

# Optimization Of Process Planning Parameters Using Genetic Algorithm For Cylindrical Components

<sup>1</sup>Mohammad Zahid Rayaz Khan<sup>\*</sup>, <sup>2</sup>Dr. A K Bajpai

1. M.Tech Student , Department Of Mechanical Engineering , Madan Mohan Malaviya Engineering college, Gorakhpur , U.P, INDIA

2. Professor, Department Of Mechanical Engineering , Madan Mohan Malaviya Engineering college, Gorakhpur , U.P, INDIA

**Abstract:** Optimization of process planning parameter is most important element in Computer Aided Process Planning (CAPP). Economy of machining operation play important role in competitiveness in the market. This paper presents Optimization Of Process Planning Parameters for machining of cylindrical component on lathe. The Process Planning Parameter are depth of cut, cutting speed , feed rate . The optimal Process Planning Parameter for continuous profile machining are determined with respect to minimum machining time. To obtain minimum machining time, optimal machining Process Planning Parameters are to be obtained. A mathematical model has been developed for relating machining time to Process Planning Parameter (depth of cut, cutting speed, feed rate). Techniques of Design of Experiment (Response Surface methodology, Central Composite Design) have been applied for developing the model. Hence an empirical relation is developed which is quadratic in nature. Obtained empirical relation is use in Genetic Algorithm tool box on MATLAB and in Design Expert software as objective function for optimization (modeling of problem and optimization), here machining time is considered as the objective function and constraints are limits of feed rate, depth of cut, cutting speed and results obtained from Genetic Algorithm optimization and Design Expert optimization are compared.

**Keywords:** Machining time, Design Expert Software, Response Surface Methodology, Genetic Algorithm, Optimtool.

## 1.Introduction

Optimization of process planning is one of the foremost targets of Manufacturing Systems. Numbers of research works are performed for generating optimum process plan. The optimum process plan may be on the basis of time or cost or on the basis of some weighted combination of these two. Tool selection, machine selection, process selection and tool path selection, process parameter selection are the most important areas for optimization in process planning. Process parameter optimization is the final stage of a CAPP system. Determination of optimum parameters is one of the vital stages of process planning since the economy of machining operation plays the most important role in increasing productivity and competitiveness. Genetic algorithm is one of the most efficient tools for optimization of such problems. This paper presents the application of GA in process planning parameters optimization.

Cnc lathe machine produce finished components consists of number of operation straight turning,

facing. Taper and circular machining. Finish profile from a circular bar is done in two stages rough machining and finish machining. Numbers of passes are required for rough machining and single pass required for finish machining so large machining time required for rough machining. So optimization of machining parameter is more important for rough machining (multipass). The machining parameter for multipass turning are depth of cut, cutting speed, feed. The optimal machining process parameter (depth of cut, cutting speed, feed)are selected with respect to minimum machining time. This paper present the optimal process planning parameter for machining of circular component is determined with respect to minimum production time. To obtained minimum machining time, optimal machining process parameter (depth of cut, cutting speed , feed)

have to be obtained. A Genetic Algorithm optimization in Matlab and Design Expert (modeling of problem and optimization) are applied to resolve the problem here machining time is considered as the objective function and constraints are limits of feed rate, depth of cut, cutting speed and results obtained from Genetic Algorithm optimization and Design Expert optimization are compared.

### 1.1 Turning process

Turning is a form of machining or a material removal process which is used to create rotational parts by cutting away unwanted material. The turning process requires a turning machine or lathe, work piece, fixture, and cutting tool. The cutter is typically a single-point cutting tool that is also secured in the machine. The cutting tool feeds into the rotating work piece and cuts away material in the form of small chips to create the desired shape.[1]

In turning, the speed and motion of the cutting tool is specified through several parameters. These parameters are selected for each operation based upon the workpiece material, tool material, tool size, and more. Turning parameters that can affect the processes are:

**a) Cutting speed** - The speed of the work piece surface relative to the edge of the cutting tool during a cut, measured in surface feet per minute (SFM).

**b) Spindle speed** - The rotational speed of the spindle and the work piece in revolutions per minute (RPM). The spindle speed is equal to the cutting speed divided by the circumference of the work piece where the cut is being made. In order to maintain a constant cutting speed, the spindle speed must vary based on the diameter of the cut. If the spindle speed is held constant, then the cutting speed will vary.

