Mital[3] used regression method to develop empirical relation between SR and cutting parameter. An effort[4] was made to predict SR in turning of high strength steel based on Response Surface Methodology (RSM). Polynomial networks[5] were considered to construct the relationship between the cutting parameters and cutting performance. An abductive network[6] was developed from experimental data to simulate SR in turning operation. Fang & Jawahir[7] used fuzzy set method to build a prediction model that concurrently defined SR. Azouzi & Guillot[8] utilized a neural network to construct an on-line prediction model for SR.

This paper proposes a new approach, Adaptive Neuro-Fuzzy Inference System (ANFIS), for predicting SR of the workpiece in turning operation for set of given cutting parameters, namely cutting speed, feed rate and depth of cut. In this study, two different types of membership functions (triangular and bell-shaped) are adopted for analysis in ANFIS training and compared their differences regarding the accuracy rate of SR prediction.

Adaptive Neuro-Fuzzy Inference System (ANFIS)

Fuzzy modelling[9] has found numerous practical applications in control and prediction. ANFIS is a new inference system, in which a universal approximator is introduced to represent highly non-linear functions. An adaptive neural network is a network structure consisting of a number of nodes connected through directional links. Each node is characterised by a node function with fixed adjustable parameters. Learning or training phase of a neural network is a process to determine parameter values to sufficiently fit the training data. ANFIS are fuzzy Sugeno models put in the framework of adaptive systems to facilitate learning and adaptation[10]. Considering a first-order Takagi, Sugeno and Kang (TSK) fuzzy inference system, a fuzzy model contains two rules[11]:

Rule 1: If v is V_1 and d is D_1 then $f_1= p_1v+q_1d+r_1$
Rule 2: If v is V_2 and d is D_2 then $f_2= p_2v+q_2d+r_2$

where p_1, p_2, q_1, q_2, r_1 and r_2 are linear parameters and V_1, V_2, D_1 and D_2 are non-linear parameters. A circle

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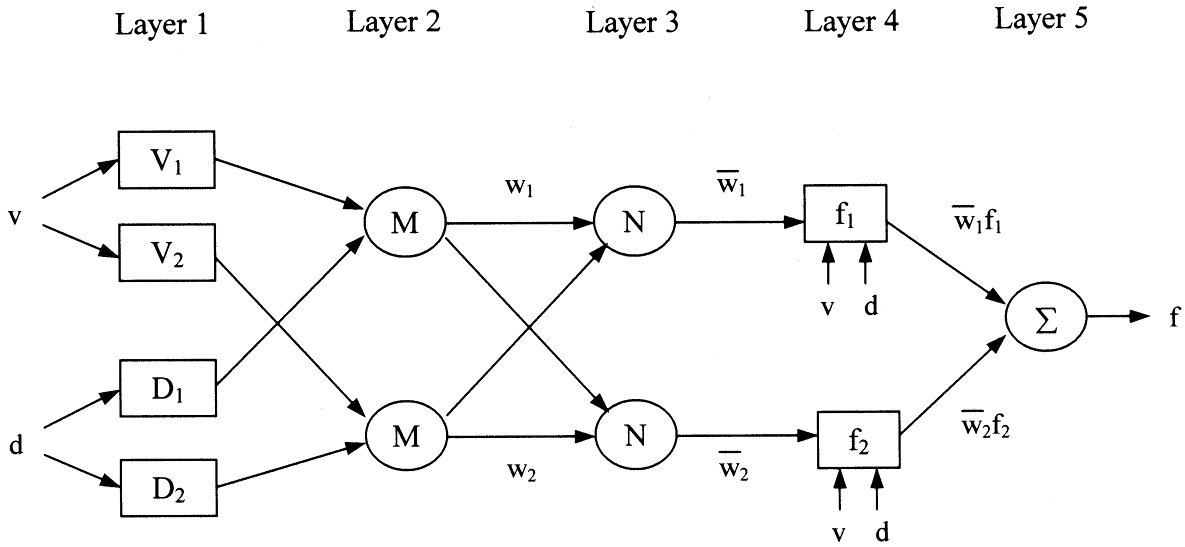

Fig. 1— Basic ANFIS architecture

indicates a fixed node whereas a square indicates an adaptive node i.e. the parameters are changed during adaptation or training and $O_{j,i}$ denotes the output of the i^{th} node in layer j. The entire system architecture consists of five layers, namely, the fuzzy layer, product layer, normalized layer, de-fuzzy layer and total output layer (Fig. 1).

