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Research Paper

MULTI OBJECTIVE OPTIMIZATION OF TOOL LIFE AND TOTAL COST USING 3-LEVEL FULL FACTORIAL METHOD IN CNC END MILLING PROCESS

D S Sai Ravi Kiran[1]* and S Phani Kumar[1]

*Corresponding Author: **D S Sai Ravi Kiran,** ✉ sairavionline@gmail.com

In many production contexts it is still necessary to rely on engineering judgment to optimize a multi-response problem, therefore uncertainty seems to prevail during the decision making process. Therefore, development of efficient multi response phenomena is required. The present project deals with the optimization of tool life and machining cost while performing machining on CNC Milling machine. The experiments are conducted through Design of Experiments (DOE). The experiment has been carried out by using solid carbide flat end mill as cutting tool and stainless steel (S.S-304) as work piece. The approach is carried out using 3-level full factorial method and is performed using Minitab V15 package. The input parameters are taken as cutting speed, feed and depth of cut while the responses are tool life and machining cost. The experimental results display that the cutting speed and depth of cut are the significant parameters that influence the tool life.

Keywords: Design of Experiments (DOE), Full factorial method, Tool life, Prediction, Regression analysis

INTRODUCTION

Today's manufacturing industries are very much concerned about the quality of their products. The machinability of AISI 304 stainless steel is difficult since it has high strength, low thermal conductivity, high ductility and high work hardening tendency. Poor surface finish, high force, and high tool wear are also observed when machining the material. Tool life is defined as the time interval for which tool works satisfactorily between two successive grinding and re-sharpening of the tool. The life of tool is affected by many factors such as: cutting speed, depth of cut, chip

1 Department of Mechanical Engineering, Anil Neerukonda Institute of Technology & Sciences (Affiliated to Andhra University), Sangivalasa, Visakhapatnam, Andhra Pradesh, India.

thickness, tool geometry, material or the cutting fluid and rigidity of machine. Physical and chemical properties of work material influence tool life by affecting form stability and rate of wear of tools. The nose radius tends to affect tool life.

Cutting Speed has the great influence on tool life. As the cutting speed increases the temperature also rises. The heat is more concentrated on the tool than on the work piece and the hardness of tool matrix changes so the relative increase in the hardness of the work accelerates the abrading action. The criterion of wear is dependent on cutting speed because the predominant wear may be wear for flank or crater if cutting speed is increased. It has been found that at cutting speed greater than 100 m/min in carbide turning of steel, crater wear may become predominant.

The relation between the cutting speed to tool life is expressed by the formula.

$V.T^n = C$

where, V – Cutting speed in m per min.

T – Tool Life in minutes.

n – Exponent depends on the tool and the work piece.

C – Constant this is numerically equal to cutting speed that gives a tool life of one minute.

The uncut chip thickness or the cutting feed has a direct influence on the quality, productivity, and efficiency of machining. It is believed that the tool life decreases (and, thus, tool wear increases) with increasing cutting feed. Such a conclusion follows from the generally adopted equation for tool life.

$$Tool\ Life = \frac{48.36 \times 10^6}{v^4 f^{1.6} d^{0.48}}$$

If the cutting speed v and the depth of cut d are both constant, then the tool life decreases when the cutting feed f is increased.

When the depth of cut increases and the uncut chip thickness is kept the same, the specific contact stresses at the tool-chip interfaces, the chip compression ratio (defined as the ratio of the chip and the uncut chip thicknesses and the average contact temperature remain unchanged. Therefore, an increase in the depth of cut should not change the tool wear rate if the machining is carried out at the optimum cutting regime.

MATERIALS AND METHODS

In this project a work piece made of stain less steel SS-304 (as per AISI) is used. 300 series stainless steel having approximately (not exactly) 18% chromium and 8% nickel. The term "18-8" is used interchangeably to characterize fittings made of 302, 302HQ, 303, 304, 305, 384, XM7, and other variables of these grades with close chemical compositions. There is little overall difference in corrosion resistance among the "18-8" types, but slight differences in chemical composition do make certain grades more resistant than others do against particular chemicals or atmospheres. "18-8" has superior corrosion resistance to 400 series stainless, is generally nonmagnetic, and is hardenable only by cold working.

Type 304 (18-8) is an austenitic steel possessing a minimum of 18% chromium and 8% nickel, combined with a maximum of 0.08% carbon. It is nonmagnetic steel which cannot be hardened by heat treatment, but instead must be cold worked to obtain higher tensile strengths (Table 1).

