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TOOL LIFE OPTIMIZATION IN 2.5D MILLING BY COUPLING REGRESSION MODEL AND GENETIC ALGORITHM

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ABSTRACT

In the present study, the optimum combination of machining parameters has been analyzed for maximizing the tool life with the constraints of material removal rate (MRR) and surface finish. To optimize these parameters the correct relationship of process parameters with tool life has been found. Mathematical relations have been developed for predicting the objectives with different combinations of parameters under the specified constraints. As there is a variety of milling processes, cutting tool geometries, cutting tool material, work piece material and machine tool conditions, hence difficult to develop a single robust analytical relation for tool life. Therefore, the explicit relations have been developed with the help of regression analysis considering the responses of experiments using design of experiments. The number of experiments has been considered using of response surface methodology. In these uncertainties fractional factorial centrally composite design has been applied to obtain the combinations of machining parameters and conducting the experiments. In the present study, five-levels of different machining parameters such as speed, feed, and depth of cut (DOC) have been considered. A Genetic Algorithm has been proposed for the tool life with constraint of material removal rate (MRR) and surface finish. For a fixed value of MRR, approximately 41% improvement in optimum tool life has been reported when compared with the catalogue recommendations.

Key words: Optimization of Machining Parameters, 2.5D Milling, End Milling, Genetic Algorithm, DOE, RSM and CCD.

1. INTRODUCTION

Milling is the most important metal removing process for manufacturing the different mechanical components. In today's competitive environment, increasing the total profit rate and quality product can be achieved by optimizing the different machining parameters of milling. During machining of different components in milling, the object can translate in all three axes but perform the cutting operation only in two of the three axes at a time and called as 2.5 D milling. The estimation of tool life in 2.5 D milling with controllable process parameters with specified accuracy is very difficult and found to be very essential in automatic machining for replacing the wear off tool using automatic tool changer. The tool life mainly depends upon controllable process parameter such as cutting speed, feed, DOC and width of cut (WOC) with selection of tool material, cutting environment and machine tool condition also affects the tool life.

An optimum machining parameters can be achieved for improving the machining efficiency in term of cost and accuracy in optimization of machining parameters (OMP) Problem. The production cost comprises of the machining and tooling cost and hence maximizing the tool life becomes important for minimizing the tooling cost for high expensive tools. Generally, gradual flank wear or fracturing is responsible for tool failure. As fracturing is the matter of chance and hence gradual flank wear has been considered in the present work.

Significant work has been reported for optimizing the machining parameters for milling but is limited to predicting surface finish and cutting forces. As tool life and tool wear are also the significant factor that affects the production cost and quality of the manufactured product. Very Few researchers have optimized the machining parameters for predicting the tool life and tool wear. Alauddin et al, (1997) developed mathematical model for tool life using Response Surface Methodology for end milling of steel. Onwubolu et al, (2008) also developed tool wear model using enhanced GMDH learning network. Kadirgama et al, (2007) developed the model for predicting the surface finish using statistical methods. The results have also been verified experimentally. The model has been developed using response surface method (RSM) with 95% confidence level. Ginta et al, (2009) used response surface methodology to create an efficient analytical model for surface roughness in terms of cutting speed, axial depth of cut and feed per tooth. Yang and Chen (2001), conducted different experiments using Taguchi method and analyze S/N ratio for optimize the cost and time with speed, feed, depth of cut and tool diameter. Oktem et al, (2006) predicted the surface finish with variation of machining parameters with the help of regression model and Taguchi method. Mustafa, (2011) also developed surface finish and cutting force regression model using Taguchi method. Similarly, Gopalsamy et al,

(2009) optimized the machining parameters in context of tool wear by Taguchi method.

