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Development Of Tool Wear Model And Wear Estimation During Turning Of Hard Alloy Steel Using Acoustic Emission Technique

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Abstract: This study presents the development of a tool wear model aimed at estimating the tool wear during the turning process of E0300 alloy steel. The acoustic emission technique is employed for this purpose. Various process parameters, including cutting speed, feed rate, and depth of cut, are utilized as input variables, while the corresponding flank wear under these conditions serves as the output of the neural network model. The efficacy of the trained neural network is evaluated using experimental data. The research demonstrates the effective application of fuzzy logic techniques for monitoring tool wear in turning operations. Specifically, the paper outlines a predictive approach for detecting tool wear, employing a neural network model to predict the flank wear of a CCMT 09 T3 08 WF 1525 insert during the turning of E0300 alloy steel. Actual cutting tool flank wear data are employed in the study, and a backpropagation neural network model is developed to forecast the flank wear during turning operations.

Keywords: tool wear detection, flank wear, artificial neural network model, fuzzy logic technique.

1 Introduction:

Recently the applications of high speed machining have increased due to the need for high precision and high accuracy machining and machining of difficult-to-cut material. However, the high speed machining also accompanies problems: the product quality can be degraded due to the tool wear and the product cost can be increased due to frequent tool replacements. Therefore, it is necessary to develop a technique of quantitative tool wear measurement to determine the precise timing for tool replacement. Automation in metal cutting process is reliable methods of monitoring the cutting tool wear and tool failure. Sensors and automatic control can monitor the variation of cutting parameters during metal cutting. Indirect, on line tool wear monitoring is one of the most difficult tasks in the context of the process monitoring of metal cutting machining process.

Tool wear influences cutting power, machining quality, tool life and machining cost. When tool wear reaches a certain value, it increases cutting force, vibration and cutting temperature. This causes deterioration of surface integrity and dimensional error greater than tolerance limits. The cutting tool must be replaced or ground before reaching this limit. The cost and time for tool replacement and adjusting machine tool increase machining cost and decreases productivity. Hence tool wear relates to the economics of machining and prediction of tool wear is of great significance for the optimization of cutting process.

Some researchers concentrate on the study of wear mechanism and investigate the mathematical relationship between wear due to various wear mechanism and some cutting process variables such as relative sliding velocity of work piece material along tool face, cutting temperature of tool face and normal pressure on tool face.

Using multi sensor system based on a continuous acquisition of certain process parameters (signals such as cutting forces or acoustic emission) it is possible to estimate or to classify certain wear parameters. However, despite of intensive scientific research during the past decades, the development of reliable flexible tool wear monitoring systems is an ongoing attempt. Artificial neural network (ANN) which has the learning capability can be used as a tool war, which can further be used to optimize a machining operation in terms of productivity and quality. To fulfill the object several sensing technique have been developed in the recent year for estimating and automatic control the variation of cutting parameters during metal cutting. Some of these techniques have provided quiet useful under laboratory conditions, few of them have been discussed by Sick B. [2] reviewed the current literature and discussed in the context of tool condition monitoring with neural networks, according to the review, two methods have been applied, direct or indirect monitoring of tool wear. Direct methods rely on sensing techniques that measure the wear during process by using optical, radioactive, proximity sensors and electrical resistance measurement techniques. Elanayar and Shin [1] proposed a model, which approximates flank and crater wear propagation and their effects on cutting forces by using radial basis function neural networks. The genetic approximation capabilities and their effects on cutting forces by using radial basis function neural networks. The generic approximation capabilities of radial basis function neural networks can be used to identify a model and state estimator was designed based on this identified model. A wide range of tool modeling techniques utilizing neural networks has been reviewed by Dimla et.al.[3].They concluded that neural networks are adequate for tool condition monitoring. Author pointed out the confusion in their interpretation of TCM techniques in literature as on line or off line systems. They concluded that the methods that are proposed to be an online technique should be tested in real time and their success should be decided afterwards. Ghasempoor et.al.[4] proposed a tool wear classification and continuous monitoring neural network system for turning by employing recurrent neural network design Li.et.al.[5]form a hybrid machining model for the prediction of tool wear and work piece surface roughness. Neural network are used to predict difficult to model machining characteristics factors. Liu and Altintas [6] derived an expression to calculated flank wear in terms of cutting force ratio and other machining parameters. The calculated flank wear, force ratio, feed rate and cutting speed were used as an input to a neural network to predict the flank wear in the next step. Casto S. Lo. et al. Jurkovic J.

