International Journal of Machine Design and Manufacturing
Vol. 1: Issue 1
www.journalspub.com

An Experimental Investigation of Optimum Flank Wear of Carbide Inserts for Dry Turning of EN19 Tool Steel

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Abstract
Flank wear of cutting tools is often selected as the tool life criterion because it determines the diametric accuracy of machining, its stability and reliability. In this work the effect of cutting parameters like RPM, feed rate and depth of cut is studied on dry turning of EN19 tool steel and input parameters are optimized for minimum tool wear. RSM technique is employed to achieve the minimum tool wear. Combined effects of the cutting parameters on tool wear (V_B) are investigated.

Keywords: dry turning, feed rate and depth of cut, RPM, RSM, tool wear

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INTRODUCTION
The turning of EN19 tool steel material, which have high tensile strength yields desirable results only when optimum process parameters are selected. This tool steel has a very high usage in automobile industry. Turning operation is used and flank wear as well as optimum condition are studied.

Tool wear in machining is defined as the amount of volume loss of tool material on the contact surface due to the interactions between the tool and work piece.

Specifically, tool wear is described by wear rate (volume loss per unit area per unit time) and is strongly determined by temperature, stresses, and relative sliding velocity generated at the contact interface. Tool wear have significant influences on the accuracy of the finished product. [1–3]

Response surface method (RSM) is very useful for modelling and analysis of a process. It adopts both mathematical and statistical techniques in which a response of interest is influenced by several variables.

Tool Wear
High contact stress between the tool rake-face and the chip causes severe friction at the rake face. This results into a variety of wear patterns and scars which can be observed at the rake face and the flank face.

Flank Wear (Clearance Surface)
Flank wear creates inaccuracy of the product size and results in the formation of a wear land. It is observed that wear and formation of wear is not always uniform throughout the wear land.

In fact, flank wear can be monitored in production by examining the tool or by tracking the change in size of the tool or machined part. Flank wear is generally measured by using the land size VB and VB_{max} (Figures 1, 2). [4, 5]

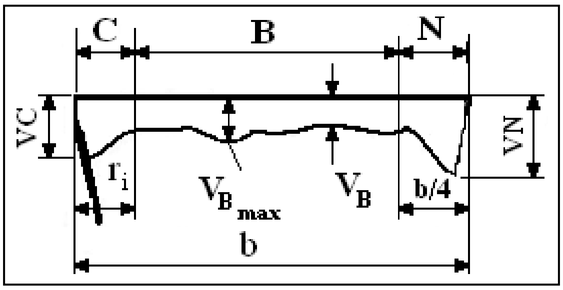

Fig. 1. *Flank Wear.*

Different Stages of Tool Wear

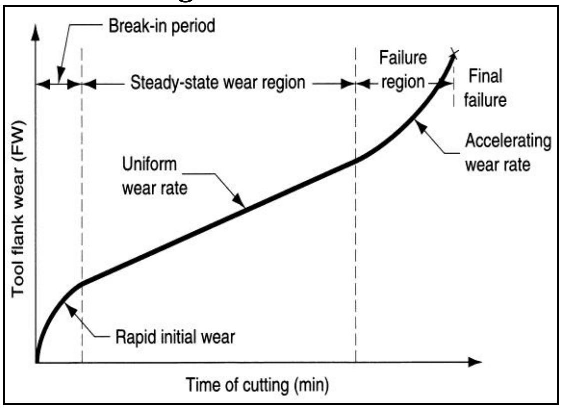

Fig. 2. *Different Stages of Wear.*

Initial (Preliminary) Wear Region

The initiation of wear is due to by micro-cracking, surface oxidation and carbon loss layer, as well as micro-roughness at the cutting tool tip. For a brand new cutting edge, the small contact area and high contact pressure will result in high wear rate. The initial wear size is VB=0.05–0.1 mm normally.

Steady Wear Region

After the initial (or preliminary) wear (cutting edge rounding), the micro-roughness is improved, in this region the wear size is proportional to the cutting time. The wear rate is relatively constant.

Severe (or Ultimate or Catastrophic) Wear

When the wear size increases to a critical value, the surface roughness of the machined surface decreases, cutting force and temperature increase rapidly, and the wear rate increases. Then the tool loses its cutting ability. In practice, this region of wear should be avoided.

