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Modelling of turning process for Prediction of tool wear

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Abstract: The tool wear is measured by using a Profile Projector PP-200. In this indirect measurement technique the tools wear parameters are cutting speed, feed and depth of cut. In addition to that software computer techniques adaptive neuro-fuzzy inference system is applied for Modelling prediction. The objective of this study is also to correlate flank wear in regression and compare with ANFIS in prediction studies. The proposed model is for prediction of flank wear of the mild steel work piece. The machining experiments are performed under various cutting conditions using Cutting speed, Feed and Depth of Cut. The flank wear is measured. It is also observed that the flank wear prediction accuracy of Adaptive neuro fuzzy inference system using trapezoidal membership function is better than regression analysis. The flank wear prediction accuracy with ANFIS is 87.87% as input parameters are cutting speed, feed and depth of cut.

Keywords: Turning, ANFIS, Regression, Flank Wear, Crater Wear.

I. INTRODUCTION

In any manufacturing process, numbers of operations are done with the lathe machine they are turning, facing, knurling, grooving, parting, chamfering, taper turning, drilling and threading. Turning is the most important process in an industry which is done with a lathe machine. In turning process, turning is used to remove the excess material. In this operation work piece is having a rotary motion. But there are more important things in this operation such as tool life, tool wear and tool machinability. If we discuss about tool life cutting life of tool is expressed in time. Time period measured from start of cut of failure of the tool. Wear is progressive damage, involving material loss, occurs on the surface as a result of relative motion between the surfaces. Tool wear causes the tool to lose its original shape- ineffective cutting, Tool needs to be resharpened. There is a geometry of tool wear they are flank wear (edge wear) and crater wear (face wear).

In flank wear, tool slides over the surface of the work piece and friction is developed. It occurs due to friction and abrasion. Adhesion between work piece & tool- BUE. It starts at CE and starts widening along the clearance face. In flank wear, independent of cutting conditions and tool / work piece materials, brittle and discontinuous chip. It increases as speed is increased. The work reported for turning process by acoustic emission technique and artificial intelligence technique correlative to flank wear analysis of single point turning. (et al. 2008) is that the experimental results obtained on measurement and the trained network generated attributes correlate for one complete experiment. Higher degree of accuracy may be achieved when the training of network is taken up with more number of trials and use of larger number of epochs. More than one method of wear analysis and correlatives studies is being considered for obtaining higher levels of accuracy and for optimization.

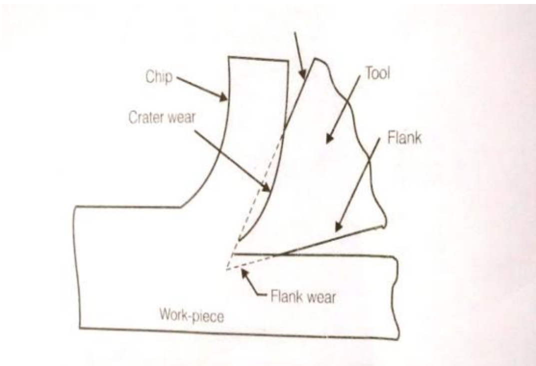

Figure 1 Flank and crater wear (Production engg. By Panday and Singh)

Heyao Shen, Minghong Wang was doing the work on the topic the simulation analysis of tool flank wear based on cutting force. They focuses on researching relationship between cutting force and tool flank wear. In different experiment conditions, the consistency of the results of simulation and experiment results was obtained through the comparative analysis between the two. It is mainly investigated into the simulation analysis of the tool flank wear. The specific content of the simulation experiment is explaining the causation for the tool flank wear through the analysis of the temperature field at the tip and obtaining the data of cutting force in different tool flank wear (10,100,200,300um).

D. Dinakaran a, S. Sampathkumar b , J. Susai Mary (et al. 2010) used the nuero fuzzy technique in turning for the real time prediction of flank wear. An ultrasonic technique

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is used to monitor the tool wear in turning. The ultrasonic waves are reflected from wear area. They were used adaptive neuro fuzzy inference system (ANFIS) for the tool wear. The experimental validation shows that ANFIS can predict the tool wear with average error of 2.5%.