et al. [7] suggested a reliable direct measuring procedure for measuring different tool wear parameters. Authors employed modern image processing techniques and machine vision systems for direct wear measurement, and concluded that these are flexible, economical, high spatial resolution and good accuracy for detection of tool wear. Suresh P. V. S. et al. [8] studied on the genetic algorithm approach for optimization of surface roughness model. This approach was used for prediction of optimal machining conditions for good surface finish and dimensional accuracy. Tarang Y. S. et al. [9] proposed an automatic fuzzy rule base generation method to control nonlinear and time varying turning processes with constant cutting forces based on this study, the optimum fuzzy rule base for the control of turning processes can be self organized without the need for experienced manufacturing engineers. Yen Yung-Chang et al. [11] developed a methodology to predict the tool wear evolution and tool life in orthogonal cutting using FEM simulations. They concluded that location of the maximum wear rate is on the tool rake face and is nearly coincident with that of the maximum cutting temperature. Tansel I. N. et. al. [10] studied on the aluminum silicon carbide during turning in CNC machine using carbide tools. Back propagation type neural network was used for the estimation of tool wear. Author concluded that the cutting force variations increased.

1 Planning for Experimentation

Hard alloy steel E0300 is used for experimental investigation. It has main alloying element is chromium. Chromium increases hardness along with increase in toughness and wear resistance of steel. It has good abrasion and wears resistance. It is fully magnetic in nature and very prone to atmospheric oxidation and rusting in corrosive and humid environment. Table-5.1 shows the chemical composition of work-piece used for experimentation.

2.1 Machine tool; cutting tools and measuring equipment used

(i) Machine Tool- Capstan Lathe (Made in West Germany)
(ii) Carbide tools (inserts) used for turning: CCMT09T308 WF1525
(iii) Tool holders used: SCLCR 12 12 F 09 M
(iv) Tool makers Microscope of resolution 0.01 mm

Table 1 Details of cutting tool used and environment for turning experiments

Cutting tool used	Cutting tool specification	Rake angle	Clear-ance angle	Nose radius	Cutting edge ngle	Environment
T-Max-P Positive	CCMT09T308 PM4225	0^0	7^0	0.8	80^0	Wet and dry

insert				mm		

Table-2 Chemical composition of E0300 used for experiments**.**

Work-piece Specification and size	%C	%Cr	%Mn	%Si	% Ni	%S	%P
E0300/ 120 dia. x 200 mm long bar	0.87	1.334	0.764	0.25	0.028	0.08	0.046

2.2 Experimental Setup

To measure and monitoring the cutting tool flank wear an AE sensor monitoring setup has been design and fabricated is shown in Fig. 1. AE sensor is mounted on the tool shank and the signal output (I_{rms} and V_{rms}, Sensor output) voltage As the measure of the AE signal the RMS value of the AE is directly related to the average power dissipation involved in the process, the AE count clearly relates to the occurrence of the discreet events like microscopic slips and fractures in the metals during metal cutting. The AE sensing clearly reveals the information about the hardness and the dislocation densities in the material and therefore has potential to be useful in the identification of individual types of tool wear.

The signal from AE the sensor is first filtered and amplified in a sufficiently wide band to encompass most of the AE spectrum and remove any unwanted noise, especially at low frequency. Assume that AE signal arises mainly from primary contact region between the tool and the chip formed as well as due to the flank wear of the cutting tool and analysis the estimated data.

