Regression versus neuro-fuzzy model: A comparison for tool wear estimation

VISHAL S. SHARMA[1*], MANU DOGRA[2], RAMAN BEDI[3], PUNEET SHARMA[4]

To improve the overall efficiency of turning, it is necessary to have a complete process understanding. To this end, a great deal of research has been performed in order to quantify the effect of various cutting parameters on tool wear. It is impossible to find all of the variables that impact tool wear in turning. This paper presents the experimental investigation of machining Grey Cast Iron (GCI) with uncoated carbide tools. Two models are developed for tool wear estimation, the first model is regression based and the second one is neuro-fuzzy based. These models are capable of estimating the wear rate at different cutting conditions. The results obtained by both the models are compared with the actual experimental results. Finally it was observed that both the models are capable of predicting tool wear with good accuracy but the regression model performed marginally better than the neuro-fuzzy model.

Key words: tool wear, regression, fuzzy logic, Adaptive Neuro-Fuzzy Inference System (ANFIS)

1. Introduction

The most crucial and determining factor for successful optimization of the manufacturing process and its automation in any typical metal cutting process is tool wear. Thus monitoring of tool wear is an important requirement for realizing automated manufacturing. In finish turning, tool wear becomes an additional

[1] Department of Industrial Engineering, National Institute of Technology, Jalandhar, India
[2] Department of Mechanical Engineering, SSG Punjab University Regional Centre, Hoshiarpur, India
[3] Department of Mechanical Engineering, National Institute of Technology, Jalandhar, India
[4] Department of Electronics and Communication, National Institute of Technology, Jalandhar, India
[*] Corresponding author, e-mail address: sharmavs@nitj.ac.in, vishal_sim@yahoo.com

parameter affecting surface quality of finished parts. Due to its non-linear and stochastic nature, predicting or monitoring tool wear is a difficult task. The quest for tool wear estimation is based on the requirement that machining systems should operate without human assistance and/or interruption. These systems should recognize and estimate most or all forms of the tool wear in metal cutting. This paper deals with the estimation of gradual tool wear using two models, i.e. regression and ANFIS.

2. Estimating tool wear

For analytical prediction of tool life, Taylor equation is used as presented in Eq. (1):

$$VT^{\alpha} = C_{\mathrm{T}}, \tag{1}$$

where V is the cutting velocity in m min^{-1}, T is tool life in minutes, α is tool life exponent, C_{T} is Taylor tool life constant.

Equation (1) is found to be good provided the cutting velocity varied over a narrow range. This limitation is obvious, because the only cutting variable included in Eq. (1) is cutting velocity, but it is known that the cut depth, cut width and tool geometry all separately influence the life of a cutting tool. In order to overcome these deficiencies Taylor and many others have developed an extended form of Eq. (1), which includes terms for feed rate and depth of cut. This equation is as follows:

$$VT^{\alpha} f^{n1} d^{n2} = C_1, \tag{2}$$

where T, V are the same quantities as defined above, f is feed rate, d is depth of cut, C_1 is the tool life constant, $n1$, $n2$ are exponents.

The relationships of tool wear and tool life to the cutting conditions, such as feed and speed are therefore essential for the economical utilization of the cutting process. The classical formula interrelating those variables is the Taylor equation, which can be stated as in Eq. (3):

$$T = \frac{C_{\mathrm{T}}}{V^{\alpha} f^{m}}, \tag{3}$$

where T is the mean tool life, V is the cutting speed and f is feed, C_{T} and m are constants that depend on tool and work piece materials.

3. Past works

Rahman et al. [1] presented a neural-network-based approach for on-line fault diagnosis scheme, which monitored the level of tool wear, chatter vibration and chip breaking in a turning operation. The experimental results showed that the neural network had a high prediction success rate.

Feng and Wang [2] developed an empirical model using non-linear regression analysis with logarithmic data transformation during turning of steel (8620) HRB86 with carbide inserts having multiphase coatings. They studied an impact of work piece hardness, feed, tool point angle, depth of cut, spindle speed and cutting time on the surface roughness. The values of surface roughness predicted by the model were then verified experimentally and observed that the model produced smaller error.

Sharma et al. [3] used ANFIS model for predicting tool wear using cutting forces, vibrations and acoustic emissions. They could establish close relation between the predicted and the actual tool wear values.

Ozel and Yigit [4] reported neural network modelling to predict tool flank wear and surface roughness over the machining time for a variety of cutting conditions in finish hard turning. Regression models were also developed in order to capture process specific parameters. The data sets from measured tool flank wear were employed to train the neural network models. Trained neural network models were used predicting tool wear and surface roughness for other cutting conditions. A comparison of neural network model with regression models is carried out. Predictive neural network models are found more capable of predicting surface roughness and tool flank wear within the range that they have been trained.