The 18% minimum chromium content provides corrosion and oxidation resistance. The alloy's metallurgical characteristics are established primarily by the nickel content (8% mm), which also extends resistance to corrosion caused by reducing chemicals. Carbon, a necessity of mixed benefit, is held at a level (0.08% max) that is satisfactory for most service applications in manufacturing.

The stainless alloy resists most oxidizing acids and can withstand all ordinary rusting. However, it will tarnish. It is immune to foodstuffs, sterilizing solutions, most of the organic chemicals and dyestuffs, and a wide variety of inorganic chemicals. Type 304, or one of its modifications, is the material specified more than 50% of the time whenever a stainless steel is used.

Because of its ability to withstand the corrosive action of various acids found in fruits, meats, milk, and vegetables, Type 304 is used for sinks, tabletops, coffee urns, stoves, refrigerators, milk and cream dispensers, and steam tables. It is also used in numerous other utensils such as cooking appliances, pots, pans, and flatware. In the marine environment, because of it slightly higher strength and wear resistance than type 316 it is also used for nuts, bolts, screws, and other fasteners. It is also used for springs, cogs, and other components where both wear and corrosion resistance is needed.

Work Piece Specification

The size of work piece used in the machining is 170 × 50 × 12

Length of each machining cut is 50 mm

Table 1: Chemical Composition of AISI 304 Stainless Steel

Composition	Percentage (%)
Carbon	0-0.07
Manganese	0-2.0
Silicon	0-1.0
Phosphorous	0-0.05
Sulphur	0-0.02
Chromium	17.5-19.5
Nickel	8-10.5
Iron	Balance

Table 2: Properties of AISI 304 Stainless Steel

Property	Value
Density	8.00 gm/cm^3
Melting Point	1450 °C
Modulus of Elasticity	193 Gpa
Electrical Resistivity	0.072×10^{-6}U.m
Thermal Conductivity	16.2 W/Mk
Thermal Expansion	17.2×10^{-6}/K
BHN	123
VHN	129

Tools and Equipment Used

Solid Carbide Flat End Mill of 10 mm diameter.

CNC Vertical Machining Center – AGNI BMV 45 T20

Process Variables Used in the Experimentation

The level of cutting parameter ranges and the initial parameter values are chosen from the manufacturer's data book recommended for the tested material. These cutting parameters are shown in Table 3.

Design of Experiments (DOE)

Design of Experiment is an experimental or analytical method that is commonly used to

Table 3: Process Parameters Used in the Experimentation

S. No.	Cutting Parameter	Units	Level 1	Level 2	Level 3
1.	Cutting Speed	m/min	50	75	100
2.	Feed	mm/rev	0.10	0.20	0.30
3.	Depth of Cut	m m	0.30	0.40	0.50

statistically signify the relationship between input parameters to output responses. DOE has wide applications especially in the field of science and engineering for the purpose of process optimization and development, process management and validation tests. DOE is essentially an experimental based modeling and is a designed experimental approach which is far superior to unplanned approach whereby a systematic way will be used to plan the experiment, collect the data and analyze the data. A mathematical model has been developed by using analysis techniques such as ANOVA and regression analysis whereby the mathematical model shows the relationship between the input parameters and the output responses. Among the most prominently used DOE techniques are Response Surface Methodology with Central Composite Design, Taguchi's method and Factorial Design. In DOE, synergy between mathematical and statistical techniques such as Regression, Analysis of Variance (ANOVA), Non-Linear Optimization and Desirability functions helps to optimize the quality characteristics considered in a DOE under a cost effective process. ANOVA helps to identify each factor effect versus the objective function.

Experimental design was first introduced in the 1920s by R A Fischer working at the agricultural field station at Rothamsted in England. Fischer concerned with arranging trials of fertilizers on plots to protect against the underlying effect of moisture, gradient, nature of soils, etc. Fischer developed the basic principles of factorial design and the associated data analysis known as ANOVA during research in improving the yield of agricultural crops.

Factorial Method

Factorial designs allow for the simultaneous study of the effects that several factors may have on a process. When performing an experiment, varying the levels of the factors simultaneously rather than one at a time is efficient in terms of time and cost, and also allows for the study of interactions between the factors. Interactions are the driving force in many processes. Without the use of factorial experiments, important interactions may remain undetected. DOE is used because it saves time and cost in terms of experimentation. DOE function in such manner that the number of experiments or the number of runs is determined before the actual experimentation is done. This way, time and cost can be saved as we do not have to repeat unnecessary experiment runs. Most usually, experiments will have error occurring. Some of them might be predictable while some errors are just out of control. DOE allows us to handle these errors while still continuing with the analysis. DOE is excellent when it comes to prediction linear behavior.