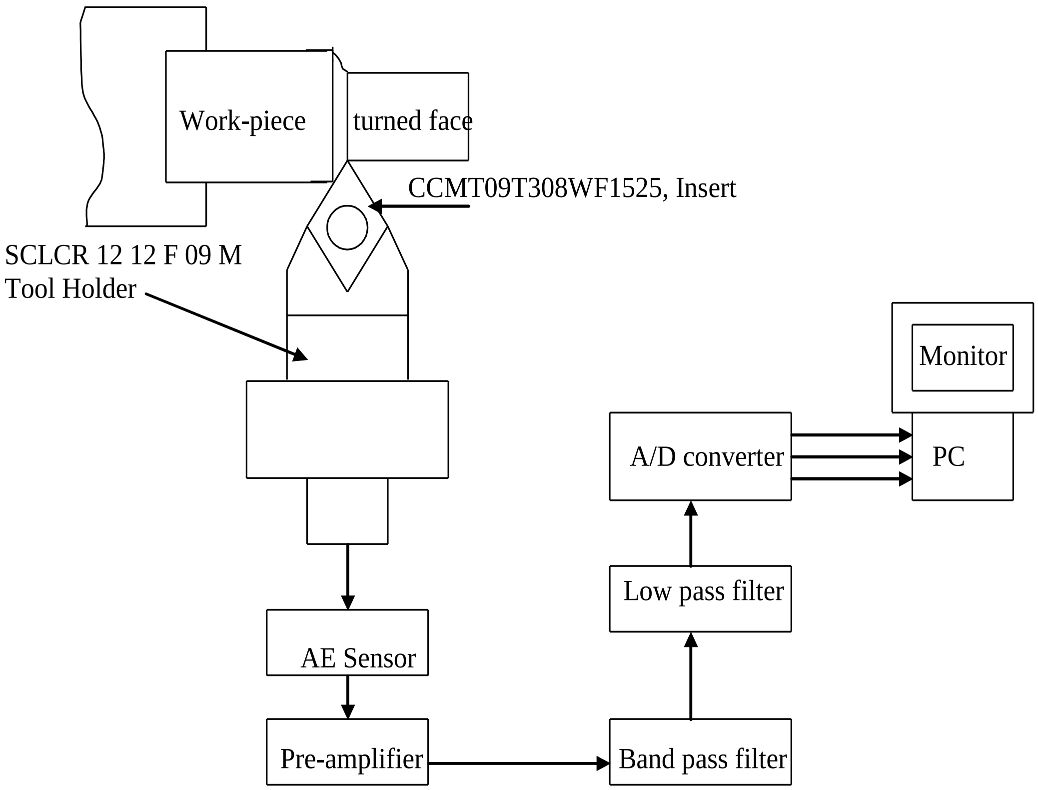

Fig.1 Scheme of the experimental setup

Flow chart

Fig. 2 shows the detail work undertaken in the form of a flow chart and presented in this chapter.

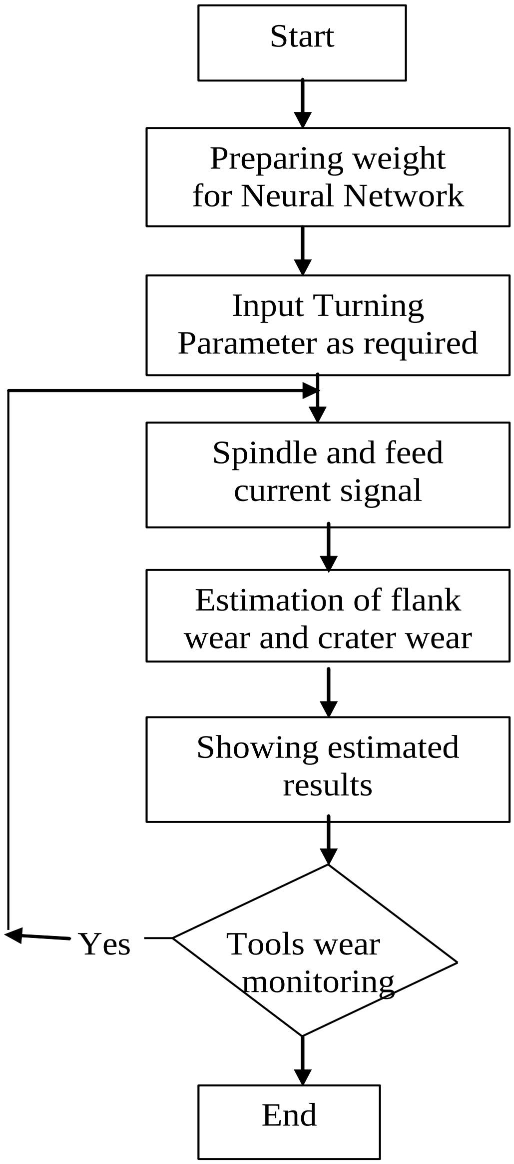

Fig. 2 Flow chart of on-line FNN model

3 Tool wear detection with FNN model

The flow diagram of the user interface is shown in Fig. 2 The basic function of the developed user interface are promoting the user to enter the necessary information such as turning parameters setting conditions and tool wear size and as well as display the estimated wear to the user. The modeling of the current signal was developed considering the effects of tool wear, cutting speed, feed rate and depth of cut during turning. In this study, the flank wear width was categories into Category-A, Category-B, Category-C, Category-D, Category-E, Category-F and Category-G according to the width of the cutting tool wear during turning of E0300 alloy steel using CCMT

