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Cutting tool wear estimation for turning

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Abstract The experimental investigation on cutting tool wear and a model for tool wear estimation is reported in this paper. The changes in the values of cutting forces, vibrations and acoustic emissions with cutting tool wear are recoded and analyzed. On the basis of experimental results a model is developed for tool wear estimation in turning operations using Adaptive Neuro fuzzy Inference system (ANFIS). Acoustic emission (Ring down count), vibrations (acceleration) and cutting forces along with time have been used to formulate model. This model is capable of estimating the wear rate of the cutting tool. The wear estimation results obtained by the model are compared with the practical results and are presented. The model performed quite satisfactory results with the actual and predicted tool wear values. The model can also be used for estimating tool wear on-line but the accuracy of the model depends upon the proper training and section of data points.

Keywords Tool wear · Fuzzy logic · Adaptive neuro fuzzy inference system

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Introduction

The most crucial and determining factor for successful maximization 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. Due to its nonlinear and stochastic nature, predicting or monitoring tool wear is a difficult task (Bernhard, 2002). Initial efforts to develop tool condition monitoring systems focused mainly on the development of mathematical models of the cutting process which 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. The lack of an accurate model for wear prediction led researchers to resort to other methods of sensor integration. The quest for such methods was based on the requirement that these systems to 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 three methods i.e. Acoustic emission (Ring down count), vibrations (acceleration) and cutting forces.

Overview of the methods

The study undertaken employs three methods for condition monitoring i.e. Acoustic emissions, vibrations and cutting forces.

Acoustic emission (AE): It may be defined as acoustic waves generated by a material when subjected to an external stimulus. The terms "acoustic emission" and "acoustic emission signal" are often used interchangeably. Strictly speaking an acoustic emission is an acoustic wave generated by

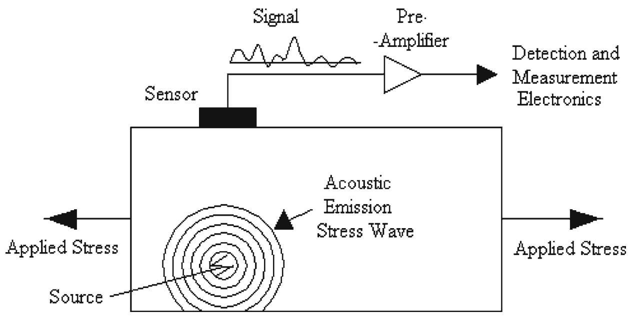

Fig. 1 Acoustic emission generation and sensing

a material and an acoustic emission signal is the electrical signal produced by a sensor in response to the wave. In other words acoustic emission refers to the stress waves generated by dynamic processes in materials. Emission occurs as a release of a series of short impulsive energy packets. The energy thus released travels as a spherical wave front and can be picked from the surface of a material using highly sensitive transducers, usually electro mechanical type placed on the surface of the material. The mechanical wave thus picked up is converted into electrical signal, which on suitable processing and analysis can reveal valuable information about the source causing the energy release (Miller & Hill, 2000). The basics of acoustic emission generation and sensing with a sensor is indicated in Fig. 1.

The acoustic emission can be used to detect gradual and abrupt tool wear (Moriwaki & Okushima, 1980; Xiaoli, 2002). The AE parameter used for the study is Ring down count (RDC). RDC is number of times the signal amplitude exceeds the pre-set reference threshold values. All values of RDC are recorded for the test in the computer. The analysis of the data is done using the average value of RDC. The changes in the RDC with tool wear are investigated.

Vibrations: Cutting tool vibrations during machining are produced due to rubbing action at the work-piece tool flank interface, formation of built-up edge, waviness of the work surface. They are also associated with gear contacts. The research work indicated that the vibrations of a lathe tool in stable machining are mainly caused by the friction of the flank face of the tool against the work-piece (Pandit & Kashov, 1983; Selvam, 1975). The fundamental frequency of tool vibrations is the resonant frequency of the system excited by the friction at the cutting edge. The current study makes use of tool acceleration which is measured in "g's". Acceleration is best measure of vibrations when they are occurring at high frequencies i.e. above 60,000 cpm (1 kHz) range (Rao, 1986). Since cutting tool vibration are high frequency vibrations (i.e. above 1 kHz) vertical tool acceleration is chosen as the parameter to monitor tool wear.

Cutting Forces: The parameter that is comparatively easy to measure is cutting forces (Ravindra & Krishanamurthy, 1983; Ravindra & Srinivasa, 1993). The resultant cutting

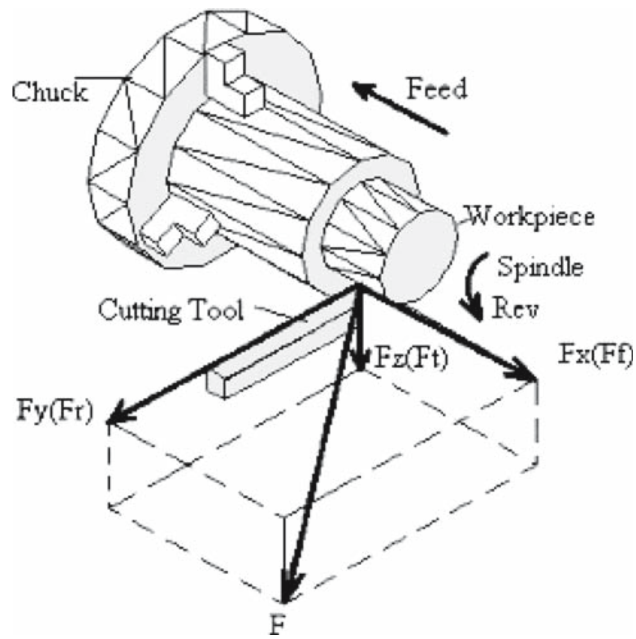

Fig. 2 Cutting force components on the tool

force 'F' acting in the oblique direction can be resolved along the three perpendicular axes viz. X, Y and Z as shown in Fig. 2.

