

# Optimization of Cutting Tool Life on CNC Milling Machine Through Design of Experiments-A Suitable Approach – An overview

Ishan B Shah, Kishore. R. Gawande

**Abstract-** This paper discuss of the literature review of Optimization of tool life in milling using Design of experiment implemented to model the end milling process that are using solid carbide flat end mill as the cutting tool and stainless steels s.s-304 as material due to predict the resulting of Tool life. Data is collected from CNC milling machines were run by 8 samples of experiments using DOE approach that generate table design in MINITAB packages. The inputs of the model consist of feed, cutting speed and depth of cut while the output from the model is Tool life calculated by Taylor's life equation. The model is validated through a comparison of the experimental values with their predicted counterparts. The optimization of the tool life is studied to compare the relationship of the parameters involve.

**Keywords-** Design of experiment(DOE), Two level Full and Fractional designs, ANOVA, Optimization of tool life, Minitab .

## 1. INTRODUCTION

In order to establish an adequate functional relationship between the tool life and the cutting parameters (cutting speed, feed, and depth of cut), a large number of tests are needed, requiring a separate set of tests for each and every combination of cutting tool and workpiece material. This increases the total number of tests and as a result the experimentation cost also increases. Most researchers have investigated the effects of these cutting parameters on tool life by the one-variable- at-a-time approach. The present study takes into account the simultaneous variation of speed, feed, and depth of cut and predicts the tool life (response).[1] Factorial designs are used widely in experiments involving several factors where it is necessary to study the combined effect of these factors on a response. The meaning of factorial design is that each complete trial or replication of all the possible combinations of the levels of the factors are investigated.[1] I.A. Choudhury, M.A. El-Baradie Presents a study for the development of first- and second-order tool-life

models at 95% confidence level for turning high strength steel. The effects of the main cutting variables (cutting speed, feed, and depth of cut) on tool life have been investigated by the application of the factorial design method. [1]Dong-Woo Kim, Myeong -Woo Cho, Tae-Il Seo, Eung - Sug Lee attempt to minimize the thrust forces in the step-feed micro drilling process by application of the DOE (Design of Experiment) method. Taking into account the drilling thrust, three cutting parameters, federate, step-feed, and cutting speed, are optimized based on the DOE method.[4] Ilhan Asiltürk , Harun Akkus Performed optimization parameters based on the Taguchi method to minimize surface roughness (Ra and Rz). Experiments have been conducted using the L9 orthogonal array in a CNC turning machine. Dry.Each experiment was repeated three times and each test uses a new cutting insert to ensure accurate readings of the surface roughness[5] Yung-Kuang Yang, Ming-Tsan Chuang, Show-Shyan Lin Used the designs of experiments (DOE) approach to optimize parameters of a computer numerical control (CNC) in end milling for high-purity graphite under dry machining. The analysis of variance (ANOVA) was adapted to identify the most influential factors on the CNC end milling process. Simultaneously, applying regression analysis a mathematical predictive model for predictions of the groove difference and the roughness average has been developed in terms of cutting speed, feed rate, and depth of cut.[6]J.A. Ghani, I.A. Choudhury, H.H. Hassan Used Taguchi optimization methodology, which was applied to optimize cutting parameters in end milling when machining hardened steel AISI H13 with TiN coated P10 carbide insert tool under semi-finishing and finishing conditions of high speed cutting. The milling parameters evaluated were cutting speed, feed rate and depth of cut.. Using Taguchi method for design of experiment (DOE), other significant effects such as the interaction among milling parameters were also investigated.[7]

## 2. TOOL-LIFE MODEL

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

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$$T = C (V^l f^m d^n) e \quad (1)$$