Layer 1

Each node 'i' in this layer generates a membership grades of a linguistic label. It is the fuzzy layer, in which v and d are the input of nodes. V_1, V_2, D_1 and D_2 are the linguistic labels used in the fuzzy theory for dividing the membership functions. The membership relationship between the output and input functions of this layer can be expressed as below:

$$O_{1,i} = \mu_{Vi}(v); \qquad i=1, 2 \qquad \ldots (1)$$

$$O_{1,j} = \mu_{Dj}(d); \qquad j=1, 2 \qquad \ldots (2)$$

where $O_{1,i}$ and $O_{1,j}$ denote the output functions and μ_{Vi} and μ_{Dj} denote the membership functions.
Example 1: If the triangular membership function is employed, $\mu_{Vi}(v)$ is given by:

$$\mu_{V_i}(v) = \max\left[\min\left(\frac{v-a_i}{b_i-a_i}, \frac{c_i-v}{c_i-b_i}\right), 0\right] \qquad \ldots (3)$$

where a_i, b_i, and c_i are the parameters of the Membership Function (MF), governing the triangular membership functions accordingly.
Example 2: If the generalised bell-shaped membership function is employed, $\mu_{Vi}(v)$ is given by:

$$\mu_{V_i}(v) = \frac{1}{1+\left\{\left(\frac{v-c_i}{a_i}\right)^2\right\}^{b_i}} \qquad \ldots (4)$$

where a_i, b_i, and c_i are the parameters of the MF, governing the bell-shaped functions accordingly. Parameters in this layer are referred to as the 'premise parameters'

Layer 2

Each node in this layer calculates the 'firing strength' of each rule via multiplication:

$$O_{2,i} = w_i = \mu_{Vi}(v)\,\mu_{Dj}(d); \quad i=1, 2 \qquad \ldots (5)$$

where $O_{2,i}$ denotes the output of layer 2.

Layer 3

The i^{th} node of this layer calculates the ratio of the ith rule's strength to the sum of all rules' firing strengths.

$$O_{3,i} = \overline{w}_i = \frac{w_i}{w_1+w_2}, \ i=1, 2 \qquad \ldots (6)$$

For convenience, outputs of this layer $O_{3,i}$ will be called 'normalized firing' strength.

Layer 4

Every node 'i' in this layer is a square node with a node function:

$$O_{4,i} = \overline{w}_i f_i = \overline{w}_i(p_i v + q_i d + r_i), \ i=1, 2 \quad \ldots (7)$$

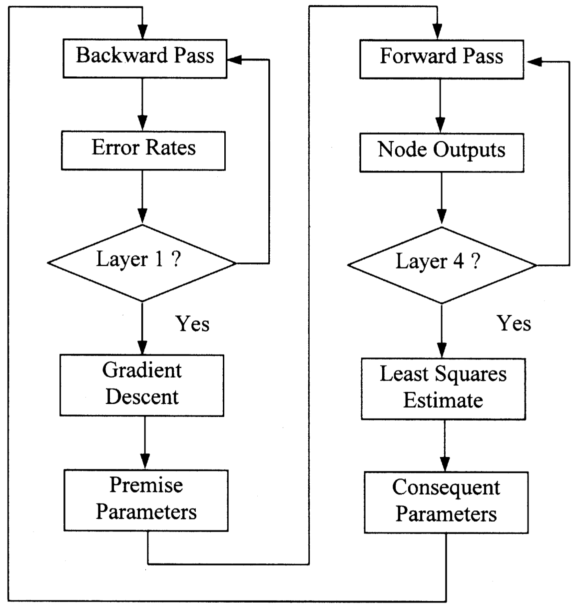

Fig. 2— A flowchart of hybrid learning procedure of ANFIS

where $O_{4,i}$ denotes the layer 4 output. In this layer, p_i, q_i, and r_i are called linear parameters or consequent parameters.