F_z is the main or tangential component that determines the torque on the main drive mechanism, the deflection of the tool and the required power. This component acts in the direction of the cutting speed. F_x, the axial component acts is the direction of the tool transverse and it is at right angles to F_z. F_y, the radial component acts along the tool shank and perpendicular to the other two components.

Description of experimental setup and procedure

The experimental setup for the current study is shown in Fig. 3. This figure indicates various equipments employed and their respective location on the tool.

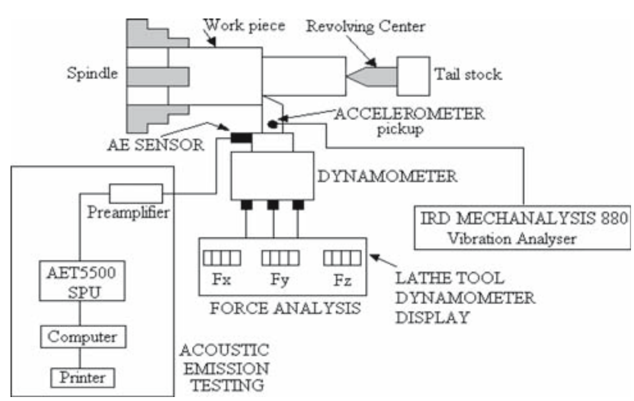

Fig. 3 Experimental setup

Table 1 Experiments 1–4

Experiment number	Work-piece material	Tool material	Cutting speed (m/min)	Cutting feed (mm/rev)	Depth of cut (mm)
1	Cast iron (FG 15)	Uncoated carbide CCMT060204 TTS	94	0.06	0.7
2	Cast iron (FG 15)	Uncoated carbide CCMT060204 TTS	94	0.08	0.7
3	Cast iron (FG 15)	Uncoated carbide CCMT060204 TTS	188	0.06	0.7
4	Cast iron (FG 15)	Uncoated carbide CCMT060204 TTS	188	0.08	0.7

The conventional tool post of the lathe machine is removed and the tool dynamometer is fixed in its place. The cables are connected to the dynamometer and the display unit. Display unit is further connected to the power supply. Then the tool is mounted in the tool dynamometer slot with the help of Allen screws. For measuring acceleration, the accelerometer's prod is placed on the top surface of the tool. The cable of the accelerometer is connected with the vibration analyzer, which is further connected to power supply. After mounting this accelerometer the test run is carried out in order to check the connections and the output obtained. The AE Sensor (piezoelectric transducer) is fixed on the tool holder using a layer of couplant. The pencil lead break test was used to calibrate AE to estimate the attenuation factor of the AE signal when the signal was transmitted from the work piece to the cutting tool. Electrical signals produced by the transducer were first amplified with a pre-amplifier of 60 dB gains. The detected signals were amplified and filtered through band-pass filter. The threshold voltage was set to 1.00 V (automatic) using the AET software command. The tuning operation was carried out and the gain switch of the signal-processing unit (SPU2) was adjusted until the LED on the front panel of the SPU2 started flashing indicating threshold crossing by the AE signal. The conditional signals were recorded in the computer for further analysis. Cutting fluid was not used during the cutting process.

The experimental study was carried out for turning operations on cast iron (Grey Cast Iron-FG 15) work piece material and uncoated coated carbide insert tool material (CCMT060204 TTS). The tool holder was SCLCR1010E06 (WIDIA make). The process parameters were: cutting speed (94 m/min and 188 m/min), feed: 0.06 mm/rev and 0.08 mm/rev, depth: 0.7 mm (constant). The turning operations were carried out on High Precision Lathe Machine (Kirloskar make). Acoustic emission (Ring down count), vibrations (acceleration), cutting forces and tool wear were recorded for each cut on the machine. The AE data were collected using an AET 5500 acoustic emission tester, vibrations were measured using IRD MODEL 970 Accelerometer

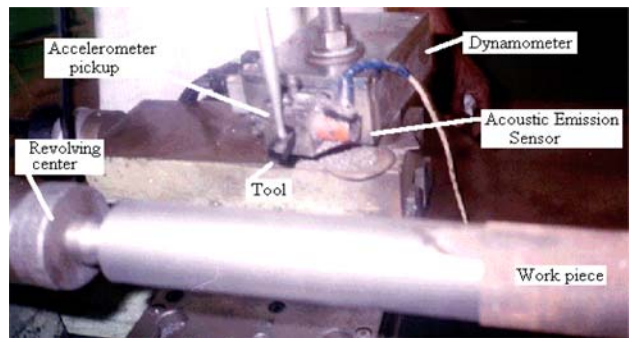

Fig. 4 Close-up view of mounted sensors on the tool (Opposite operator view)

and IRD 880 Vibration Analyzer (Mechanalysis make). Cutting forces were measured using Lathe Tool Dynamometer. The tool wear (flank wear) was measured off-line using tool makers microscope (Labo make).

The turning operation was carried out for different combinations of speed and feed. The combinations were selected such that the tool was subjected to progressive wear (Table 1). AE (Ring down count), vibrations (accelerations), cutting forces (F_x, F_y, F_z) and tool wear (Flank wear—VB_{max}) was measured for each cut. The closeup view of the setup is shown in Fig. 4.