The effect of cutting tool on machining performance can be summarized as follows:

- Cutting force increases
- Surface roughness increases
- Dimensional accuracy deceases
- Temperature increases
- Production efficiency, component quality decreases
- Cost increases

Experimental Details

The following studies are carried out:

- Identification of important process parameters and selection of their levels.
- Development of the design matrix. Conducting the experiments as per the design matrix.
- Recording of the response.
- Development of mathematical model using response surface methodology.
- Calculation of the co-efficient of the polynomials.
- Analysis of experimental result for tool wear.
- Optimization of process parameter using response surface methodology.[6]

RESPONSE SURFACE METHODOLOGY

The quadratic equation used for modelling of the system is:

$$y = b_0 + \sum_{i=1}^{n} b_i x_i + \sum_{i=1}^{n} b_{ii} x_i^2 + \sum\sum_{i<j} b_{ij} x_i x_j + \varepsilon$$

Where, ε represents the noise or error observed in the response y such that the expected. Response is (y–ε) and b’s are the regression coefficients to be determined. To check the adequacy of the model for the responses in the experimentation, Analysis of Variance (ANOVA) is used.[7,8]

In the ANOVA table, there is a P-value or probability of significance for each independent variable in the model the value of which shows whether the variable is significant or not. If the P-value is less or equal to the selected α-level, then the effect of the variable is significant. If the P-value is greater than the selected α-value, then it considered that the variable is not significant. Sometimes the individual variables may not be significant. If the effect of interaction terms is significant, then the effect of each factor is different at different levels of the other factors. ANOVA for different response variables are carried out in the present study using commercial software Minitab (Minitab user manual, 2001) with confidence level set at 95%, i.e., the α-level is set at 0.05. [9]

EXPERIMENTATION

Factorial points are vertices of the n-dimensional cube which are coming from the full or fractional factorial design where the factor levels are coded to -1, +1. Central point is the point at the center of the design space. Axial points are located on the axes of the coordinate system symmetrically with respect to the central point at a distance α from the design center (Table 1). [10]

Table 1. *Components of Central Composite Second Order Rotatable Design (Cochran and Cox, 1962).*

Variable (K)	Fractional points (2^k)	Star point (2k)	Centre point (n)	Total (N)	Value of α
3	8	6	6	20	1.682
4	16	8	7	31	2.000
5	16	10	6	32	2.000
6	32	12	9	53	2.378

Considering uniform precision, for three factor experimentation, eight (2^3) factorial points, 6 axial points (2 × 3) and six center runs, a total of 20 experimental runs may be considered and the value of α is $(8)^{1/4}$ = 1.682. The components of central composite second order rotatable design for different number of variables are given in Table 2. A pictorial representation of different points for the case of 3 variables is shown in Figure 3. [11]

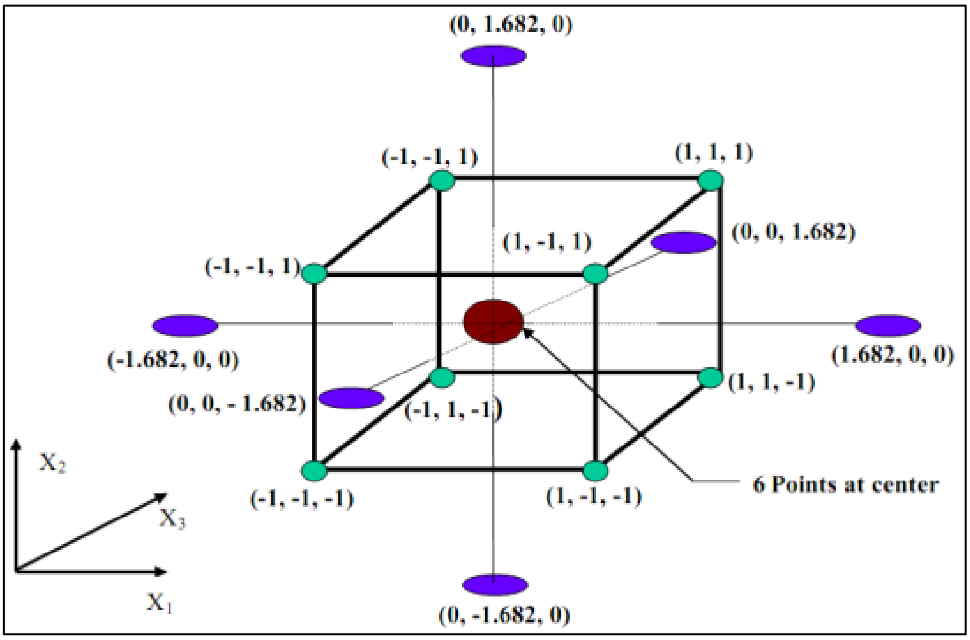

Fig. 3. *Central Composite Rotatable Design in 3X-Variables (Cochran and Cox, 1962).*