Layer 5

The single node in this layer is a circle node labelled 'Σ' that computes the 'overall output' as the summation of all incoming signals i.e.

$$O_{5,i} = \sum_i \overline{w}_i f_i = \frac{\sum_i \overline{w}_i f_i}{\sum_i w_i}, \qquad i=1, 2 \quad \ldots(8)$$

First and fourth layers are adaptive layers in ANFIS architecture. The modifiable parameters are so-called premise parameters in the first layer and consequent parameters in the fourth layer. The task of the learning is to tune all the modifiable parameters to make ANFIS output match the training data. To improve the rate of convergence, a hybrid learning algorithm (Fig. 2) combining the least square method and gradient descent method is adopted. The least square method is used to optimize the consequent parameters with the premise parameters fixed. Once the optimal consequent parameters are found, the gradient descent method is used to adjust optimally the premise parameters corresponding to the fuzzy sets in input domain. The output of ANFIS is calculated by employing consequent parameters. The output error is used to adapt the premise parameters by means of a standard back propagation algorithm.

Results and Discussion

A training database with regard to cutting parameters and surface roughness is essential to build an ANFIS for predicting SR of the turning operation. The experiment[12] was carried out using a CNC lathe with a tungsten carbide tool and working on S45C steel bars. Cutting speed (v), feed rate (f) and depth of cut (d) were selected as the cutting parameters to analyze their effect on SR (R_a). The ranges of the cutting parameters were selected as follows: v, 53.44-199.49 m/min; f, 0.06-0.52 mm/rev; and d, 0.5-1.5 mm. Based on the cutting parameter combinations, 70 turning experiments were performed. The SR (R_a) i.e. CLA value, was measured by a profile meter (Surfcorder SE-1100) within a sampling length of 8 mm and measurement speed of 0.5 mm/s.

In this study, a total of 50 sets of data were selected from the total of 70 sets obtained in the turning experiments[12] for the purpose of training in ANFIS (Table 1). This training adjusts the membership function parameters. In some cases, data is collected using noisy measurements, and the training data cannot be representative of all the features of the data that will be presented to the model. So, model

Table 1— Experimental data [12] for training data

Sl No	Cutting speed m/min	Feed rate mm/rev	Depth of cut, mm	Surface roughness µm
1	53.44	0.06	1.5	1.454
2	53.44	0.29	1.5	9.625
3	53.44	0.52	1.5	22.25
4	57.95	0.29	0.5	6.6
5	57.95	0.4	0.5	14.42
6	57.95	0.52	0.5	21.79
7	59.85	0.16	1.0	2.167
8	59.85	0.52	1.0	25.7
9	59.85	0.06	1.0	1.66
10	75.44	0.29	0.8	5.462
11	75.44	0.26	0.8	5.462
12	75.44	0.35	0.8	11.71
13	75.7	0.16	1.5	2.465
14	75.7	0.29	1.5	9.573
15	75.7	0.52	1.5	22.33
16	77.5	0.32	1.2	11.23
17	77.5	0.35	0.8	11.28
18	77.5	0.45	0.8	21.16
19	77.5	0.45	1.2	20.06
20	81.58	0.06	0.5	0.824
21	81.58	0.52	0.5	23.15
22	81.58	0.29	0.5	6.815
23	81.58	0.4	0.5	14.75
24	84.78	0.52	1.0	23.71
25	84.78	0.16	1.0	1.871
26	84.78	0.29	1.0	6.432
27	88.79	0.2	1.0	3.596

Contd—...

Table 1— Experimental data [12] for training data—(Contd.)

Sl No	Cutting speed m/min	Feed rate mm/rev	Depth of cut, mm	Surface roughness µm
28	106.88	0.29	1.5	8.332
29	106.88	0.06	1.5	0.815
30	106.88	0.16	1.5	2.336
31	106.88	0.52	1.5	22.72
32	115.17	0.16	0.5	2.184
33	115.17	0.29	0.5	7.176
34	115.17	0.4	0.5	15.97
35	115.17	0.52	0.5	23.46
36	119.69	0.06	1.0	0.825
37	119.69	0.52	1.0	24.72
38	119.69	0.16	1.0	2.265
39	129.12	0.2	1.0	3.797
40	129.12	0.26	1.0	5.332
41	178.13	0.16	1.5	2.545
42	178.13	0.4	1.5	17.01
43	178.13	0.52	1.5	23.26
44	191.95	0.06	0.5	0.664
45	191.95	0.16	0.5	2.161
46	191.95	0.29	0.5	7.273
47	191.95	0.4	0.5	15.08
48	199.49	0.16	1.0	2.385
49	199.49	0.52	1.0	26.39
50	199.49	0.29	1.0	7.026