Results and discussions

Four experiments have been conducted at different cutting parameters as shown in the Table 1. These experiments have been conducted to investigate that out of the parameters i.e. Cutting forces, Vibrations (accelerations) and AE (RDC) which is maximum affected by tool wear. Then using these parameters for cutting tool wear estimation model.

Figure 5 depicts various graphs between cutting forces and tool wear at different cutting conditions. It has been observed that the cutting force component F_x show small variations with tool wear while F_y component show almost constant

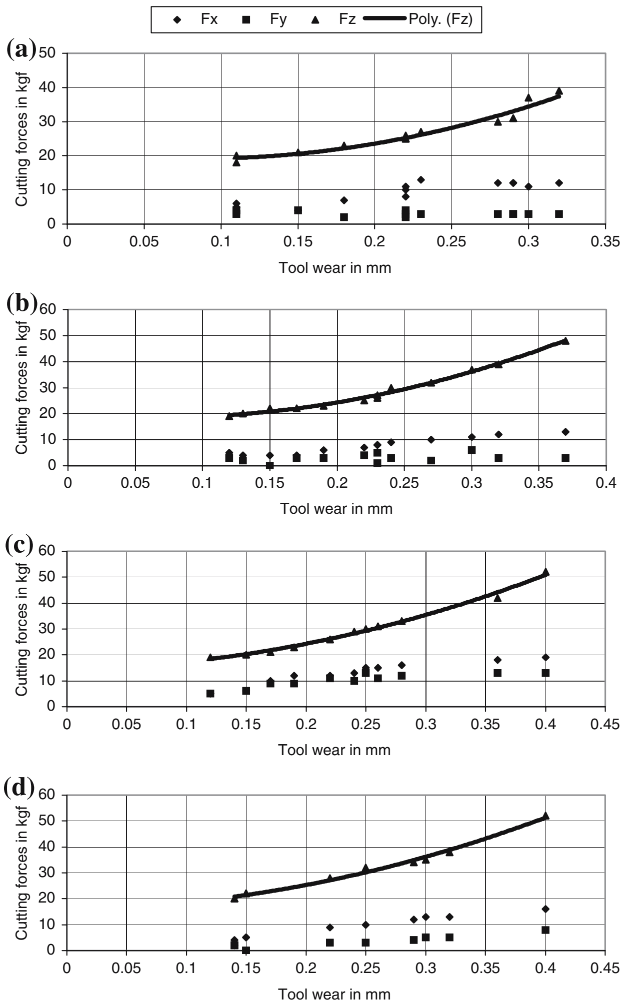

Fig. 5 Cutting forces versus Tool wear. (**a**) Experiment-1; (**b**) Experiment-2; (**c**) Experiment-3; (**d**) Experiment-4

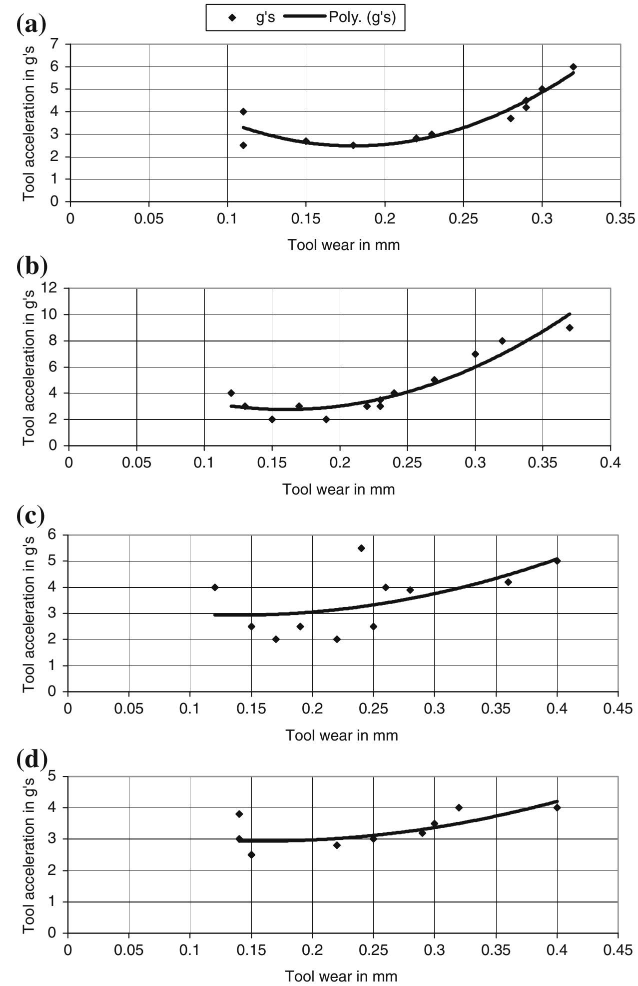

Fig. 6 Tool acceleration versus Tool wear. (**a**) Experiment-1; (**b**) Experiment-2; (**c**) Experiment-3; (**d**) Experiment-4

trend with time. Further it was seen that the cutting force component F_z is more sensitive to tool wear as compared to F_x and F_y components. The values of the F_z component of the cutting forces increases gradually after a wear of about 0.15 mm as shown in Fig. 5a–d. The values of the cutting forces also increase with increase in the feed from 0.06 to 0.08 mm/rev for experiments 1, 2 and 3, 4, respectively. So merely increase in the cutting force values is not always an indicator of tool wear.

Figure 6 shows various graphs between tool acceleration and tool wear. In general the acceleration is slightly more at the beginning of the wear, it settles down in the stable wear zone and then it increases with increase in tool wear. The minimum value of the tool acceleration is near 0.15 mm of tool wear and it begins to increase after this point as shown in Fig. 6a–d.

