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Experimental Investigation of Cutting Force and Tool Wear In Turning Process for A HSS Single Point Cutting Tool Using Mathematical Model and ANN Model

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Abstract— **In turning process, the machinability and tool wear are mainly stochastic rather than deterministic because of its complexity in nature. Tool change strategies are now based on the most conservative estimate of tool life from the past tool wear data. Always a complex relationship exists between various process parameters viz., speed, feed, depth of cut, cutting time, tool geometry and cutting forces. Hence there is a need to develop models, which can capture this complex interrelationship between the parameters. In the present work, an empirical relationship has been developed between these parameters based on the experimental data.**

By considering speed, feed, depth of cut and cutting time as the input variables, the cutting forces and the flank wear were found out experimentally for a given tool - material combination. Based on these experimental data, a mathematical model has been developed. This model can be applied to all circumstances to estimate the cutting forces and the flank wear.

An artificial neural network model has also been developed to estimate the flank wear under varying cutting conditions. The results achieved by both the approaches have been compared and found to be closely related.

Keywords:- *turning, flank wear, cutting force, neural network.*

I INTRODUCTION

Computer Integrated Manufacturing (CIM) systems have emerged in response to the requirements of greater flexibility, productivity, high precision and quality of the product. The need to improve the quality and decrease the scrap rate while increasing the production rate is forcing industry to consider untended machining[9] as a viable alternative. But this leads the operator, who attempts to sense the effect of process variables and adjust the conditions accordingly, misguided in the many cases. Also some times the operator is incapable of responding fast to alter the conditions of operation accordingly.

The former leads to high scrap rate and higher cost with the need for rework. The later leads to reduced productivity. Therefore appropriate sensors and associated monitors are, therefore, the key to successful implementation of an untended machining process. Online monitoring methodology [11] of a machining process is the key success of an untended machining process.

The availability of product quality information on-line enables us to control a manufacturing process is real time, realizing the objective of building quality into product by minimizing the viability in the product’s characteristic.

Tool wear is an important factor directly affecting the surface quality of the machined surface. In particular, flank wear [11] requires close monitoring in turning. Wear development during machining can reach unacceptable levels very fast in some cutting conditions resulting in poor surface finish. The prediction and detection of tool wear before tool causes any damage on the machined surface becomes highly valuable in order to avoid loss of product, damage to the machine tool and associated loss in productivity. Developments in computer technology have made faster computation possible and economically viable for common users.

Most of the indirect approaches have been developed for fixed cutting conditions. In practical applications, however the cutting conditions are not fixed. The depth of cut changes because of part geometry and the feed might change according to control strategies and the speed will change according to the surface finish requirement. Therefore wear estimation strategy [11] under varying cutting conditions is needed. A Model-based methodology [3] has been developed to estimate the flank wear and the tool life in turning process under varying cutting conditions. The cutting force in a machining operation depends on the cutting variables like the cutting speed ‘v’, the feed ‘f’, the depth of cut ‘d’, the time ‘t’ and on the tool wear ‘W’. The wear itself depends on the cutting variables, i.e., W (v, f, d, t). Any change in the cutting condition affects the force measurements both directly and also indirectly through the wear. The key idea is to employ the relationship between force and the flank wear. Results confirm the effectiveness of this strategy in turning with varying speed, feed, and depth of cut or cutting time.

The main objective of this work is to develop an intelligent on-line monitor[8], to recognize the process irregularities in terms of tool wear and to estimate the the corrective actions to untended machining operation. By exploring the advantages of neural networks[12] , an artificial Neural Network monitor is developed.

Objective

1). To conduct an experimental study on Mild Steel work piece with High Speed Steel cutting tool and to estimate the tool life of HSS cutting tool using the experimental cutting force and flank wear data.

2). To develop a new methodology for the estimation of flank wear using neural networks.

II EXPERIMENTAL PROCEDURE & ANALYSIS

As machining is a very complex process, it is necessary to have a systematic and quantitative study so as to obtain a typical sample of data to study the major influencing factors on machining performance like tool wear. So a series of experiments have been conducted using the following experimental set up[11].