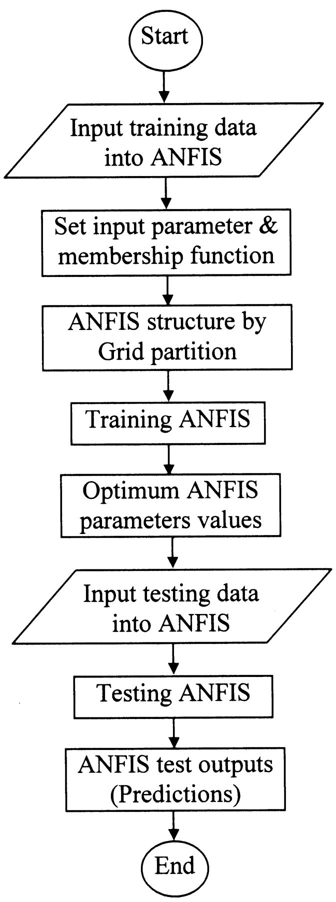

Fig. 3— A flowchart for predicting surface roughness using ANFIS

validation is needed to cross validate the fuzzy inference system using testing data set. The testing data set is useful in checking the generalization capability of the resulting fuzzy inference system. That is why the other 20 sets were then used for testing after the training was completed to verify the accuracy of the predicted values of SR. Fig. 3 shows the flowchart for predicting the SR using ANFIS. The schematic of the structure of the ANFIS used in here is shown in Fig. 4. The ANFIS was implemented by using the MATLAB version 6.0 software package.In this study, v, f and d are the inputs and R_a is the output of the system. Triangular shape and bell shape are used for the MF distribution for the input variables. First-order TSK fuzzy inference system is used in this work. The number of fuzzy rules in a fuzzy system is related to the number of fuzzy sets for each input variables. The three inputs (v, f, d) of the fuzzy inference system are classified into 3 fuzzy sets each (Table 2). Therefore, maximum number of rules for this system can be 27. Thus, a typical rule will look as follows:

$$SR = p_i v_i + q_i f_i + r_i d_i + c_i$$

where p_i, q_i, r_i, c_i are the design parameters referred as consequent parameters; v_i is medium cutting speed; f_i is high feed rate; and d_i is shallow depth of cut.

During training in ANFIS, 50 sets of experimental data were used to conduct 500 cycles of learning. ANFIS learning numbers for predicting SR are as follows: nodes, 78; linear parameters, 108; non-linear parameters, 27; total number of parameters, 135; and fuzzy rules, 27. The values of premise parameters of the triangular MF (Table 3) and bell–shaped MF (Table 4) and that of consequent parameters for triangular MF (Table 5) and bell-shaped MF (Table 6) were tabulated for fuzzy system obtained after training for modelling SR. Table 7 compares the predicted values and experimental data[12] of SR after training by ANFIS with triangular and bell shaped MFs for some of the training cases. Simulation result shows that the average error of the prediction of SR in triangular MF (1.88 %) is more than in bell-shaped MF (1.52 %). The average error of the prediction (Table 8) of SR is 3.87 percent (accuracy, 96.13 %) when triangular MF is used in ANFIS. When the bell shaped MF is adopted, the average error is 2.16 percent (accuracy, 97.84 %). These results indicate that the training of ANFIS with the bell-shaped MF obtains a higher accuracy rate in the prediction of SR.

