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*Corresponding author: Ch. Sanjay,
GITAM University, Hyderabad, India
E-mail: sasch_cheen2007@yahoo.com

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Technology, China

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Hybrid intelligence systems and artificial neural network (ANN) approach for modeling of surface roughness in drilling

Ch. Sanjay^{1*} and Ch. Prithvi¹

Abstract: In machining processes, drilling operation is material removal process that has been widely used in manufacturing since industrial revolution. The useful life of cutting tool and its operating conditions largely controls the economics of machining operations. Drilling is most frequently performed material removing process and is used as a preliminary step for many operations, such as reaming, tapping, and boring. Drill wear has a bad effect on the surface finish and dimensional accuracy of the work piece. The surface finish of a machined part is one of the most important quality characteristics in manufacturing industries. The primary objective of this research is the prediction of suitable parameters for surface roughness in drilling. Cutting speed, cutting force, and machining time were given as inputs to the adaptive fuzzy neural network and neuro-fuzzy analysis for estimating the values of surface roughness by using 2, 3, 4, and 5 membership functions. The best structures were selected based on minimum of summation of square with the actual values with the estimated values by artificial neural fuzzy inference system (ANFIS) and neuro-fuzzy systems. For artificial neural network (ANN) analysis, the number of neurons was selected from 1, 2, 3, ... , 20. The learning rate was selected as .5 and .5 smoothing factor was used. The inputs were selected as cutting speed, feed, machining time, and thrust force. The best structures of neural networks were selected based on the criteria as the minimum of summation of square with the actual value of surface roughness. Drilling experiments with 10 mm size were performed at two cutting speeds and feeds. Comparative analysis has been done between the actual values and the estimated values obtained by ANFIS, neuro-fuzzy, and ANN analysis.

Keywords: twist drills, surface roughness, artificial neural fuzzy inference system (ANFIS), neuro-fuzzy, artificial neural network (ANN)

ABOUT THE AUTHOR



Ch. Sanjay received his in BTech from Walchand Institute of Technology, ME in CAD/CAM, Pune University, PhD on "Manufacturing Engineering" by RGPV, Bhopal (QIP). He has joined as a Director Campus in GITAM University, Hyderabad in May, 2009. He is the recipient of several national and international awards. He is well-known academician, researcher, academic administrator, and consultant. An expert in Mechanical Engineering, he has published 4 books and 60 research articles. He has been a research guide for various universities at national and international level and has delivered expert lectures all over the country and guided 3 PhD and 56 MTech Students. He has carried out research projects for the Government University of Malaysia and has organized many national and international seminars/ workshops/ conferences/FDP. He is a reviewer and a member of editorial boards for 26 national and international journals in various areas.

1. Introduction

Due to increasing demand of higher precision components for its functional aspect, surface roughness of a machined part plays an important role in the modern manufacturing process. Drilling is a complicated process and many factors determine the life and wear of a drill. Because of their importance in nearly all production operations, twist drills have been the subject of numerous investigations. The various factors that affect surface roughness are vibrations, material of the work piece, type of machining, rigidity of the system consisting of machine tool, work holding devices, material of tool and work piece, cutting conditions, and type of coolants used. Surface finish has been an important design feature and quality measure in many situations such as parts subject to fatigue loads, precision fits, fastener holes, and esthetic requirements; furthermore, surface roughness, in addition to tolerances, imposes one of the critical constraints for cutting parameter selection in manufacturing process pl artificial neural network (ANN). Surface roughness is a vital property of machined surface for fatigue and corrosion resistance. Therefore, it is an important aspect to obtain lower surface roughness for a longer life of machined surface parts. A considerable amount of studies have investigated the general effects of speed, feed, and depth of cut on surface roughness.

Surface roughness measurements can be divided into two approaches such as direct and indirect contact methods. Direct method depends upon using stylus instruments, which require direct contact with the surface to be investigated. Stylus instruments have limited flexibility in handling the different geometrical parts to be measured. In addition to this, measurement speed of stylus instruments is also slow. Indirect method measurement methods use optical instruments, which are inherently no contact measurement and are easy to operate. A considerable amount of studies have investigated the general effects of speed, feed, and depth of cut on surface roughness. The surface roughness models developed by Grieve et al. (2004), Dickinson (1967/1968), and Fischer and Elrod (1971) considered the effect of feed rate and nose radius in turning operation. The depth of cut and effect of cutting fluid was considered in the mathematical models developed by Karmakar (1970), Taraman and Lambert (1972). Miller, O'Kane, Niec, Carmichael, and Carmichael (2013), Boothroyd and Knight (1989), and Feng and Wang (2003) have demonstrated that cutting speed had significant impact on surface roughness despite its complex nature of cutting (Venkatesh & Zhou, 1997).

Li and Wu (1998) used fuzzy pattern recognition techniques for estimation of wear states in drilling operation. Li and Wong (1999) used optical scattering image and hybrid intelligent techniques for tool wear detection in turning operation. Feng and Wang (1999) have demonstrated the use of regression and neural network approach for predicting the surface roughness in drilling operation. Lee and Tarang (2001) used computer vision technique for modeling of surface roughness in turning operation. Jantuen (2002) has described in detail the various methods applied for tool condition monitoring in drilling. Ho and Lee (2002) have used computer vision techniques in modeling and prediction of surface roughness in turning operation. Abu Mahfouz (2003) has demonstrated the use of vibration signals and ANN in drill wear detection and classification.