Process Variables and Their Limits

The working ranges of the parameters for subsequent design of experiment, based on Response Surface Methodology with rotatable design have been selected. In the present experimental study spindle speed, feed rate and depth of cut have been considered as process variables. The process variables with their units (and notations) are listed in Table 2 (Figures 4–6). [12]

Table 2. *Process Variables.*

	Level				
Variables	–1.682	–1	0	1	1.682
DOC (mm)	0.159	0.5	1	1.5	1.841
FEED RATE(mm/rev)	0.032	0.1	0.2	0.3	0.368
RPM	230	400	650	900	1070

Selection of Work Piece Material

The EN 19 Tool Steel rod of size 70mm in length and diameter 32mm has been used as a work piece material for the present experiments because EN19 is a high quality, high tensile alloy steel usually supplied readily machinable in 'T' condition, giving good ductility and shock resisting properties combined with resistance to wear. The chemical composition and mechanical properties of the work-piece materials are shown in Table 3.

Table 3. *Chemical Composition of EN 19T.*

Element	Chemical composition (wt%)
Carbon	0.36–0.44
Silicon	0.10–0.35
Manganese	0.70–1.00
Chromium	0.90–1.20
Molybdenum	0.25–0.35

Tool Holder Specification: MCLNL 2020-K12.

Cutting Tool Used
CERATIZIT make Carbide tool inserts
Specification: CNMG 1200408EN-TMR (insert).

Machine Tool Used: SIEMENS controlled CNC turner wit maximum speed of 6000 RPM feed rate 10,000 mm/min.

Equipment Used to Measure Tool Wear: Tool Maker's Microscope Mitutoyo (TM 500) least count 0.005 mm (Table 4).

Table 4. *Tool Wear Data (FW) With Coded an Uncoded Values.*

Run order	Coded values			Response
	RPM	FEED	DOC	FW(mm)
1	0	0	1.681793	0.116
2	–1	–1	–1	0.081
3	–1	–1	1	0.105
4	–1	1	–1	0.09
5	1	–1	–1	0.115
6	1.681793	0	0	0.143
7	0	0	0	0.121
8	1	1	–1	0.118
9	1	1	1	0.135
10	–1.68179	0	0	0.088

11	0	1.681793	0	0.127
12	0	0	0	0.124
14	1	–1	1	0.131
15	0	–1.68179	0	0.118
16	0	0	0	0.123
17	0	0	0	0.121
18	0	0	0	0.12
19	–1	1	1	0.1
20	0	0	–1.68179	0.079

RESULT AND DISCUSSION

A second order quadratic model have been developed using speed, feed, and depth of cut as input and tool wear as response (Tables 5–7).

$$\text{Tool Wear} = 0.121893 + 0.01578 \times \text{RPM} + 0.001914 \times \text{Feed Rate} + 0.009462 \times \text{Depth of Cut} - 0.00263 \times \text{RPM} \times \text{RPM6} - 0.008994 \times \text{Depth of Cut} \times \text{Depth of Cut}$$

Table 5. *Estimated Regression Coefficients for Tool Wear*

Term	Coef	SE Coef	T	P
Constant	0.121893	0.001164	104.681	0.000
A	0.01578	0.000773	20.425	0.000
B	0.001914	0.000773	2.477	0.033
C	0.009462	0.000773	12.248	0.000
A*A	–0.00263	0.000752	–3.497	0.006 (Significant)
B*B	–0.000155	0.000752	–0.206	0.841
C*C	–0.008994	0.000752	–11.959	0.000 (Significant)
A*B	0.000375	0.001009	0.372	0.718
A*C	–0.000125	0.001009	–0.124	0.904
B*C	–0.001625	0.001009	–1.61	0.139
S = 0.00285504			PRESS = 0.000596219	
R-Sq = 98.64%, R-Sq(pred) = 90.06%, R-Sq(adj) = 97.42%				