S.Thamizhmanii* and S.Hasan (et al. 2010) wear discussed about CBN and PCBN tools due to cutting forces. High cutting forces are identified and this may be due to heat and flank wear combinations. Flank and crater wear on the rake face and hard metal deposition due to diffusion of metals on the cutting tool surface are the damages occurred during process.

J. U. Jeon and S. W. Kim works on the optical flank wear monitoring of cutting tools by image processing. The method is based on real time vision technology in which the tool is illuminated by the beam of a laser and the wear zone is visualized using a Videocon camera. The image is converted into digital pixel data and processed, to detect the wear land width. It has been proved that the average and maximum peak values of the flank wear width can be monitored effectively to a measuring resolution of 0.1 mm.

Yoram Koren, Tsu-Ren Ko, A. Galip Ulsoy, Kourosh Danai designed to operate under varying cutting conditions. For online estimation of flank wear rate based on cutting force measurements is introduced. The main aim is to employ a model of the relationship between force and flank wear, together with on-line parameter estimation method. Experiments, conducted for turning operations with a varying depth of cut, results good agreement between estimated wear values and the actual values of tool wear measured intermittently during the cut.

A mechanics of cutting analysis for orthogonal cutting with tool flank wear is presented based on an experimental investigation by J. Wang, C.Z. Huang, W.G. Song (et al. 2003). Tool flank wear results in a substantial increase in the force components and that the thrust force is more sensitive to tool flank wear. These may be used as a primary basis for developing tool condition monitoring strategies.

Tool flank wear analyses on martensitic stainless steel by turning S. Thamizhmnaii*, B. Bin Omar, S. Saparudin, S. Hasan (et al. 2008). The flank wear was caused by abrasive action between cutting tool and work piece. The heat generated between work piece and tool tip help to form built up edge. The generated heat was conducted easily due to low thermal conductivity of the work piece material. At low cutting speed of 125 m / min with high feed rate of 0.125 mm / rev and 1.00 mm DOC.

Vishal S. Sharma, Manu Dorga, Raman Bedi, Puneet Sharma (et al. 2008) 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. They were 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.

The modelling work is not reported using tool wear area as an input parameter in prediction of tool wear. The published work focus on flank wear in which input parameters are cutting speed, feed and depth of cut for experimentation and prediction work.

II. EXPERIMENTAL DETAILS

Experimental set up includes lathe machine, Profile Projector PP 200. To approach these points Mild Steel is used to study flank wear.

The experimental set up was set for the three machining parameters cutting speed (rpm), feed (mm/rev), and depth of cut (mm). The mild steel material chemical composition was Carbon 0.16-0.18%, Sulphur 0.040% max, Phosphorus 0.040% max. The following specifications are selected for this study:

Table 1: Specifications of workpiece, Cutting conditions, Profile projector and lathe machine.

Work piece (Mild steel)	
Length of the workpiece	60 mm
Cutting Conditions	
Cutting Speed	32,52,88,150,250 rpm
Feed	0.05,0.06,0.07,0.08,0.09 mm/rev
Depth Of Cut	0.5,0.7,0.9,1.1,1.3 mm
Profile Projector(PP-200)	
Focussing	Through rack and pinion system
Screen	Antiglare hard glass 200 mm diameter with cross line, 360 degree rotatable
Nosepiece	Single nose or optically provided quadrapule ball bearing
Magnification	10x, 20x, 50x & 100x
Work Stage	150*150 mm with X-Y movement of 25*25 mm
Working Distance	30 mm approximately under 10x magnification
Micrometer	Zero adjustment, 25 mm graduations with least count 0.005 mm
Illumination	Counter illuminator of 12V-100W & 2 Surface lamps of 6V/20W
Optional	Vinyl cover , duster & fuse 2 nos.
Accessories	Objective 40x , 80x , Halogen Bulb, Digital Micrometers
Lathe Machine(CENTRE LATHE HMT LTM20-Centre Lathe)	
Swing Over Bed(dia)	420 mm
Distance Between Centres	1000 mm
Spindle Drive	Gear
Spindle Speed	32 to 1200 rpm
Spindle Socket Taper	60 metric
Taper of Tails Stock Sleeve	MT 4
Travel of Tails Stock Spindle	150 mm
Main Motor	3 K.W.
Net Weight	1250 kg