Benardos and Vosnikos (2003) have described the various methods in prediction of surface roughness in machining operations. Ho and Lee (2004) have used adaptive fuzzy inference systems in accurate modeling and prediction of surface roughness in turning operation. Lee and Jang (2004) estimated surface roughness from the texture features of the surface image using an adaptive neuro-fuzzy inference system in drilling operation. Du and Yeung (2004) have utilized fuzzy transition probability, a new approach for monitoring progressive faults in machining operations. Kindi and Bau (2005) have demonstrated the use of machine vision technique in automated inspection of engineering surface in turning operation. Panda and Chakraborty (2008) have applied back propagation neural network approach and radial basis function network for prediction flank wear in drilling operation. Ciurana and Arias (2009) have used neural network modeling for the influence of process parameters on feature geometry and surface quality in pulsed laser micromachining of hardened AISI H13 steel. Salimi and Zadshakoyan have studied drill wear predication system using motar current and fuzzy logic method (Salimi, Zadshakoyan, Özdemir, & Seidi, 2013). Kalaichelvi and Karthikeyan have demonstrated tool wear classification using fuzzy logic for machining of AL/SIC

Composite Material (Ganesh Ram, Dsouza, Kalaichelvi, & Karthikeyan, 2014). Chandrasekaran and Devarasiddappa have described various models of surface roughness in end Milling (Chandrasekaran & Devarasiddappa, 2014). Marek Vrabel and Ildiko Mankova have used ANN for Udimet 720 for prediction of surface roughness drilling (Beňo, Maňková, Vrabel, & Kottfer, 2013). Harun Akkus and Ilhan Asiturk have predicted surfaces of AISI 4140 Steel in Hard Turning process through ANN (Asiltürk & Akkuş, 2011). Panda and Chakraborty have studied drill flank wear using radial basis function neural network (Singh, Panda, Chakraborty, & Pal, 2005). Sivarao and Castillo have used expert system such as neural network and fuzzy logic for prediction of surface roughness in drilling process (Sivarao, 2005).

Fuzzy logic is a body of concepts and techniques for dealing with imprecision, information granulation, approximate reasoning, and computing with words. Neural networks, on the other hand, are used to induce knowledge or functional relationships from instances of sampled data. A contrasting feature of neural and fuzzy techniques is that while traditionally fuzzy knowledge is obtained from human experts, neural network relationships are usually automatically learned from a training process that iterates through a sample data. Fuzzy system design does not incorporate any learning, while neural networks do not possess mechanisms for explicit knowledge representation. Fuzzy logic and neural networks are natural complementary tools in building intelligent systems. Neural networks are low-level computational structures that perform well when dealing with raw data, whereas fuzzy logic deals with reasoning on a higher level, using linguistic information acquired from domain experts. However, fuzzy systems lack the ability to learn and cannot adjust themselves to a new environment. The merger of a neural network with fuzzy systems therefore forms a promising approach for building intelligent systems. Hybrid intelligent systems are systems that combine at least two intelligent technologies. Artificial neural fuzzy inference system (ANFIS) method is superior to the modeling methods such as autoregressive model, cascaded-correlation NN, back propagation NN, sixth-order polynomial, and linear methods, and by a chaotic time series prediction problem. To improve the accuracy of predicting surface roughness, this study uses three more powerful learning tools ANFIS, neuro-fuzzy systems, and ANN. ANFIS corresponds to the first-order Sugeno fuzzy model. It applies the combination of the least square method and the back propagation gradient descent method for training fuzzy inference system membership function parameters to emulate a given training data-set. The ANFIS is represented by a neural network with six layers such as input, fuzzification, fuzzy rule, normalization, defuzzification, and summation. In the forward pass, a training set of input patterns is presented, neuron outputs are calculated on a layer by layer basis, and rule consequent parameters are identified by the least square method. In the backward pass, the error signals are propagated back and the rule antecedent parameters are updated according to the chain rule. Using hybrid-learning procedure, ANFIS can construct an input-output mapping based on human knowledge (in the form of fuzzy, if-then rules) and stipulate input-output data pairs [23]. The inputs were selected as cutting speed, machining time, and thrust force; the resulting network represented model can effectively predict process outputs, when the process inputs are given.

The fuzzy inference system is a popular computing framework based on concepts of fuzzy set theory, fuzzy if-then rules, and fuzzy reasoning. It has found successful applications in a wide variety of fields such as automatic control, data classification, decision analysis, expert systems, time series prediction, robotics, and pattern recognition. Integrated neuro-fuzzy can combine the parallel computation and learning abilities of neural networks with the human, like knowledge representation and explanation abilities of fuzzy systems. A neuro-fuzzy system is in fact a neural network that is functionally equivalent to a fuzzy inference model. The network consists of five layers such as input, fuzzification, fuzzy rule, output membership, and defuzzification. It can be trained to develop if-then fuzzy rules and determine membership functions for input and output variables of the system. Expert knowledge can be easily incorporated into the structure of the neuro-fuzzy system.