Ezugwa et al. [5] developed an Artificial Neural Network (ANN) model for analysis and prediction of the relationship between cutting and process parameters during turning of inconel-718 alloy. Input parameters for the ANN model are cutting speed, feed rate, depth of cut, cutting time and coolant pressure. The output parameters of the model are tangential force, axial force, spindle power, surface roughness, average flank wear and maximum flank wear. The model consists of three-layer back propagation neural network. A very good performance of the neural network in terms of agreement with the experimental data was achieved.

Initial efforts to develop mathematical models for the prediction of tool wear in the cutting process were dependent upon large amounts of experimental data. These methods did not take into account the complex and diverse nature of the metal cutting operations and uncertainty of the factors responsible for the tool wear. The lack of an accurate model for the tool wear prediction has led researchers to resort to other methods based on soft computing also. These systems can take into account all factors responsible for tool wear in metal cutting. This paper makes use of two methods for tool wear estimation. The first method is conventional method, which makes use of regression model. The second method uses soft computing approach for estimation, i.e. adaptive neuro-fuzzy inference system. Then a comparison of estimated tool wear with an actual one by both models is given.

Detections of tool fracture have been successful however the technique of tool wear monitoring seems to lack reliability in industrial setting and summarization has not occurred yet. One of the problems is a lack of clear relationship between the amount of tool wear and cutting parameters. Many researchers have given theoretical models but machine tool structure and cutting process dynamics are so complex that a theoretical model cannot be relied upon.

4. Experimentation

The turning operations were carried out for different cutting parameters as shown in the Table 1.

The experiments are planned and conducted as per the Appendix I. In total, 36 experiments are conducted and 13 runs are used to construct the model. In order to ensure the repeatability of experiments, each experiment is replicated twice and average values of the tool wear are noted. The 13 experiments, which are taken for creating model, are shown in the Appendix II. Then a regression model is obtained and ANOVA table is formulated (Appendix III). After this, the same set of experiments is used for adaptive neuro-fuzzy inference model. The models constructed are evaluated for all the 36 runs. Further the results obtained by both the models are compared with the actual experimental values.

Table 1. Data of experiments

Work piece material	Grey Cast Iron (GCI) carbon 2 %, manganese 0.46 %, silicon 0.16 %, phosphorus 0.04 %	hardness 220 BHN
Tool material	uncoated carbide inserts	CNMG 120408 THM
Tool holder		PCLNR2020 K 12
Cutting parameters		
Speed V_c 45, 90, 112 m min^{-1}	Feed f 0.08, 0.14, 0.20, 0.26 mm rev^{-1}	Depth of cut ap 0.2, 0.4, 0.6 mm

5. Analysis of the tool wear

The data presented in the Appendix I are analysed by formulating an ANOVA table. The objective is to determine which factors and factor interactions are statistically significant in affecting the tool wear. The ANOVA table also indicates the significance of the model obtained. ANOVA table is formulated as shown in the Appendix III. The "Model F-value" of 13.75 implies the model is significant. There is only a 2.69 % chance that a "Model F-value" this large could occur due to noise. Values of "Prob > F" less than 0.0500 indicate model terms are significant. In this case A and B are significant model terms, i.e. speed and feed.

The regression equation obtained for the tool wear in terms of cutting parameter is as follows:

$$\begin{aligned} TW(V_\mathrm{B}) = [&+ 0.30165 - 2.25125\mathrm{E}\text{–}003' V_\mathrm{c} - 0.68117' f - 0.25456' ap \\ &+ 9.38347\mathrm{E}\text{–}006' V_\mathrm{c}^2 + 2.43968' f^2 + 0.42646' ap^2 \\ &+ 1.73393\mathrm{E}\text{–}003' V_\mathrm{c}' f - 4.80638\mathrm{E}\text{–}004' V_\mathrm{c}' ap \\ &+ 0.041056' f' ap], \end{aligned} \tag{4}$$

where V_c is speed, f is feed, ap is depth of cut, V_B is tool wear.

6. Neuro-fuzzy model

6.1. Brief background

Fuzzy logic methods have been used to model various highly complex and non-linear systems based on a set of sample data and fuzzy "if-then rules". A fuzzy inference system can model the qualitative aspects of human knowledge without employing any quantitative analyses. For describing the fuzzy modelling structure for the tool wear prediction, it will be specified as follows:

Linguistic variables: Form the basic concept underlying fuzzy logic, i.e. a variable whose values are words rather than numbers. The input linguistic variables to be specified herein for the specific problem of tool wear modelling are the following: speed (V_c), feed (f) and depth of cut (ap). The tool wear (V_B) is used as the only output variable.