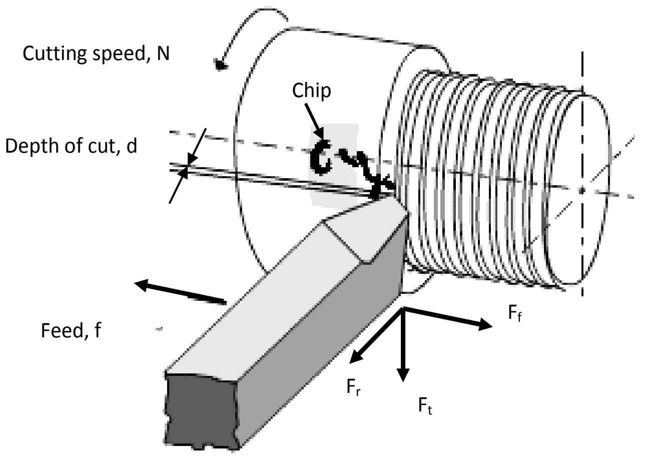
Machine tool : PSG A124 lathe
Work piece : MILD STEEL (hard ness 320 BHN), Diameter 30mm
Cutting tool : HIGH SPEED STEEL (18 - 4 - 1)
Tool geometry : 8^0 - 10^0 - 5^0 - 5^0 - 15^0 - 15^0 – 0.2 mm

Machining conditions:

Speed : 30 ---- 60 m/min
Feed : 0.1 ---- 0.3 mm/ rev
Depth of cut : 0.5 ---- 2 mm.

Mild steel work piece is mounted on PSG A124 lathe. By varying the cutting conditions (speed, feed, depth of cut and cutting time) the three cutting forces (tangential, feed and radial) are measured by using the strain gauge type dynamometer.

The flank wear is measured in mm by using profile projector[9]. After measuring the readings, tool is reground to the original geometry



The experiments have revealed that the cutting forces in turning process are functions of speed, feed, depth of cut and cutting time, and can be expressed[1] as

Tangential force $F_t = k_1 v^{t1} f^{t2} d^{t3} t^{t4}$
Feed force $F_f = k_2 v^{f1} f^{f2} d^{f3} t^{f4}$
Radial force $F_r = k_3 v^{r1} f^{r2} d^{r3} t^{r4}$ …... 1

Where v is cutting speed in mm/min
f is feed in mm/rev
d is depth of cut in mm
t is cutting time in min

Table1: Design matrix used in the experimental investigation(L9 orthogonal array)

Exp no	Cutting speed	Feed	Depth of cut	Cutting time
	Levels			
1	1	1	1	1
2	1	2	2	2
3	1	3	3	3
4	2	1	2	3
5	2	2	3	1
6	2	3	1	2
7	3	1	3	2
8	3	2	1	3
9	3	3	2	1

Planning Of Experiments

The important parameters that are considered in the experiment are cutting speed, feed, depth of cut and cutting time. Three levels were chosen for each of these four parameters. They are shown in the table

Table 2: List of process variables and their levels

Sl.No	Parameter	Level – 1	Level – 2	Level - 3
1	Cutting speed	33	46	56
2	Feed	0.1	0.2	0.3
3	Depth of cut	0.5	1.0	1.5
4	Cutting time	1	2	3

L9 orthogonal array was chosen for optimization and the array is shown in the table .Nine experiments have been conducted on the lathe machine. Since the objective is to aim at the optimization of the cutting parameters, by varying the cutting parameters the cutting forces values and the flank wear value have been measured after each experiment[2].

Analysis of Data

After conducting the experiments, analysis of data is undertaken as per the following steps:

- Compute the appropriate summary statistics, such as signal to noise ratio.
- Compute the main effects of factors (cutting speed, feed, depth of cut and cutting time) on the cutting force and Flank wear.
- Perform analysis of variance to evaluate the relative performance of factors and the error variance.
- Determine the optimum level for each factor based on the S/N ratio.