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. Eq. (1) can be written in the following logarithmic form:

$$\ln T = \ln C + l \ln V + m \ln f + n \ln d + \ln e \quad (2)$$

The linear model of Eq. (2) is:

$$y = b_0 x_0 + b_1 x_1 + b_2 x_2 + b_3 x_3 + e \quad (3)$$

where y is the measured tool life to a logarithmic scale,  $x_0 = 1$  (dummy variable),  $x_1 = \ln V$ ,  $x_2 = \ln f$ ,  $x_3 = \ln d$ ,  $e = \ln e$  %, where e is assumed to be a normally-distributed uncorrelated random error with zero mean and constant variance,  $\beta_0 = \ln C$ , and  $\beta_1$ ,  $\beta_2$ , and  $\beta_3$  are the model parameters. The estimated response can be written as:

$$\hat{y} = b_0 x_0 + b_1 x_1 + b_2 x_2 + b_3 x_3 \quad (4)$$

where  $\hat{y}$  is the estimated response, and  $b_0$ ,  $b_1$ ,  $b_2$ , and  $b_3$  are estimates of  $\beta_0$ ,  $\beta_1$ ,  $\beta_2$ , and  $\beta_3$  respectively.[1] The significance of these variables is judged by statistical analysis.[1].

## 2. DESIGN OF EXPERIMENT(DOE)

Design of experiment (DOE) has been a very useful tool to design and analyze complicated industrial design problems. It helps us to understand process characteristics and to investigate how inputs affect responses based on statistical backgrounds. In addition, it has been used to systematically determine the optimal process parameters with fewer testing trials.[2]

Recently, the DOE procedure has been used to systematically investigate process variables or product variables that influence the quality of products. It is possible to identify the process conditions and product components that influence product quality and costs, which in turn enhance the product manufacturability, quality, reliability, and productivity. The DOE procedure consists of the following four steps:

- Planning: definition of the problem and the objective, and development of an experimental plan.
- Screening: reduction of the number of variables by identifying the key variables that affect product quality.
- Optimization: determination of the optimal values for various experimental factors.
- Verification: performing a follow-up experiment at the predicted best processing conditions to confirm the optimization results.[2]

The DOE approach can be divided into a full factorial design and a fractional factorial design. The full factorial design has the advantages that all kinds of main effects and interactions can be considered. However, since all combinations are to be tested, the number of experiments ( $N_{full}$ ) increases exponentially as follows:

$$N_{full} = m(nl)^k \quad (5)$$

where k is the number of factors to be investigated, nl the experiment level, and m the number of replicates. Thus the

number of experiments increases considerably when there are numerous input factors.[2]

If higher order interactions are negligible, it is possible to use a fraction of the full factorial. It is generally recognized that three-way and higher interactions are so rare as to be negligible and can be thus ignored. The fractional factorial experiment is usually designed to be able to consider main effects and two-way interactions. It is efficiently used in the screening DOE procedures when there are a large number of factors. The number of experiments required ( $N_{fractional}$ ) is then reduced as follows:

$$N_{fractional} = m(nl)^{k-q} \quad (6)$$

where q is the degree of fractionating. While an increase of q decreases the number of experiments, it may also cause loss of reliability in analyzing the results of experiments. A term commonly used to describe the reliability of an experimental design is resolution. The meaning of different resolutions is tied to the degree of aliasing in the fractional factorial design matrix.[2]

### Usefull plan of Design of Experiments in Tool life optimization

A short compilation of most useful designs for the purpose of tool life optimization, based onto a their capability from this area will be discussed in this section. The compilation will be categorized into the following groups:

- Hadamard or Plackett–Burman matrices;
- two-level full factorial designs ( $2^k$ );
- two-level fractional factorial designs ( $2^{k-m}$ );[3]

#### 3.1 Hadamard (Plackett–Burman) matrix (screening matrix)

The Hadamard matrix is used to start the optimization by screening a great number of factors  $X_i$ , ( $i > 4$ ) that can potentially influence the response Y. Each factor can take two levels (- 1 or + 1) in coded variables, corresponding to two levels of natural variables. Tables 1 and 2 show the construction of two equivalent Hadamard matrices (called H8) which make it possible to study of the effects of 7 factors ( $X_1$  to  $X_7$ ). [3]