Fuzzy sets: In contrast to a classical set a fuzzy set does not have a crisp boundary, i.e. the transition from the case "belong to a set" to the case "not belong to a set" is gradual. Normally this smooth transition is characterized by a *membership function* that gives to the fuzzy sets flexibility in modelling commonly used linguistic expressions.

Membership function (*MF*): It is a curve that defines the way that each point in the input space is mapped to a membership value (or degree of membership) between 0 and 1. The membership function type can be any appropriate parameterized membership function like triangle, Gaussian or bell-shaped.

Linguistic rules: A set of linguistic "if-then" rules, which operate on the defined linguistic variables. A single fuzzy "if-then" rule assumes the form "if x is A then y is B" where A and B are linguistic values defined by fuzzy sets on the ranges (universe of discourse) X and Y, respectively. The if-part of the rule "x is A" is called the *antecedent* or *premise*, while the then-part of the rule "y is B" is called the *consequent* or *conclusion*. Fuzzy "if-then" rules with multiple antecedents are often used e.g. as follows:

The resulting output after the described fuzzy logic method has to be *defuzzified* or else converted to a crisp value by using any of the available defuzzification methods, like the centre of gravity method etc. The membership functions used to represent linguistic variables may have an important effect on the modelling performance as the type of the MF being used determines when a given rule is to be put in effect (in fuzzy logic "the rule is fired") or not.

6.2. Artificial Neural Networks

Artificial Neural Networks (ANNs) are very efficient in adaptation and learning and for this reason they are used as modelling tools in a number of applications. An ANN is made of three types of layers: an input layer which accepts the input variables, herein $S(V_\mathrm{c})$, $F(f)$, $D(ap)$ set of hidden layers (one or more), and an output layer made of one neuron that in the case examined herein gives the tool wear (V_B). Hidden and output layers are composed of a number of neurons that perform a specific non-linear function such as sigmoid. The neurons of one layer are interconnected to the neurons of the pre- and after- layers through weighted links. Each neuron of the hidden and output layers is offset by a threshold value. The back-propagation training algorithm is commonly used to iteratively minimize the cost function with respect to the interconnection weights and neuron thresholds. The training process is terminated either when the Mean-Square Error (MSE) between the measured data points and the predicted ANN values for all elements in the training set has reached a pre-specified threshold or after the completion of a pre-selected number of learning iterative processes, called learning epochs.

6.3. Adaptive Neuro-Fuzzy Inference System (ANFIS)

Although the fuzzy inference system has a structured knowledge representation in the form of fuzzy "if-then" rules, it lacks the adaptability to deal with changing external environment. Therefore neural network learning concepts have been incorporated in fuzzy inference systems, resulting in adaptive neuro-fuzzy modelling. The adaptive inference system is a network that consists of a number of interconnected nodes. Each node is characterized by a node function with fixed or adjustable parameters. The network is "learning" the behaviour of the available data during the training phase by adjusting the parameters of the node functions to fit the data. The basic learning algorithm, the back propagation, aims on the minimization of a set measure or a defined error, usually the sum of squared differences between the desired and the actual model outputs. The fuzzy modelling was first explored by Takagi and Sugeno [6, 7]. The ANFIS architecture that was used in the present study was based on the first order Takagi and Sugeno model and is schematically presented in Fig. 1.

It was assumed that the tool wear (V_B) is a function of speed [$S(V_\mathrm{c})$], feed [$F(f)$] and depth of cut [$D(ap)$]. Thus $S(V_\mathrm{c})$, $F(f)$, $D(ap)$ were considered as the input parameters, while the tool wear which corresponds to each combination of the three input parameters was considered as the unique output of the ANFIS model. In this model, the i^th rule for the prediction of tool wear can be expressed as follows:

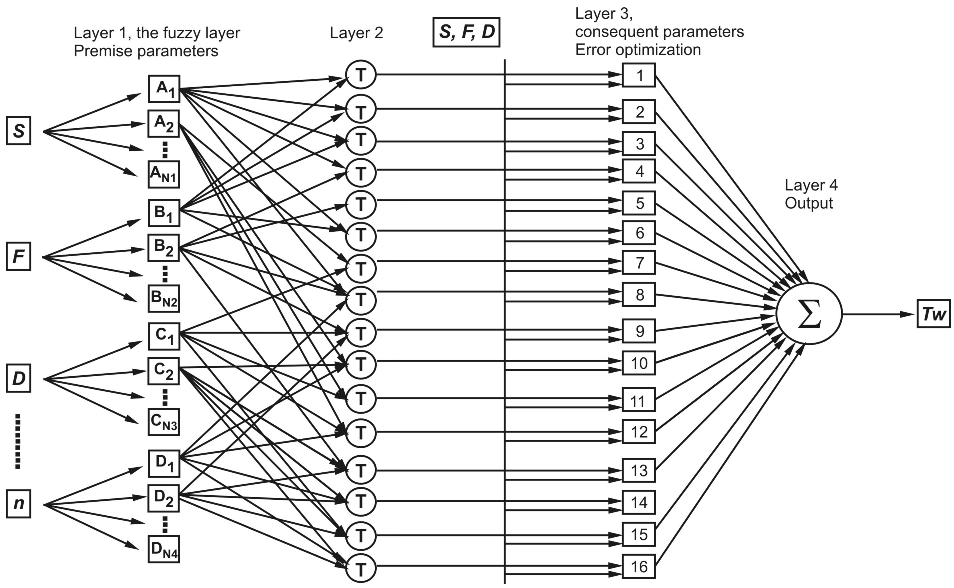

Fig. 1. ANFIS architecture.

Rule I:

$$If \text{ S } is\ A_j,\ F\ is\ B_k,\ D\ is\ C_l\ \ then\ \ f_i = n_i S + o_i F + p_i D + r_i,$$

where $j = 1, \ldots, N_1$, $k = 1, \ldots, N_2$, $l = 1, \ldots, N_3$ and $i = 1, \ldots, N_1 N_2 N_3 N_4$. A, B and C are the fuzzy sets defined for S, F and D, respectively. N_1, N_2, N_3 and N_4 indicate the number of membership functions defined on the indicated fuzzy input variables, f is a linear consequent function defined in terms of the input variables and n, o, p and r are the consequent parameters of the Takagi and Sugeno fuzzy model [6, 7]. In this model, nodes of the same layer have similar functions, as described below. The output of the i^{th} node in layer l is denoted as $Q_{1,i}$.

The fuzzy inference system shown in Fig. 1 is composed of four layers. Each layer involves several nodes, which are described as the node functions. The output signals from nodes in the previous layer will be accepted as the input signals in the current layer. After manipulation by the node function in the current layer, the output will serve as an input signal for the subsequent layer.

Layer 1: The first layer of this architecture is the fuzzy layer. Each node of this layer makes the membership grade of a fuzzy set. The membership relationship between the output and input functions of this layer can be expressed as

$$\begin{aligned} O_{1,j} &= m_{A_j}(S), & j &= 1,\ldots,N_1, \\ O_{1,k} &= m_{B_k}(F), & k &= 1,\ldots,N_2, \\ O_{1,l} &= m_{C_l}(D), & l &= 1,\ldots,N_3. \end{aligned} \tag{5}$$

In this layer, the membership function is Gaussian or bell-shaped membership function.

Layer 2: Every node in the layer 2 is a fixed node, marked by a circle, whose output is the product of all the incoming signals, i.e. T-norm operation:

$$O_{2,i} = m_{A_j}(S)m_{B_k}(T)m_{C_l}(D) = w_i. \tag{6}$$

The output signal w_i denotes the firing strength of the associated rule. The firing strength is also called "degree of fulfilment" of the fuzzy rule, which represents the degree to which the antecedent part of the rule is satisfied.

Layer 3: Every node in layer 3 is an adaptive node (as the consequent parameters in this layer are to be adapted) marked by a square node with the node function as:

$$O_{3,i} = \overline{w}_i f_i, \tag{7}$$

where $\overline{w}_i = \dfrac{w_i}{\sum_{L=1}^{N_1 N_2 N_3} w_L}$ is known as the normalized firing strength.

The consequent parameters of f_i in this layer are to be adapted in order to minimize the error between the ANFIS outputs and their experimental results.

Layer 4: Every node in the layer 4 is a fixed node, marked by a circle node with the node function to compute the overall output by summation of all incoming signals, i.e.:

$$O_{4,i} = \sum \overline{w}_i f_i = N_{\mathrm{f}}. \tag{8}$$

This ANFIS structure represents a three-dimensional space partitioned into N_1' N_2' N_3' regions, each of which is governed by a fuzzy "if-then" rule. In other words, the premise part of a rule defines the fuzzy region, while the consequent part specifies the output within the region.

A hybrid learning algorithm is used to adapt the layer 1 parameters called premise parameters or antecedent parameters and layer 3 parameters referred as consequent parameters to optimize the network, which is a combination of back--propagation and the least squares method to estimate membership function parameters. More specifically, in the forward pass of the hybrid learning algorithm, node outputs go forward till layer 3 and the consequent parameters are identified by the least squares method. In the backward pass, the error signals propagate backward and the premise parameters are updated by the gradient descent.