Different types of designs available in Factorial Method are,

- Two-level full factorial designs.
- Two-level fractional factorial designs.
- Plackett-Burman designs.
- General full factorial designs.

Table 4: Design of Experiments

S. No.	Cutting Speed (m/min)	Feed (mm/rev)	Depth of Cut (mm)
1.	75	0.3	0.3
2.	75	0.3	0.5
3.	100	0.3	0.3
4.	100	0.3	0.5
5.	100	0.1	0.5
6.	100	0.1	0.4
7.	50	0.1	0.4
8.	50	0.1	0.3
9.	75	0.3	0.4
10.	75	0.1	0.5
11.	50	0.2	0.5
12.	75	0.2	0.5
13.	50	0.3	0.4
14.	50	0.1	0.5
15.	100	0.1	0.3
16.	50	0.2	0.4
17.	100	0.2	0.3
18.	50	0.3	0.3
19.	100	0.3	0.4
20.	75	0.1	0.3
21.	50	0.3	0.5
22.	100	0.2	0.4
23.	75	0.1	0.4
24.	100	0.2	0.5
25.	75	0.2	0.3
26.	50	0.2	0.3
27.	75	0.2	0.4

Measurement of Tool Life

Tool Life is the time elapsed between two successive grindings of a cutting tool. Tool life may be measured in the following ways.

- Number of pieces machined between tool sharpening.
- Time of actual operation, viz, the time the tool is in contact with the job.
- Total time of operation.
- Equivalent cutting speed.
- Volume of material removed between tool sharpening.

In practice it is more profitable to assess the tool life in terms of the volume of metal removed because the wear is related to the area of the chip passing over the tool surface. The volume of metal removed from the work piece between tool sharpening for a definite depth of cut, feed and cutting speed can be determined by Taylor's tool life equation.

The proposed relationship between the machining response (tool life) and machining independent variables can be represented by the following:

$T = C(V\, l\, f\, m\, d\, n)e$

where T is the tool life in minutes, V, f, and d are the cutting speeds (m/min), feed rates (mm/rev), and depths of cut (mm) respectively, C, l, m, n are constants and e is a random error.

Taylors Extended Tool life Equation

$$V \times T^n \times f^{n_1} \times d^{n_2} = k$$

where

T = Tool life in min

f = feed in mm per revolution

d = depth of cut in mm

n = Tool constant for solid carbide – 0.25 (from tool manufacturer's data book)

n_1 = feed exponent constant – 0.5 (from tool manufacturer's data book)

n_2 = depth of cut exponent constant – 0.20 (from tool manufacturer's data book)

k = constant – 47 (from tool manufacturer's data book)

$$Tool\ Life(T) = \frac{k^{1/n}}{v^{1/n} \times f^{\frac{n_1}{n}} \times d^{\frac{n_2}{n}}}$$

By replacing the values in the above equation,

$$Tool\ Life = \frac{47^4}{v^4 f^2 d^{0.3}}$$

Calculation of Tool Life While Manufacturing Each Part

Material need to remove = 1 mm

Length of cut in one pass = 50 mm

Spindle speed is = 2000 rpm

Feed is = 0.15 mm/rev

Depth of cut is = 0.25 mm

Cutting speed = 50 m/min

for, Cutting speed = 75 m/min

Feed = 0.3 mm/rev

Depth of cut = 0.3 mm

$$Tool\ Life = \frac{47^4}{75^4 \times 0.3^2 \times 0.3^{0.3}}$$

Tool Life = 4.489 min

Calculation of Machining Cost/Piece and Tooling Cost/Piece for the Selected Part

Cost of tool is = Rs. 995

Total cost being used by machine in one hour = VMC machine hour rate = Rs. 500

The cycle time for the part for each set of cutting parameters is obtained by performing machining.

Number of parts being made by one tool =

$$\frac{tool\ life}{cycle\ time} = \frac{4.489}{0.185} = 24.26$$

Machining cost of one part is being given

by $= \dfrac{Cycle\ time \times VMC\ hour\ rate}{60}$

$= \dfrac{0.185 \times 500}{60}$ = Rs. 1.541/-

Tooling cost of one part is being given by =

$$\frac{Cost\ of\ one\ tool}{No.\ of\ workpieces\ made\ bye\ one\ tool}$$

Tooling Cost = $\dfrac{995}{24}$ = Rs. 41.458/-

Total cost being obtained for producing one part = Tooling cost + Machining cost

= 41.458 + 1.541

= Rs. 42.991/-

Analysis of Variance

In statistics, analysis of variance (ANOVA) is a collection of statistical models, and their associated procedures, in which the observed variance in a particular variable is partitioned into components attributable to different sources of variation. In its simplest form, ANOVA provides a statistical test of whether or not the means of several groups are all equal, and therefore generalizes t-test to more than two groups. Doing multiple two-sample t-tests would result in an increased chance of committing a type I error. For this reason, ANOVAs are useful in comparing three, or more means.