To find whether the factors are influent, a simple first degree polynomial is proposed:

$$y = b_0 + \sum b_i X_i \quad (7)$$

Table 1 Hadamard matrix for 7 variables

No of experiments	X1	X2	X3	X4	X5	X6	X7
1	-1	-1	-1	-1	-1	-1	-1
2	1	-1	-1	1	-1	-1	1
3	-1	1	-1	1	1	1	1
4	1	1	-1	-1	1	1	-1
5	-1	-1	1	-1	1	1	1
6	1	-1	1	1	1	1	-1
7	-1	1	1	1	-1	-1	-1
8	-1	1	1	-1	-1	-1	1

Table 2 Another type of Hadamard matrix for 7 variables being also the fractional  $2^{(7-4)}$  matrix for 7 variables

No of experiments	X1	X2	X3	X4= X1X2	X5= X1X3	X6= X3X2	X7= X1X2 X3
1	-1	-1	-1	1	1	1	-1
2	1	-1	-1	-1	-1	1	1
3	-1	1	-1	-1	1	-1	1
4	1	1	-1	1	-1	-1	-1
5	-1	-1	1	1	-1	-1	1
6	1	1	1	-1	1	-1	-1
7	-1	-1	1	-1	-1	1	-1
8	1	1	1	1	1	1	1

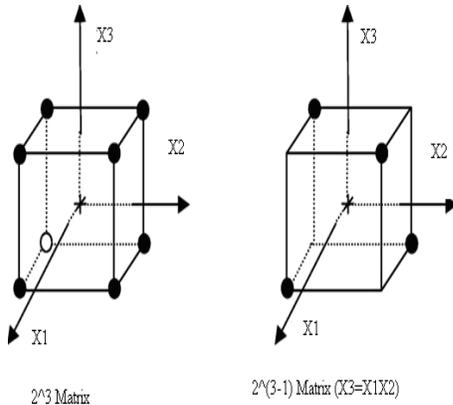


Fig. 1. Graphical representation of the matrices:  $2^3$  (a) and  $2^{(3-1)}$  designed using simplification  $X3=X1X2$  (b).

3.2. Two-Level full factorial design ( $2^k$ )

This design is used when interactions between the factors  $X_i$  and  $X_j$  factors are suspected. The first order polynomial taken from Hadamard matrix is completed by adding interaction terms  $X_iX_j$  until  $X_1X_2...X_k$  with  $i \neq j \neq \dots \neq k$ . Usually coefficients of interest are the main effects  $b_j$  and the first order interaction  $b_{ij}$ . If the interaction coefficients are not significant the effect of factor  $X_i$  can be examined as for the Hadamard matrix. If they are, say e.g. the first order interaction coefficient  $b_{ij}$  is significant then both effects of  $X_i$  and  $X_j$  factors have to be studied together with these of an interaction diagram. The first three columns of Table 1 and 2 present the  $2^3$  matrix for 3 variables and its graphical representation is shown in Fig. 1(a).[3]

3.3. Two-level k factors fractional factorial designs ( $2^{k-m}$ )

The number of runs required by full factorial design increase geometrically as k is increased. It turns out, however, that when k is not small, the desired information can be often obtained by performing only a fraction of the full factorial design.[3]