Researchers have also developed numerous optimization techniques for optimization of machining parameters such as Grey Taguchi, Simulated annealing, Particle swarm optimization, Genetic Algorithm etc. Among these techniques GA is easy to apply for variety of problems and provides better solutions under given constraints, thus making it more popular for engineering applications such as scheduling and machining parameters optimization problems in last two decades. Dhingra and Chandna, (2010a) minimized multi criteria SDST flow shop scheduling including weighted sum of total tardiness, total earliness and make span by developing special heuristic based on hybrid genetic algorithm in which initial feasible sequence has been obtained by special heuristic. Dhingra and Chandna, (2010b) extended the work to evaluate the performance of the proposed modified heuristic based genetic algorithm for Bi-criteria flow shop scheduling problems by implementing computational analysis. Ozcelik et al, (2005) developed surface roughness model using response surface methodology and Artificial Neural Network and optimize the machining parameters using GA. Gupta et al, (2011a) proposed a hybrid GA to optimize non productive movement for 2.5 D milling for different job size. Gupta et al, (2011b) proposed GA to optimize machining parameters for 2.5 D milling for minimum unit cost and unit time with the constraints of maximum power, surface finish and tool life.

In the present work, a mathematical model has been developed for predicting the tool life using response surface methodology (RSM). A five-level central composite design has been used and the responses have been observed at different combination of controllable process parameters. The regression model has been obtained for predicting the tool life by multiple regression statistical tools. Significant parameters responsible for maximum tool life has also been found using ANOVA. The optimum combination parameters for maximum tool life with the constraints of MRR and surface finish have also been found with Genetic Algorithm (GA).

2. PROBLEM FORMULATION

The tool life is primarily influenced by speed, feed and depth of cut with other factors such as tool diameter, width of cut, geometry of tool and condition of machine tool are kept constant. Therefore tool life can be represented as:

$$T = f(v, f, a)$$

Where 'T' is tool life in minutes, 'v' is cutting speed in m/min, 'f' is feed per tooth in mm/tooth and 'a' is axial depth of cut in mm.

2.1 Constraint Function

There are certain limitations regarding cutting and machine tool such as maximum spindle speed, feed rate, maximum power and required surface finish. To avoid built up edges and smooth running of cutting tool, manufacturers have been provided a definite range of speed, feed rate and depth of cut. Therefore, the parameters have to be optimized in the specified range for satisfying the constraint regarding the range of permissible spindle speed, range of feed, minimum material removal rate and required surface finish which is shown in table 1.

Table 1 Constraints

S. No.	Name of Constraint	Constraint
1	Depth of Cut (mm)	$0.40 < a < 1.10$
2	Machining Speed (m/min)	$55.10 < V < 84.10$
3	Feed per tooth (mm/tooth)	$0.18 < f < 0.32$
4	Minimum MRR (cm^3/min)	MRR > 10
5	Surface Finish (mm)	$S_f < 0.5$

3. METHODOLOGY

3.1 Design of Experiments

The mathematical models of responses are developed on the basis of certain experiments. The RSM requires developing an approximate model with the help of true response surfaces. The most popular response surface method (RSM) design is the central composite design (CCD). A CCD has three groups of design points fractional factorial design points, axial points (sometimes called "star" points) and center points. CCD is used for estimating the coefficients of a quadratic model. Number of experiments is substantially reduced with the help of RSM (CCD). The five-levels of each parameter have been considered. 15 combinations of experiments have been considered by fractional factorial CCD model. The range of theses process parameter has been shown in table 2.

Table 2 Range of Parameters

	Lower Level	Higher Level
DOC (mm)	0.5(-1)	1.0(+1)
Speed (m/min)	60.0(-1)	80.0(+1)
Feed (mm)	0.2(-1)	0.3(+1)

The response in RSM is tool life and the results of different combinations of process parameters are shown in table 3.

3.2 Genetic Algorithm

A Genetic Algorithm (GA) has been proposed for selecting an optimum combination of process parameters for maximum tool life under specified limit of material removal rate. The GA works on probabilistic selection for evolving a population of problem solutions. The random combination of process parameter has been selected as solution and converted into a binary string. An initial population has been created and subsequent generations have been generated according to a pre-specified breeding and mutation methods inspired by nature.