ANOVA is used in the analysis of comparative experiments, those in which only the difference in outcomes is of interest. The statistical significance of the experiment is determined by a ratio of two variances. This ratio is independent of several possible alterations to the experimental observations: Adding a constant to all observations does not alter significance. Multiplying all observations by a constant does not alter significance. So ANOVA statistical significance results are independent of constant bias and scaling errors as well as the units used in expressing observations.

Response Surface Methodology

In statistics, Response Surface Methodology (RSM) explores the relationships between several explanatory variables and one or more response variables. The method was introduced by G E P Box and K B Wilson in 1951. The main idea of RSM is to use a sequence of designed experiments to obtain an optimal response. Box and Wilson suggest using a second-degree polynomial model to do this. They acknowledge that this model is only an approximation, but use it because such a model is easy to estimate and apply, even when little is known about the process.

Response surface methodology uses statistical models, and therefore practitioners need to be aware that even the best statistical model is an approximation to reality. In practice, both the models and the parameter values are unknown, and subject to uncertainty on top of ignorance. Of course, an estimated optimum point need not be optimum in reality, because of the errors of the estimates and of the inadequacies of the model.

Nonetheless, response surface methodology has an effective track-record of helping researchers improve products and services: For example, Box's original response-surface modeling enabled chemical engineers to improve a process that had been stuck at a saddle-point for years. The engineers had not been able to afford to fit a cubic three-level design to estimate a quadratic model, and their biased linear-models estimated the gradient to be zero. Box's design reduced the costs of experimentation so that a quadratic model could be fit, which led to a (long-sought) ascent direction.

Mathematical Model of Response Surface Methodology

The Response Surface is described by a second order polynomial equation of the form,

$$Y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \beta_{ii} x_{i^2} + \sum\sum_{i<j} \beta_{ij} x_i x_j + \varepsilon$$

where, Y is the corresponding response (1, 2, ..., S) are coded levels of S quantitative process variables. The terms are the second order regression coefficients. Second term is attributable to linear effect. Third term corresponds to the higher-order effects; Fourth term includes the interactive effects. The last term indicates the experimental error.

Different Terms and Graphs in Response Surface Methodology

Regression Table

P-values: *p*-values (P) to determine which of the effects in the model are statistically significant.

- If the *p*-value is less than or equal to a (0.05), conclude that the effect is significant.
- If the *p*-value is greater than a, conclude that the effect is not significant.

Coefficients: Coefficients are used to construct an equation representing the relationship between the response and the factors.

R-squared: R and adjusted R represent the proportion of variation in the response that is explained by the model.

- R (R-Sq) describes the amount of variation in the observed responses that is explained by the model.
- Predicted R reflects how well the model will predict future data.
- Adjusted R is a modified R that has been adjusted for the number of terms in the model. If we include unnecessary terms, R can be artificially high. Unlike R, adjusted R may get smaller when we add terms to the model.

Analysis of Variance Table: P-values (P) are used in analysis of variance table to determine which of the effects in the model are statistically significant. The interaction effects in the model are observed first because a significant interaction will influence the main effects.

Estimated Coefficients Using Uncoded Units

- Minitab displays the coefficients in uncoded units in addition to coded units if the two units differ.
- For each term in the model, there is a coefficient. These coefficients are useful to construct an equation representing the relationship between the response and the factors.

Graphs

Histogram of Residuals: Histogram of the residuals shows the distribution of the residuals for all observations.

Normal Plot of Residuals: Graph is plotted between the residuals versus their expected values when the distribution is normal. The residuals from the analysis should be normally distributed. In practice, for balanced or nearly balanced designs or for data with a large number of observations, moderate departures from normality do not seriously affect the results. The normal probability plot of the residuals should roughly follow a straight line.

Residuals vs. Fits: Graph is plotted between the residuals versus the fitted values. The residuals should be scattered randomly about zero.

Residuals vs. Order: This graph plots the residuals in the order of the corresponding observations. The plot is useful when the order of the observations may influence the results, which can occur when data are collected in a time sequence or in some other sequence. This plot can be particularly helpful in a designed experiment in which the runs are not randomized.