In practice, the number  $n = 2^k$  of experiments increases rapidly with the number of factors and for e.g.  $k = 5$ ,  $n = 32$  etc. Moreover, a lot of calculated coefficients corresponding to interactions of second (and higher) order can be supposed to be not significant. Consequently, the aim of the fractional  $2^k - m$  factorial design is to extract the part of experiments from the full factorial design which enables to obtain the main effects and some first order interaction. To construct a  $2^k - m$  matrix one may start with a  $2^k$  one and replace some interactions with the variables. Fig. 1b shows the principle of such

replacement for a design  $2^3 - 1$ . Table 2 presents the construction of the  $2^7 - 4$  with the columns X1, X2 and X3 which correspond to the full  $2^3$  matrix and the following columns obtained by the multiplication  $X4 = X1X2$ , etc. Moreover, the  $2^7 - 4$  matrix is equivalent as to the Hadamard matrix of type H8.[3]

4. EXPERIMENTAL PROCEDURES

4.1 Material and method

In this study, a work piece made of AISI 304 grade (04Cr18Ni11) steel was used. Its sizes were  $\varnothing 08 \times 80$  mm. Stainless steel 304 has excellent corrosion resistance in a wide variety of environments and when in contact with different corrosive media. Pitting and crevice corrosion can occur in environments containing chlorides. Stress corrosion cracking can occur at temperatures over  $60^\circ\text{C}$ . It has good resistance to oxidation in intermittent service up to  $870^\circ\text{C}$  and in continuous service to  $925^\circ\text{C}$ . However, continuous use at  $425-860^\circ\text{C}$  is not recommended if corrosion resistance in water is required. In this instance 304L is recommended due to its resistance to carbide precipitation.[5]

Table-3 shows the chemical composition of AISI 304 material and table-4 shows the physical properties of AISI 304 grade material[5]

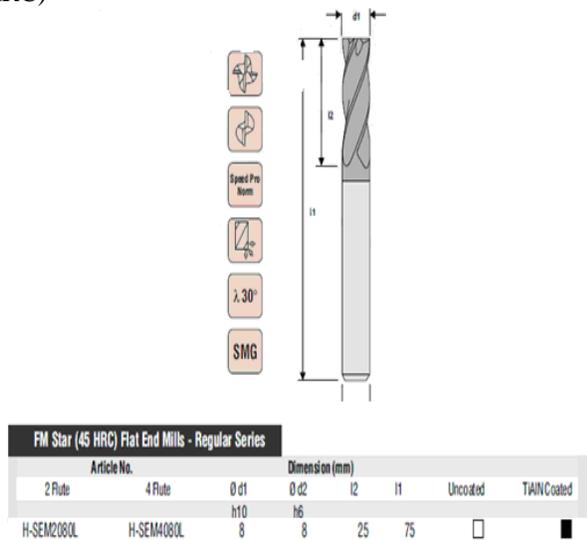
**Table-4 chemical composition of s.s304 Material**

%	Composition
C	0-0.07
Mn	0-2.0
Si	0-1
P	0-0.05
S	0-0.02
Cr	17.5-19.5
Ni	8-10.5
Fe	Balance

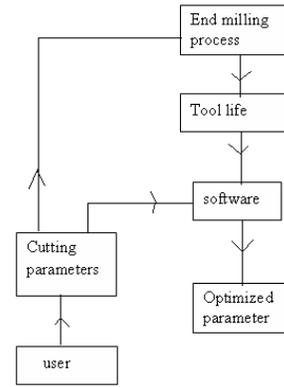
**Table-5 shows physical properties of s.s304**

Property	Value
Density	8.00 g/cm <sup>3</sup>
Melting point	1450°C
Modulus of elasticity	193Gpa
Electrical resistivity	0.072X10 <sup>-6</sup> Ω.m
Thermal conductivity	16.2W/m.K
Thermal expansion	17.2x 10 <sup>-6</sup> /K

experimental studies were carried out on a Cincinnati Vmc lathe. The experiments were conducted under dry cutting conditions. The tool holder used was model FM STAR (45HRC)



**Fig-4.1-solid carbide tool (from tool manufacturer's catalogue)**



**Figure 4.2 workpiece for experiment**

The level of cutting parameter ranges and the initial parameter values were chosen from the manufacturer's handbook recommended for the tested material. These cutting parameters are shown in Table 6. Fig-4 shows the experiment scheme for experiment