Table 3: Experimental values of cutting force & Flank wear

Exp.No	Speed(m/min)	Feed(mm/rev)	Depth of cut(mm)	Time (min)	Tangential force(F_t) N	Initial tan. Force (F_{t0})N	Feed force (F_f)N	Radial force(F_r)N	Flank wear (mm)
1.	33	0.1	0.5	1	294.3	289.4	220.72	147.15	0.060
2.	33	0.2	0.5	1	510.12	500.3	382.6	181.49	0.100
3.	33	0.1	1.0	1	623	603.31	441.45	166.77	0.120
4.	33	0.1	0.5	2	402.21	289.34	328.63	186.4	0.075
5.	33	0.1	1.0	2	852.24	823.95	657.25	211.25	0.160
6.	33	0.2	1.0	1	1080.5	1044.2	765.2	205.9	0.230
7.	33	0.2	1.0	2	1476.1	1425.5	1139.3	260.54	0.260
8.	33	0.3	0.5	1	703.74	689.14	527.8	205.17	0.140
9.	46	0.1	0.5	1	264.87	259.96	240.34	176.58	0.110

The experimental values 1 and 9 in the above table have been used to calculate the exponent of cutting speed (V)i.e.,t_1.The experimental values 1 and 2 in the above table have been used to calculate the exponent of feed (f)i.e.,t_2. The experimental values 4 and 5 in the above table have been used to calculate the exponent of depth of cut (d)i.e.,t_3. The experimental values 3 and 4 in the above table have been used to calculate the exponent of cutting time(t)i.e.,t_4[2,9,10,11].

Cutting force

$$f(y) = 11751.5 \times x_1^{-0.317} \times x_2^{0.79} \times x_3^{1.08} \times x_4^{0.45}$$

Flank wear

$$w(y) = 0.00117 \times x_1^{1.82} \times x_2^{0.74} \times x_3^{0.74} \times x_4^{0.32}$$

Where, x_1=cutting speed in mm/min
x_2=feed in mm/rev
x_3=depth of cut in mm
x_4=cutting time in min
………(2)

III MATHEMATICAL MODEL

The effect of cutting variables v, f, d and t on each of the three cutting force components can be expressed in terms of the following relationship[1].

$$F = k_1 v^{t1} f^{t2} d^{t3} t^{t4} \qquad ....(3)$$

Where k_1, t_1,t_2,t_3 and t_4 are depending on the tool geometry and work-tool material. The typical values for the tangential component when Mild steel cut with HSS tool are $t_1 \approx -0.3$, $t_2 \approx 0.8$, $t_3 \approx 1.08$, $t_4 \approx 0.45$.

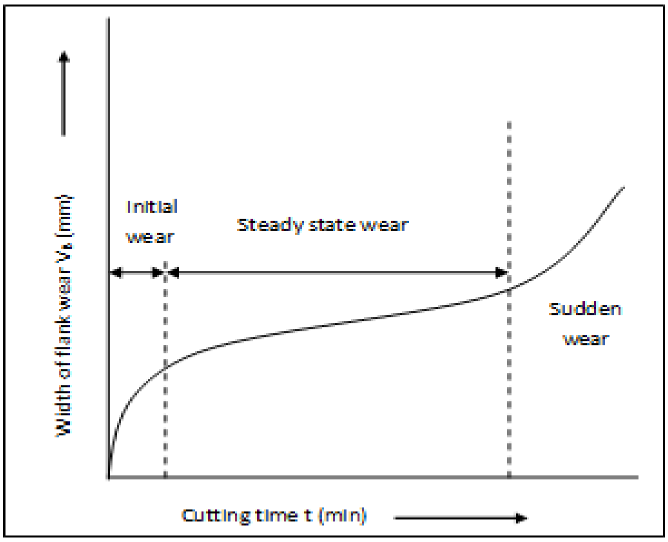


Figure 1 ***Width of flank wear variation with cutting time***

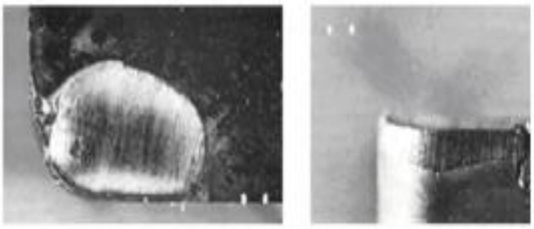


Figure 2 : (a). Crater wear (b) Flank wear

Growth of the wear on the flank face of the tool consists of three distinct stages, a short initial region, constant wear rate region and rapid wear rate region which indicates the tool failure as shown in the figure 5.1. In practice, the tool is replaced during the second stage. Therefore the flank wear is expressed[3,4]as