Table 6. *ANOVA Table for Tool Wear (FW) After Backward Elimination.*

Term	Coef	SE Coef	T	P
CONSTANT	0.1217662	0.000945	128.899	0.000
A	0.0157795	0.000738	21.371	0.000
B	0.0019138	0.000738	2.592	0.021
C	0.0094624	0.000738	12.815	0.000
A*A	-0.002615	0.000715	-3.656	0.003
C*C	-0.008978	0.000715	-12.554	0.000
S = 0.00272861			PRESS = 0.000277213	
R-Sq = 98.26%, R-Sq(pred) = 95.38%, R-Sq(adj) = 97.64%				

Table 7. *Analysis of Variance for Tool Wear (FW).*

	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	5	0.005894	0.005894	0.001179	158.34	0
Linear	3	0.004673	0.004673	0.001558	209.23	0
Square	2	0.001221	0.001221	0.006917	41.93	0
Interaction	3	0.015304	0.015304	0.000611	82	0
Residual error	14	0.000104	0.000104	0.000007		
Lack-of-fit	9	0.000093	0.000093	0.00001	4.79	0.05
Pure error	6	0.000011	0.000011	0.000002		
Total	19	0.005999				

Twenty numbers of experiments have been conducted and the corresponding tool wear measured. Average tool wear is computed. The adequacy of the model is then checked using ANOVA. [13]

Checking the Adequacy by Response Surface Methodology Variation of Tool Wear with respect to input parameters