**c) Feed rate** - The speed of the cutting tool's movement relative to the work piece as the tool makes a cut. The feed rate is measured in mm per revolution.

**d) Depth of cut** - The depth of the tool along the radius of the work piece as it makes a cut, as in a turning or boring operation. A large depth of cut will require a low feed rate, or else it will result in a high load on the tool and reduce the tool life. Therefore, a

feature is often machined in several steps as the tool moves over at the depth of cut.

### 1.2. Ga And Natural Evolution Process

Genetic Algorithms (GAs) are search strategy which are able to search very large solution spaces efficiently by providing a concise computational cost, since they use probabilistic transaction rules instead of deterministic ones. They are easy to implement and are increasingly used to solve inherently intractable problems quickly. Although GAs are heuristic procedures themselves, they test a wealth of samplings from different regions of the search space for fitness simultaneously, and sort out and exploit regions of interest very quickly [2][3].

The idea behind genetic algorithm is based on the natural evolution phenomena. Rabbits are taken as example: at any given time there is a population of rabbits. Some of them are faster and smarter than the other rabbits. These faster, smarter rabbits are less likely to be eaten by foxes, and therefore more of them survive and make more rabbits. Of course, some of the slower, dumber rabbits will survive just because they are lucky. This surviving population of rabbits starts breeding. The breeding results in a good mixture of rabbits' genetic material: some slow rabbits breed with fast rabbits, some fast with fast, some smart rabbits with dumb rabbits, and so on. As a resulting baby rabbits will (on average) be faster and smarter than those in the original population because faster, smarter rabbits survived the foxes. (It is a good thing that the foxes are undergoing a similar process otherwise the rabbits might become too fast and smart for the foxes to catch any of them). In the similar fashion, in an artificial genetic algorithm, a crude population is refined through a series of generations while some genetic operators work on the population. Genetic algorithms are good at taking larger, potentially huge, search spaces and navigating them looking for optimal combinations of things and solutions which we might not find in a life time[4].

### 1.3 GA Procedure

Genetic algorithms (GAs) begin with a set of solutions represented by chromosomes, called population. Solutions from one population are taken and used to form a new population, which is motivated by the possibility that the new population will be better than the old one. Further, solutions are selected according to their fitness to form new solutions, that is, offspring's. The above process is repeated until some condition is satisfied. Algorithmically, the basic genetic algorithm (GAs) [5] is outlined as below.

**Step i** [Start] Generate random population of chromosomes, that is, suitable solutions for the problem.

**Step ii** [Fitness] Evaluate the fitness of each chromosome in the population.

**Step iii** [New population] Create a new population by repeating following steps until the new population is complete.

- a) [Selection] Select two parent chromosomes from a population according to their fitness. Better the fitness, the bigger chance to be selected to be the parent.
- b) [Crossover] With a crossover probability, cross over the parents to form new offspring, that is, children. If no crossover was performed, offspring is the exact copy of parents.
- c) [Mutation] With a mutation probability, mutate new offspring at each locus.
- d) [Accepting] Place new offspring in the new population.

**Step iv** [Replace] Use new generated population for a further run of the algorithm.

**Step v** [Test] If the end condition is satisfied, stop, and return the best solution in current population.

**Step vi** [Loop] Go to step 2.

## 2. Problem Statements

Cylindrical Component, which have surfaces symmetric to the part axis, are usually machined by lathes machine. Depending on the required surface finish, rough turning or other finishing operations are required. But initially rough turning operation creates the shape of the surface from the blank by removing

a materials and the major part of the machining time is usually required for rough turning operation. For this reason cutting parameters such as feed rate, depth of cut, cutting speed etc. are optimized only for rough turning operation.

Again, a machine shop may have several lathes with different power and rpm. So, it is also necessary to identify the machine and rpm that will require minimum time for machining a specific surface. Though total time includes machining time, setup time, and approach and over travel of the cutting tool, in most of the cases, machining time is responsible for the major part of total cost. Other cost is not as significant as machining time. So, in this optimization problem the cutting parameters are determined by minimizing the machining time.