09 T3 08 WF 1525 insert and by utilizing SCLCR 12 12 F 09 M cutting tool holder. Table-3 shows the tool wear and their category. The effect of the cutting parameters e.g. cutting speed(V, m/min), feed rate (f, mm/rev) and depth of cut (d, mm) on the spindle and feed current signal can be expressed in the form of the general mathematical function for the different categories of the tool wear during turning. The spindle and feed current signals under different flank wear width are

$I_{spindle} = C_1.V^{n1}.f^{n2}.d^{n3}$ -----Eqn.1

$I_{feed} = C_2.V^{m1}.f^{m2}.d^{m3}$ -----Eqn. 2

Where, $I_{spindle}$ = spindle current (I_S, A), I_{feed} = feed current (I_F, A), C1 and C2 are the constant depends on the properties of the work materials and cutting tool and as well as insert geometry. n_1,n_2,n_3 and m_1,m_2,m_3 are the exponential for spindle peak current and feed current respectively.

Table-3 Cutting tool flank wear categorization

Category of Flank wear width	A	B	C	D	E	F	G
Flank wear width(mm)	00-0.08	0.08-0.16	0.16-0.24	0.24-0.32	0.32-0.40	0.40-0.48	0.48-0.56

The logarithmic values of the spindle current (I_S, A) can be expressed as follows

$$\begin{pmatrix} I_{S1} \\ I_{S2} \\ I_{S3} \\ I_{S4} \\ I_{S5} \\ I_{S6} \\ I_{S7} \end{pmatrix} = \begin{pmatrix} n_{10} & n_{11} & n_{12} & n_{13} \\ n_{20} & n_{21} & n_{22} & n_{23} \\ n_{30} & n_{31} & n_{32} & n_{33} \\ n_{40} & n_{41} & n_{42} & n_{43} \\ n_{50} & n_{51} & n_{52} & n_{53} \\ n_{60} & n_{61} & n_{62} & n_{63} \\ n_{70} & n_{71} & n_{72} & n_{73} \end{pmatrix} \text{x} \begin{pmatrix} 1 \\ \log V \\ \log f \\ \log d \end{pmatrix}$$

The logarithmic values of the feed current (I_F , A) can be expressed as follows

$$\begin{pmatrix} I_{F1} \\ I_{F2} \\ I_{F3} \\ I_{F4} \\ I_{F5} \\ I_{F6} \\ I_{F7} \end{pmatrix} = \begin{pmatrix} m_{10} & m_{11} & m_{12} & m_{13} \\ m_{20} & m_{21} & m_{22} & m_{23} \\ m_{30} & m_{31} & m_{32} & m_{33} \\ m_{40} & m_{41} & m_{42} & m_{43} \\ m_{50} & m_{51} & m_{52} & m_{53} \\ m_{60} & m_{61} & m_{62} & m_{63} \\ m_{70} & m_{71} & m_{72} & m_{73} \end{pmatrix} \times \begin{pmatrix} 1 \\ \log V \\ \log f \\ \log d \end{pmatrix}$$

Where, $I_{S1}, I_{S2} \ldots\ldots I_{S7}$ and $I_{F1}, I_{F2} \ldots\ldots I_{F7}$ are the algorithmic values of the spindle peak current and feed current respectively. The input variables for this analysis are 1, log V, log f and log d for turning parameters cutting speed (V, m/min), feed rate (f, mm/rev) and depth of cut (d, mm) respectively. Output variables are $I_{S1}, I_{S2} \ldots\ldots I_{S7}$ and $I_{F1}, I_{F2} \ldots\ldots I_{F7}$ respectively for spindle peak current and feed current. Utilizing the above input-output relational matrix the weights of the neural network can be calculated by regression analysis.

