Scientific Journal Impact Factor (SJIF): 1.711
International Journal of Modern Trends in Engineering and Research
IJMTER
ISSN (ONLINE) : 2349 - 9745
ISSN (PRINT) : 2393 - 8161

MODELLING OF TURNING PROCESS FOR FLANK AND CRATER WEAR OF TOOL USING ANFIS

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Abstract- In today's world the leading industries are very much concerned about reducing down time and to increase the productivity as well as the quality. To increase the product quality the tool should have good performance. Turning process is widely used in the manufacturing operations in all the manufacturing industries. Tool wear monitoring in manufacturing operations is the combined effect of crater wear and flank wear. In direct measurement technique, the tool wear is measured directly at the cutting edge of the worn tool using a tool maker's microscope or tactile sensors. Whereas, in the indirect measurement technique the tool wear parameters are observed in the form of signals during the machining process which helps to determine the degree of tool wear. In opposite to direct measurement techniques, indirect measurement techniques allow to monitor the cutting process on-line, which is one of the biggest advantages in this method. In addition to that soft computing tools applied for this purpose are neural networks, fuzzy sets, genetic algorithms, simulated annealing, and colony optimization, and particle swarm optimization. In which we have to compares the different techniques to find out the tool wear.

Index Terms*:* ANFIS, Tool wear monitoring, Turning.

I. INTRODUCTION

Machining process is commonly considered as secondary process in manufacturing operations and widely used in the manufacturing industry in the world. Machining is widely used for metal removal and it involves turning, milling, boring and cutting. The realisation of surface finish is a diagnostic tool that is needed to guarantee product functionality. Choice of optimized cutting parameters is very important to control the required surface quality. Four basic types of machining operations are turning, drilling, milling, and grinding which are performed by different machine tools. The importance of maximizing a tool's working time and doing the ulmost to keep tools from breaking is directly related to process optimization.[1]

In the turning process, the tool is influenced by the combined action of large mechanical stress, high temperatures, and corrosion caused in part by cutting fluids. Thus, edges are gradually worn down and in extreme cases; it leads to premature catastrophic failure. Some important causes of tool breakage are plastic deformation, the material fluency at high temperature, and fatigue and brittle fracture because of combined stresses and low tenacity of the tool. For all these reasons, modelling, estimation and monitoring of tool wear are essential in any turning process. The possibilities of introducing increased cutting speeds, leads to decrease in cutting time resulting in substantial overall savings of the total machining cost. Tool wear is one of the important factors affecting manufacturing process and becomes as an obstacle in achieving manufacturing automation. The tool should be retracted and changed well before it wears out totally, otherwise the part to be machined will not comply with the specified accuracy. This results in poor surface finish of the job, leading to an increase in overall production cost, rework and scrap. Therefore on-line measurement of the tool wear is important; to change the tool because of the deviation in the profile that affects quality of the products.[1]

II. TOOL WEAR (TURNING)

Tool wear is generally caused by a combination of various phenomena, although it is an intrinsic event of cutting processes. Tool wear can occur gradually or in drastic breakdowns. Gradual wear may occur by adhesion, abrasion, or diffusion and it may appear in two ways: wear on the tool's face or wear on its flank. Contact with the chip produces a crater in the tool's face. Flank wear, on the other hand, is commonly due to friction between the tool and the workpiece material.[2]The importance of maximising a tool's working time and doing the utmost to keep tools from breaking is directly related with cutting-process optimisation. One of the main goals in turning (as in other machining processes) is to achieve an economic tool-life through wisely chosen cutting speeds, cutting feeds and depths of cut. The key issue is to find an appropriate trade-off between tool wear and productivity considering the tool's cost, its replacement cost, the cost of writing off the machine's idle time, and so forth. Avoiding breakage is another capital factor, because replacing the tool after it breaks means increased costs, since the post-breakage stage is one of the trickiest, most unpredictable times, aside from the damage that might be done to the part and, not unusually, to the whole machine itself. Tool wear is not a physical variable value which is easily measured by some specific method, but rather a subjective estimate a specialist can make, depending on the condition of the tool's edges and surfaces. Since there is no single criterion for deciding when a tool needs sharpening, different lifetimes may be predicted for the same tool employed in the same process. Two widely used criteria are catastrophic failure and changes in tool geometry.