## 3. Experimental Procedure

In the present work cutting time has been considered for evaluating the machining process parameter. Cutting time is correlated with the machine process parameter such as cutting speed, feed rate, depth of cut. Proper selection of above process parameter results optimum machining time. Experiments were conducted with range of above process parameter. For the productivity cutting time (ct) was the optimized characteristic. The cutting speed (V), feed (f), depth of cut (d) were considered as input parameters. The objective functions between the input parameters and responses were initially unknown, such relationships were designed using Response surface methodology (RSM). Thus, data were collected from turning experiments performed with work pieces of 12L14 free machining steel (0.09% C; 0.03% Si; 1.24% Mn; 0.046% P; 0.273% S; 0.15% Cr; 0.08% Ni; 0.26% Cu; 0.001% Al; 0.02% Mo; 0.28% Pb; 0.0079% N<sub>2</sub>), with dimensions of f40×295 mm. The machine tool used was a NARDINI CNC lathe, with 7.5 cv power and maximum rotation of 4,000 rpm. Table 1 presents the range defined for input parameters.[6]

Table 1  
Parameters and their levels

Machining parameters	Symbols	Units	Levels				
			-1.682	-1	0	1	1.682
Cutting speed	V	m/min	180	220	280	340	380
Feed rate	f	mm/re v	0.07	0.08	0.10	0.12	0.13
Depth of cut	d	mm	0.53	0.70	0.95	1.20	1.37

#### 4. Design of Experiment

The design factor, response variable as well as solution methodology which are employed in this work are explained below.

##### 4.1 Design Parameter

The design parameter considered in this work are Cutting speed, Feed rate, depth of cut. These parameter are selected because they had more influence on cutting time.

##### 4.2 Response Variables

Machining time is the response variable and it depend on feed rate, cutting speed, and depth of cut. [7]

$$T_m = \frac{L}{f \times N_w}$$

##### 4.3 Factorial design employed

So, the case of the second order model turned out to be made up of a total of 20 experiments, the previous 14 from the first order model plus the six center points. Based on the Central Composite Design (CCD), experiments were conducted to develop empirical models for cutting time in terms of the three input variables: Depth Of Cut, Cutting Speed, Feed. Each input variable (factor) was varied over five levels:  $\pm 1$ , 0 and  $\pm \alpha$ . Table 2 shows the relationship between the machining process

parameters and their corresponding selected variation levels, taking into account the entire range of machine process parameter.

#### 5. Response surface Methodology

Response surface Methodology (RSM) is used for designing the model. According to Montgomery [8], RSM is a collection of mathematical and statistical techniques that are useful for the modeling and analysis of problems in which a response of interest is influenced by several variables and the objective is to optimize this response. The second order polynomial developed for a response surface that relates a given response  $y$  with  $k$  input variables presents the following format described by Eq. (1):

$$y = \beta_0 + \sum_{i=1}^k \beta_i x_i + \sum_{i=1}^k \beta_{ij} x_i^2 + \sum_{i < j} \beta_{ij} x_i x_j \quad (1)$$

where  $y$  is the response of interest,  $x_i$  are the input parameters,  $\beta_0$ ,  $\beta_i$ ,  $\beta_{ii}$ ,  $\beta_{ij}$  are the coefficients to be estimated, and  $k$  is the number of input parameters considered

## 5.1 Experimental Matrix

On the basis of the experiment Experimental Matrix was developed which is shown in the table .2

Table 2  
Experimental matrix

Std	Run	Factor 1 A:cutting Velocity(v) m/min	Factor 2 B:Feed Rate(f) mm/rev	Factor 3 C:Depth of Cut (d) Mm	Response 1 Cutting Time(ct) min
1	1	220.00	0.08	0.70	2.11
13	2	340.00	0.08	0.70	1.36
6	3	220.00	0.12	0.70	1.4
8	4	340.00	0.12	0.70	0.91
3	5	220.00	0.08	1.20	2.11
11	6	340.00	0.08	1.20	1.36
20	7	220.00	0.12	1.20	1.4
7	8	340.00	0.12	1.20	0.91
14	9	180.00	0.10	0.95	2.06
2	10	380.00	0.10	0.95	0.98
19	11	280.00	0.07	0.95	1.89
4	12	280.00	0.13	0.95	1.02
18	13	280.00	0.10	0.53	1.32
15	14	280.00	0.10	1.37	1.32
17	15	280.00	0.10	0.95	1.32
10	16	280.00	0.10	0.95	1.32
9	17	280.00	0.10	0.95	1.32
5	18	180.00	0.10	0.95	2.06
16	19	220.00	0.12	0.70	1.4
12	20	280.00	0.10	0.53	1.32