Figure 7 shows various graphs between tool wear (flank) and time. All the graphs shown in Fig. 7a–d indicate a gradual increase of the wear with passage of time. The tool wear value varies from 0.11 to 0.32 mm and 0.12 to 0.37 mm at 90 and 1,170 s for experiment 1 and 2, respectively as indicated in Fig. 7a and b. Figure 7c and d indicates this variation from 0.12 to 0.36 mm and 0.14 to 0.4 mm at 60 and 600 s for experiment 3 and 4.

Figure 8 shows various graphs between AE (RDC_{avg}) and tool wear. It is observed that AE (RDC_{avg}) values increase with tool wear. Gradual slope of the AE (RDC_{avg}) value is observed after tool wear of about 0.15 mm as shown in Fig. 8a–d. The values of AE (RDC_{avg}) vary between 170 to 1,662.25 and 114.4 to 2,545.5 at time intervals of 90 and 1,170 s for experiment 1 and 2, respectively. In case of experiment 3 and 4 the variation in AE (RDC_{avg}) values is between 308.6 to 1,576.6 and 1,046.3 to 2,058.7 at time intervals of 60 and 600 s, respectively. Here burst acoustic emissions are observed during the experiment, they are not because of the tool wear but because of nonhomogeneous work piece material. So it may interfere with the actual condition of the tool wear.

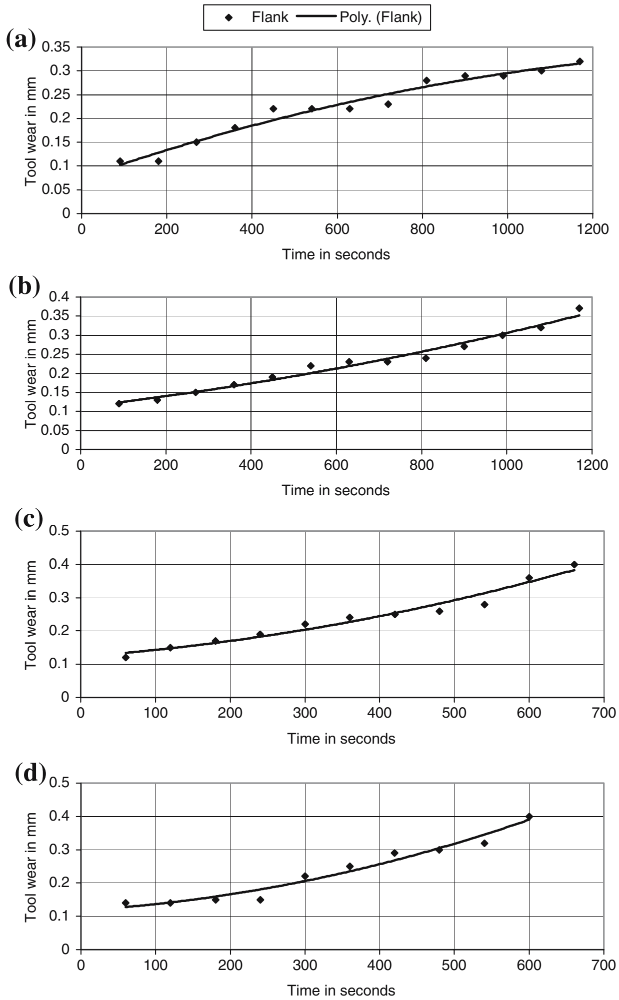

Fig. 7 Tool wear (Flank) versus time. (**a**) Experiment-1; (**b**) Experiment-2; (**c**) Experiment-3; (**d**) Experiment-4

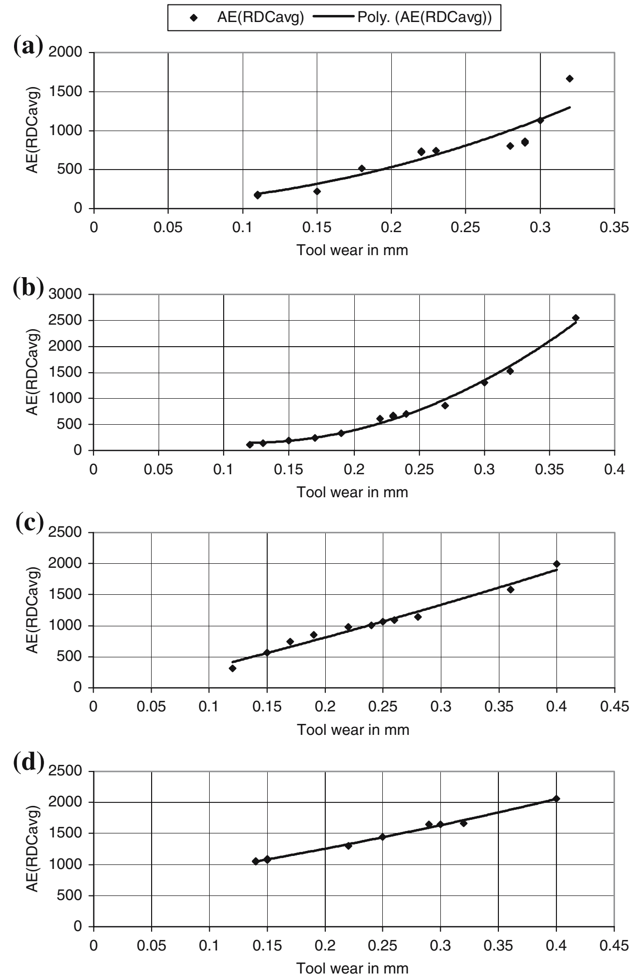

Fig. 8 AE (RDC_{avg}) versus Tool wear. (**a**) Experiment-1; (**b**) Experiment-2; (**c**) Experiment-3; (**d**) Experiment-4

From the above results and observations it has been investigated that machining of Cast iron with uncoated carbide tool at various cutting conditions generate chips that are discontinuous and short so giving rise to flank wear only. In most of the cases cutting forces show an upward trend with the increase in the tool wear rate. The tangential component (F_z) of force is more sensitive to tool wear as compared to axial component (F_x) and radial component (F_y). The values of the cutting forces start to increase more rapidly after tool wear of about 0.15 mm. The cutting forces varied from 18 to 52 kgf during various experiments. In general results reveal that the cutting forces (F_z) also show increase in its values with the increase in feed rate that could hinder in revealing true status of the cutting tool.