$$W = W_0 + \bar{W} t \qquad ………...(4)$$

Where W = total wear,
W_0= initial wear,
W = wear rate,
t = time

When the flank wear starts to develop the rubbing mechanism causes a force increase, ΔF.

$$F = F_0 + K W \qquad ………...(5)$$

Where F = total force,
F_0 = initial force,
W = flank wear,
K = slope of the curve drawn between Force and Flank wear.

Theoretically K should be proportional to the depth of cut d, since the rubbing area is Wd. However, for generality let us assume that the feed f, and even cutting speed v, and time t, may also affect ‘ΔF’. Therefore we assume that

$$K = K(v, f, d, t) = Cp\, v^{\beta1} f^{\beta2} d^{\beta3} t^{\beta4}$$

Typically, $\beta_3 > \beta_2 > \beta_4 > \beta_1$. The experiments conducted with HSS tools on Mild steel shows that $\beta_1 \approx 0$, $\beta_2 \approx .27$, $\beta_3 \approx 1$, $\beta_4 \approx 0.15$. The flank wear can be represented by utilizing the extended Taylor tool life equation

$T\, v^{\gamma1} f^{\gamma2} d^{\gamma3} C_n = 1$ ....(6)

Where the γ1, γ2, γ3,Cn depends on the workpiece material and the tool geometry. The tool life T may be defined by a flank wear W(T)=W at which the tool is replaced.

$W = (W - W_0)\, v^{\gamma1} f^{\gamma2} d^{\gamma3} C_n$ ....(7)

$\therefore F = (F_0 + K W_0) + K \bar{W} t$ ....(8)

So the additional measured force component due to wear is

$\Delta F = K \bar{W} t$ ....(9)

$\Delta F = Cp\, v^{\beta1} f^{\beta2} d^{\beta3} t^{\beta4} W (v^{\gamma1} f^{\gamma2} d^{\gamma3})$

The wear rate is expressed in equation as a function of the cutting variables. We will consider the case where the wear rate depends on the cutting variables, but only one of the cutting variables varies. The equation can be written as

$\Delta F = C\, b^{\beta}\, W (b^{\gamma})\, t$ ....(10) Where b is the particular cutting variable, which is varied (i.e., b, might be v, f, d). The coefficient C depends on the tool and the work piece material as well as on the other cutting variables that are treated as constant. A change in ‘b’ has both a direct effect on the force measurement through the equation and ‘b^{β}’ in the equation , and the indirect effect through the change in the wear rate. The challenge is to separate the two effects by using the estimation techniques. In principle three possible cases exist for equation :

Case #1: $\beta \approx 0$ and $\gamma \neq 0$,

Case #2: $\beta \neq 0$ and $\gamma \approx 0$

Case #3: $\beta \neq 0$ and $\gamma \neq 0$

A practical example of the case is case #2 is when b=d, since the ANOVA results shows that the percentage contribution of the depth of cut in force is very much high compared to the other variables.

The cutting variable ‘b’ changed in steps. A step change from ‘b_{k-1}’ to ‘b_k’ at time t_k will cause an abrupt change in the cutting force from F_{k-1} to F_k. this cutting force change is sensitive to the variations of ‘f ’and ‘d’, but not to the variations in the ‘v’. The cutting variable k is defined here as the k^th segment of cut in which the cutting variable ‘b_k’ is kept constant. The initial force at interval k, $F_{k-1} (b_k, t_k)$ might be considered as a reference point for the segment. The force increase during the interval ‘k’ $\Delta F_k (b_k , t_k)$ is calculated at every sampling period ‘i’ from