An ANN consists of a number of very simple and highly interconnected processors called neurons, which are analogous to the biological neurons in the brain. The neurons are connected by weighted links that pass signals from one neuron to another. A multi-layer perceptron is a feed forward neural

network with an input layer of source neurons, hidden layer, and output layer. These networks are designed to stimulate the information processing of the human brain. These networks have been successfully applied to industrial problems in the areas of pattern classification and automatic control [24]. An ANN that uses back propagation algorithms for modeling of surface roughness has been developed using machining process parameters as inputs and surface roughness as output. Making connections from the input layer to the output layer improves the learning efficiency. Two data-sets were used for the training of neural network, the learning rate used was .01, and no smoothing factor was used. The initial weights are assigned randomly between .1 and .8; the learning process was stopped after 15,000 iterations.

2. Experimental procedure

The parameters that affect surface roughness like tool hardness, tool geometry, work piece hardness, temperature, and rigidity of machine tool were assumed as constant in the different set of tests. The drilling experiments were carried out on a radial drilling machine. The twist drills were made up of high-speed steel and the diameter of the drill was selected as 10mm. Cutting speeds were selected as (12.31 and 17.9m/min) and feeds were selected as (.19 and .285 mm/rev). Indian tool Manufacture (tuper shank twist drills) as per the twist drill machy data for mild steel recomended as suitable and easy available Indian cutting tool manufacture. The number of holes was selected as 1–40. The work piece material was selected as mild steel bar and the drill depth was maintained as 30 mm. Two experiments were carried out using two cutting speeds and feeds. A digital type of drill dynamometer was used to measure the thrust force and torque. Surf test (S J 400) was used to measure the actual values of surface roughness. The experimental data have been shown in Tables 1 and 2.

Table 1. Diameter: 10 mm, speed: 12.31 m/min, feed: .95 mm/rev

Hole No.	MT (min)	Force (N)	Torque (Nm)	Ra (microns)
1	.358	2015.21	8.83	4.7
5	1.8	2077.51	9.125	4.9
10	3.59	2160.89	9.615	5.46
15	5.376	2250	10.1	5.51
20	7.166	2355.4	10.7	5.94
25	8.96	2469	16.58	6.43
30	10.746	2608.12	17.72	7.83
35	12.536	2783	17.85	8.54
40	14.326	3010	18.44	9.28

Table 2. Diameter: 10 mm, speed: 17.9 m/min, feed: .285 mm/rev

Hole No.	MT (min)	Force (N)	Torque (Nm)	Ra (microns)
1	.1723	2453	10.79	4.39
5	.8615	2580.16	10.86	4.71
10	1.723	2678.67	12.078	5.32
15	2.6	2796.42	12.848	5.49
20	3.45	2923.98	13.614	5.87
25	4.307	3031.9	14.35	6.54
30	5.17	3179	15.01	7.84
35	6.03	3316.5	16.587	8.47
40	6.912	3579.65	19	10

3. ANFIS analysis

Jang's ANFIS is normally represented by a six-layer feed forward neural network. Figure 1 shows the ANFIS architecture that corresponds to the first-order Sugeno fuzzy model. In this network, ANFIS has two inputs x_1 and x_2 and one output y . Each input is represented by two fuzzy sets and the output by a first-order polynomial.

The ANFIS system used in this study implements four rules:

Rule 1:

IF x_1 is A1
 AND x_2 is B1
 THEN $y = f_1 = k_{10} + k_{11}x_1 + k_{12}x_2$

Rule 2:

IF x_1 is A2
 AND x_2 is B2
 THEN $y = f_2 = k_{20} + k_{21}x_1 + k_{22}x_2$

Rule 3:

IF x_1 is A2
 AND x_2 is B1
 THEN $y = f_3 = k_{30} + k_{31}x_1 + k_{32}x_2$

Rule 4:

IF x_1 is A1
 AND x_2 is B2
 THEN $y = f_4 = k_{40} + k_{41}x_1 + k_{42}x_2$

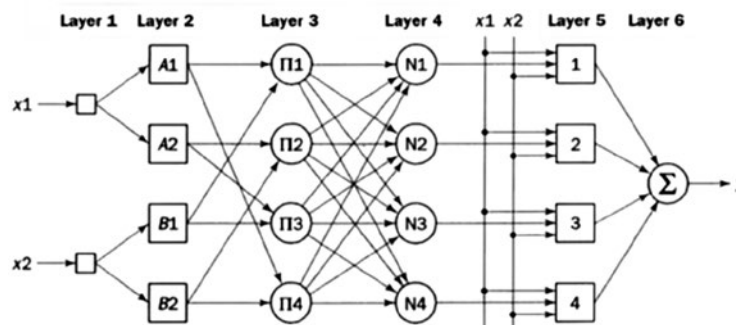
where x_1 and x_2 are input variables, A1 and A2 are fuzzy sets on the universe of discourse x_1 , B1 and B2 are fuzzy sets on the universe of discourse x_2 , and k_{i0} , k_{i1} , and k_{i2} is a set of parameters specified for rule i .