## 6. Empirical Relationship

On the basis of above experimental table following Empirical Model is designed using Central Composite. Design of Design Expert for cutting time (ct).

$$\begin{aligned} \text{CUTTING TIME} = & 8.73375 - 0.021855*v - \\ & 58.24778*f + 0.052748*d + 1.99000E- \\ & 005*v^2 + 141.05014*f^2 - 0.028237*d^2 \\ & + 0.054846*v*f - 5.43316E- \\ & 005*v*d + 0.16299*f*d \end{aligned}$$

## 6.1 Model Adequacy Test for Cutting Time

A pre-ANOVA model statistics, the ANOVA results and the post-ANOVA model adequacy for the developed model of cutting time are shown in Table 3,4 and 5 respectively. Least SD and PRESS of quadratic model confirm that quadratic model is most suitable.

TABLE 3  
Model Summary Statistics For Cutting Time

Source	SD	R <sup>2</sup>	Adj. R <sup>2</sup>	Pred.R <sup>2</sup>	PRESS
Linear	0.091	0.9546	0.9461	0.9290	0.21
2FI	0.087	0.9667	0.9513	0.9349	0.19
*Quadratic	<u>0.010</u>	<u>0.9996</u>	<u>0.9993</u>	<u>0.9981</u>	<u>5.582E-003</u>
** Cubic	5.052E-003	0.9999	0.9998	-	-

\*=Suggested, \*\*=Aliased ,SD=Std. Dev.

Table 4  
ANOVA for Quadratic Model Of Cutting Time

Source	SS	D F	MS	F -Value	Prob > F
Model	2.92	9	0.32	3105.62	< 0.0001*
V	1.61	1	1.61	15409.28	< 0.0001*
f	1.11	1	1.11	10611.93	< 0.0001*
d	3.394E-008	1	3.394E-008	3.247E-004	0.9860
V <sup>2</sup>	0.068	1	0.068	648.07	< 0.0001*
f <sup>2</sup>	0.027	1	0.027	262.04	< 0.0001*
d <sup>2</sup>	4.227E-005	1	4.227E-005	0.40	0.5391
Vf	0.038	1	0.038	358.91	< 0.0001*
Vd	5.752E-006	1	5.752E-006	0.055	0.8193
fd	5.752E-006	1	5.752E-006	0.055	0.8193
Residual	1.045E-003	10	1.045E-004		
Lack of Fit	1.045E-003	5	2.090E-004		
Pure Error	0.000	5	0.000		
Cor Total	2.92	19			

#### \*significant terms

The Model F-value of 3105.62 implies the model is significant. There is only a 0.01% chance that a "Model F-value" this large could occur due to noise. Values of "Prob>" less than 0.500 indicate model terms are significant. Values greater than 0.1000 indicate the model terms are not significant. There is no Lack of fit.

Table 5  
Post ANOVA Model Adequacy for Cutting Time

R-Squared	0.9996
Adj R-Squared	0.9993
Pred R-Squared	0.9981
Adeq Precision	168.001

The "Pred R-Squared" of 0.9981 is in reasonable agreement with the "Adj R-Squared" of 0.9993. "Adeq precision" measures the signal to noise ratio.

A ratio greater than 4 is desirable. Here ratio of 168.001 indicates an adequate signal.

## 7. Optimization of objective function

The objective function from design expert software is to be optimized by two method Design Expert optimization and Genetic algorithm optimization

### 7.1. Genetic Algorithms optimization

Optimization tool of MATLAB is used for optimizing the problem. In optimization tool genetic algorithm solver is selected. Objective function obtained from design expert software use as a fitness function of GA Tool. Objective function is used for optimization as follows

#### Objective function

function Y= zahid(x)  
 $Y(1)=(8.73375)-(0.021855*x(1))-$   
 $(58.24778*x(2))+(.052748*x(3))+((1.99000e-$   
 $005)*(x(1)*x(1))+(141.05014*x(2)*x(2))-$   
 $(.028237*x(3)*x(3))+(.054846*x(1)*x(2))-$   
 $(5.43316e-005*x(1)*x(3))+(.16299*x(2)*x(3)));$   
 End