$\Delta F_k = F_k (b_k) - F_{k-1} (b_k)$ ....(11) The equation (10) becomes

$(\Delta F_k / T_k) = X\, b_k^{\beta} (b_k^{\gamma})$ ....(12)

Where $T_k = k \Delta t_k$

$X (b^{\gamma}) = C\, W (b^{\gamma})$ ....(13)

The wear estimation is done by first computing the variable X from the rate of cutting force increase during the cutting. The quantity CW is then estimated by approximately integrating X at each sampling period from the equation

$CW(t) = CW_0 + (\sum_{j=1}^{k-1} C\, W_j) + X_k T_k$

where $C\, W_j = X_j t_j$, ...(14)

t_j = time elapsed during the interval.,

$T_k = k\, \Delta t$

The actual tool wear can only be estimated from CW when C is known. For the estimation of the X we are considering the case # 2 i.e., $\beta \neq 0$ and $\gamma \approx 0$ because this is the most practical case, since the machining is always performed with different depths of cut which depends on the part geometry.

$\Delta F_k = X\, b_k^{\beta}\, T_k$ ....(15)

$S = (\Delta F_k / T_k) = X\, b_k^{\beta}$ ....(16)

S is estimated for each segment of cut, and then X is estimated at each sampling period.

Estimation Of Status Of Flank Wear

Generally tool wear consists of flank wear and crater wear. For monitoring the tool wear the cutting forces acting on the tool can be measured. But the cutting forces are proportional to the cross sectional area of the chip. To minimize the effects of cutting conditions on cutting forces, the normalized cutting forces are used in the analysis. The normalized cutting force is the ratio of the cutting force and the resultant force. They induce an increase in the cutting force components. Normalized cutting forces are not sensitive to the changes in cutting conditions and show a consistent result. The normalized cutting forces are defined by[1,2]:

$NF_t = (F_t / R)$

$NF_f = (F_f / R)$

$NF_r = (F_r / R)$ ....(17)

Where F_t, F_f, F_r are the tangential ,feed, radial components of the cutting force, R is the resultant force

As the cutting proceeds with time, all the cutting forces especially tangential and the feed force, increase with some fluctuations in their magnitudes. However the normalized cutting forces shows the gradual increase in their magnitudes without any fluctuations. Therefore normalized cutting forces will be useful to detect the tool wear.

Relationships Between Flank Wear And Normalized Cutting Force

Cutting forces can be divided into static and dynamic components as follows[1]:

$$F = F_s + F_d \quad \ldots\ldots\ldots\ldots(18)$$

Where F is the cutting force,

F_s is the static component of the cutting force, and it means the average or mean value of the cutting force.

F_d is the dynamic component of the cutting force, and it means the fluctuating component with respect to static component.

The normalized cutting force is taken as criterion for finding out the status of flank wear. The normalized cutting force depends on the cutting conditions like speed, feed and depth of cut. Hence a relationship between the normalized cutting forces and the cutting conditions should be constructed for a particular tool-work material combination as follows[1]:

$F_{rs} = k_1 f^{x1} d^{y1}$

$NF_t = k_2 f^{x2} d^{y2}$

$NF_f = k_3 f^{x3} d^{y3}$

$NF_r = k_4 f^{x4} d^{y4}$ …………..(19)

Where $F_{rs}=(F_r)_s/1000$; x,y are the exponents, and k_1, k_2, k_3, k_4 are coefficients.

$(F_r)_s$ is the static component of the radial force, and this component is turned out to be a proper component for representing the status of the flank face. Since the $(F_r)_s$ is so big in comparison with the other normalized force components (<1),the model parameters (coefficients and exponents) in this term are unbalanced with other terms. Hence F_{rs} is obtained from dividing $(F_r)_s$ by 1000 (correction number) to make the parameters into the same order, and there is no special meaning.