Layer 1: Is the input layer.

$$y_i^{(1)} = x_i^{(1)} \tag{1}$$

where $x_i^{(1)}$ is the input and $y_i^{(1)}$ is the output of input neuron i in Layer 1.

Figure 1. Artificial neural fuzzy inference system (ANFIS).



Layer 2: In this model, fuzzification neurons have a bell activation function.

A bell activation function, which has regular bell shape, is specified as:

$$y_i^{(2)} = \frac{1}{1 + \left(\frac{x_i^{(2)} - a_i}{c_i}\right)^{2b_i}} \quad (2)$$

where $x_i^{(2)}$ is the input and $y_i^{(2)}$ is the output of neuron i in Layer 2, and a_i , b_i and c_i are parameters that control center, width, and slope of the bell activation function of neuron i , respectively.

Layer 3: Is the rule layer. Each neuron in this layer corresponds to a single Sugeno-type fuzzy rule. A rule neuron receives inputs from the respective fuzzification neurons and calculates the firing strength of the rule it represents. Thus, the output of neuron i in Layer 3 is obtained as:

$$y_i^{(3)} = \prod_{j=1}^k x_{ji}^{(3)} \quad (3)$$

where $x_{ji}^{(3)}$ are the inputs and $y_i^{(3)}$ is the output of rule neuron i in Layer 3. For example,

$$y_{\Pi 1}^{(3)} = \mu_{A1} \times \mu_{B1} = \mu_1 \quad (4)$$

where the value of μ_i represents the firing strength, or the truth value, of Rule 1.

Layer 4: Is the normalization layer. The normalized firing strength is the ratio of the firing strength of a given rule to the sum of firing strengths of all rules. It represents the contribution of a given rule to the final result.

The output of neuron i in the Layer 4 is determined as:

$$y_i^{(4)} = \frac{x_{ii}^{(4)}}{\sum_{j=1}^n x_{ji}^{(4)}} = \frac{\mu_i}{\sum_{j=1}^n \mu_j} = \mu_i \quad (5)$$

where $x_{ji}^{(4)}$ is the input from neuron j located in Layer 3 to neuron i in Layer 4, and n is the total number of rule neurons.

$$y_{N1}^{(4)} = \frac{\mu_1}{\mu_1 + \mu_2 + \mu_3 + \mu_4} = \mu_1 \quad (6)$$

Layer 5: Is the defuzzification layer. Each neuron in this layer is connected to the respective normalization neuron, and also receives initial inputs, x_1 and x_2 . A defuzzification neuron calculates the weighted consequent value of a given rule as:

$$y_i^{(5)} = x_i^{(5)} [k_{i0} + k_{i1}x_1 + k_{i2}x_2] = \mu [k_{i0} + k_{i1}x_1 + k_{i2}x_2] \quad (7)$$

where $x_i^{(5)}$ is the inputs and $y_i^{(5)}$ is the output of defuzzification neuron i in Layer 5, and k_{i0} , k_{i1} , and k_{i2} is a set of consequent parameters of rule i .

Layer 6: Is represented by a single summation neuron. This neuron calculates the sum of outputs of all defuzzification neurons and produces the overall ANFIS output, y (Ho & Lee, 2004; Lee & Jang, 2004).

$$y = \sum_{i=1}^n x_i^{(6)} = \sum \mu_i [k_{i0} + k_{i1}x_1 + k_{i2}x_2] \quad (8)$$

Table 3. Drill dia: 10 mm, speed: 12.31 m/min, feed: .95 mm/rev

Hole	Act. R_a	Gbellmf2	$(E_2)^2$	Gbellmf3	$(E_3)^2$	Gbellmf4	$(E_4)^2$	Gbellmf5	$(E_5)^2$
5	4.9	4.9599	.00358	4.7799	.01441	4.8938	.000038	4.897	.000009
10	5.46	5.2834	.03118	5.3848	.00577	5.3544	.01151	5.3578	.010444
15	5.51	5.5512	.00169	5.4851	.00062	5.5428	.00107	5.5518	.0000174
20	5.94	5.91	.0009	5.9214	.00036	5.878	.00384	5.8647	.00567
25	6.43	6.5063	.00582	6.4137	.00026	6.4758	.00209	6.46	.000010
30	7.83	7.493	.11356	7.8271	.0029	7.7245	.01113	7.7051	.01560
35	8.54	8.5971	.3260	8.5359	.00001	8.4135	.01600	8.4083	.01734
40	9.28	8.8107	.2202	9.2763	.00001	8.5899	.47623	11.1544	3.5133
Sum			.70297		.02434		.52091		3.56
Best					.02434				

Table 4. Drill dia: 10 mm, speed: 17.9 m/min, feed: .285 mm/rev

Hole	Act. R_a	Gbellmf2	$(E_2)^2$	Gbellmf3	$(E_3)^2$	Gbellmf4	$(E_4)^2$	Gbellmf5	$(E_5)^2$
5	4.71	4.8244	.01308	4.6009	.0121	4.7503	.00162	4.7879	.00684
10	5.32	5.0565	.06945	5.3126	.000054	5.098	.04928	5.1942	.01582
15	5.49	5.3861	.01079	5.4752	.00021	5.4644	.00065	5.4301	.003568
20	5.87	6.0496	.03225	5.8422	.00077	5.8169	.00281	5.8157	.002948
25	6.54	6.5285	.00013	6.5252	.0001	6.4643	.00573	6.3713	.028459
30	7.84	7.6073	.05414	7.8251	.0001	7.7523	.00769	7.738	.010404
35	8.47	8.2806	.03587	8.4546	.0001	8.4161	.00290	8.3013	.028459
40	10	9.7338	.0708	9.94928	.0025	10.6594	.4348	10.0899	.096494
Sum			.2865		.015993		.50548		.2617
Best					.015993				