Table 5: Calculated Tool Life Under Given Set of Cutting Conditions

S. No.	Cutting Speed (m/min)	Feed (mm/rev)	Depth of Cut (mm)	Tool Life (min)
1.	75	0.3	0.3	4.489
2.	75	0.3	0.5	2.983
3.	100	0.3	0.3	1.42
4.	100	0.3	0.5	0.944
5.	100	0.1	0.5	8.496
6.	100	0.1	0.4	10.156
7.	50	0.1	0.4	162.5
8.	50	0.1	0.3	204.55
9.	75	0.3	0.4	3.566
10.	75	0.1	0.5	26.85
11.	50	0.2	0.5	33.98
12.	75	0.2	0.5	6.712
13.	50	0.3	0.4	18.05
14.	50	0.1	0.5	135.93
15.	100	0.1	0.3	12.78
16.	50	0.2	0.4	40.62
17.	100	0.2	0.3	3.196
18.	50	0.3	0.3	22.72
19.	100	0.3	0.4	1.128
20.	75	0.1	0.3	40.406
21.	50	0.3	0.5	15.104
22.	100	0.2	0.4	2.539
23.	75	0.1	0.4	32.09
24.	100	0.2	0.5	2.124
25.	75	0.2	0.3	10.101
26.	50	0.2	0.3	51.13
27.	75	0.2	0.4	8.02

Table 6: Total Cost Obtained for Given Set of Cutting Conditions

S. No.	Cutting Speed m/min	Feed mm/ rev	Depth of Cut mm	Cycle Time min	Machining Cost Rs.	Tooling Cost Rs.	Total Cost Rs.
1.	75	0.3	0.3	0.1850	1.5410	41.250	42.991
2.	75	0.3	0.5	0.1100	0.9166	36.849	37.766
3.	100	0.3	0.3	0.1388	1.1566	98.843	100.660
4.	100	0.3	0.5	0.0833	0.6941	90.454	91.148
5.	100	0.1	0.5	0.2500	2.0830	26.264	28.347

Table 6 (Cont.)

S. No.	Cutting Speed m/min	Feed mm/ rev	Depth of Cut mm	Cycle Time min	Machining Cost Rs.	Tooling Cost Rs.	Total Cost Rs.
6.	100	0.1	0.4	0.3125	2.6041	30.1510	32.755
7.	50	0.1	0.4	0.6250	5.2083	3.8257	9.034
8.	50	0.1	0.3	0.8330	6.9410	4.0440	10.985
9.	75	0.3	0.4	0.1388	1.1566	38.2680	39.425
10.	75	0.1	0.5	0.3330	2.7750	12.2830	15.058
11.	50	0.2	0.5	0.2500	2.0830	7.3100	9.393
12.	75	0.2	0.5	0.1660	1.3830	24.8750	26.258
13.	50	0.3	0.4	0.3125	2.6004	17.1590	19.759
14.	50	0.1	0.5	0.5000	4.1660	3.6580	7.824
15.	100	0.1	0.3	0.4165	3.4700	32.0640	35.534
16.	50	0.2	0.4	0.3125	2.6040	7.6500	10.254
17.	100	0.2	0.3	0.2080	1.7330	33.1660	34.899
18.	50	0.3	0.3	0.2770	7.3083	12.1130	19.442
19.	100	0.3	0.4	0.1040	0.8660	90.4540	91.320
20.	75	0.1	0.3	0.5500	4.5830	9.5050	14.088
21.	50	0.3	0.5	0.1660	1.3830	10.9340	12.317
22.	100	0.2	0.4	0.1560	1.3000	62.1870	63.487
23.	75	0.1	0.4	0.4166	3.4710	12.9740	16.391
24.	100	0.2	0.5	0.1250	1.0410	58.5290	59.570
25.	75	0.2	0.3	0.2770	2.3083	27.6380	29.946
26.	50	0.2	0.3	0.4160	3.4660	8.0840	11.550
27.	75	0.2	0.4	0.2083	1.7358	26.1140	27.850

RESULTS AND DISCUSSION

Above experimental data is inputted into the Minitab software and analysis of factorial design is being done. The following mathematical relationship and graphs are being generated by software which gives important results.

Analysis of variance (ANOVA) is as shown. It shows the value of $p < 0.05$ for all linear,

Table 7: Analysis of Variance for Tool Life

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	9	63715.0	63715.0	7079.44	20.26	0.000
Linear	3	41284.6	21687.5	7229.17	20.69	0.000
Square	3	6657.6	6657.6	2219.19	6.35	0.040
Interaction	3	15772.8	15772.8	5257.60	15.04	0.000
Residual Error	17	5941.1	5941.1	349.47		
Total	**26**	**69656.0**				

square and interactions terms, i.e., all these effects are significant on the tool life.