Using this measured F_{rs} and NF_f in addition to the coefficients and exponents in Equation (19), the locus of feed rate (d_{int}) and depth of cut (f_{int})for satisfying those measured forces can be calculated, and the Equation(20) represents this locus as follows[1]:

$$d_{int} = \exp\left[\frac{1}{\left(\frac{x_3 y_1}{x_1} - y_3\right)} \log\left\{\left(\frac{F_{rs}}{k_1}\right)^{\frac{x3}{x1}} \left(\frac{k_3}{NF_f}\right)\right\}\right]$$

$$f_{int} = \exp\left[\frac{1}{x_1}\log\left(\frac{F_{rs}}{k_1 * d_{int}}\right)\right] \quad \ldots(20)$$

Where d_{int} and f_{int} is the estimated depth of cut and feed rate at the intersection point.

The changed (increased/decreased) normalized cutting forces have been calculated by substituting these new cutting conditions (f_{int}, d_{int}) in Equation (19). The difference between these normalized cutting force (NF_t', NF_f', NF_r') and the actual measured normalized cutting force (NF_t, NF_f, NF_r) is called disparity. So the simple disparities (d_1, d_2, d_3) of three cutting forces have been calculated. In addition to these simple disparities, the first derivatives of normalized cutting forces should be considered in order to estimate the normalized disparities. Therefore normalized disparities are given by[1,2]:

$$Nd_1 = \frac{d_1}{\sqrt{\left(\frac{dNF_c}{d(f,d)}\right)^2 + \left(\frac{dNF_f}{d(f,d)}\right)^2}}$$

$$Nd_2 = \frac{d_2}{\sqrt{\left(\frac{dNF_c}{d(f,d)}\right)^2 + \left(\frac{dNF_r}{d(f,d)}\right)^2}}$$

$$Nd_3 = \frac{d_3}{\sqrt{\left(\frac{dNF_f}{d(f,d)}\right)^2 + \left(\frac{dNF_r}{d(f,d}\right)^2}} \ldots(21)$$

where $\left|\frac{dNF_i}{d(f,d)}\right| = \sqrt{\left(\frac{\partial NF_i}{\partial f}\right)^2 + \left(\frac{\partial NF_i}{\partial d}\right)^2}$

$$= \sqrt{(k_i * x_i * f^{xi-1} * d^{yi})^2 + (k_i * y_i * f^{xi} * d^{yi-1})^2}$$

Where Nd_1, Nd_2 and Nd_3 are the normalized disparities.

Total tool wear grades= sum of individual tool wear grades

From the above table we can conclude that, if the values of Nd_1, Nd_2 and Nd_3 are less than 0.06, 0.15 and 0.15 respectively and the total tool wear grade and wear land are less than 2 and 0.2 respectively, the severity of the flank wear can be categorized as low.

Similarly if the values of Nd_1, Nd_2 and Nd_3 are less than 0.12, 0.35 and 0.35 respectively and the total tool wear grade and wear land are less than 4 and 0.3 respectively, the severity of the flank wear can be categorized as medium. If the values of Nd_1, Nd_2 and Nd_3 are greater than 0.12, 0.35 and 0.35 respectively and the total tool wear grade and wear land are greater than 4 and 0.3 respectively, the severity of the flank wear can be categorized as severe.

By considering the threshold values with respect to these normalized disparities the severity of the flank wear has been estimated. The threshold values with respect to normalized disparities are shown in the table given below:

Table 3 : Threshold values of normalized disparities

Severity of flank wear	Individual tool wear grade	Total tool wear grades	Wear land width (V_B)	Nd_1	Nd_2	Nd_3
Low(L)	0	<2	<0.2	<0.06	<0.15	<0.15
Medium(M)	1	<4	<0.3	<0.12	<0.35	<0.35
Severe(S)	2	>4	>0.3	>0.12	>0.35	>0.35