The software used for this analysis was MAT-LAB. The ANFIS training data include 96 samples. Twelve experiments were conducted for this cutting speed and feed combination. For each experiment, eight holes were measured only out of 40 holes, namely 5, 10, 15, 20, 25, 30, 35, 40 [12×8=96 samples]. The inputs were selected as cutting speed, thrust force, and machining time and surface roughness as an output. The analysis was conducted with four membership function, so it is necessary to take four variables to get one output. The analysis was carried out with 2, 3, 4, and 5 membership functions. The estimated values of surface roughness are shown in Tables 3 and 4. The best structures were selected by a simple criterion, the minimum of summation of square error with the actual values and the estimated values. As per this criterion, the best structures for Table 3 are results obtained by membership function 3 and best structure for Table 4 is result obtained by membership function 3.

4. Neuro-fuzzy system

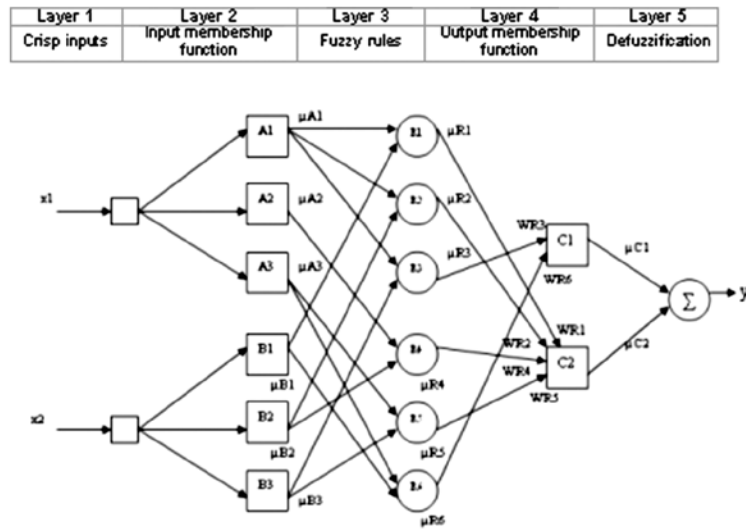
Figure 2 shows a Mamdani fuzzy inference model similar to neuro-fuzzy system that corresponds to this model. The fuzzy system has two inputs x_1 and x_2 and one output y . Input x_1 is represented by fuzzy sets A1, A2, and A3; input x_2 by fuzzy set B1, B2, and B3; and output y by fuzzy sets C1 and C2.

Each layer in the neuro-fuzzy system is associated with a particular step in the fuzzy inference process.

Layer 1 is the input layer. Each neuron in this layer transmits external crisp signals directly to the next layer.

$$y_i^{(2)} = x_i^{(2)} \tag{9}$$

Figure 2. Neuro-fuzzy equivalent system.



where $x_i^{(2)}$ is the input and $y_i^{(2)}$ is the output of input neuron i in Layer 1.

Layer 2 is the input membership of fuzzification layer. Neurons in this layer represent fuzzy sets used in the antecedents of fuzzy rules. A fuzzification neuron receives a crisp input and determines the degree to which this input belongs to the neuron’s fuzzy set. The activation function of a membership neuron is set to the function that specifies the neuron’s fuzzy set.

A triangular membership function can be specified by two parameters $\{a, b\}$ as follows:

$$y_i^{(2)} = \begin{cases} 0 & \text{if } x_i^{(2)} \leq a - \frac{b}{2} \\ 1 - \frac{2x_i^{(2)} - a}{b} & \text{if } a - \frac{b}{2} < x_i^{(2)} < a + \frac{b}{2} \\ 0 & \text{if } x_i^{(2)} \geq a + \frac{b}{2} \end{cases}$$

when a and b are parameters that control the center and the width of the triangle, respectively, $x_i^{(2)}$ is the input and $y_i^{(2)}$ is the output of fuzzification neuron i in Layer 2.

Layer 3 is the fuzzy rule layer. Each neuron in this layer corresponds to a single fuzzy rule. A fuzzy rule neuron receives inputs from the fuzzification neurons that represent fuzzy sets in the rule antecedents. Neuron R1, which corresponds to Rule 1, receives inputs from neurons A1 and B1 using the fuzzy operation union.

$$y_i^{(4)} = x_{1i}^{(4)} \oplus x_{2i}^{(4)} \oplus \dots \oplus x_{li}^{(4)} \tag{10}$$

where $x_{1i}^{(4)} \oplus x_{2i}^{(4)} \oplus \dots \oplus x_{li}^{(4)}$ are the inputs and $y_i^{(4)}$ is the output of output membership neuron i in Layer 4.

$$y_{C1}^{(4)} = \mu R3 \oplus \mu R6 = \mu C1 \tag{11}$$

Layer 5 is the defuzzification layer. Each neuron in this layer represents a single output of the neuro-fuzzy system. It takes the output fuzzy sets clipped by the respective integrated firing strengths and combines them into a single fuzzy set.