Table 2— Fuzzy expressions for different parameters

(a) Spindle speed

Abbreviation	Fuzzy expression
SS	Slow speed
MS	Medium speed
HS	High speed

(b) Feed rate

Abbreviation	Fuzzy expression
LF	Low feed
MF	Medium feed
HF	High feed

(c) Depth of cut

Abbreviation	Fuzzy expression
SA	shallow
MD	Medium deep
DE	Deep

Table 3— Premise parameters of fuzzy system for triangular MF

	a_i	b_i	c_i
Cutting speed			
SS	-19.585	53.4400	126.4649
MS	53.4399	126.4650	199.4899
HS	126.4649	199.4899	272.515
Feed rate			
LF	-0.17	0.0575	0.2943
MF	0.0845	0.2842	0.5205
HF	0.2966	0.5176	0.7499
Depth of cut			
SA	-1.6050	0.5000	0.9997
MD	0.5002	1.0000	1.4999
DE	1.0000	1.4999	2.0000

Table 4— Premise parameters of fuzzy system for Bell-shaped MF

	a_i	b_i	c_i
Cutting speed			
SS	36.5123	2.0003	53.4399
MS	36.5124	2.0010	126.4650
HS	36.5125	2.0000	199.4899
Feed rate			
LF	0.1401	2.0002	0.0846
MF	0.0819	2.0003	0.2235
HF	0.1228	2.0006	0.5037
Depth of cut			
SA	0.2516	2.0002	0.5029
MD	0.2446	2.0000	1.0033
DE	0.2496	2.0001	1.4996

Table 5— Consequent parameter of the fuzzy system for triangular MF

Rule No	p_i	q_i	r_i	t_i
1	-0.17060	-11.64476	44.30318	-9.69684
2	0.15649	-99.51514	-24.83805	24.32295
3	0.02816	-79.98314	2.14700	1.43133
4	0.21546	13.71289	37.86299	-27.67066
5	-0.28536	-78.77041	-7.52525	53.37916
6	0.03722	-41.91655	12.33587	2.09562
7	-0.36337	10.33789	-93.34798	82.33232
8	1.55282	-252.08611	107.28321	-32.52566
9	0.44583	-45.37420	8.71821	9.32337
10	-0.10699	-16.40513	23.23995	4.09537
11	0.18210	-159.07070	-16.90325	4.29305
12	0.03490	-29.94511	-0.90651	-0.60434
13	0.22465	2.19996	-66.28189	11.69619
14	-0.25471	-162.32660	77.28198	9.65695
15	0.06775	-12.25540	3.18980	-0.88473
16	-0.40461	-12.09159	231.39895	-34.79706
17	1.68536	59.85889	-232.48613	13.76989
18	0.54888	-53.07793	-8.48588	-3.93193
19	0.01126	-12.56613	0.000029	0.000058
20	0.10278	-19.13504	-9.23500	-9.23501
21	0.00626	-18.65535	0.000052	0.000035
22	0.01609	9.14125	0.00004	0.00008
23	0.24415	-2.19976	-20.42272	-20.42272
24	0.02431	12.60998	0.00020	0.00013
25	0.12656	2.14091	0.00032	0.00065
26	0.08594	17.86401	0.00043	0.00043
27	0.04839	4.17814	0.00041	0.00027

Table 6— Consequent parameter of the fuzzy system for bell-shaped MF

Rule No	p_i	q_i	r_i	t_i
1	0.07310	-33.10297	175.34154	-89.94133
2	0.38514	22.77621	-157.05416	132.50356
3	-0.00738	-15.36495	1.20214	5.64829
4	0.63080	12.45609	32.18072	-40.47414
5	-0.44922	51.70986	31.58688	-19.17141
6	0.17450	57.06958	-30.12885	32.74632
7	-0.49890	56.15830	7.27829	14.11275
8	-0.01277	56.40696	53.17510	-55.25740
9	-0.00237	46.20957	-22.55829	32.30843
10	0.34876	-65.38954	-30.71980	-21.88283
11	0.58470	-71.94376	-13.17707	-54.09891
12	0.16146	-12.87065	-9.64537	-0.78141
13	1.30340	-9.71655	-171.53032	-49.70191
14	-0.66257	8.20286	180.41080	-81.55698
15	0.55361	25.02264	-41.26352	-1.97607
16	-1.19073	40.70998	183.62246	48.10388
17	0.18375	192.12029	-159.00193	56.49753
18	0.31064	19.71633	-8.76109	-3.18570
19	-0.00660	-21.61128	0.67975	0.35946
20	-0.08057	-20.79546	7.70445	7.69763
21	-0.01186	-25.71681	0.24755	0.47531
22	-0.01625	21.65732	-3.41829	-0.37620
23	0.05386	17.33856	1.77075	-4.28392
24	-0.01515	31.86826	-1.31750	-0.18095
25	0.01163	50.75483	3.50842	-0.02172
26	-0.04056	82.61509	-6.42134	-1.90987
27	-0.01816	43.64783	-0.43259	-0.14132