S = 18.6942

R-Sq = 95.47%

R-Sq(pred) = 91.45%

R-Sq(adj) = 86.96%

Table 8: Statistical Analysis of All Terms for Tool Life

Predictor	Coefficient	P-Value
Constant	881.94	0.000
X_1 (mm/min)	–11.48	0.000
X_2 (mm/rev)	–2477.80	0.000
X_3 (mm)	530.48	0.420
X_1^2	0.04	0.004
X_2^2	2151.77	0.012
X_3^2	147.65	0.849
X_1X_2	13.970	0.000
X_1X_3	2.920	0.194
X_2X_3	640.520	0.252

Mathematical Relationship Between Input Parameters and Tool Life

The mathematical relationship for correlating the Tool life and the considered process variables has been obtained as follows:

$$Tool\ Life = 881.94 - 11.48 * X_1 - 2477.80 * X_2 - 530.48 * X_3 + 0.04 * X_1^2 + 2151.77 * X_2^2 + 147.65 * X_3^2 + 13.97 * X_1 * X_2 + 2.920 * X_1 * X_3 + 640.520 * X_2 * X_3$$

The second-order polynomial models were developed for Tool life. The fit summary indicates that the quadratic model is statistically significant for analysis of Tool life.

The value of R^2 is 95.47%, which indicates that the developed regression model is adequately significant at a 95% confidence level.

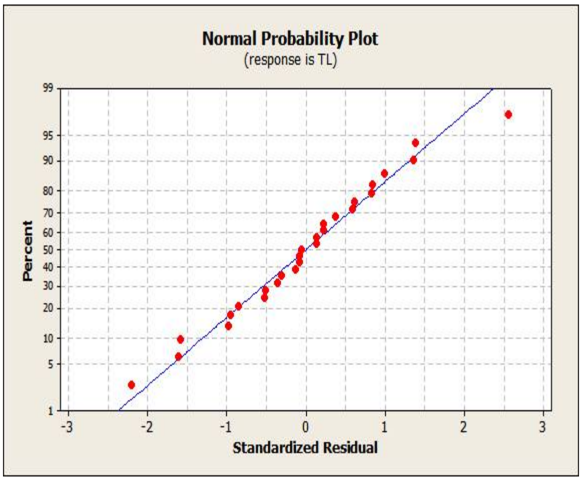
Graphs

Normal Probability for Tool Life: The normal probability plot, shows a clear pattern (as the points are almost in a straight line) indicating that all the factors and their interaction given in are affecting the tool life. In addition, the errors are normally distributed and the regression model is well fitted with the observed values.

Table 9: Pattern Curvature for Normal Probability Plot

Pattern	Indicates
Not a Straight Line	Non Normality
Curve in the Tails	Skewness
A Point Far Away from the Line	Outlier
Changing Slope	Unidentified Variable

Figure 1: Normal Probability for Tool Life



Minitab provides three types of residuals:

- Regular residual: Observed Value-Predicted Value.
- Standardized residual: Regular Residual/ Standard Deviation of Regular Residual.

The standardization eliminates the effect of the location of the data point with respect to the predictors or factors.

- Studentized deleted residual: for the ith data point, the formula follows the same expression as the standardized residual. However, the ith fitted value and the standard deviation are calculated for the studentized deleted residual by deleting the ith case in the analysis. Compared to the standardized residual, the studentized deleted residual becomes larger in the presence of an unusual data point.

Figure 2: Standardized Residual vs. Fitted Value for Tool Life

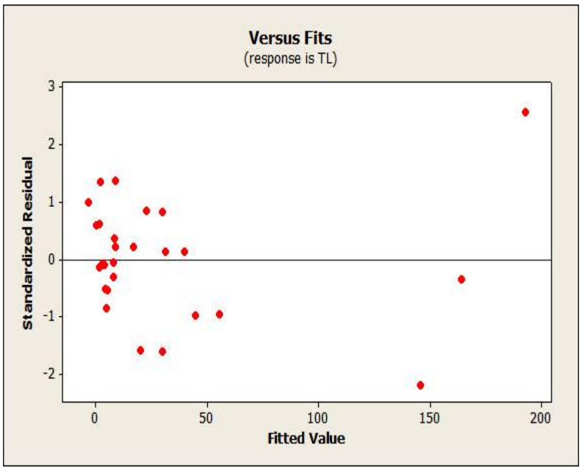


Figure indicates that the maximum variation of 0 to 200, which shows the high correlation that, exists between fitted values and observed values.