**Table-6 cutting parameters**

Symbol	Cutting parameter	Level-1(low) (-1)	Level-2(High) (+1)
V	Cutting speed(m/min)	50	75
F	Feed(mm/revolution)	0.15	0.20
D	Depth of cut(mm)	0.25	0.50

Now tool life can be calculated by using extended Taylor's equation for above shown practical range of cutting parameters and results being tabulated manually then whole data is being entered into the Minitab software dataset and optimization being carried out in Minitab software. According to the results being obtained by the Minitab, suitable suggestion should be made to improve the tool life.

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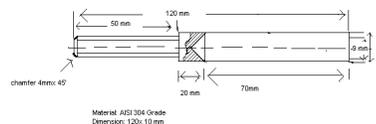


Figure 4.3-workpiece of casestudy

Fig shown above is part on which selected solid carbide tool performing machining operation. machining operations being done on above part at N=2500 rpm, depth of cut = 0.25 mm and feed = 450mm/min. tool life of solid carbide flat end mill is being calculated for this workpiece by using extended Taylor's tool life equation.

Now from Taylor's extended tool life equation we get,  
 $V \times T^n \times f^{n1} \times d^{n2} = k$

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 databook)

n1 = feed exponent constant – 0.5 (from tool manufacturer's databook)

n2 = depth of cut exponent constant – 0.20 (from tool manufacturer's databook)

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

Now calculations of tool life:

$$T = (k^{1/n}) / (V^{1/n} \times f^{n1/n} \times d^{n2/n})$$

Putting the values of n, n1, n2, k in above equation tool life equation becomes,

$$T = 47^{0.25} / (63^{0.25} \times 0.18^{0.5} \times 0.25^{0.2})$$

$$T = 47^{0.25} / (63^{0.25} \times 0.18^{0.5} \times 0.25^{0.2}) = 32 \text{ min}$$

Now we calculate the cycle time for part and machining cost/piece and tooling cost/piece for selected part.

Material need to remove is 1 mm, Length of cut in one pass 50 mm, Spindle speed is = 2500 rpm, Feed is = 0.18 mm/rev, Depth of cut is = 0.25 mm, V = 63 m/min N = 2500 rpm f = 0.18 mm/rev, d = 0.25 mm, Material need to remove = 1 mm, Length of cut in one pass = 50 mm

Total cut required = Material need to remove / Depth of cut = 1/0.25 = 4

So Total Travel length = Length of cut in one pass x Total cut required = 50 x 4 = 200

Now feed in mm/min = feed x rpm = 0.18 x 2500 = 450 mm/min

So cycle time = Total Travel length / feed in mm/min = 200/450 = 0.4444 min

Cost of tool is = 995 rs (from tool supplier's catalogue)

Vmc machine hour rate = 850 rs = total cost being used by vmc machine in one hour (from machine supplier's catalogue)

So no of parts being made by one tool = tool life / cycle time = 32/0.4444 = 72.

Now machining cost of one part is being given by = (cycle time x vmc hour rate) / 60 =  $0.4444 \times 850 / 60 = 6.30$  rs/part

60

Now Tooling cost of one part is being given by = cost of tool / no of no of piece made by one tool = 995/72 = 13.21 rs/part

So total cost being obtained for producing one part = 6.30 + 13.21 = 19.51 rs

Table 7 operational tool life and cost

V(m/min)	F (mm/rev)	d(mm)	Tool Life (min)	Cost of tool (rs)	Cycle time (min)	No of parts made/tool	Machining cost per piece	Tooling cost per piece	Total cost per piece
63	0.18	0.25	32	995	0.44	72	6.30	13.21	19.51

Same way for 8 experiments tool life can be calculated and tabulated as shown below and being analyzed in Minitab  
 Table 8 experimental tool life

Experiment number	Cutting speed (m/min)	Feed (mm/revolution)	Depth of cut (mm)	Tool Life (min)
1	50	0.15	0.25	105
2	50	0.20	0.25	60
3	50	0.15	0.50	60
4	50	0.20	0.50	34
5	75	0.15	0.25	21
6	75	0.20	0.25	17
7	75	0.15	0.50	12
8	75	0.20	0.50	07

4.2 Analysis in Minitab software : Above experimental data is being inserted into the Minitab software and analysis of factorial design is being done. The following graphs are being generated by software which gives us important results.