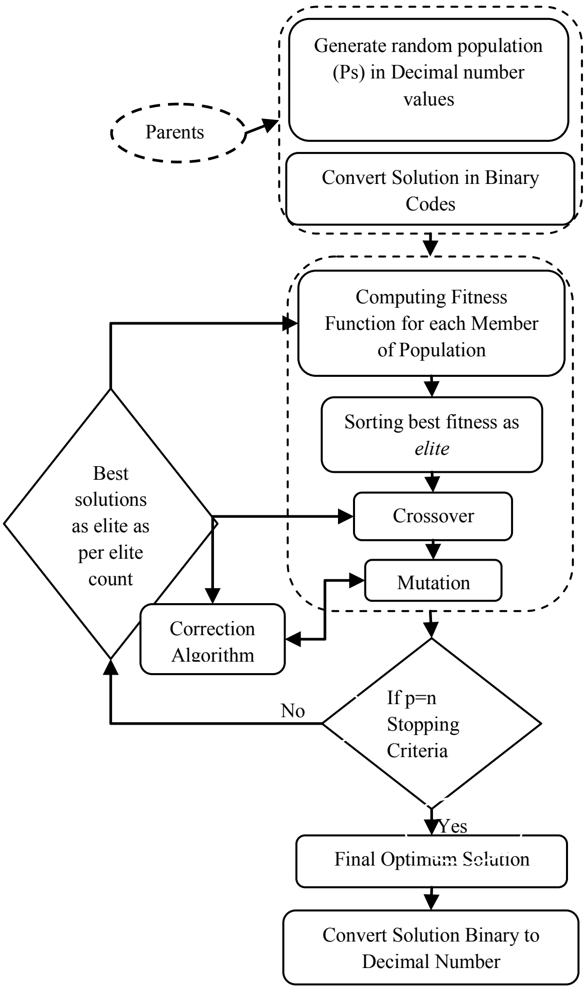


Fig. 1 Proposed Genetic Algorithm

GA generates initial population randomly according to constrained mentioned. Best solution is selected from the population as evaluated by fitness function. This best solution is termed as elite solution. The new population is again passed from the same process and the process is repeated to calculate best solution. The process remains continue till the stopping limit has not been achieved. The detailed procedure for GA is shown in fig 1.

Table 2 Parameters for Genetic Algorithm

Parameter	Value
Population Size	100
Crossover Function	Partially Matched Crossover (PMX)
Mutation Function	Reciprocal Exchange (RX)
Elite Count	2
Crossover Fraction	0.85
Mutation Fraction	0.15
Stopping Condition	100 Generations

The multiplicative Regression Model has been obtained for tool life using experimental data and coupled with GA for calculating the fitness value. After crossover and mutation, the population is checked for the constraints of surface finish and MRR and the solutions are corrected on the basis of pre decided constraint values as shown in fig. 1. The considered parameters of proposed GA are shown in table 2.

4. EXPERIMENTATION AND ANALYSIS

Experiments have been performed on a vertical milling machine (11 KW) with milling of a casting made of material GS-563 series steel with 0.24% C, 0.3%S and 0.3% P along with Mn, Si, Cr, Ni and Mo alloys with 210 BHN hardness. The 100 mm diameter end mill (CoroMill 390) with inserted carbide (uncoated) of grade TPAN - 1603-SMA (SANDVIK) has been considered. There are six cutting edges with 90^{o} entering angle and tool life has been observed in minutes between two successive tool wears. The tool wear can be identified by tool marks, chip formation and level of machine vibrations. The width of cut is taken as 50% of tool diameter. The responses i.e. Tool life and MRR have been shown in table 3 for different combination of process parameters.

Table 3 Responses at different combinations of process parameters

Exp No.	Block No.	DOC (mm)	Speed (m/min)	Feed (mm/tooth)	Coding			Tool Life (min)	MRR (cm^3/min)
					A	B	C		
1	Block 1	1.00	80.0	0.20	1.00	1.00	-1.00	25	15.3
2	Block 2	1.00	60.0	0.30	1.00	-1.00	1.00	82	17.2
3	Block 1	0.50	80.0	0.30	-1.00	1.00	1.00	42	11.5
4	Block 1	0.50	60.0	0.20	-1.00	-1.00	-1.00	155	5.7
5	Block 3	0.40	70.0	0.25	-1.41	0.00	0.00	94	6.6
6	Block 2	1.10	70.0	0.25	1.41	0.00	0.00	34	18.5
7	Block 1	0.75	55.9	0.25	0.00	-1.41	0.00	144	10.0
8	Block 1	0.75	84.1	0.25	0.00	1.41	0.00	24	15.1
9	Block 2	0.75	70.0	0.18	0.00	0.00	-1.41	56	9.0
10	Block 2	0.75	70.0	0.32	0.00	0.00	1.41	51	16.1
11	Block 3	0.75	70.0	0.25	0.00	0.00	0.00	56	12.5
12	Block 2	0.75	70.0	0.25	0.00	0.00	0.00	54	12.5
13	Block 3	0.75	70.0	0.25	0.00	0.00	0.00	50	12.5
14	Block 3	0.75	70.0	0.25	0.00	0.00	0.00	58	12.5
15	Block 3	0.75	70.0	0.25	0.00	0.00	0.00	54	12.5