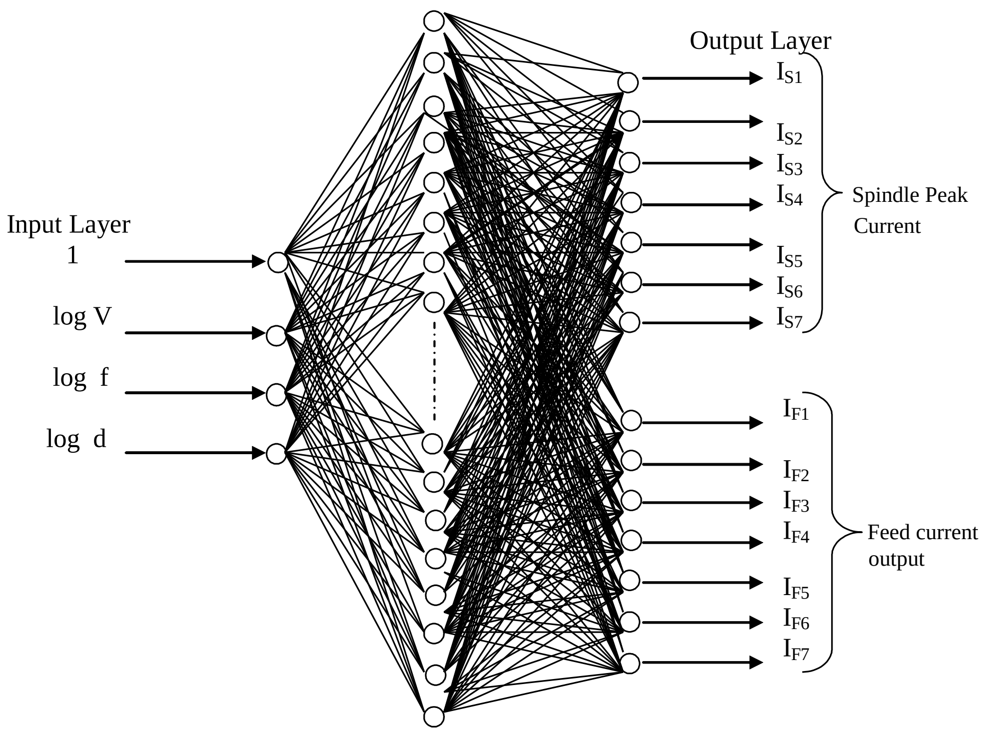

Fig 3 Spindle current signal and feed current signal with Neural Network

The FNN model can be expressed in four separate heads such as fuzzy logic based tool wear classification, input normalization, neural network base tool wear estimation and fuzzy logic based adjustment of tool wear. Spindle current signal and feed current signal models at the various cutting tool wear can be explained with neural network is shown in Fig. 3. The above matrix between the current and turning parameters can be expressed with the help of the neural network structure as shown above. The measure spindle current and feed current are considered as real value and estimated spindle currents for I_{S1}, I_{S2}….I_{S7} and feed current for I_{F1}, I_{F2}….I_{F7} considered as mid value of a bunch of various tool wear classifications. The measure values are compared with the estimated values by utilizing fuzzy logic based classification and membership degree of the tool wear can be determined by utilizing the fuzzy curve line is shown in Fig. 4

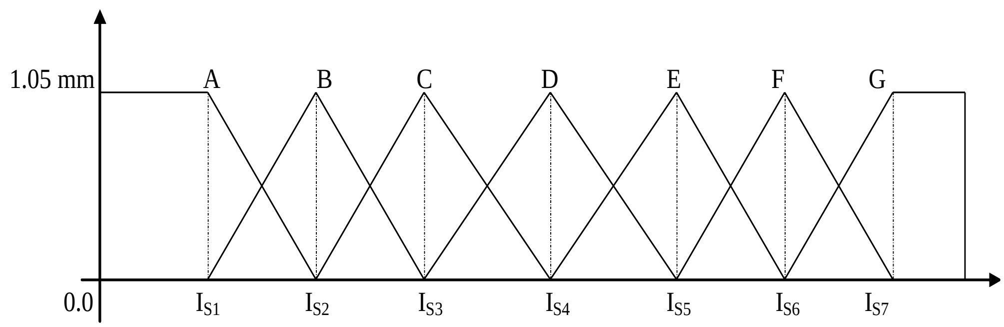

Fig. 4 Classification of the membership degree of the tool wear using fuzzy logic based curve

4 Discussions and Results

Stress energy in the materials gets dissipated as thermal energy and micro-elastic pulses as AE generated during metal cutting mostly originates in the plastic deformation zones on the work piece and related to the associated stress relaxation. A large number of pulses are emitted by sources randomly distributed over the plastic deformation zone. The AE signal detected from the process appears as a continuous noise. During experiment it was found that V_{rms} monotonically with all three turning parameters such as cutting speed, feed, depth of cut. The parameter AE-mode measures the value of the voltage amplitude corresponding to the peak in the amplitude distribution of the digitized AE signal envelope. It is important to extract the feature of the signals during turning to ensure the reliability of the tool monitoring system. In monitoring the cutting tool flank wear AE signal monitored the complicated information during turning.