Moreover, it has been observed that the vertical accelerations are initially slightly more then reduces during the stable cutting conditions and finally it again starts to increase with increase in tool wear. The accelerations of the tool show minimum value near 0.15 mm of tool wear and there after the value of g's increased. The overall variation of the acceleration with tool wear is 2.5–6 g's for various experiments.

During experimentation it was observed that the Acoustic Emissions parameters AE (RDC_{avg}) show a significant increase with tool wear. The AE parameter also showed gradual rise in their values after tool wear of 0.15 mm. The burst AE emissions (abrupt) could interfere with the actual tool wear state.

Force, vibrations and AE signals with tool wear gives promising results. Only one signal i.e. either force, vibration or AE is not sufficient in order to obtain reliable prediction of the tool wear therefore a combination of two signals is recommended. The limitations that were encountered with cutting forces, tool accelerations and AE signals measurement are the physical contact of transducer with the cutting tool under test.

Fuzzy modeling

Fuzzy logic is a convenient way to map an input space to an output space. Fuzzy inference is the process of formulating the mapping from a given input to an output using fuzzy logic. The mapping then provides a basis from which decisions can be made. The process of fuzzy inference involves membership functions, fuzzy logic operators, and if-then rules. A membership function is a curve that defines how each point in the input space is mapped to a membership value (or degree of membership) between 0 and 1. There are two types of fuzzy inference systems Mamdani-type and Sugeno-type. These two types of inference systems vary somewhat in the way outputs are determined (Jang & Sun, 1995).

Mamdani's fuzzy inference method is the most commonly seen fuzzy methodology. Mamdani's method was among the first control systems built using fuzzy set theory. It was proposed in 1975 by Ebrahim Mamdani (Mamdani & Assilian, 1975) as an attempt to control a steam engine and boiler combination by synthesizing a set of linguistic control rules obtained from experienced human operators. Mamdani's effort was based on Lotfi Zadeh's 1973 paper on fuzzy algorithms for complex systems and decision processes (Zadeh, 1973).

Mamdani-type inference, expects the output membership functions to be fuzzy sets. After the aggregation process, there is a fuzzy set for each output variable that needs defuzzification. It's possible, and in many cases much more efficient, to use a single spike as the output membership functions rather than a distributed fuzzy set. This is sometimes known as a singleton output membership function, and it can be thought of as a pre-defuzzified fuzzy set. It enhances the efficiency of the defuzzification process because it greatly simplifies the computation required by the more general Mamdani method, which finds the centroid of a two-dimensional function. Rather than integrating across the two-dimensional function to find the centroid, the weighted average of a few data points is used. Sugeno-type systems support this type of model.

Sugeno, or Takagi-Sugeno-Kang method of fuzzy inference first introduced in 1985 (Sugeno, 1985). It is similar to the Mamdani method in many respects. In fact the first two parts of the fuzzy inference process, fuzzifying the inputs and applying the fuzzy operator, are exactly the same. The main difference between Mamdani-type of fuzzy inference and Sugeno-type is that the output membership functions are only linear or constant for Sugeno-type fuzzy inference. A typical fuzzy rule in a zero-order Sugeno fuzzy model has the form

If x is A and y is B then $z = k$

where A and B are fuzzy sets in the antecedent, while k is a crisply defined constant in the consequent. When the output of each rule is a constant like this, the similarity with Mamdani's method is striking. The only distinctions are the fact that all output membership functions are singleton spikes, and the implication and aggregation methods are fixed and cannot be edited. The implication method is simply multiplication, and the aggregation operator just includes all of the singletons.

Adaptive neuro fuzzy inference system (ANFIS)

In this section ANFIS architecture and its learning algorithm for Takagi and Sugeno model is explained. To explain the procedure of the ANFIS simply, we consider two inputs x and y and one output f in the fuzzy inference system. For a first order Takagi and Sugeno fuzzy model, a typical set with two fuzzy "if-then" can be expressed as follows:

$$\text{Rule1}: \text{if } x \text{ is } A_1 \text{ and } y \text{ is } B_1 \text{ then } f = p_1 x + q_1 y + r_1 f$$
$$\text{Rule2}: \text{if } x \text{ is } A_2 \text{ and } y \text{ is } B_2 \text{ then } f = p_2 x + q_2 y + r_2$$

where p_1, p_2, q_1, q_2, r_1 and r_2 are linear parameters and A_1, A_2, B_1, B_2 are nonlinear parameters.

The corresponding equivalent ANFIS architecture is shown in Fig. 9. Then, the node function in each layer, which gives the same function family, is described below.