1/24/2012 1:09:56 PM

Welcome to Minitab, press F1 for help.

Results for: TOOL LIFE.MTW

Factorial Fit: tool life(mi versus cutting speed, feed(mm/rev), ...

Estimated Effects and Coefficients for tool life(mi) (coded units)

Term	Effect	Coef	SE Coef	T	P
Constant	39.50	39.50	2.500	15.80	0.040
cutting speed(m/min)	-53.50	-25.25	2.500	-10.10	0.063
feed(mm/revolution)	-21.00	-10.00	2.500	-4.00	0.139
depth of cut(mm)	-22.50	-11.25	2.500	-4.50	0.139
cutting speed(m/min)* feed(mm/revolution)	15.50	7.75	2.500	3.10	0.139
cutting speed(m/min)* depth of cut(mm)	13.00	6.50	2.500	2.60	0.234
feed(mm/revolution)*depth of cut(mm)	4.50	2.25	2.500	0.90	0.533

S = 7.07107 PRESS = 2200  
 R-Sq = 99.36% R-Sq(pred) = 99.09% R-Sq(adj) = 95.53%

From session window, we can say that p-values of cutting speed and depth of cut are 0.063 and 0.139 which are less than the value of alpha-0.15. So cutting speed and depth of cut are very significant parameters which affect the tool life also the p-value of feed is 0.156 which is nearly equal to the value of alpha-0.15. So it is also mildly significant while other interactions of three parameters cutting speed, feed and depth of cut are insignificant.



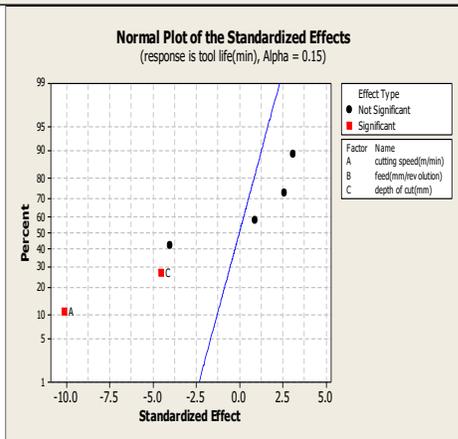
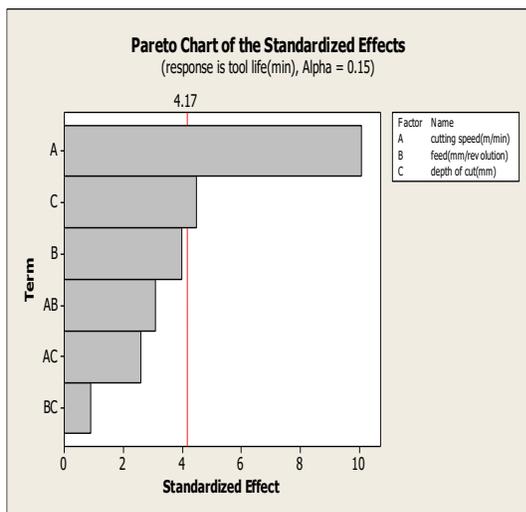