Table 10: Pattern Indication for Standardized Residual Vs Fitted Values

Pattern	Indicates
Fanning or uneven spreading of residuals across fitted values	Non-constant variance
Curvilinear	A missing higher order term
A point far away from zero	An outlier

Figure 3: Comparison Between Experimental and Predicted Values

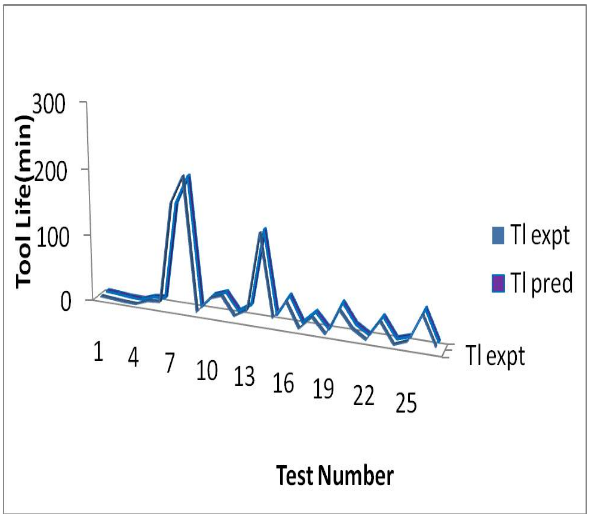


Table 11: Analysis of Variance for Total Cost

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	9	17452.0	17452.00	1939.113	2.82	0.000
Linear	3	14651.9	754.32	251.439	5.42	0.008
Square	3	543.4	543.43	181.142	3.91	0.027
Interaction	3	2256.7	2256.73	752.243	4.23	0.000
Residual error	17	788.2	788.17	46.363		
Total	**26**	**18240.2**				

The nearness of the both the experimental and predicted tool life curves indicates that the experimental and predicted tool life values are approximately equal.

Table 12: Statistical Analysis of All Terms for Total Cost

Predictor	Coefficient	P-Value
Constant	82.1430	0.048
X_1 (mm/min)	–2.3190	0.006
X_2 (mm/rev)	–381.4860	0.020
X_3 (mm)	108.5380	0.049
X_1^2	0.0130	0.009
X_2^2	435.7000	0.035
X_3^2	–182.1000	0.021
X_1X_2	5.4270	0.000
X_1X_3	0.6810	0.099
X_2X_3	–104.0000	0.004

S = 6.80902

R-Sq = 95.68%

R-Sq(pred) = 91.37%

R-Sq(adj) = 93.39%

The mathematical relationship for correlating the Total Cost and the considered process variables has been obtained as follows:

Total Cost = 82.143 + 2.391 * X_1 381.486 * X_2 + 108.538 * X_3 + 0.013 * X_1^2 + 435.700 * X_2^2 + 182.100 * X_3^2 + 5.427 * X_1 * X_2 + 0.681 * X_1 * X_3 – 104.000 * X_2 * X_3.

The second-order polynomial models were developed for Total Cost. The fit summary indicates that the quadratic model is statistically significant for analysis of Total Cost.

The value of R^2 is 95.68%, which indicates that the developed regression model is adequately significant at a 95% confidence level.

The normal probability plot, shows a clear pattern (as the points are almost in a straight line) indicating that all the factors and their interaction given in are affecting the total cost. In addition, the errors are normally distributed and the regression model is well fitted with the observed values.