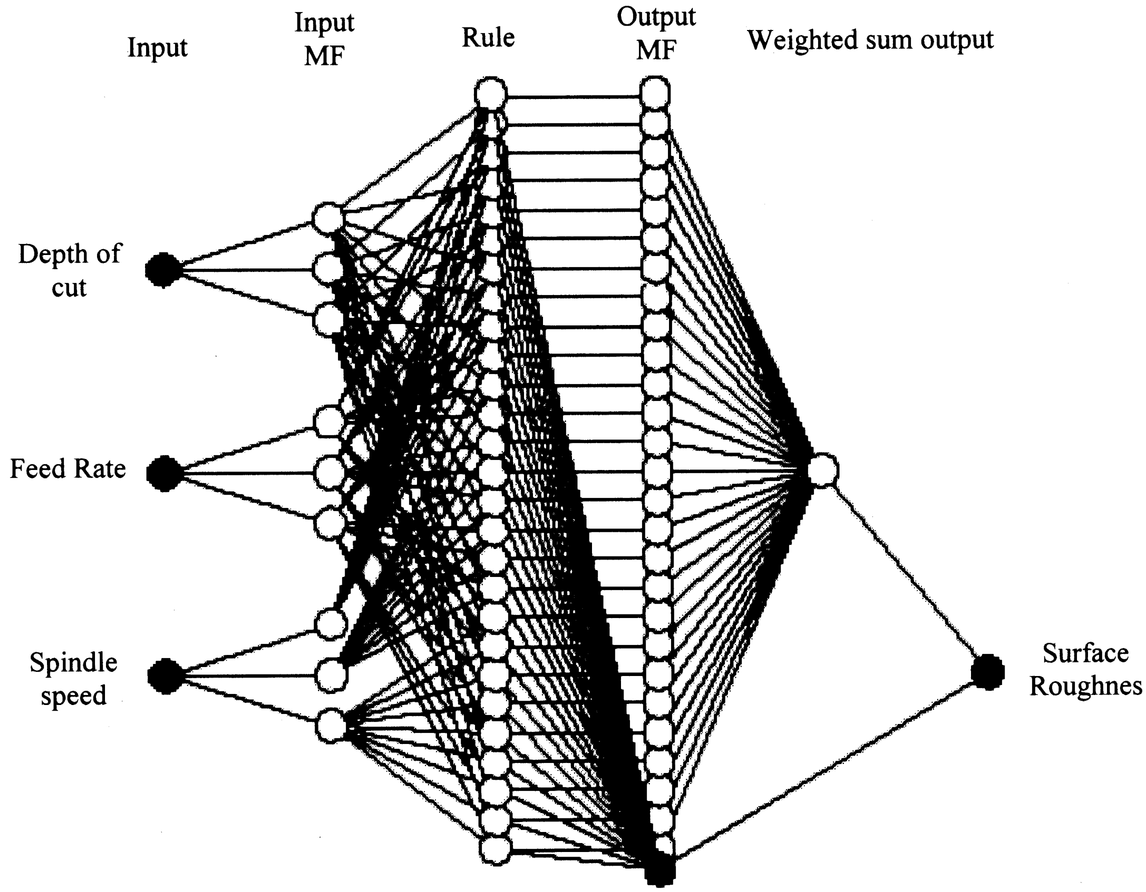

Fig. 4— Schematic ANFIS structure used for modeling surface roughness

Table 7— Comparison of surface roughness predicted from ANFIS and experimental values for some of the training cases[12]