6.4. Clustering of data

Clustering of numerical data is the basis of many classifications and system modelling algorithms. The purpose of clustering is to identify natural groupings of data from a large data set to produce a concise representation of the system behaviour. Clustering technique can be used to generate a Sugeno type fuzzy inference system that best models the data behaviour using a minimum number of fuzzy rules and thus prevents the explosion of rules. The rules partition themselves according to the fuzzy qualities associated with each one of the data clusters. Various methods of clustering have been described in the literature. The subtractive clustering method, which is an extension of the mountain clustering method, has been used in this paper to estimate the number of clusters and cluster centres in the fatigue life data. This method assumes each data point as a potential cluster centre and calculates a measure of the likelihood that each data point would define the cluster centre, based on the density of surrounding data points. The steps of the fuzzy model algorithm can be summarized as: (1) select the data point with the highest potential to be the first cluster centre, (2) remove all data points in the vicinity of the first cluster centre as determined by the range of influence (radius), and (3) iterate this process until all the data are within the radii of a cluster centre. Data clustering was performed herein in order to assist ANFIS modelling performance.

7. ANFIS model for tool wear estimation

Here ANFIS is used for estimation of the tool wear. ANFIS is a fuzzy inference system implemented within the architecture and learning procedure of adaptive networks. An adaptive network is a superset of all kinds of feed forward neural network with supervised learning capability. ANFIS can be used to optimize membership function to generate stipulated input-output pairs and has the advantage of being able to subsequently construct fuzzy "if-then" type rules representing these optimized membership functions.

The model shown in Fig. 2 is ANFIS model for the tool wear estimation. It considers the cutting speed, feed and depth of cut as input parameter and tool wear as output.

Figures 3, 4, 5 show various membership functions of cutting speed, feed and depth of cut for the proposed tool wear estimation model. These membership functions are computed based on the input and output data, which are used to train the system. The training patterns have been selected from a population of patterns such that they represent all possible wear values in the population (Refer Appendix II for training data). These are tuned using a hybrid system that contains

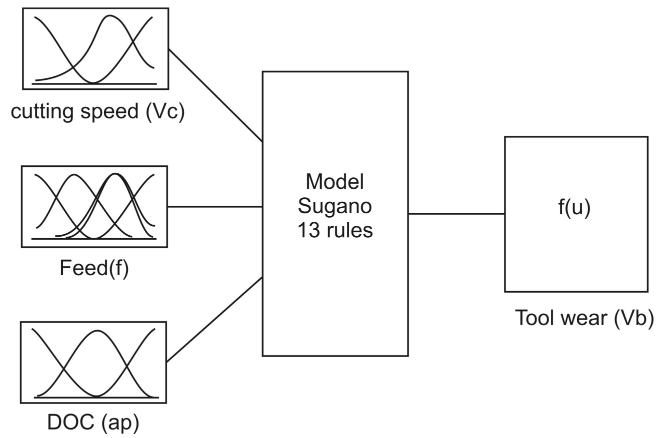

Fig. 2. ANFIS Model.

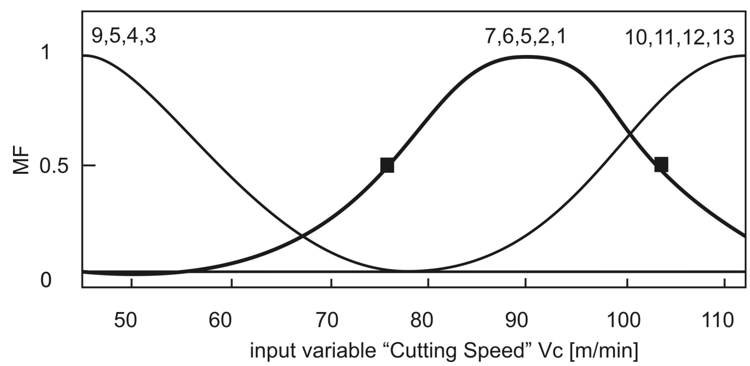

Fig. 3. MF – membership function (cutting speed).

the combination of back propagation and least squares type method. The error tolerance of 0 is used and number of epochs are 3. The "if-then rule" statements are used to formulate the conditional statements that comprise fuzzy logic. By the model, 13 rules have been obtained which are sufficient to match the requirements of the data. Corresponding to each rule there is one output membership function. Subtractive clustering has been used in this paper for estimating the number of clusters and the cluster centres in a set of data. This algorithm is single pass and fast. Here 13 cluster centres were located and for each cluster separate membership function and rule is created as described below:

1. If (Cutting speed (V_c) is in1mf1) and (Feed (f) is in2mf1) and (DOC (ap) is in3mf1) then (Tool wear (V_B) is out1mf1)(1)
2. If (Cutting speed (V_c) is in1mf2) and (Feed (f) is in2mf2) and (DOC (ap) is in3mf2) then (Tool wear (V_B) is out1mf2)(1)
3. If (Cutting speed (V_c) is in1mf3) and (Feed (f) is in2mf3) and (DOC (ap) is in3mf3) then (Tool wear (V_B) is out1mf3)(1)
4. If (Cutting speed (V_c) is in1mf4) and (Feed (f) is in2mf4) and (DOC (ap) is in3mf4) then (Tool wear (V_B) is out1mf4)(1)
5. If (Cutting speed (V_c) is in1mf5) and (Feed (f) is in2mf5) and (DOC (ap) is in3mf5) then (Tool wear (V_B) is out1mf5)(1)
6. If (Cutting speed (V_c) is in1mf6) and (Feed (f) is in2mf6) and (DOC (ap) is in3mf6) then (Tool wear (V_B) is out1mf6)(1)
7. If (Cutting speed (V_c) is in1mf7) and (Feed (f) is in2mf7) and (DOC (ap) is in3mf7) then (Tool wear (V_B) is out1mf7)(1)
8. If (Cutting speed (V_c) is in1mf8) and (Feed (f) is in2mf8) and (DOC (ap) is in3mf8) then (Tool wear (V_B) is out1mf8)(1)
9. If (Cutting speed (V_c) is in1mf9) and (Feed (f) is in2mf9) and (DOC (ap) is in3mf9) then (Tool wear (V_B) is out1mf9)(1)
10. If (Cutting speed (V_c) is in1mf10) and (Feed (f) is in2mf10) and (DOC (ap) is in3mf10) then (Tool wear (V_B) is out1mf10)(1)
11. If (Cutting speed (V_c) is in1mf11) and (Feed (f) is in2mf11) and (DOC (ap) is in3mf11) then (Tool wear (V_B) is out1mf11)(1)
12. If (Cutting speed (V_c) is in1mf12) and (Feed (f) is in2mf12) and (DOC (ap) is in3mf12) then (Tool wear (V_B) is out1mf12)(1)
13. If (Cutting speed (V_c) is in1mf13) and (Feed (f) is in2mf13) and (DOC (ap) is in3mf13) then (Tool wear (V_B) is out1mf13)(1)

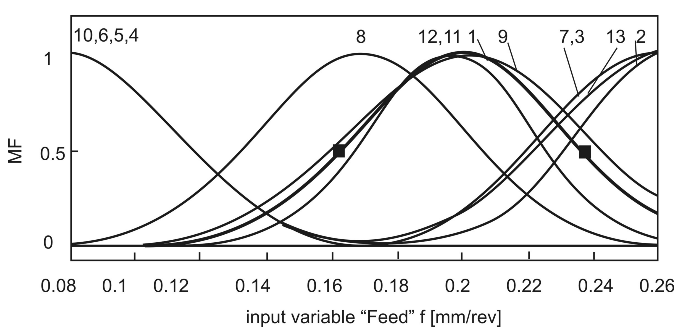

Fig. 4. MF – membership function (feed).

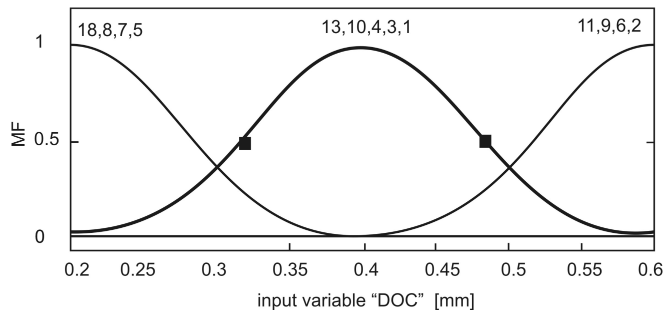

Fig. 5. MF – membership function (DOC).

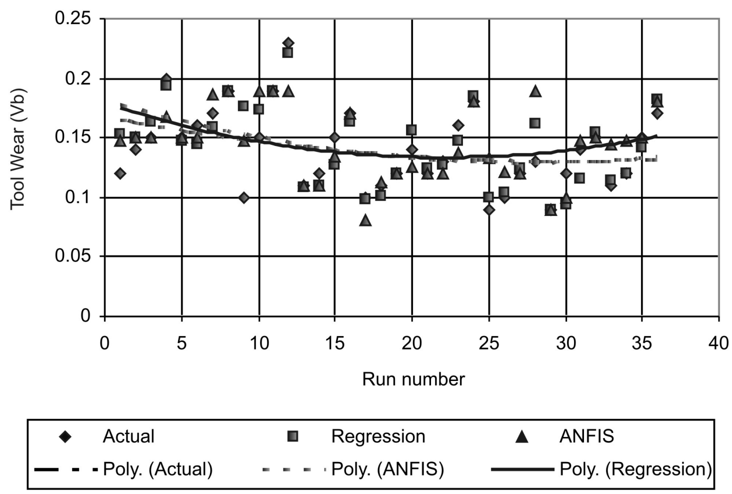

Fig. 6. Comparison of models.