Layer 1 is the fuzzy layer in which x and y are the input of nodes A_1, B_1 and A_2, B_2, respectively. A_1, A_2, B_1, B_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:

$$O_{1,i} = \mu_{Ai}(x) \quad i = 1, 2$$
$$O_{1,i} = \mu_{Bi-2}(y) \quad i = 3, 4$$

where x(or y) is the input of node, and A_i (or B_{i-2}) is the linguistic variable. The membership function usually adopts a bell-shape with maximum and minimum equal to 1 and 0, respectively:

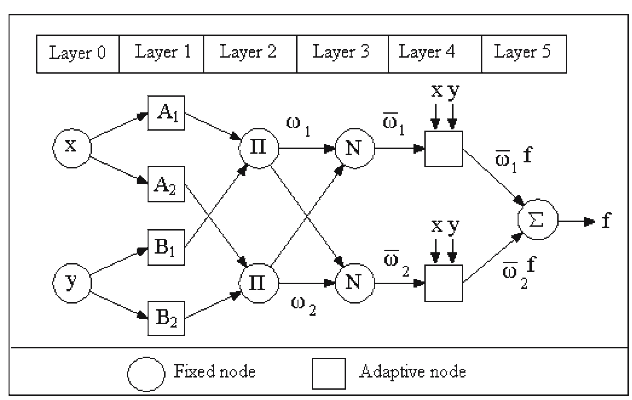

Fig. 9 ANFIS architecture

$$\mu(x) = \frac{1}{1 + \left|\frac{x-c_i}{a_i}\right|^{2bi}}$$

where $\{a_i, b_i, c_i\}$ represents the parameter set. It is significant that if the value of these parameters sets changes, the bell-shape function will be changed accordingly.

The adaptive-network-based fuzzy inference system can simulate and analyze the mapping relation between the input and output data through a hybrid learning to determine the optimal distribution of membership function. It is mainly based on the fuzzy "if-then" rules from the Takagi and Sugeno type. It involves a premise part and consequent part. The equivalent ANFIS architecture of the type from Takagi and Sugeno is shown in Fig. 9. It comprises five layers in this inference system. Each layer involves several nodes, which are described by the node function. The output signals from nodes in the previous layers will be accepted as the input signals in the present layer. After manipulation by the node function in the present layer, the output will be served as input signals for the next layer. Here, square nodes, named adaptive nodes, are adopted to demonstrate that the parameter sets in these nodes are adjustable. Whereas, circle nodes, named fixed nodes, are adopted to demonstrate that the parameter sets are fixed in the also different in linguistic label A_i. The parameters in this layer are named as premise parameters. Every node in the second layer is a fixed node, marked by a circle node, with the node function to multiply input signals to serve as output signal.

$$\begin{aligned} O_{2,i} &= t(\mu_{Ai}(x), \mu_{Bi}(y)) \\ &= \mu_{Ai}(x) x \mu_{Bi}(y) \\ &= \omega_i \end{aligned}$$

The output signal ω_i means the firing strength of a rule.

Every node in third layer is a fixed node, marked by a circle node, with the node function to normalize firing strength by calculating the ratio of this node firing strength to the sum of the firing strength:

$$O_{3,1} = \varpi_i = \frac{\omega_i}{\omega_1 + \omega_2}$$

Every node in fourth layer is an adjustable node, marked by a square node, with node function as:

$$O_{4,i} = \varpi_i f_i = \varpi_i (p_i x + q_i y + r_i)$$

where ω_i is the output of Layer 3 $\{pi, qi, ri\}$ is the parameter set, which is referred to as the consequent parameters.

Every node in fifth layer is a fixed node, marked by a circle node, with the node function to compute the overall output by:

$$O_{5,i} = \sum_i \varpi_i f_i = \frac{\sum_i \omega_i f_i}{\sum_i \omega_i}$$

Explicitly, this layer sums the node's output in the previous layer to be the output of the whole network.

ANFIS model for tool wear estimation

The application of Artificial intelligence is one of the techniques for analyzing and improving the performance of any system. The functional combination of multiple sensors signal analysis and artificial intelligence techniques leads to more promising approach to meet the present demands of high performance (Fang, 1995; Dimla & Lister, 2000; Dimla, Lister, & Leighton, 1998; Li & Elbestawi, 1996). Few of the researchers in the past have used Adaptive Neuro-Fuzzy inference system (ANFIS). Here in this Paper an effort has been made to demonstrate the use the Adaptive Neuro-Fuzzy inference system (ANFIS) 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. 10 is for tool wear estimation based upon ANFIS. It considers the time, cutting forces (F_z), Vibrations (acceleration), Acoustic emissions (Ring down count-average) as input parameter and tool wear as output (Refer Appendix I). In the model only cutting force component F_z is used the because it is more sensitive to tool wear as compared to F_x and F_y components.

Figures 11–14 shows various membership functions of time, forces, vibrations and AE (RDC) for the proposed wear estimation model. These membership functions are computed based on the input and output data which is 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 I for training data). These are tuned using a hybrid system that contains the combination of back propagation and least squares type method. The error tolerance of 0 is used and number of epochs are 3.