2.1 FORMS OF TOOL WEAR:

Cutting tool wears are classified as shown below:

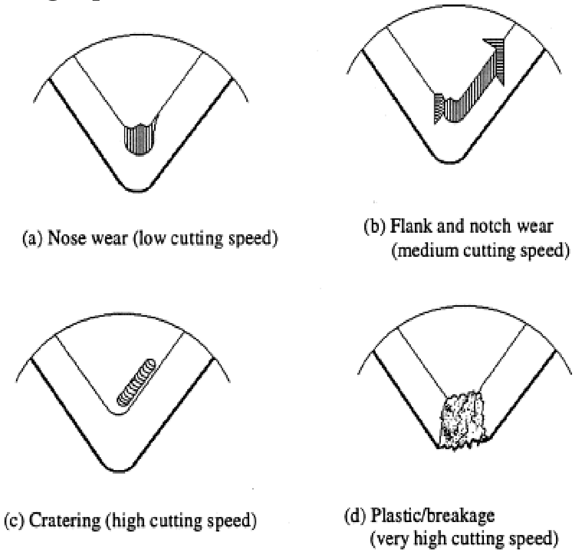
1) Crater wear
2) Notch wear
3) Flank wear
4) Adhesion

- Crater wear: It is a chemical or metallurgical wear. Crater wear is produced because small particles of the tool rake surface diffuse or adhere on fresh chip. Scar like shape is produced on the rake face due to mechanical friction and it is parallel to the major cutting edge. In turning of titanium alloys and low thermal conductivity materials crater wear is produced.
- Notch wear: It is a combination of flank wear and rake face wear which occurs just in the point where major cutting edge intersects the work surface. This type of wear is produced in those materials which have a tendency to surface hardening due to mechanical loads. When tool passes rub the fresh machined surface increases hardness of the outer layer. In turning of austenitic stainless steels and nickel-based alloys notch wear is produced.
- Flank wear: This type of wear is produced on the flank face of the tool. Wear land formation is not uniform along major and minor cutting edge of the tool. This type of wear is produced in case of hard materials because there is not any chemical affinity between tool and material. The wear mechanism is due to abrasion in this case.
- Adhesion: Welding occurs between the fresh surface of the chip and tool rake face because high pressure and temperature. If materials have metallurgical affinity the there will be better welding and that will produce a thick adhesion layer and tearing of the softer rubbing surface at high wear rate. In Aluminium alloys this type of wear is produced in dry conditions. In hard machining this type of wear is not produced.[2]

Tool wear process generally occurs in combination with the wear mode depending on the cutting conditions, workpiece, tooling material and tool insert geometry. The tool life is considerably reduced if the area of cut and area swept by the cutting tool are increased (i.e. mainly by increasing depth of cut).At low cutting speeds, the tool wears by rounding–off the cutting point and

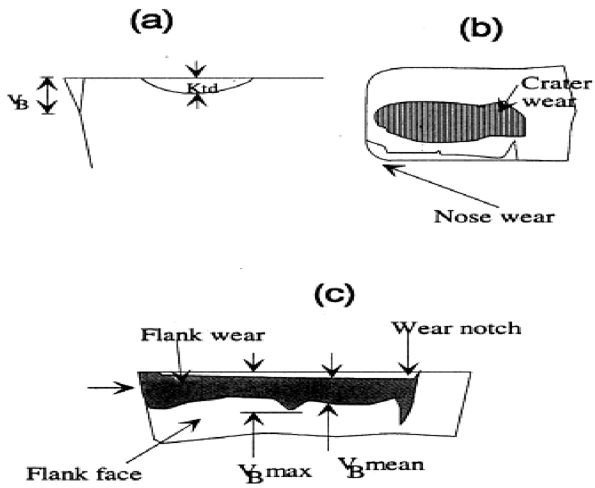
Volume 03, Issue 01, [January – 2016] ISSN (Online):2349–9745 ; ISSN (Print):2393-8161

subsequently looses sharpness. The cutting speed increases the wear-land pattern changes to plastic flow at the tool point.[6] Crater wear depends largely on the cutting temperature than the cutting speed. The various forms of wear-land pattern are shown in Figure 2.1 for a turning operation. The cutting tool wear often identified as the principles types of tool wear (nose, flank, notch and crater wear) in metal turning using single point tools.