TABLE6  
Output From Genetic Algorithms

S.N	Cutting Velocity	Feed Rate	Depth of Cut	Cutting time (min)
1	371.304	.13	.536	.84258
2	374.914	.129	.531	.84371
3	374.913	.13	.53	.8423
4	348.692	.13	1.369	.8528
5	376.309	.13	.533	.84265
6	365.48	.13	.532	.84228
7	371.111	.13	.53	.8422
8	371.837	.13	1.37	.8420
9	372.212	.13	1.37	.8420
10	370.91	.13	.541	.8428
11	<b>370.708</b>	<b>.13</b>	<b>.53</b>	<b>.8419</b>

Table 7 GA output results

Cutting Velocity	Feed Rate	Depth of Cut	Cutting time (min)
<b>370.708</b>	<b>.13</b>	<b>.53</b>	<b>0.8419</b>



## 7.2.optimization on Design Expert

$$\text{Cutting Time} = 8.73375 - 0.021855*v - 58.24778*f + 0.052748*d + 1.99000E-005*v^2 + 141.05014*f^2 - .028237*d^2 + .054846*v*f - 5.43316E-005*v*d + .16299*f*d$$

After designing the above equation on design Expert. This equation is optimized we get the following result.

Table 8: Design Expert output results

Cutting Velocity	Feed Rate	Depth of Cut	Cutting time (min)
318.60	0.13	1.25	0.905482

## 8. Result and Discussion

The results obtained from GA and Design Expert are discussed below. Table9 shows the optimal cutting parameters such as speed, feed and depth of cut obtained from GA and Design Expert for the minimum cutting time. Minimum cutting time obtained from GA and Design Expert are 0.8419 and 0.905482 respectively. We had seen that result obtained from above two methodology (GA and Design Expert ) GA result is minimum cutting time 0.8419 and corresponding to this optimum process parameter were obtained.

Table9

Comparison of result obtained from GA And Design Expert

Process Planning Parameter	Output of Genetic Algorithm	Output of Design Expert
Cutting Velocity	370.708	318.60
Feed Rate	.13	0.13
Depth of Cut	.53	1.25
Cutting time (min)	<b>0.8419</b>	0.905482

## 9. Conclusion

Optimization of process parameters is one of the important tasks of the CAPP system. The impact of AI techniques in CAPP has been proved by many research projects. GA is promoted as one of the promising AI techniques for solving nonlinear and combinatorial problems involved in process planning. Based upon the result obtained by GA methodology the final optimize value of Cutting time is found to be 0.8419 min. Corresponding values of process parameters are shown in their respective rows. Some of the readings are found to be out of range so they are neglected. Cutting Velocity and Depth of Cut are the most influencing parameters. With the GA-base optimization system developed in this work, it would be possible to increase machining efficiency by using optimal cutting parameters. A model of the process planning parameter has been formulated, GA and Design Expert had been employed to find the optimal machining parameters for the circular component. Genetic Algorithm (GA) produces better results. Using this technique machining time can be further minimized.

## References

1. Krishankant, Taneja Jatin, Bector Mohit, Kumar Rajesh ,” Application of Taguchi Method for Optimizing Turning Process by the effects of Machining Parameters”, International Journal of Engineering and Advanced Technology , ISSN: 2249 – 8958, pp 263-264.
2. Dereli, T. and Filiz, H.I., “ Optimization of Process Planning functions by Genetic algorithm”, Computers and Industrial Engineering, Vol. 36, pp281-308, 1999
3. Khan Mohammad Zahid Rayaz, Bajpai A.K, Genetic Algorithm And Its Application In Mechanical Engineering, International Journal of Engineering Research & Technology, Vol. 2 Issue 5, May – 2013, ISSN: 2278-0181, pp 677-683.
4. Rajasekaram. S and VijayalakshmiPai A.G, “ Neural Network, fuzzylogic, and Genetic algorithms, synthesis and application “ISSN: 978-81-203-2186-1,pp 27-28.
5. Chu-Kuei Tu and Tseng-Hsien Lin. “Applying Genetic Algorithms On Fuzzy Logic System For Underwater Acoustic Signal Recognition, Proceedings of the 2000 International Symposium on Underwater Technology, pp. 405-410.
6. Anonymous, “Global Criterion Method Based on Principal Components to the Optimization of Manufacturing Processes with Multiple Responses” , Journal of Mechanical Engineering, pp 348-350
7. Gosh .A, Mallik A K, Manufacturing science, east –west press , second edition ,pp 221-225
8. Montgomery, D.C. “Design and Analysis of Experiments”. 5th edition , John Wiley, India ,pp 427-435.