The output of the neuro-fuzzy system is crisp, and thus a combined output fuzzy set must be defuzzified. Neuro-fuzzy systems can apply standard defuzzification methods, including the centroid technique. The sum-product composition calculates the crisp output as the weighted average of the

centroids of all output membership functions. For example, the weighted average of the centroids of the clipped fuzzy sets C1 and C2 is calculated as:

$$y = \frac{\mu_{C1} \cdot a_{C1} \cdot b_{C1} + \mu_{C2} \cdot a_{C2} \cdot b_{C2}}{\mu_{C1} \cdot b_{C1} + \mu_{C2} \cdot b_{C2}} \tag{12}$$

where a_{C1} and a_{C2} are the centers, and b_{C1} and b_{C2} are the widths of fuzzy sets C1 and C2, respectively.

The software used for this analysis was MAT-LAB. The neuro-fuzzy training data include 96 samples. The inputs were selected as cutting speed, thrust force, and machining time and surface roughness as an output. The analysis was done with 2, 3, 4, and 5 membership functions and the estimated results are shown in Tables 5 and 6. The best structures were selected by a simple criterion, the minimum of summation of square error with the actual values and the estimated values. As per this criterion, the best structures for Tables 5 and 6 are results obtained by membership function 3, and best structure for Table 6 is result obtained by measuring function 3.

5. ANN analysis

These networks are designed to stimulate the information processing of the human brain. These networks have been successfully applied to industrial problems in the areas of pattern classification and automatic control (Ciurana & Arias, 2009) [16]. An ANN that uses back propagation algorithm

Table 5. Drill dia: 10 mm, speed: 12.31 m/min, feed: .95 mm/rev

Hole	Act. R_a	Gbellmf2	$(E_2)^2$	Gbellmf3	$(E_3)^2$	Gbellmf4	$(E_4)^2$	Gbellmf5	$(E_5)^2$
5	4.9	4.9390	.00152	4.7150	.03422	4.8840	.000256	4.888	.00014
10	5.46	5.2678	.0369	5.3215	.0191	5.3356	.015475	5.3563	.01322
15	5.51	5.5022	.00006	5.4556	.00295	5.5331	.000533	5.5411	.000967
20	5.94	5.890	.0025	5.8916	.00232	5.860	.0064	5.85421	.007396
25	6.43	6.4878	.00334	6.4005	.00087	6.4579	.00077	6.4457	.000246
30	7.83	7.4837	.11990	7.7704	.00355	7.7052	.01557	7.7021	.01635
35	8.54	8.5833	.00187	8.5109	.00084	8.4013	.01923	8.4003	.01951
40	9.28	8.8012	.22924	9.255	.000625	8.5690	.50552	11.1410	3.4632
Sum			.39533		.06447		.56375		3.521144
Best					.06447				

Table 6. Drill dia: 10 mm, speed: 17.9 m/min, feed: .285 mm/rev

Hole	Act. R_a	Gbellmf2	$(E_2)^2$	Gbellmf3	$(E_3)^2$	Gbellmf4	$(E_4)^2$	Gbellmf5	$(E_5)^2$
5	4.71	4.8056	.00913	4.4009	.09	4.7407	.0009	4.7709	.00370
10	5.32	5.0327	.08254	5.2706	.0025	5.00	.1024	5.1709	.02223
15	5.49	5.3710	.01461	5.4232	.0036	5.4410	.00240	5.4176	.005241
20	5.87	6.021	.02280	5.8002	.0049	5.800	.0049	5.800	.0049
25	6.54	6.5116	.00080	6.5112	.0008	6.4432	.00937	6.3538	.03467
30	7.84	7.600	.0576	7.805	.0009	7.7308	.0121	7.7265	.01276
35	8.47	8.2701	.03996	8.424	.0016	8.4010	.00476	8.30	.0289
40	10	9.7210	.07784	9.9128	.0064	10.6322	.39994	10.05	.0025
Sum			.30526		.11070		.53625		.11490
Best					.11070				

for modeling of surface roughness has been developed using machining parameters as inputs and surface roughness as output. The first step of the calculation is to normalize all the raw input data to values between .1 and .9 [17], as shown in the following equation:

$$x_i = \frac{0.8}{d_{\max} - d_{\min}}(d_i - d_{\min}) + 0.1 \quad (13)$$

where d_{\max} and d_{\min} are the maximum and minimum input data, respectively, and d_i is the i th input data. The input of the i th neuron on the hidden layer I_{yi} is calculated by:

$$I_{yi} = \sum_{i=1}^M w_{xy} x_i \quad (14)$$

where M is the number of neurons in the input layer, w_{xy} is the numerical weight value of the connection between the two neurons, and x_i is the i th normalized output value from the input layer.