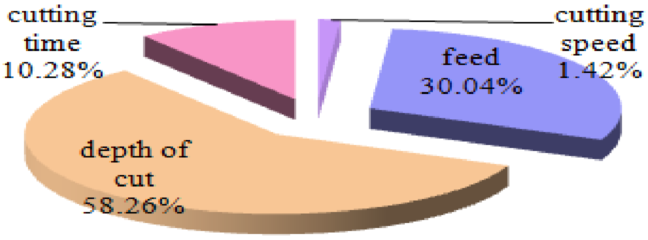


Figure 3: Contributions of process parameters to cutting force

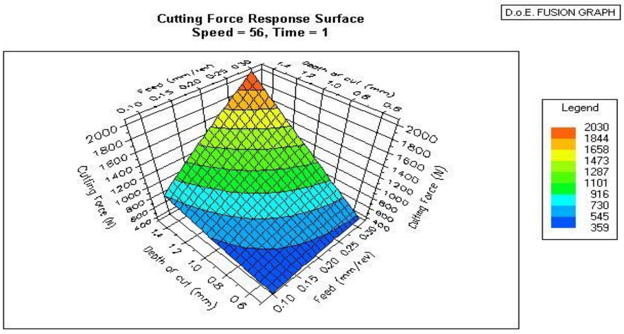


Figure 4 : Cutting force response to the feed and depth of cut.

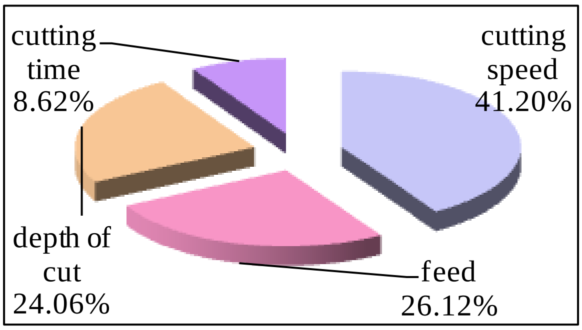


Figure 5: Contributions of process parameters to Flank wear

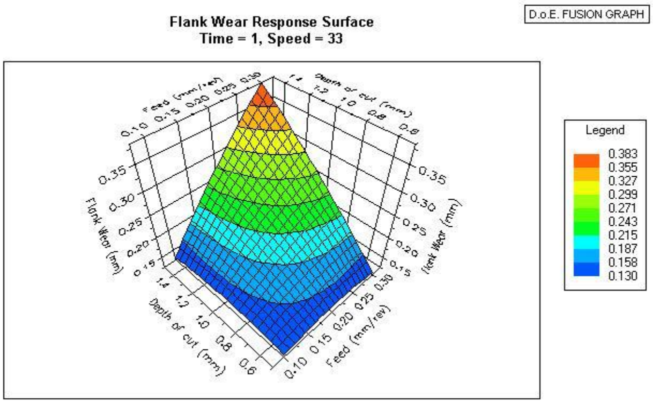


Figure 6: Flank wear response to feed and depth of cut

IV COMPARATIVE STUDY

Table 4 Values of flank wear by neural network model and mathematical model.

s.no	Cutting speed (m/min)	Feed (mm/rev)	Depth of cut (mm)	Time (min)	Flank wear by neural network method (mm)	Flank wear by mathematical model (mm)
1	55	0.1	0.5	1	0.148	0.165
2	55	0.1	0.5	2	0.195	0.207
3	55	0.1	0.5	3	0.22	0.237
4	55	0.1	0.5	4	0.24	0.2609
5	55	0.1	0.5	5	0.263	0.28
6	55	0.1	0.5	6	0.277	0.2979
7	55	0.1	0.5	7	0.298	0.313
8	55	0.1	0.5	8	0.31	0.327
9	55	0.1	0.5	9	0.33	0.34
10	55	0.1	0.5	10	0.34	0.352

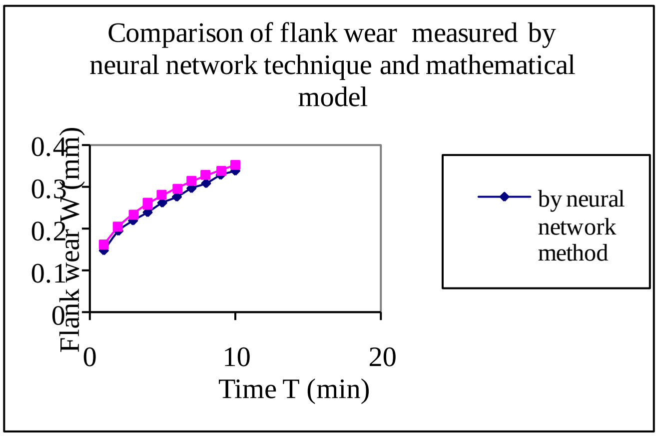


Figure 7 Comparison of Flank wear measured by neural network technique and mathematical model