2.1 Cutting tool wear forms in orthogonal metal cutting

Figure 2.2 shows the measurement of wear features in a turning process through implementation of appropriate International Standards Organization criteria. Nose wear or edge rounding occurs through the abrasion wear on the cutting tool's edges resulting in an increase in negative rake angle. Nose wear depend on the cutting conditions with tool sharpness lost through plastic or elastic deformation. As cutting speed increases, the edge deforms plastically and results in loss of entire nose that are shown in fig. a and b. Edge chipping and cracking occurs during periodic breaks of the built-up edge in interrupted cuts with brittle tool and thermal fatigue. Flank wear occurs because of both adhesive and abrasive wear mechanisms from the intense rubbing action of the two surfaces in contact, with reference to the clearance face of the cutting tool and the newly formed surface of the workpiece. At the beginning, the rate of wear is rapid, settling down to a steady state during the process and accelerating again at the end of tool life. The flank wear leads to a deterioration of surface quality, increase contact area and increase in heat generation as shown in Figures 2.1 b and 2.2 c.



2.2 Conventional features of turning tool wear measurements

The wear notch forms during the time that the tool rubs against the shoulder of the work piece as shown in Figures 2.2 b and c. This wear notch leads to abrasion by the surface layers accelerated by oxidation or chemical reactions, possibly leading to total tool failure. High cutting temperatures and high shear stresses creating a crater on the rake face some distance away from the tool edges, quantified by depth and cross-sectional area as shown in Figure 2.1c.The crater wear also arises due to a combination of wear mechanisms such as adhesion, abrasion, diffusion or thermal softening and plastic deformation.

III. ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS)

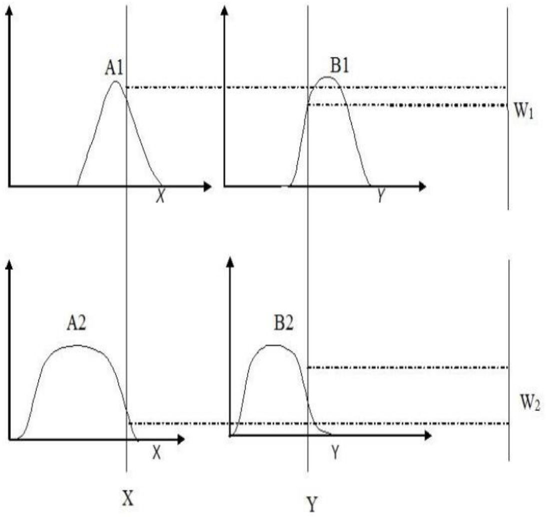
Neuro-Fuzzy systems are hybrid intelligent systems which combine features of both paradigms-fuzzy logic and artificial neural networks. Adaptive Neuro Fuzzy Inference System (ANFIS) is one of such architecture which is widely used as solution for various real world problems. Model can be realized with hardware descriptive language thus making it reusable, reconfigurable and independent of applications. This digital ANFIS firmware can be proven to be optimal solution in terms of cost, speed of operation and flexibility in design methodology**.** In machining process, a tool has a fixed life time in accordance with tool manufacturer recommendations or past experiences. This tool change policy has two drawbacks, at one end; a worn tool without being exchanged in time will produce out of specification parts or even cause tool breakage, and at the other tools being thrown away permanently over time will incur a huge waste of manufacturing resource. Zurada (1995) reviewed many fuzzy logic and neural networks [3]. Several monitoring methods have been developed during last few decades by many researchers. These methods may be classified into two groups, direct and indirect methods. Direct methods are based upon direct measurements of the worn area of the tool using optical sensors, vision systems etc. These methods have the advantage of high measurement accuracy, but cannot be easily adopted for on-line applications. Various indirect methods have also been developed in which the state of the wear is estimated from measurable parameters such as cutting forces, vibration, acoustic emission, cutting temperature and surface roughness. However few reliable indirect methods are established for industrial use. This is mainly due to complexity of machining process and the uncertainty in the correlation between the process parameters and the tool wear. Adaptive neuro-fuzzy inference system (ANFIS) is a modelling algorithm which relates the signal parameters with the on-line tool wear prediction. Kuo et al (1999) have analyzed on – line tool wear estimation through radial basis function networks and fuzzy neural network. The supervision of tool wear was found to be the most difficult task in the context of tool condition monitoring for metal-cutting processes. Based on a continuous acquisition of signals with multi-sensor systems they found it possible to estimate or to classify certain wear parameters by means of neural networks. Geethanjali and Mary Raja Slochanal (2008) described about optimal design of the over current relay using the ANFIS[4]. The ANFIS simulated results are quite encouraging than the fuzzy models and will be useful as an effective tool for modelling. Jang (1993) described the architecture of adaptive network based fuzzy inference systems with type-3 reasoning mechanisms. By employing a hybrid learning procedure, the proposed architecture can refine fuzzy if-then rules obtained from human experts to describe the input-output behaviour of a complex system. Peyman et al (2008) discussed about the utilization of the Adaptive Neuro-Fuzzy Inference Systems (ANFIS) in the continuous on-line monitoring and the diagnosis necessary for complex dynamic system which makes the proposed scheme fast, computationally simple and accurate. Dinakaran et al (2010) introduced a new approach for tool wear monitoring using ANFIS[4]. The basic inferences shows that the amplitude level of the ultrasonic signal, RMS of the received ultrasonic signal pulse width duration during cutting process is affected by the tool wear. The frequency domain of signal shows the distribution of frequency components and frequency shift in the received signal which can be related to flank wear. Correlation between the ultrasonic parameters and flank wear shows that every parameter is contributing in the of flank wear growth. The decision making algorithm presented in their work determines the tool wear status in real time.[5,6,7]

IV. TOOL WEAR MONITORING USING ANFIS

The fuzzy inference system under consideration has two inputs *x* and *y*, and one output *z*. suppose that the rule base contains two fuzzy if-then rules of Takagi and Sugeno's type.

Rule 1: If *x* is A1 and *y* is B1, then $f1 = p1\,x + q1\,y + rl$

Rule 2: If *x* is A2 and *y* is B2, then $f2 = p2\,x + q2\,y + r2$



Then the node functions in the same layer are of the same function family described as given below:
The general architecture of ANFIS:

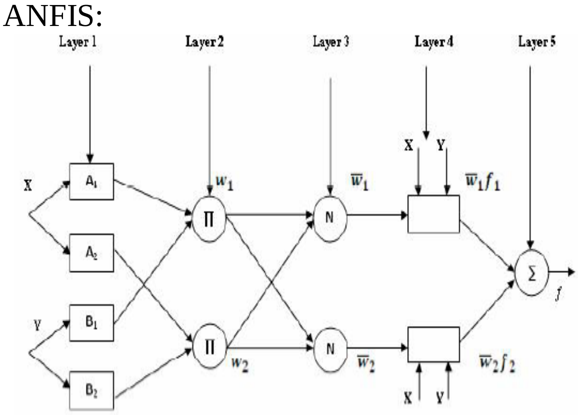


Fig: Equivalent ANFIS

Layer 1: Every node *i* in this layer is a square node with a node function

$O_i^1 = \mu_{A_i}(X)$

Where, *x* is the input to node i and Ai is the linguistic label (small, large, etc.) associated with this node function. In other words, O_i^1 is the membership function of Ai, and it specifies the degree to which the given *x* satisfies the quantifier A*i*. Usually μ_{A_i} to be bell-shaped with maximum equal to 1 and minimum equal to 0, such as

$$\mu_{A_i} = \frac{1}{1 + \left[\left(\frac{x - c_i}{a_i}\right)^2\right]^{b_i}}$$

where {ai, bi, ci} is the parameter set. As the values of these parameters change, the bell-shaped functions vary accordingly, thus exhibiting various forms of membership functions on linguistic label Ai.