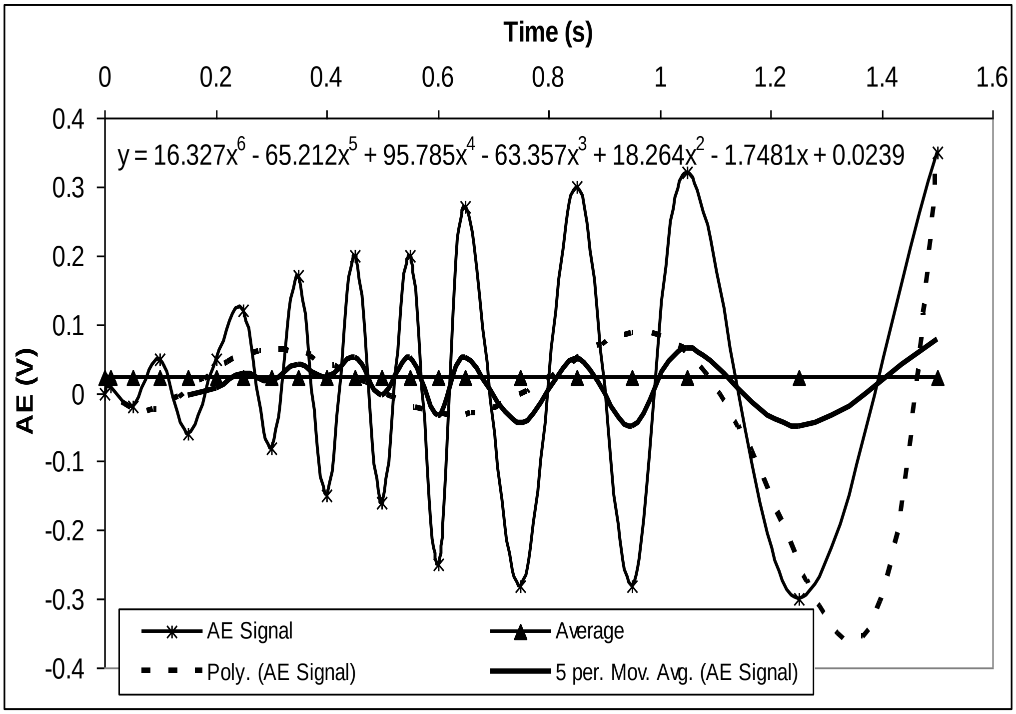

Fig. 5 Moving Average trend of AE signal

Figure 5 shows the detail AE signal generated during turning through various graphical representations such as average, polynomial trend and moving average trend of the AE signal. Polynomial equation 5.3 represents the polynomial trend of the cutting tool wear AE signal during turning.

$$y = 16.327x^6 - 65.212x^5 + 95.785x^4 - 63.357x^3 + 18.264x^2 - 1.7481x + 0.0239 \text{ …….Eqn. 3}$$

Fig.5 also shows the 5 % moving average trend of the generated AE signal during turning. Average AE signal generated is slightly above the zero value and as shown in the Fig. 5. The behavior of the AE signal due to the appearance of the cutting tool wear can be predicted from the above polynomial relation. From the polynomial trend of the AE signal and mathematical relation it is clear that AE signal increases rapidly after 1.2 s of the turning operation was started. Hence, it is concluded that at the very beginning the AE signal was very small as the cutting tool was fresh and sharp edge, but after certain time (S) the AE signal increases as the cutting tool wear appears and increases with time phenomenon. During experiment it was observed that the generated AE signal increases with increase of cutting time.