Figure 5- pareto chart

Figure 6-normal probability chart

From pareto chart,we can easily say that cutting speed are most effective parameter which affect tool life,while depth of cut and feed are less significant and effective than cutting speed parameter, while interactions of cutting speed and feed(AB),cutting speed and and depth of cut(AC), feed and depth of cut(BC) are not much effective parameter which affects the tool life worstly. From Normal plot for effects, we can easily conclude the result by observing the inclined line, here points near the line does nt give so much significance to the tool life,but points situated away from line give significance to the tool life. Here point A and C are such points which means cutting speed and depth of cut are two most dominant parameters which badly affect the toollife

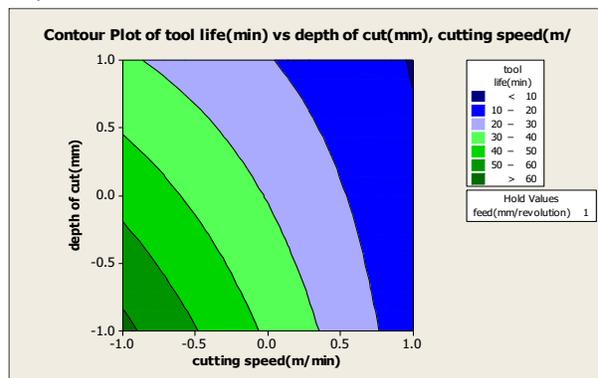
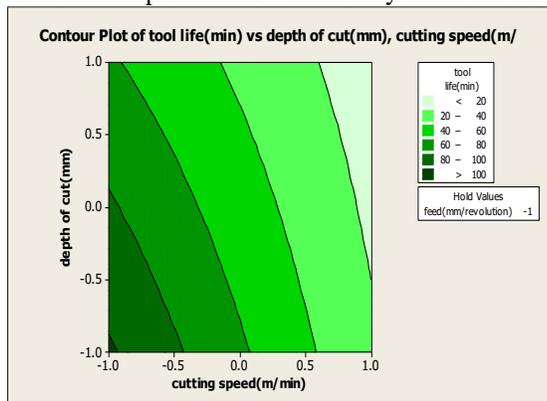


Figure 7 contour plots

From both of contour plots we can say that, For a low level of feed we are getting maximum tool life of 100 min at low level of cutting speed and depth of cut and for a high level of feed we are getting a maximum life of tool is 60 min at low cutting speed and depth of cut. so finally conclusion being given by the contour plot is to get maximum tool life cutting speed and depth of cut should be at low level while depending upon the cycle time and accuracy being achived, feed level should be choosen as low or high.

From Above graphas,we can say that maximum tool life for selected tool being obtained by low level cutting speed,depth of cut,and feed. But in practical we can not perform machining operations at low level parameters cause of increasing cycle time.we have to also

consider the cycle time for getting optimum tool life and then we can predict the suitable results.so as for all possible cases cycle time,maching cost and tooling cost is being calculate as shown in above methods and being tabulated as shown below:

From table shown below it can be seen easily that optimum tool life is 60 min at V= 50 m/min f = 0.15 mm/rev d= 0.50 mm Nw to get the final results comparisions is necessary with the initial conditions an which is being tabulated as shown below:

Table 9 Total cost and cycle time for all cases

V(m/min)	F (mm/r)	d(m)	Tool Life (min)	Cost of tool (rs)	Cycle time(mi n)	No of parts made/tool	Machini ng cost per piece	Toolin g cost per piece	Total cost per piece
50	0.15	0.25	105	995	0.67	157	9.50	6.34	15.84
50	0.20	0.25	60	995	0.50	120	7.08	8.29	15.37
50	0.15	0.50	60	995	0.33	182	4.67	5.46	10.13
50	0.20	0.50	34	995	0.25	136	3.54	7.32	10.86
75	0.15	0.25	21	995	0.44	48	6.23	20.7	26.93
75	0.20	0.25	17	995	0.33	52	4.68	19.1	23.81
75	0.15	0.50	12	995	0.22	55	3.12	18.1	21.22
75	0.20	0.50	07	995	0.16	44	2.27	22.6	24.88