Cutting speed m/min	Feed rate mm/rev	Depth of cut, mm	Surface roughness Experimental result µm	ANFIS predicted value			
				Triangular MF		Bell-shaped MF	
				Surface roughness µm	Abs. % error	Surface roughness µm	Abs % Error
53.44	0.06	1.5	1.454	1.36	6.464	1.42	2.338
53.44	0.29	1.5	9.625	9.93	3.168	9.61	0.156
57.95	0.52	0.5	21.79	21.9	0.504	22	0.964
59.85	0.06	1.0	1.66	1.64	1.204	1.65	0.602
75.44	0.26	0.8	5.462	5.46	0.036	5.39	1.318
75.7	0.16	1.5	2.465	2.24	9.127	2.33	5.477
77.5	0.32	1.2	11.23	11.2	0.267	11.2	0.267
77.5	0.45	1.2	20.06	20.1	0.199	20.1	0.199
81.58	0.52	0.5	23.15	23	0.648	22.9	1.079
84.78	0.16	1.0	1.871	1.91	2.084	1.86	0.588
88.79	0.2	1.0	3.596	3.63	0.945	3.52	2.113
106.88	0.06	1.5	0.815	0.746	8.466	0.807	0.982
106.88	0.52	1.5	22.72	23	1.232	22.8	0.352
115.17	0.4	0.5	15.97	15.8	1.064	15.9	0.438
119.69	0.06	1.0	0.825	0.811	1.697	0.746	9.575
119.69	0.16	1.0	2.265	2.29	1.104	2.29	1.103
129.12	0.26	1.0	5.332	5.29	0.788	5.36	0.525
178.13	0.4	1.5	17.01	17	0.059	17	0.058
191.95	0.29	0.5	7.273	7.28	0.096	7.28	0.096
199.49	0.52	1.0	26.39	26.4	0.038	26.4	0.038

Table 8— Comparison of surface roughness predicted from ANFIS and experimental values for some of the test cases[12]

Cutting speed m/min	Feed rate mm/rev	Depth of cut, mm	Surface roughness Experimental result μm	ANFIS predicted value			
				Triangular MF		Bell-shaped MF	
				Surface roughness, μm	Abs. % Error	Surface roughness, μm	Abs. % Error
53.44	0.16	1.5	2.213	2.36	6.642	2.32	4.835
53.44	0.40	1.5	17.16	16.5	3.846	16.6	3.263
57.95	0.06	0.5	2.375	2.28	4.00	2.32	2.315
57.95	0.16	0.5	2.525	2.68	6.138	2.66	5.346
59.85	0.29	1.0	7.042	7.02	0.312	7.03	0.170
75.44	0.32	0.80	8.143	8.21	0.822	8.06	1.019
75.44	0.45	0.8	19.89	20.0	0.553	20.1	1.055
75.70	0.06	1.5	0.883	1.04	17.78	0.925	4.756
75.70	0.40	1.5	15.05	16.2	7.641	15.8	4.983
79.07	0.23	1.5	5.653	5.61	0.761	5.65	0.053
81.58	0.16	0.5	2.331	2.07	11.196	2.15	7.765
84.78	0.06	1.0	0.979	0.989	1.021	0.995	1.634
88.79	0.2	1.0	4.911	4.74	3.482	4.98	1.405
106.88	0.40	1.5	17.9	17.4	2.793	17.8	0.559
115.17	0.06	0.5	0.882	0.816	7.483	0.86	2.494
119.69	0.29	1.0	6.713	6.67	0.193	6.69	0.342
129.12	0.23	1.0	4.555	4.66	2.305	4.52	0.768
191.95	0.52	0.5	22.44	22.4	0.178	22.4	0.178
178.13	0.29	1.5	9.034	9.03	0.044	9.04	0.066
199.49	0.40	1.0	15.26	15.30	0.262	15.30	0.262

This is because SR exhibits non-linearity with respect to cutting parameters.

Conclusions

An ANFIS based on first-order Takagi, Sugeno and Kang fuzzy inference system is used to predict SR in turning operation. By employing the hybrid learning algorithm, ANFIS can obtain the optimal triangular and bell shaped membership functions of the fuzzy system. A total of 50 sets of experimental data are used for training in ANFIS. After the training is completed, another 20 sets of data are used as testing data. SR values predicted by ANFIS are compared with the measurement values derived from the 20 data sets in order to determine the error of ANFIS. The error of SR values predicted by ANFIS with triangular membership function is 3.87 percent (accuracy, 96.13 %). In contrast, the error by ANFIS with bell-shaped membership function is 2.16 percent (accuracy, 97.84 %). The comparison indicates that the adoption of both triangular and bell-shaped membership functions in ANFIS achieved very satisfactory accuracy. The bell-shaped membership function in ANFIS achieves slightly higher prediction accuracy than triangular membership function.

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