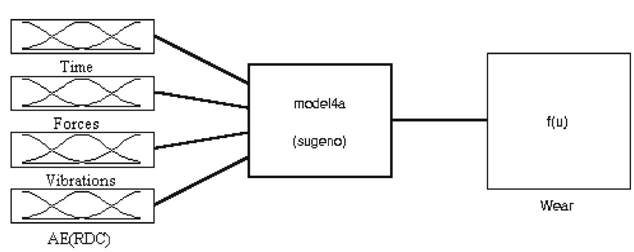

Fig. 10 Model

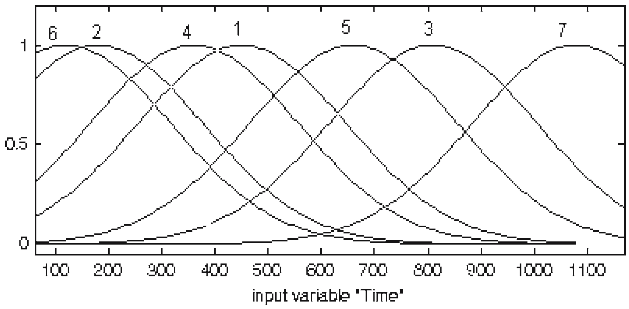

Fig. 11 Time membership function

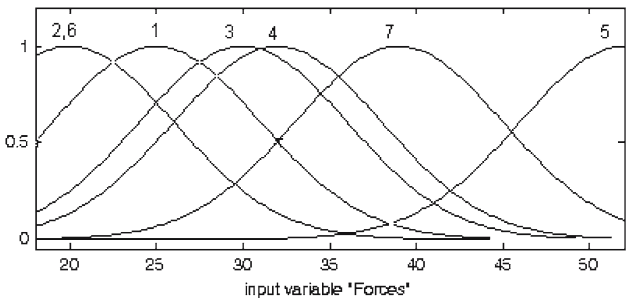

Fig. 12 Forces membership function

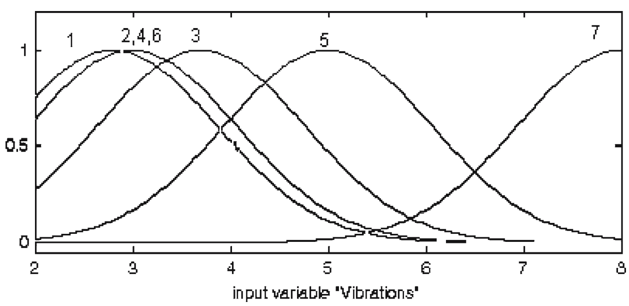

Fig. 13 Vibrations membership function

The "if-then rule" statements are used to formulate the conditional statements that comprise fuzzy logic. Figure 15 represents various rules used by the model; seven rules have been obtained which are sufficient to match the requirements of the data. Corresponding to each rule there is one output membership function. The problem of explosion the number of rules is solved by using clustering. The purpose of clustering is to identify natural groupings of data from a large data set to produce a concise representation of a system's behavior. Subtractive clustering has been used in this paper for estimating the number of clusters and the cluster centers in a set of data. This algorithm is single pass and fast. Here seven cluster centers were located and for each cluster separate membership function and rule is created.

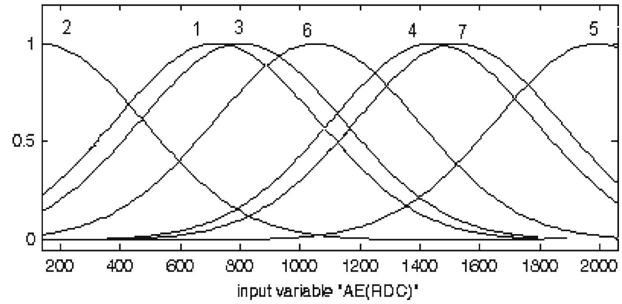

Fig. 14 AE (RDC) membership function

The comparisons of the estimated tool wear using model (ANFIS) and the experiments actually conducted are shown in Fig. 16. The total average error for experiment 1 is 7.12%. Out of the various outputs generated by the model for experiment 1 only 3 data point crosses the individual error of more than 10%. The comparison of the actual and predicted values for experiment 2 is shown in Fig. 16b. The total average error for experiment 14 is 40.4%. Here 4 data point cross the individual error of 10% mark. Figure 16c shows the difference between the predicted and actual values for experiment 3. The total average error for the experiment 3 is 3.46%. Here 1 data points cross the individual error of 10% mark. For experiment 4 the comparison of predicted and actual values is shown in Fig. 16d. The average error for experiment 4 is 1.97%. No data point crosses 10% individual error mark.

In this model in total 47 data points were involved 8 data point crossed the mark of 10% individual error. Thus system gave an over all 82.9% accuracy. 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.

Conclusions

From the experiments it was found that machining of Cast iron with uncoated carbide tool at various cutting conditions

Fig. 15 Rules used for the model

1. If (Time is 1mf) and (forces is 2mf) and (vibrations is 3mf) and (AE (RDC) is 1mf) then (Wear is out1mf1) (1)
2. If (Time is 2mf) and (forces is 2mf) and (vibrations is 2mf) and (AE (RDC) is 2mf) then (Wear is out1mf2) (1)
3. If (Time is 3mf) and (forces is 3mf) and (vibrations is 3mf) and (AE (RDC) is 3mf) then (Wear is out1mf3) (1)
4. If (Time is 4mf) and (forces is 4mf) and (vibrations is 4mf) and (AE (RDC) is 4mf) then (Wear is out1mf4) (1)
5. If (Time is 5mf) and (forces is 5mf) and (vibrations is 5mf) and (AE (RDC) is 5mf) then (Wear is out1mf5) (1)
6. If (Time is 6mf) and (forces is 6mf) and (vibrations is 6mf) and (AE (RDC) is 6mf) then (Wear is out1mf6) (1)
7. If (Time is 7mf) and (forces is 7mf) and (vibrations is 7mf) and (AE (RDC) is 7mf) then (Wear is out1mf7) (1)