V OBJECTIVE FUNCTION FOR CUTTING FORCE

The objective is to minimize the cutting force by varying the process parameters. The objective function obtained from empirical model is given below[3,4]:

Minimize Cutting force

$$f(y) = 11751.5 \times x_1^{-0.317} \times x_2^{0.79} \times x_3^{1.08} \times x_4^{0.45}$$

$$30 \le x_1 \le 60$$

$$0.1 \le x_2 \le 0.3$$

$$0.5 \le x_3 \le 2$$

$$1 \le x_4 \le 60$$

Where, x_1=cutting speed in mm/min
x_2=feed in mm/rev
x_3=depth of cut in m x_4=cutting time in min

VI OBJECTIVE FUNCTION FOR FLANK WEAR

The objective is to minimize the flank wear by varying the process parameters. The objective function obtained from empirical model is given below:

Minimize Flank wear

$$w(y) = 0.00117 \times x_1^{1.82} \times x_2^{0.74} \times x_3^{0.74} \times x_4^{0.32}$$

$$30 \le x_1 \le 60$$

$$0.1 \le x_2 \le 0.3$$

$$0.5 \le x_3 \le 2$$

$$1 \le x_4 \le 60$$

Where, x_1=cutting speed in mm/min
x_2=feed in mm/rev
x_3=depth of cut in mm x_4=cutting time in min

VII OBJECTIVE FUNCTION FOR TOOL LIFE

The objective is to minimize the tool life by varying the process parameters. The objective function obtained from empirical model is given below[3,4]:

Maximize Tool life $T(y) = 19.85 \times x_1^{-5.88} \times x_2^{-3.4} \times x_3^{-2.4}$

$$30 \le x_1 \le 60$$

$$0.1 \le x_2 \le 0.3$$

$$0.5 \le x_3 \le 2$$

Where, x_1=cutting speed in mm/min
x_2=feed in mm/rev
x_3=depth of cut in mm

VIII RESULTS

Table 5: The results of optimized tool life as shown in the table below

Parameter	***Optimal parameter for tool life***
Cutting speed (mm/min)	30
Feed (mm/rev)	0.1
Depth of cut (mm)	0.5
Objective function	233 min

Table 6 The results of optimized cutting force and the flank wear are tabulated as shown below:

Parameter	**Optimal parameter for Cutting force**	**Optimal parameter for Flank wear**
Cutting speed (mm/min)	59.9278	30
Feed (mm/rev)	0.1	0.1
Depth of cut (mm)	0.5	0.5
Cutting time (min)	1	1
Objective function	246.30 N	0.0478 mm

IX CONCLUSION

The new methodology proposed in the present study found to be the best alternative to traditionally known methods for assessing the tool wear. The flank wear can be quantitatively predicted for any given set of input cutting conditions. The methodology presented here is suitable in practice to any arbitrary machining work conditions. The solutions obtained by the proposed method are validated with conducting experiments.

The results show that with the increase in speed, feed and depth of cut, the flank wear increases due to increase in the friction between tool and the work piece. The flank wear also increases with time. As the time proceeds the wear on the tool increases so that the forces on the tool face also increases. The proposed method is very much suitable for the estimation of tool wear under varying cutting conditions. Prediction of the flank wear without using any sensors would definitely improve the implementation of the present approach in the shop floor practice. A predetermined flank wear is set as the wear limit, so that whenever wear curve crosses that limit the corresponding time value gives the tool life at that cutting conditions

A trained neural network system has been used in predicting the flank wear for various cutting conditions. In addition to this, the neural network technique can be used in different areas like drilling, milling etc. based on the applications. The reason for including the neural network technique in the present study is that turning process is complex and uncertain in nature. The major advantage of the neural network method of tool wear prediction is that this algorithm can estimate the flank wear quite accurately.

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