The mathematical model for tool life has been obtained using central composite design in RSM for analyzing the effect of process parameters on tool life. The optimum machining parameters have been analyzed using Genetic Algorithm for maximum tool life. The multiplicative Regression Model has been coupled with Genetic Algorithm for optimum fitness values and compared with the catalogue recommendations.

4.1 Regression Model

On comparing F-values of different possible regression models in fit summery as shown in table 4, the quadratic regression model has been found significant for given response.

Table 4 Sequential Model Sum of Squares

Source	Sum of Squares	DF	Mean Square	F Value	Prob > F	
Mean	63896.07	1	63896.07			
Linear	18743.92	3	6247.97	28.98	< 0.0001	
2FI	302.57	3	100.86	0.39	0.7635	
Quadratic	2024.34	3	674.78	76.51	0.0001	Suggested
Cubic	8.89	1	8.89	1.01	0.3717	Aliased
Residual	35.20	4	8.80			
Total	85011	15	5667.40			

The quadratic Regression Model obtained for Tool Life with the help of experimental data is obtained as:

$$T= Q+c_1 \times a+ c_2\times v+c_3\times f + c_4\times a^2+ c_5\times v^2+ c_6\times f^2+ c_7\times a \times v+ c_8\times a\times f+ c_9\times v\times f \quad (1)$$

Table 5 Coefficient of regression models at different width of cut for Tool life

Q	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9
1536.38	-559.27	-30.16	-256.95	86.96	0.154	74.074	4.892	5.887	2.573

The quadratic equation is converted into linear or first order polynomial model and expression is converted to following form by taking natural logarithm for similar form of expression developed in past practices by the researchers.

$$\ln T = \ln c + \alpha . \ln v + \beta . \ln f + \gamma . \ln a \quad (2a)$$

$$T = C . v^{\alpha} f^{\beta} a^{\gamma} \quad (2b)$$

Where C, α, β and γ are the model parameters for estimating the tool life using experimental data.
Linear equation for these logarithmic values is:

$$\ln T = 22.023 - 4.358 . \ln v - 0.155 . \ln f - 0.905 . \ln a \quad (2c)$$

$$T = 3.67 \times 10^{9} . v^{-4.358} f^{-0.155} a^{-0.905} \quad (2)$$

To validate the above tool life models, the predicted values have been plotted with the experimental values for different combination of machining parameters as shown in Fig 2.

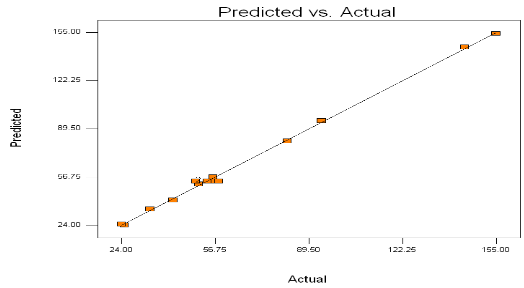


Fig 3 predicted vs. Actual value of tool life

The straight line shows the ideal trend and dots represent the observed values. It has been found that the predicted tool life is very close to the observed values and hence the results obtained by the regression model are very realistic.

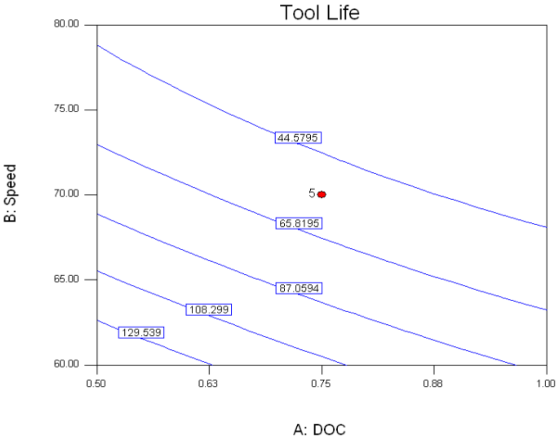
4.2 Significant Testing of Individual Parameters with Tool Life