Fig: Lathe Machine (CENTRE LATHE HMT LTM20-Centre Lathe)`

III.REGRESSION

Since multiple regression is used to determine a correlation between a criterion variable and a combination of predictor variables, the statistical multiple regression method is applied. It can be used to analyze the data from any of the major quantitative research designs such as causal-comparative, correctional and experimental.

This method is able to handle interval, ordinal, or categorical data and provide estimates both of the magnitude and statistical significance of the relationships between variables Therefore, multiple regression analysis will be able to predict the criterion variable finish surface roughness via predictor variables such as feed rate, spindle speed, depth of cut and work piece material hardness (M. S. Lou et al.1998).

After experimentation on tool material 125 datasets are collected. Out of this data set 100 data sets are used for training and randomly selected 25 data sets (1/4th of total data sets) for testing prediction accuracy. An empirical expression was established based on the regression analysis for predicting wear of dry turning.

$$VB = 0.0114465\, S^{(0.013)} F^{(-1.114)} D^{(0.803)}$$

Where, VB- Flank Wear (mm),

S-cutting speed in RPM,
F-feed in mm/rev,
D-depth of cut in mm.

The above new empirical model is developed for prediction of flank wear using speed, feed, and depth of cut. It is also observed that the proposed equation establishes the relation among input variables and response variables. The average deviation observed in measured value 28.47% at confidence level of 85%. This regression prediction values are used for comparison with ANFIS prediction model values to verify the accuracy of a prediction model.

IV. ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS)

Although the fuzzy inference system has a structured knowledge representation in the form of a fuzzy “if-then” rule, it lacks the adaptability to deal with changing external environment. Therefore neural network learning concepts have been incorporated in a fuzzy inference system, resulting in adaptive neuro-fuzzy modelling. 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 parameter. The network is “learning” the behaviour of the available data during a training phase by adjusting the parameters of the node functions to fit the data. The basic learning an algorithm, the back propagation, aims on the minimization of a set measure or a defined error, usually the sum of the squared differences between the desired and the actual model outputs.

ANFIS is a famous hybrid neuro-fuzzy network for modelling complex systems and was developed by Jang (1993). This system is a useful neural network approach for the solution of a nonlinear functions and approximating problems (2008). The system refers to the way of applying various learning techniques are developed in the literature to a fuzzy inference system (FIS). Fig. shows the basic structure of a FIS that consists of a five functional blocks: a rule base, which contains a number of fuzzy if–then rules; a database, which defines a membership functions (MF) of the fuzzy sets; a decision-making unit as the inference engine, a fuzzification interface, which transforms the crisp inputs to linguistic variables; and a defuzzification interface, which converts the fuzzy outputs to crisp outputs.

The proposed neuro-fuzzy model of the ANFIS is a multilayer neural network-based fuzzy system. Both the neural network (NN) and fuzzy logic (FL) are used in ANFIS architecture. The system has an adaptive network which is functionally equivalent to a 1st-order Sugeno fuzzy inference system Jang (1993). The ANFIS uses a hybrid-learning rule, which combines back-propagation, gradient-descent and least squares algorithm to identify and optimise the Sugeno system’s signals and a corresponding equivalent ANFIS architecture of a first-order Sugeno fuzzy model with two rules? The square nodes are the adaptive nodes, and the circular nodes are fixed nodes whose parameters change during the training process.
The system has the total of five layers. In this connected structure, the input and output nodes represents the training and a predicted values, respectively, and in the hidden layers, there are nodes functioning as the membership functions (MFs) and rules. This architecture has a benefit that it eliminates the disadvantage of a normal feed forward multilayer network, where it is a difficult for an observer to understand or modify the network.