The output of the i th neuron on the hidden layer y_i is calculated by applying an activation function to the summed input to that neuron. The output of the i th neuron on the hidden layer then becomes:

$$y_i = f(I_{yi}) = \frac{1}{1 + e^{-s(I_{yi})}} \quad (15)$$

where s is the slope of the sigmoid function. The values received by the output layer I_z are the outputs of the hidden and input layers.

$$I_{zi} = \sum_{i=1}^M w_{xz} x_i + \sum_{i=1}^N w_{yz} y_i \quad (16)$$

where M and N are the number of neurons in the input and hidden layers; w_{xz} and w_{yz} are the corresponding weights from the input to the output layer and from the hidden layer to the output layer, respectively. The actual output in the output layer is calculated by applying the same sigmoid function as in the hidden layer.

$$z_i = f(I_{zi}) \quad (17)$$

The error between the desired and actual output in the output layer is calculated by:

$$\delta_{zi} = f'(I_{zi})(T_i - z_i) \quad (18)$$

where T_i is the i th training input to the neuron and f' is the derivative of the sigmoid function.

For each neuron on the hidden layer, the calculation of the error δ_{yi}

$$\delta_{yi} = f'(I_{yi}) \sum_{i=1}^L \delta_{zi} w_{yz} \quad (19)$$

where L is the number of neurons in the output layer.

In order to analyze the ANN application to the drilling problem, the software used was MAT-LAB. Training data were used to train the neural network. The number of neurons in the hidden layer was selected from 1, 2, ..., 20. Four input variables such as cutting speed, machining time, force, and torque for predicting surface roughness were selected. The neural network structure such as $4 \times 20 \times 1$ and the neural network structure such as $4 \times 1 \times 1$, $4 \times 2 \times 1$, ... were analyzed. The learning

Table 7. Diameter: 10 mm, speed: 12.31 m/min, feed: .19 mm/rev

Hole No.	Ra (microns)	4 × 1 × 1 Ra (mm)	(d ₁) ² (mm)	4 × 5 × 1 Ra (mm)	(d ₅) ² (mm)	4 × 10 × 1 Ra (mm)	(d ₁₀) ² (mm)	4 × 15 × 1 Ra (mm)	(d ₁₅) ² (mm)	4 × 20 × 1 Ra (mm)	(d ₂₀) ² (mm)
5	4.90	2.8	4.41	2.8213	4.32099	2.8219	4.3185	2.8218	4.31892	2.82	4.3264
10	5.46	3.73	2.9929	3.8478	2.59919	3.8379	2.63121	3.8340	2.64388	3.83	2.6569
15	5.51	4.97	.2916	4.8706	.40883	4.8725	.40641	4.8723	.40666	5.32	.0361
20	5.94	5.92	.0004	5.8939	.00213	5.8941	.00211	5.8951	.00202	5.9	.0016
25	6.43	6.42	1E-04	6.9176	.23775	6.9302	.2502	6.9251	.24512	6.4	.0009
30	7.83	7.85	.0004	7.9345	.01092	7.9327	.01055	7.9501	.01442	7.8	.0009
35	8.54	8.49	.0025	8.9512	.16909	8.8767	.11337	8.9743	.18862	8.51	.0009
40	9.28	9.12	.0256	9.3100	.0009	9.1600	.0144	9.2000	.0064	9.25	.0009
Summation of difference square			7.7235		7.7498		7.74674		7.82603		7.0246

Table 8. Diameter: 10 mm, speed: 17.9 m/min, feed: .285 mm/rev

Hole No.	Ra (microns)	4 × 1 × 1 Ra (mm)	(d ₁) ² (mm)	4 × 5 × 1 Ra (mm)	(d ₅) ² (mm)	4 × 10 × 1 Ra (mm)	(d ₁₀) ² (mm)	4 × 15 × 1 Ra (mm)	(d ₁₅) ² (mm)	4 × 20 × 1 Ra (mm)	(d ₂₀) ² (mm)
5	4.71	3.9800	.5329	2.8181	3.57929	2.8190	3.57588	2.8199	3.57248	2.8200	3.5721
10	5.32	4.7800	.2916	3.8432	2.18094	3.8475	2.16826	3.8456	2.17386	3.8600	2.1316
15	5.49	5.3600	.0169	4.8895	.3606	4.8864	.36433	4.8877	.36277	4.8600	.3969
20	5.87	5.7800	.0081	5.9007	.00094	5.8959	.00067	5.8975	.00076	5.9000	.0009
25	6.54	6.5000	.016	6.9172	.14228	6.9201	.14448	6.9178	.14273	6.8300	.0841
30	7.84	7.8000	.0016	7.9424	.01049	7.9473	.01151	7.9456	.01115	7.9600	.0144
35	8.47	8.3800	.0081	8.9648	.24483	8.9599	.24	8.9636	.24364	8.0000	.2209
40	10.00	9.8800	.0144	9.9882	.00014	9.9965	1.2E-05	9.9900	1E-04	9.0000	1.0000
Summation of difference square			.8754		6.5195		6.50514		6.50748		7.4209

rate selected was .5 and .5 smoothing factor was used. The learning process was stopped after 15,000 iterations. In order to find out the best structure of ANN, for surface roughness, a simple criterion was used. The minimum of the summation of the difference square with the actual value was considered as the basis for selecting the best neural network structure for surface roughness. The analysis of neural network is shown in Tables 7 and 8. As per the criterion, the best neural network structures were 4 × 20 × 1 for Table 7 and best neural structure for Table 8 is 4 × 1 × 1.