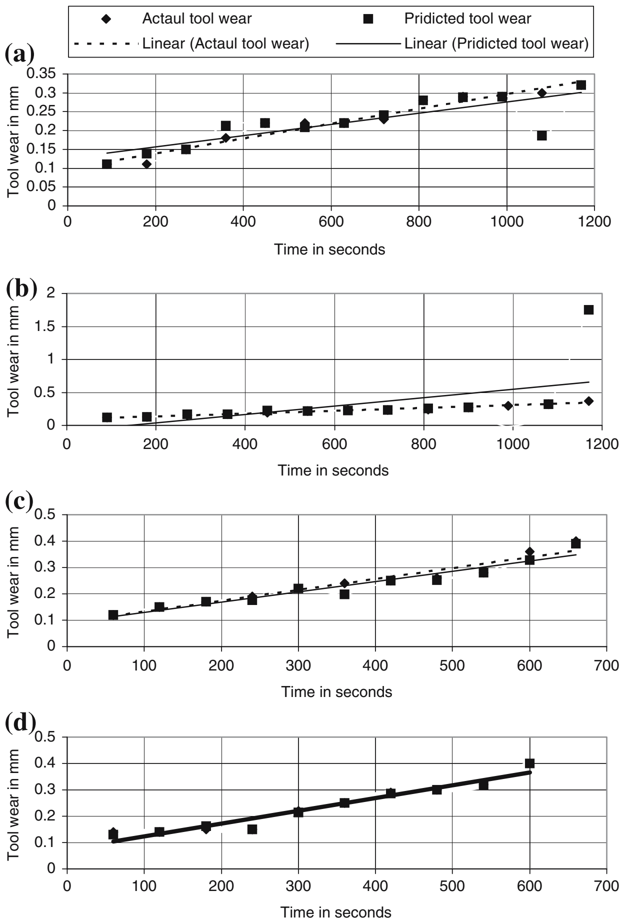

Fig. 16 Comparison of actual and predicted tool wear (**a**) Experiment-1; (**b**) Experiment-2; (**c**) Experiment-3; (**d**) Experiment-4

generate chips that are discontinuous and short so giving rise to flank wear only. In most of the cases cutting forces show an upward trend with the increase in the tool wear rate. The tangential component (F_z) of force is more sensitive to tool wear as compared to axial component (F_x) and radial component (F_y). The values of the cutting forces start to increase after tool wear of about 0.15 mm. Moreover, it was also observed that the vertical accelerations are initially slightly more then reduces during the stable cutting conditions and finally it again starts to increase with increase in tool wear. The accelerations of the tool show minimum value near 0.15 mm of tool wear and there after the value of g's increased. During experimentation it was observed that the Acoustic Emissions parameters AE (RDC_{avg}) show a significant increase with tool wear. AE parameter showed gradual rise in their values with tool wear.

Force, vibrations and AE signals show considerable changes with tool wear. But these other parameters also which govern these changes so only one signal i.e. either force, vibration or AE is not sufficient in order to obtain reliable prediction of the tool wear. Hence a combination of two signals is recommended.

A model is constructed using Adaptive Neuro Fuzzy Inference System (ANFIS). The model makes use of cutting forces (F_z), tool accelerations and AE (RDC_{avg}) signals in order to estimate the tool wear. This technique provides a method for fuzzy modeling procedure to learn information about a data set, in order to compute the membership function parameters that best allow the given input/output data. Once the model is constructed it is capable of estimating the tool wear rate for particular cutting parameters (for which it has been trained). The model provided quite satisfactory results. The model is fast to construct and it can also estimate tool wear on-line. The time taken to construct the model is dependent upon the amount of data points and the accuracy of the model is dependent upon the selection of data points.

Appendix I

Time	Fz	Acceleration	RDC_{avg}	Tool wear
Experiment 1				
90	18	4	170	0.11[a]
180	20	2.5	179.2	0.11
270	21	2.7	222	0.15[a]
360	23	2.5	517.8	0.18
450	25	2.8	721.7	0.22[a]
540	25	2.8	722.8	0.22
630	26	2.8	738.6	0.22[a]
720	27	3	745.2	0.23
810	30	3.7	805.8	0.28[a]
900	31	4.2	845.6	0.29
990	31	4.5	863.7	0.29[a]
1,080	37	5	1,128.1	0.3
1,170	39	6	1,662.25	0.32[a]
Experiment 2				
90	19	4	114.4	0.12
180	20	3	137	0.13[a]
270	22	2	190.7	0.15
360	22	3	238	0.17[a]
450	23	2	334.6	0.19
540	25	3	616.6	0.22[a]
630	26	3	654.8	0.23
720	27	3.5	667.4	0.23[a]
810	30	4	699	0.24
900	32	5	865.5	0.27[a]
990	37	7	1,302	0.3
1,080	39	8	1,526.2	0.32[a]
1,170	48	9	2,545.5	0.37

Experiment 3				
60	19	4	308.6	0.12[a]
120	20	2.5	564.4	0.15
180	21	2	742	0.17[a]
240	23	2.5	849.6	0.19
300	26	2	976.6	0.22[a]
360	29	5.5	1,006	0.24
420	30	2.5	1,067	0.25[a]
480	31	4	1,086.4	0.26
540	33	3.9	1,138.4	0.28[a]
600	42	4.2	1,576.6	0.36
660	52	5	1,992.4	0.4[a]
Experiment 4				
60	20	3.8	1,046.3	0.14
120	20	3	1,054.2	0.14[a]
180	22	2.5	1,072.5	0.15
240	22	2.5	1,092	0.15[a]
300	28	2.8	1,301	0.22
360	32	3	1,443	0.25[a]
420	34	3.2	1,644.5	0.29
480	35	3.5	1,645.7	0.3[a]
540	38	4	1,668	0.32
600	52	4	2,058.7	0.4[a]

Cutting forces (Fz), Acceleration (tool), Flank wear, Acoustic emission parameters (RDC_{avg})

[a] Training data

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