8. Results and conclusions

The regression and ANFIS models are used to estimate the tool wear for all 36 cutting runs. The regression model gave an over all accuracy of 91.67 % while the ANFIS model gave an over all 90 % accuracy. The results obtained are indicated in Fig. 6. These models gave good estimation capabilities as compared to the actual values. Thus it can be concluded that there is close relation between the simulated results and the practical results obtained at similar cutting conditions for predicting tool wear. The accuracy of the models depends upon the data point selection used for creating the model. Figure 6 shows the comparison of models for the tool wear estimation by using regression model and ANFIS model with actual experimental values. To check the effectiveness of both the modelling techniques a Chi-Square (χ^2) test for goodness of fit was conducted on the data as per Appendix IV. In this, the measure of discrepancy between observed and expected frequencies in each case is studied. The larger the value of Chi-Square (χ^2), the greater is the discrepancy between observed and expected frequencies. From Appendix IV it is clear that the value of Chi-Square (χ^2) in the case of regression model is low 0.078853 as compared with ANFIS model 0.103139. Thus it can be deduced that the tool wear values of regression model are close to the experimental values. Hence the model prepared through regression outperforms marginally the ANFIS model.

REFERENCES

[1] RAHMAN, M.—ZHOU, Q.—HONG, G. S.: The International Journal of Advanced Manufacturing Technology, *10*, 1995, p. 87.
[2] FENG, C. X.—WANG, X.: International Journal of Manufacturing Technology, *20*, 2002, p. 348.
[3] SHARMA, VISHAL S.—SHARMA, S. K.—SHARMA, AJAY K.: Journal of Engineering Manufacture, *221*, 2007, p. 635.
[4] OZEL, T.—YIGIT, K.: International Journal of Machine Tools & Manufacture, *45*, 2005, p. 467.
[5] EZUGWA, E. O.—FADARE, D. A.—BONNEY, J.—Da SILVA, R. B.—SALES, W. F.: International Journal Of Machine Tools & Manufacture, *45*, 2007, p. 1375.
[6] TAKAGI, T.—SUGENO, M.: IEEE Trans Syst Man Cybern., *15*, 1985, p. 116.
[7] JANG, J. S. R.—SUN, C. T.: Proceedings of the IEEE, *83*, 1995, p. 378.

Received: 18.7.2007
Revised: 22.10.2008

Appendix I

List of experiments

RUN number	Speed V_c [m min^{-1}]	Feed f [mm rev^{-1}]	Depth of cut ap [mm]	Actual tool wear V_b [mm]	Tool wear regression [mm]	Tool wear ANFIS [mm]
1	45	0.08	0.2	0.12	0.1492	0.1406
2	45	0.14	0.2	0.14	0.1457	0.1400
3	45	0.2	0.2	0.15	0.1598	0.1408
4	45	0.26	0.2	0.2	0.1914	0.1841
5	45	0.08	0.4	0.15	0.1458	0.1500
6	45	0.14	0.4	0.16	0.1428	0.1498
7	45	0.2	0.4	0.17	0.1573	0.1885
8	45	0.26	0.4	0.19	0.1895	0.1900
9	45	0.08	0.6	0.1	0.1765	0.1484
10	45	0.14	0.6	0.15	0.174	0.1892
11	45	0.2	0.6	0.19	0.189	0.1900
12	45	0.26	0.6	0.23	0.2217	0.1896
13	90	0.08	0.2	0.11	0.1068	0.1100
14	90	0.14	0.2	0.12	0.108	0.1084
15	90	0.2	0.2	0.15	0.1267	0.1275
16	90	0.26	0.2	0.17	0.1631	0.1700
17	90	0.08	0.4	0.1	0.0991	0.0793
18	90	0.14	0.4	0.11	0.1008	0.1121
19	90	0.2	0.4	0.12	0.12	0.1200
20	90	0.26	0.4	0.14	0.1568	0.1260
21	90	0.08	0.6	0.12	0.1255	0.1200
22	90	0.14	0.6	0.13	0.1276	0.1205
23	90	0.2	0.6	0.16	0.1474	0.1503
24	90	0.26	0.6	0.18	0.1847	0.1800
25	112	0.08	0.2	0.09	0.0999	0.1325
26	112	0.14	0.2	0.1	0.1034	0.1200
27	112	0.2	0.2	0.12	0.1244	0.1200
28	112	0.26	0.2	0.13	0.163	0.1642
29	112	0.08	0.4	0.09	0.0901	0.0900
30	112	0.14	0.4	0.12	0.094	0.0990
31	112	0.2	0.4	0.14	0.1156	0.1478
32	112	0.26	0.4	0.15	0.1547	0.1500
33	112	0.08	0.6	0.11	0.1143	0.1440
34	112	0.14	0.6	0.12	0.1188	0.1464
35	112	0.2	0.6	0.15	0.1408	0.1500
36	112	0.26	0.6	0.17	0.1804	0.2105