Layer 2: Every node in this layer is a circle node labelled which multiplies the incoming signals and sends the product out. For instance,

$w_i = \mu_{A_i}(x) * \mu_{B_i}(y) \ldots\ldots\ldots i = 1,2$

Each node output represents the firing strength of a rule.

Layer 3: Every node in this layer is a circle node labeled N. The ith node calculates the ratio of the ith rule's firing strength to the sum of all rules' firing strengths

$\bar{w}_i = \frac{w_i}{w_1+w_2} \ldots\ldots\ldots . i = 1,2$

For convenience, outputs of this layer will be called normalized firing strengths.

Layer 4: Every node *i* in this layer is a square node with a node function

$O_i^4 = \bar{w}_i f_i = \bar{w}_i(P_i\, x + q_i\, y + r_i)$

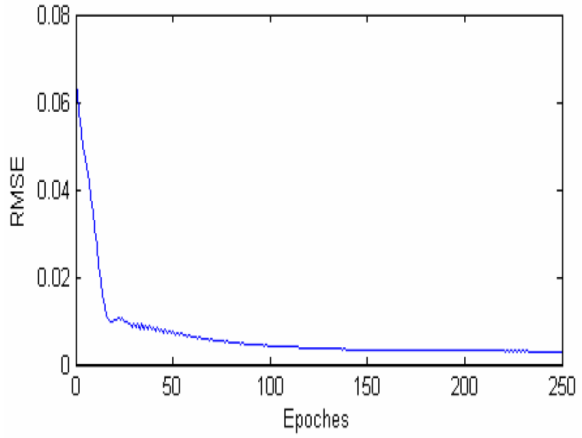
Where $\bar{w}$ is the output of layer 3, and {pi, qi, ri} is the parameter set. Parameters in this layer will be referred to as consequent parameters.

Layer 5: The single node in this layer is a circle node ∑ labelled that computes the overall output as the summation of all incoming signals, i.e. the overall output is,

$O_i^5 = \sum \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}$................[5,6,7]

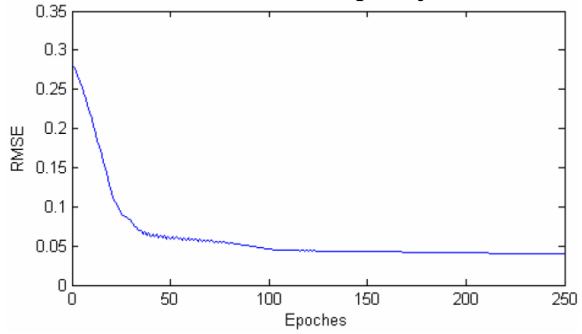
V. ANFIS SIMULATION RESULTS WITH DIFFERENT PARAMETERS

The developed model was trained by hybrid learning algorithm with 250 iterations. The performance of the model was justified by Root Mean Square Error (RMSE) value index and co-efficient of fitting (R). The training performances are of the three inputs and four input system are shown in Figures and respectively.[8]