Figure 4: Normal Probability Plot for Total Cost

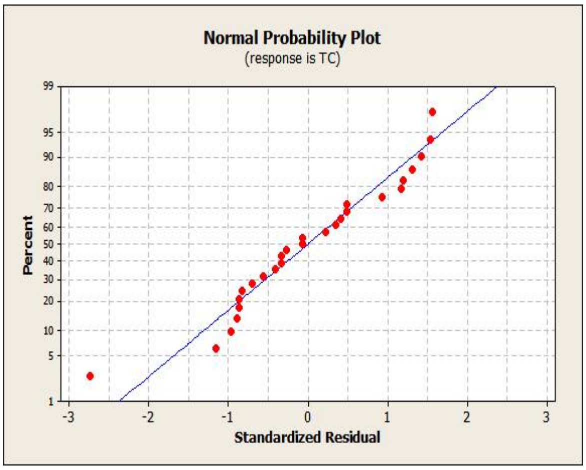


Figure 5: Standardized Residual vs. Fitted Values for Total Cost

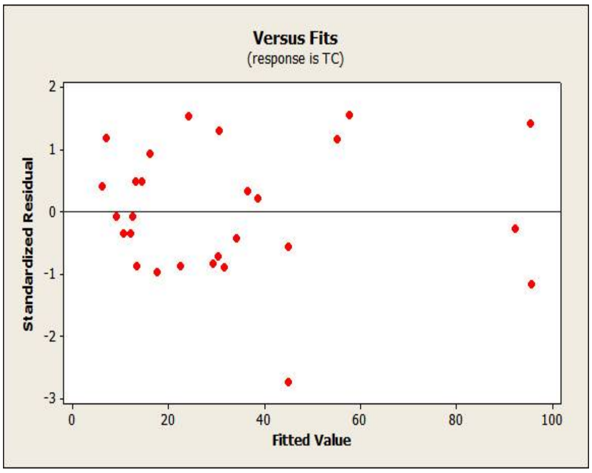
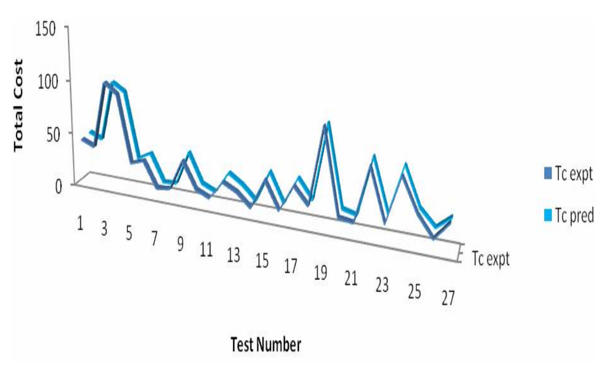


Figure indicates that the maximum variation of 0 to 100, which shows the high correlation that, exists between fitted values and observed values.

The nearness of the both the experimental and predicted total cost curves indicates that

Figure 6: Comparison Between Experimental and Predicted Values for Total Cost

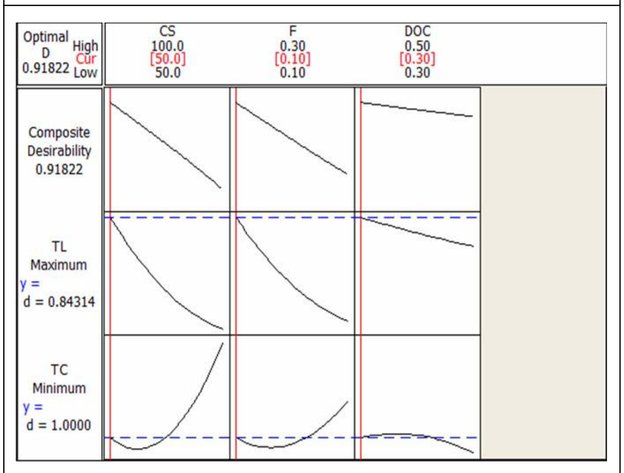


the experimental and predicted total cost values are approximately equal.

Optimization Plot

A Minitab Response Optimizer tool shows how different experimental settings affect the predicted responses for factorial, response surface, and mixture designs. Minitab calculates an optimal solution and draws the plot. The optimal solution serves as the starting point for the plot. This optimization plot allows to interactively changing the input variable settings to perform sensitivity analyses and possibly improve the initial solution.

Figure 7: Optimization Plot for Tool Life and Total Cost



From the optimization plot it can be said that the maximum tool life is 170.19 min and the least total cost is Rs. 12.22 obtained when the cutting speed = 50 m/min, feed = 0.3 mm/rev, and depth of cut = 0.3 mm.

Also from the optimization plot it can be concluded that depth of cut and cutting speed are the most influencing parameters.

CONCLUSION

The experimental results demonstrate that the cutting speed and depth of cut are the main parameters that Influence the tool life of end mill cutters of CNC milling machine.

The tool life can be improved simultaneous through DOE approach instead of using Engineering judgment.

Experimental results show that in milling operations, use of low depth of cut, low cutting speed and low feed rate are recommended to obtain better Tool life for the specific range.

FUTURE SCOPE

Tool rake angle, axial depth of cut and temperature at the tool tip can be taken as additional factors that influence the tool life with addition to cutting speed, feed and depth of cut.

Surface finish, material removal rate, tool flank wear etc can also be taken as responses in addition to tool life and total cost.

SAS software can be used for generating Design of Experiments instead of Minitab V15.

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