Appendix II

Experiments used for modelling

RUN number	Speed V_c [m min^{-1}]	Feed f [mm rev^{-1}]	Depth of cut ap [mm]	Actual tool wear V_b [mm]
1	45	0.14	0.2	0.14
2	45	0.08	0.4	0.15
3	45	0.26	0.4	0.19
4	45	0.2	0.6	0.19
5	90	0.08	0.2	0.11
6	90	0.26	0.2	0.17
7	90	0.2	0.4	0.12
8	90	0.08	0.6	0.12
9	90	0.26	0.6	0.18
10	112	0.2	0.2	0.12
11	112	0.08	0.4	0.09
12	112	0.26	0.4	0.15
13	112	0.2	0.6	0.15

Appendix III

ANOVA table for tool wear

Source	Sum of squares	DF	Mean square	F-value	Prob > F	
Model	0.011836	9	0.001315	13.74807	0.0269	significant
A	0.003983	1	0.003983	41.64235	0.0075	
B	0.005604	1	0.005604	58.58416	0.0046	
C	0.0009	1	0.0009	9.408836	0.0547	
A2	0.00019	1	0.00019	1.985683	0.2536	
B2	0.000687	1	0.000687	7.180638	0.0751	
C2	0.000661	1	0.000661	6.906364	0.0785	
AB	0.000118	1	0.000118	1.229201	0.3485	
AC	4.06E−05	1	4.06E−05	0.424139	0.5613	
BC	2.27E−06	1	2.27E−06	0.023681	0.8875	
Residual	0.000287	3	9.57E−05			
Cor Total	0.012123	12				

Appendix IV

Tool wear T_{E} (experimental)	Tool wear T_{R} (regression)	Tool wear T_{A} (ANFIS)	$(T_{\mathrm{R}} - T_{\mathrm{E}}^2)/T_{\mathrm{R}}$ χ^2 value of regression	$(T_{\mathrm{A}} - T_{\mathrm{E}}^2)/T_{\mathrm{A}}$ χ^2 value of ANFIS
0.12	0.1492	0.1406	0.005715	0.003018
0.14	0.1457	0.1400	0.000223	0
0.15	0.1598	0.1408	0.000601	0.000601
0.2	0.1914	0.1841	0.000386	0.001373
0.15	0.1458	0.1500	0.000121	0
0.16	0.1428	0.1498	0.002072	0.000695
0.17	0.1573	0.1885	0.001025	0.001816
0.19	0.1895	0.1900	1.32E−06	0
0.1	0.1765	0.1484	0.033157	0.015785
0.15	0.174	0.1892	0.00331	0.008122
0.19	0.189	0.1900	5.29E−06	0
0.23	0.2217	0.1896	0.000311	0.008608
0.11	0.1068	0.1100	9.59E−05	0
0.12	0.108	0.1084	0.001333	0.001241
0.15	0.1267	0.1275	0.004285	0.003971
0.17	0.1631	0.1700	0.000292	0
0.1	0.0991	0.0793	8.17E−06	0.005403
0.11	0.1008	0.1121	0.00084	3.93E−05
0.12	0.12	0.1200	0	0
0.14	0.1568	0.1260	0.0018	0.001556
0.12	0.1255	0.1200	0.000241	0
0.13	0.1276	0.1205	4.51E−05	0.000749
0.16	0.1474	0.1503	0.001077	0.000626
0.18	0.1847	0.1800	0.00012	0
0.09	0.0999	0.1325	0.000981	0.013632
0.1	0.1034	0.1200	0.000112	0.003333
0.12	0.1244	0.1200	0.000156	0
0.13	0.163	0.1642	0.006681	0.007123
0.09	0.0901	0.0900	1.11E−07	0
0.12	0.094	0.0990	0.007191	0.004455
0.14	0.1156	0.1478	0.00515	0.000412
0.15	0.1547	0.1500	0.000143	0
0.11	0.1143	0.1440	0.000162	0.008028
0.12	0.1188	0.1464	1.21E−05	0.004761
0.15	0.1408	0.1500	0.000601	0
0.17	0.1804	0.2105	0.0006	0.007792
			$\mathbf{\Sigma = 0.078853}$	$\mathbf{\Sigma = 0.103139}$