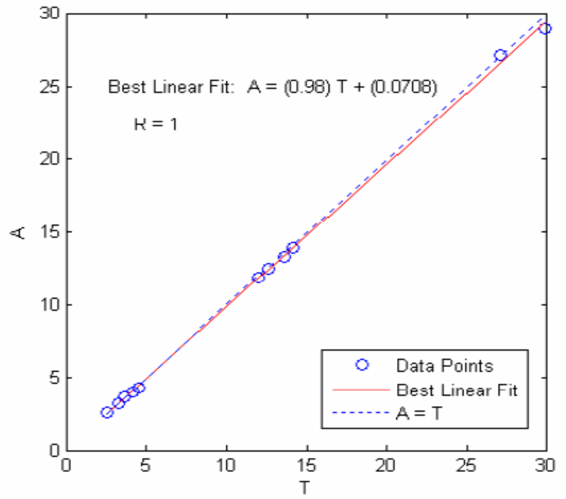


5.1 Epoch Vs error characteristics for 3 inputs

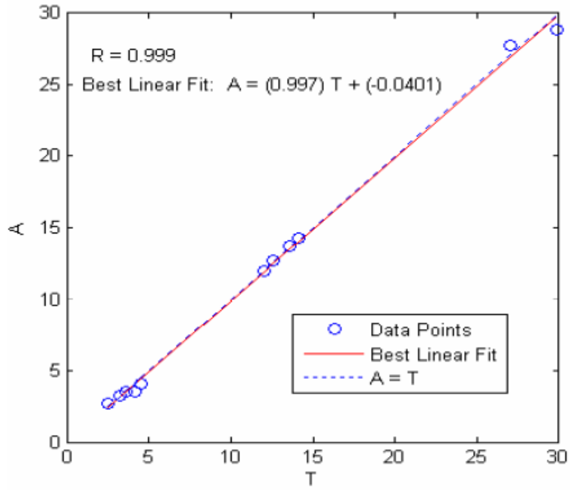
According to training performance, the three input system having According to training performance, , the three input system having minimum RMSE is 0.015 and four input system having RMSE is 0.04. The co-efficient of fitting (R) values are calculated by linear curve fitting method and the R value for three input system is 1 and R value for four input system is 0.999.



5.2 Epoch Vs error characteristics for 4 inputs



5.3 Testing performance curve for 3 inputs



5.4 Testing performance curve for 4 inputs

Based on the above performance result, the three input system ANFIS model was most suitable for predicting the crater wear. The proposed ANFIS model based predicated crater wear and experimentally measured value are tabulated in Table. The measured value and the simulation output of the Crater wear are shown.[9,10]

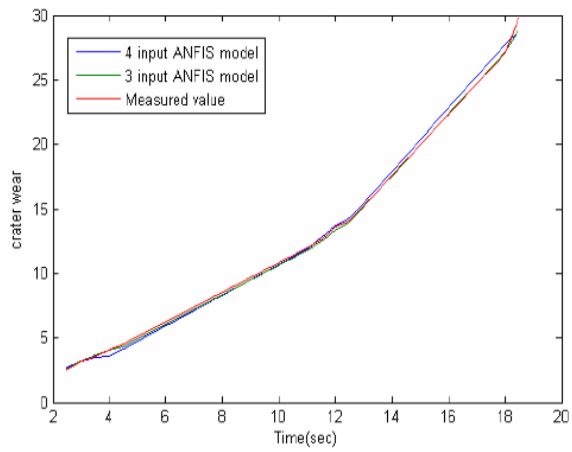


Table 1.1Crater wears comparative Results [11]

Sr no.	Measured Crater wear values	Predicted ANFIS result	Predicted ANFIS results
		For 3 Inputs	For 4 Inputs
1	2.5	2.6117	2.6969
2	3.2	3.2344	3.2307
3	3.6	3.6587	3.4952
4	4.1	4.036	3.5518
5	4.5	4.3051	4.1191
6	12	11.804	11.539
7	12.6	12.454	12.715
8	13.6	13.314	13.701
9	14.1	13.961	14.288
10	27.1	27.166	27.764
11	29.9	28.923	28.82

VI. CONCLUSION

Adaptive Nuero fuzzy inference system (ANFIS) was used by many researchers for monitoring of tool wear. Adaptive Neuro-Fuzzy Inference System was developed, which considers the ultrasonic parameters in time and frequency domain. Crater wear shows that every parameter is contributing in the definition of crater wear. The model developed by Neuro fuzzy system shows that the presented system can be used in real time with minimum error. In crater wear monitoring, the validation shows that the model can operate with 2.87% error. For non linear systems and for online application the ANFIS with minimum error of 2.87% may be suitable compared with statistical and analytical models. The online prediction of the crater wear width is possible by monitoring the pulse width duration in time path mode of ultrasonic signal. The pulse width increases with increase in crater width with the correlation co-efficient of 0.999. So three dimensional information about the wear can be seen. But the crater depth is commonly used as a tool changing criteria.

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