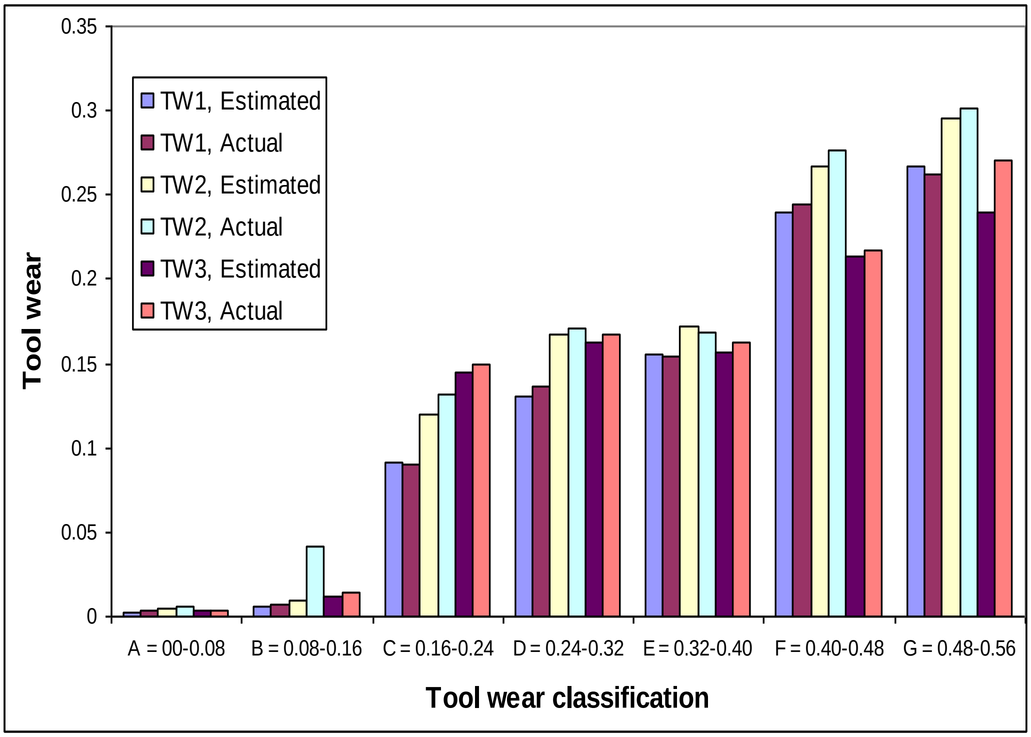

Fig.6 Cutting tool wear classification with comparison between estimated and actual wear

According to the Taguchi method, L_{27} orthogonal array, 27 x 3 = 81 experiments were performed to analyze the cutting tool wear. The membership degree of the cutting tool wear under different tool wear classification is estimated and fused using fuzzy logic and plotted in the graph is shown in Fig. 6. From the Fig. 6, it is clear that the above described method is suitable to estimate the cutting tool wear during turning.

From the above discussion it is clear that the neural networks can employed to predict the condition of the tool in a turning process and the construction of a neuro-fuzzy system that seeks to provide a linguistic model for the detection of tool wear from the knowledge embedded in the neural network.

In order to overcome the difficulties in defining the fuzzy sets, we offered a data density based adaptation scheme that tuned the fuzzy membership functions from the error information obtained by comparing the outcome of the neural network and the fuzzy mechanism. Not only that but also the study on AE during turning has lead to a better understanding of the process and AE signal parameters such as V_{rms} ,I_{Si} (i = 1,2.3-------7) and I_{Fi} (i = 1,2,…..7)is to be used in tool wear monitoring. The AE signal can be successfully employed to detect the tool failure or breakage during metal cutting. AE signal levels are very sensitive to the cutting tool wear, also strongly depends on the cutting speed and depth of cut. The use of artificial intelligence technique such as FNN to offer a lot of promise, as the method work well even when exact sensor modules are not available.

5 Conclusion The experimental data of measured tool flank wear are utilized to train the neural network models. Trained neural network models are used in predicting cutting tool flank wear for different cutting conditions. Back propagation technique can be applied for training of the network The developed prediction system is found to be capable of accurate tool wear prediction for the range it has been trained.

An ANN based model was developed using Matlab for predicting the flank wear of CCMT09T308WF1525 inserts. Three parameters VIZ. cutting speed, depth of cut and feed were considered and back propagation technique was employed for training of the model. The system was run for various set of cutting condition parameters and the flank wear predicted by ANN model considered with experimental result. It was concluded from the result that artificial neural network based model can be successfully applied for the prediction of flank wear of CCMT09TT308WF1525 insert during turning**.**

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