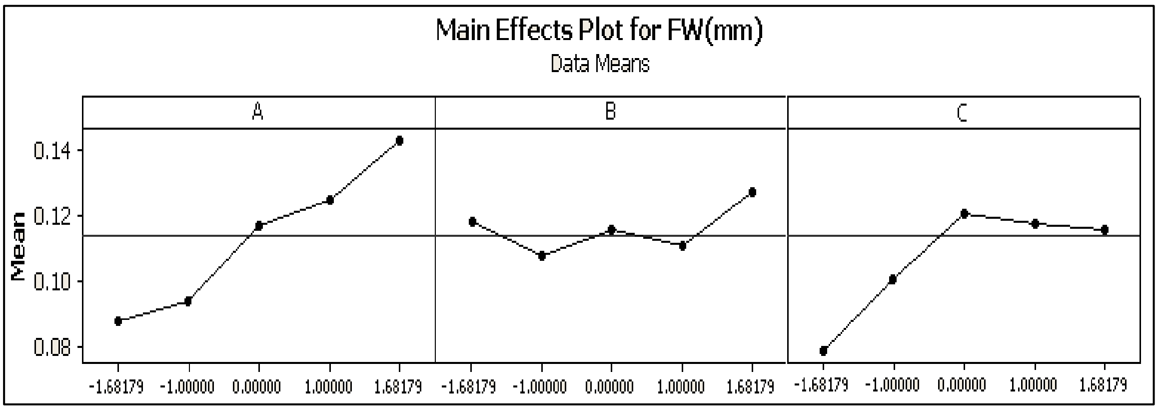

Fig. 4. *Main Effects Plot for Tool Wear (FW in mm).*

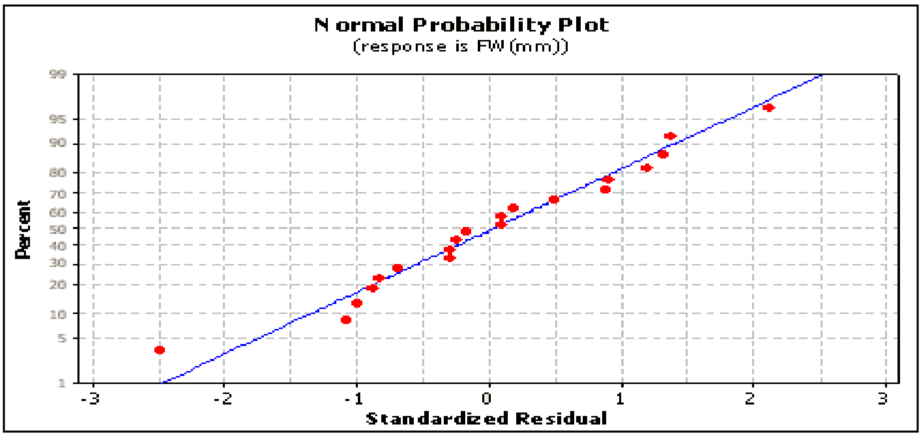

Fig. 5. *Normal Probability Plot of Residuals for Tool Wear.*

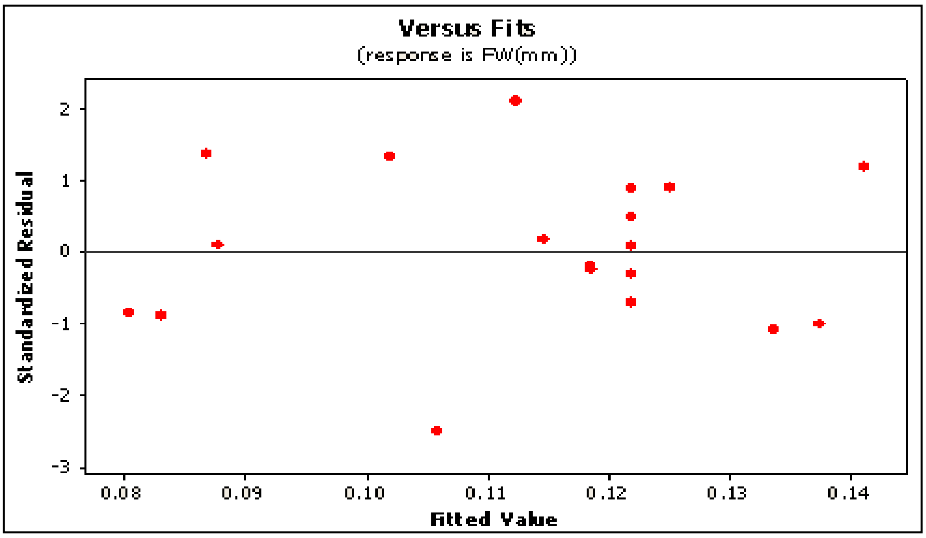

Fig. 6. *Plot of Residuals Vs Fits for Tool Wear.*

Figure 7 illustrates the contour plot and response surfaces of Tool Wear with respect to input parameters RPM and Feed Rate. The value of Tool Wear is shown to decrease with decrease of RPM and Feed Rate. In the Figure 8 contour plot and response surface of Tool Wear with Feed Rate and Depth of Cut is depicted. Tool wear decreases with decrease in Feed Rate and Depth of Cut.