To verify the adequacy of the proposed second order CCD model, ANOVA has been applied. The F-value of 265.48 implies that the quadratic model is significant. There is only a 0.01% chance that a "Model F-Value" could occur due to noise. Values of "Prob > F" less than 0.05 indicates that model terms are significant. For tool life, it has been found that DOC and speed are significant model terms. However, Feed per tooth has been found insignificant with the tool life. The value obtained for "Lack of Fit" has been found insignificant relative to the pure error. Non-significant lack of fit is good to navigate the response surface.

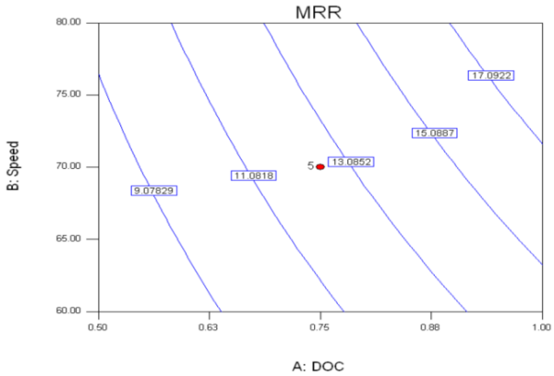
Table 6 Variation of Tool Life with respect to most significant factors

Source	Sum of Squares	DF	Mean Square	F Value	Prob > F
Model	21070.84	9	2341.20	265.48	< 0.0001
A(DOC)	1800.00	1	1800.00	204.11	< 0.0001
B(Speed)	7200.00	1	7200.00	816.46	< 0.0001
C(Feed)	12.50	1	12.50	1.41	0.2873
A2	227.88	1	227.88	25.84	0.0038
B2	1837.89	1	1837.89	208.41	< 0.0001
C2	0.26	1	0.26	0.03	0.8693
AB	299.25	1	299.25	33.93	0.0021
AC	0.01	1	0.01	0.00	0.9734
BC	3.31	1	3.31	0.37	0.5668
Residual	44.09	5	8.81		
Lack of Fit	8.89	1	8.89	1.01	0.3717
Pure Error	35.20	4	8.80		
Total	21114.93	14			

The equation 2 has been plotted in figure 4 as response surface contours at middle level of feed per tooth (0.25 mm/ tooth). The figure represents that as move away from the origin the tool life is decreases gradually. So, the tool life decreases with increase in speed and depth of cut. However, MRR increases as speed and feed increases. This shows that higher tool life can be achieve with the expense of MRR. Comparing the coefficient of equation 1, it can be concluded that tool life is more affected with speed than depth of cut.



(a)



(b)

Fig 4 Variation of Tool Life in min and MRR in cm^3/min at 0.25 mm/ tooth feed

4.3 Optimization

The GA has been run for 100 generations and the results obtained from GA have been compared with catalogue recommendations. It has been found that optimum value of tool life obtained by Genetic Algorithm is 41.04% more than the tool life obtained with Catalogue recommendations at same value of MRR i.e. 10 cm^3/min as shown in table 7.

Table 7 Comparison of GA and Catalogue Recommendations

	DOC (mm)	S (m/min)	F (mm/tooth)	Tool Life (min)	% Improvement
Recommendations using GA	0.59	60	0.30	132.30	41.04%
Catalogue Recommendations	0.50	70	0.3 0	78.00	---------

5. CONCLUSIONS

The RSM (CCD) model provides the realistic results within the specified range of 60 to 80 m/min of speed, 0.2 to 0.3 mm per tooth of feed and 0.5 to 1 mm of DOC for improving the utilization of milling operation for 210 BHN steel. Speed and DOC have been found significant with the tool life. With the increase of speed and DOC, the tool life decreases, where as MRR increases gradually. The optimization of machining parameters for tool life has been analyzed using GA with constraint of MRR and surface finish. The results obtained from GA have been compared with catalogue recommendations and has been found that the tool life is improved by 41.04% than Catalogue recommendations at same value of MRR i.e. 10 cm^3/min. It has been concluded that the regression model coupled with GA is effective for optimizing the machining parameters in milling operations.

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