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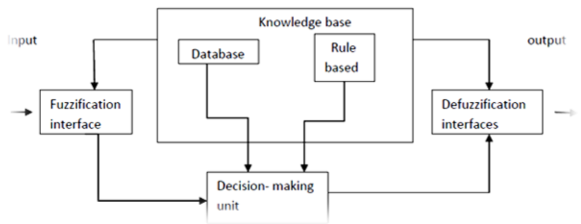

Figure 3: Block diagram of ANFIS (Jang 2004)

V. RESULTS AND DISCUSSION

The experimental data 125 set was collected out of which 100 datasets were utilized as a training data and remaining 25 data sets as a testing data. The fuzzy inference system was trained up to 100 epochs. To verify the accuracy of prediction other 25 sets were used as a testing data. In this experiment ANFIS triangular MF, VB is compared regression analysis VB value. Therefore the prediction accuracy of ANFIS triangular MF is higher as compare to regression prediction models. It is also observed that predicted flank wear accuracy is 87.87% with triangular membership function with average deviation of a 12.13%. Where as in regression analysis the average deviation observed is 28.47%. Flank Wear in Turning (Dry) Testing Data:

Table 2: Experimental, Predicted flank wear and percentage error
Flank wear Prediction using ANFIS using Trapezoidal Membership Function

Sr. no.	Speed(rpm)	Feed(mm/rev)	Depth of cut (mm)	Flank wear Experiment	ANFIS Trap MF	% Error
1	32	0.05	1.3	0.45	0.429	4.67
2	52	0.05	1.1	0.45	0.491	9.11
3	88	0.05	1.3	0.4	0.439	9.75
4	150	0.05	1.1	0.45	0.423	6
5	250	0.05	1.3	0.28	0.502	79.29
6	32	0.06	1.1	0.25	0.212	15.2
7	52	0.06	1.3	0.23	0.255	10.87
8	88	0.06	1.1	0.22	0.216	1.82
9	150	0.06	1.3	0.23	0.271	17.83
10	250	0.06	0.7	0.11	0.139	26.36
11	32	0.07	1.3	0.23	0.255	10.87
12	52	0.07	1.3	0.22	0.255	15.91
13	88	0.07	0.5	0.11	0.097	12.27
14	150	0.07	0.9	0.17	0.166	2.35
15	250	0.07	1.3	0.29	0.249	14.14
16	32	0.08	1.1	0.21	0.228	8.57
17	52	0.08	1.3	0.41	0.283	30.98
18	88	0.08	0.9	0.185	0.18	2.7
19	150	0.08	1.3	0.31	0.297	4.19
20	250	0.08	0.5	0.117	0.111	5.13
21	32	0.09	1.3	0.32	0.308	3.75
22	52	0.09	0.5	0.12	0.114	5
23	88	0.09	0.9	0.195	0.191	2.05
24	150	0.09	1.3	0.325	0.321	1.23
25	250	0.09	0.5	0.125	0.121	3.2
	Average Error			12.13		

VI. CONCLUSIONS

An ANFIS is used to measure flank wear the turning parameters Cutting speed, Feed and Depth of Cut in turning process. Out of 125 data sets 25 sets of data are used as testing data. The measured values of flank wear are compared with ANFIS predicted values. Within the ANFIS triangular membership function is used for prediction of tool wear. The flank wear prediction accuracy by ANFIS with triangular membership function is 87.87% with the error of 12.13%. The ANFIS with triangular membership function also outperforms the regression analysis model in terms of prediction accuracy. ANFIS prediction model using trapezoidal membership function are observed better with speed, feed, depth of cut as input parameters in flank wear prediction. Flank wear with regression average error is 28.47% which is not suitable for any prediction. But when this experiment is done with ANFIS then it is observed that ANFIS is more suitable for the prediction of tool wear.

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