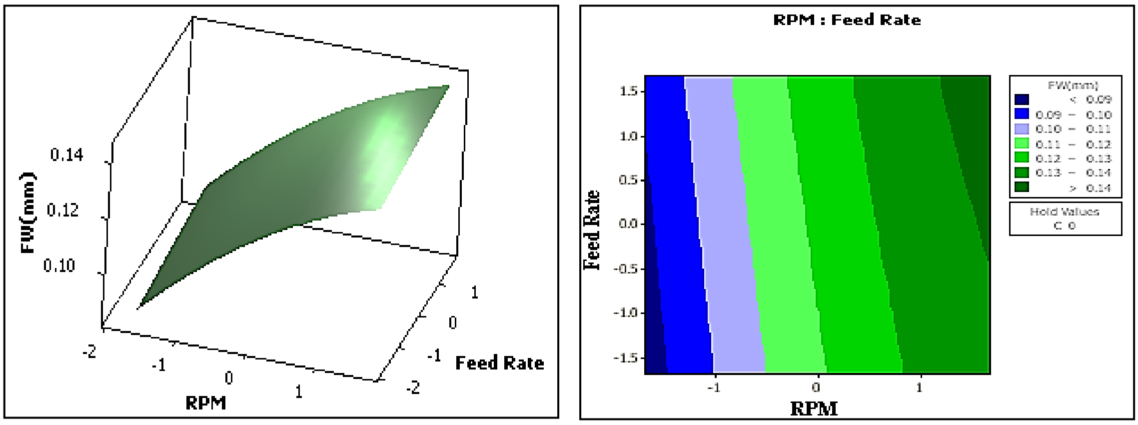

Fig. 7. *Variation in Tool Wear According to Change in RPM and Feed Rate.*

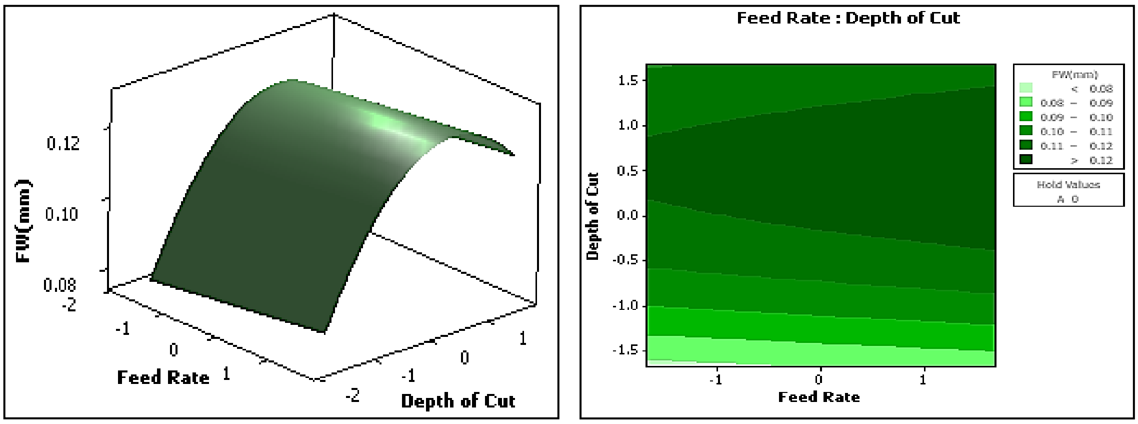

Fig. 8. *Variation in Tool Wear According to Change in Feed Rate and Depth of Cut.*

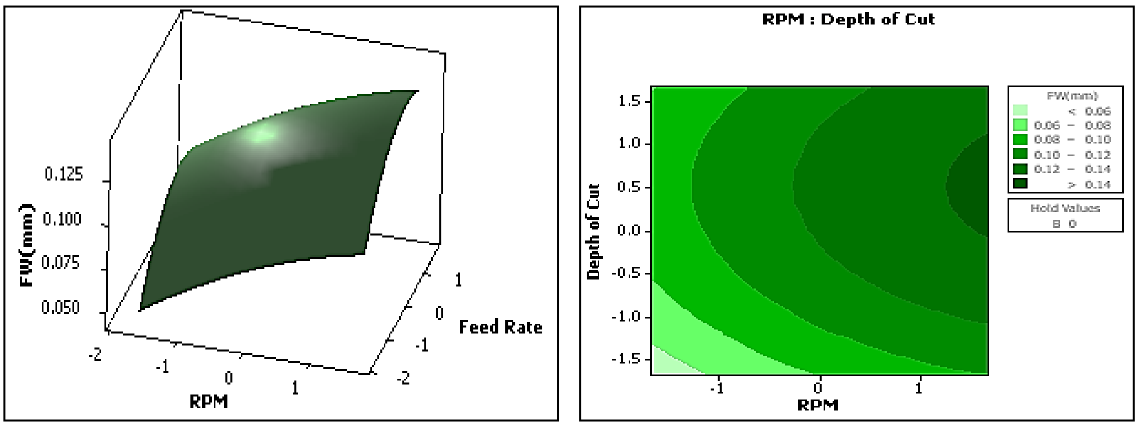

Fig. 9. *Variation in Tool Wear According to Change in RPM and Depth of Cut.*

Figure 9 also depicts that the tool wear decreases with the decrease in respective RPM and depth of cut. Thus, lower the input parameters, lower the tool wear will be.

CONFORMATION EXPERIMENT

In the present study response surface equation is derived from quadratic regression fit, so to verify taking the independent variable values within the ranges for which the formula was derived performed their validity conformation test. The one conformation experiment was performed for Tool Wear. Table 8 shows the result of the conformation run and their comparisons with the predicted values designed for Tool Wear. It is observed that the calculated error is small (within 5%). This confirms the reproducibility of experimental conclusion. [14]

Table 8. *Conformation Test Result and Comparison with Predicted Result as Per Model.*

RPM	Feed rate(mm/rev)	Depth of cut(mm)	Tool wear(mm)		
			Exp	Predicted	Error (%)
230(–1.6818)	0.032(–1.6818)	0.159(–1.6818)	0.045	0.043345	3.678673

CONCLUSION

Twenty numbers of experiments have been conducted on a CNC turning operation. EN is selected as a job material. The aim of the present investigation is to establish the correlation between the tool wear and the input variable like speed, feed, and depth of cut. The second order response model has been established and the model is validated through the ANOVA. [15]

Finally, optimum machining condition determined. This research can help other research and industries for developing a robust reliable knowledge base and early prediction of tool wear.

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