Table 10 comparison of Results

V(m/min)	F (mm/rev)	d(m)	Tool Life (min)	Cost of tool (rs)	Cycle time (min)	No of parts made/tool	Machining cost per piece	Tooling cost per piece	Total cost per piece
63	0.18	0.25	32	995	0.44	72	6.30	13.21	19.51
50	0.15	0.50	60	995	0.33	182	4.67	5.46	10.13

### 5. CONCLUSION

As There are numbers of Parameters which Affect the Tool life of end milling Cutters of Cnc milling machine, According to present Work conditions And necessary Experiment set up being situated in an industry cutting parameters being chosen for experiment. Mainly Three cutting parameters named Cutting speed, Depth of cut, Feed may be selected and optimize these three parameters using DOE in Minitab software Package.

In this case 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 judgement. The confirmation experiments were conducted to verify optimal cutting parameters.

Experimental results show that in milling operations, Use of Low depth of cut, Low cutting speed and high feed rate are recommended to obtain better Tool life for the specific Range. The following additional experimental results also being achieved through the experiment and they are:  
Improvement in tool life =  $60-32/100 = 28\%$ .  
Increment in productivity =  $182-72 = 110$  part/tool.  
Total cost reduction =  $19.51-10.13 = 9.38$  rs/part which is being tabulated as below:

**Table 11 - Final Result**

Sr no	Category	Remarks
1	Improvement in tool life = 60-32/100	28 min/tool
2	Increment in productivity = 182-72	110 part/tool
3	Total cost reduction = 19.51-10.13	9.38 rs/part

### 6. SCOPE FOR FUTURE WORK

- 1) one can go for the full factorial  $3^k$  design for obtaining greater results than the  $2^k$  factorial design .
- 2) one can also use jmp v9.0 or SAS Software rather than using minitab for the Design of experiment. Coz minitab doesn't give the description of the results and graphs being developed by itself.
- 3) One can also use the shanin's advanced Design of experiment method for the optimization of the tool life of the cnc milling machine.
- 4) One can also use tool rake angle and axial depth of cut as an additional factors with addition to cutting speed, feed, depth of cut, and make full factorial

design of  $2^5$  or Full factorial three level design in form of  $3^5$  and can do optimization process. It takes too much time and cost also.

### REFERENCES

- [1] I.A. Choudhury, M.A. El-Baradie, " Tool-life prediction model by design of experiments for turning high strength steel (290 BHN)." Journal of Materials Processing Technology 77 (1998) 319–326
- [2] Keun Park Jong-Ho Ahn, "Design of experiment considering two-way interactions and its application to injection molding processes with numerical analysis." Journal of Materials Processing Technology 146 (2004) 221–227
- [3] Christel Pierlot, Lech Pawlowski, Muriel Bigan, Pierre Chagnon, "Design of experiments in thermal spraying: A review". Surface & Coatings Technology 202 (2008) 4483–4490.
- [4] Dong-Woo Kim, Myeong-Woo Cho, Tae-Il Seo, Eung-Sug Lee, "Application of Design of Experiment Method for Thrust Force Minimization in Step-feed Micro Drilling." Sensors 2008, 8, 211-221
- [5] Ilhan Asiltürk, Harun Akkus, " Determining the effect of cutting parameters on surface roughness in hard turning using the Taguchi method." Sciencedirect Measurement 44 (2011) 1697–1704
- [6] Yung-Kuang Yang, Ming-Tsan Chuang, Show-Shyan Lin, " Optimization of dry machining parameters for high-purity graphite in end milling process via design of experiments methods." Journal of Materials Processing Technology 209 (2009) 4395–4400.
- [7] J.A. Ghani, I.A. Choudhury, H.H. Hassan, "Application of Taguchi method in the optimization of end milling parameters." Journal of Materials Processing Technology 145 (2004) 84–92.

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