6. Graphs

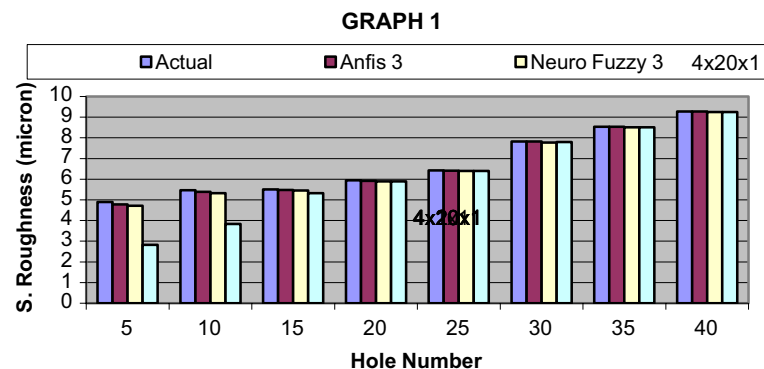
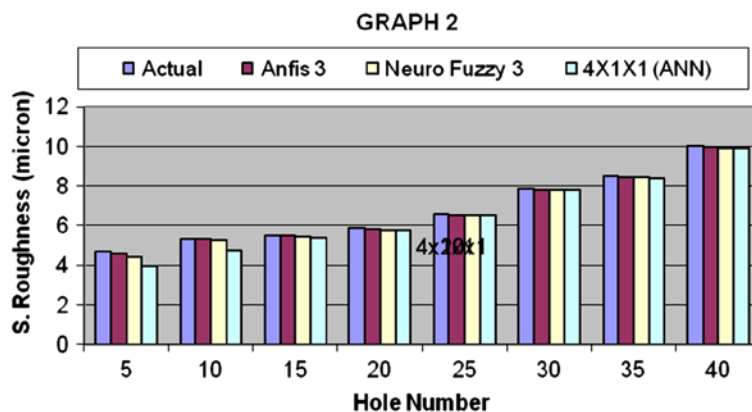


Table 9. Diameter: 10 mm, speed: 12.31 m/min, feed: .19 mm/rev

Hole	Act. R_a	Artificial neural fuzzy inference system (ANFIS) 3	Neuro-fuzzy 3	4 × 20 × 1
5	4.9	4.7799	4.7150	2.82
10	5.46	5.3848	5.3215	3.83
15	5.51	5.4851	5.4556	5.32
20	5.94	5.9214	5.8916	5.9
25	6.43	6.4137	6.4005	6.4
30	7.83	7.8271	7.7704	7.8
35	8.54	8.5359	8.5109	8.51
40	9.28	9.2763	9.255	9.250



7. Results, discussion, and conclusions

Based on observation Tables (3 and 4), following observations were made about ANFIS analysis. It has been proved that surface roughness depends on cutting speed, thrust force, and machining time. The best structure was selected on the simple criterion, the minimum of summation of square with the actual values of surface roughness. As per this criterion, the best structures were the results obtained by membership function 3 and 3. Based on observation Tables (5 and 6), following observations were made about the neuro-fuzzy analysis. As per this analysis, the best structures were the results obtained by membership function 3 and 3. For ANN analysis (Tables 7 and 8), the best neural network structures were the results obtained by 4×20×1 and 4×1×1. The comparative analysis has been done between the results obtained by ANFIS, neuro-fuzzy, and ANN analysis. As per the Graphs (1 and 2), the estimated values of surface roughness obtained by ANFIS analysis were comparing well with the actual values as compared with the estimated values obtained by neuro-fuzzy and ANN analysis (Tables 9 and 10). The result obtained by ANFIS, neuro-fuzzy, and ANN has statistical significance for the values of surface roughness. The results obtained by ANFIS structures are more accurate and reliable for all the combinations of cutting speeds and feeds. The ANFIS has shown the capability of generalization and has the ability for its application for surface roughness analysis in drilling operation. The trained system can predict surface roughness for missing, noisy, and new holes on the work piece.

Table 10. Diameter: 10 mm, speed: 17.9 m/min, feed: .285 mm/rev

Hole	Act. R_a	Artificial neural fuzzy inference system (ANFIS) 3	Neuro-fuzzy 3	4 × 1 × 1
				(Artificial neural network (ANN))
5	4.71	4.6009	4.4009	3.9800
10	5.32	5.3126	5.2706	4.7800
15	5.49	5.4752	5.4232	5.3600
20	5.87	5.8422	5.8002	5.7800
25	6.54	6.5252	6.5112	6.5000
30	7.84	7.8251	7.805	7.8000
35	8.47	8.4546	8.424	8.3800
40	10	9.94928	9.9128	9.8800

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Author details

Ch. Sanjay¹
 E-mail: sasch_cheon2007@yahoo.com
 Ch. Prithvi¹
¹ GITAM University, Hyderabad, India.

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