# Optimization of Cutting Parameters in Turning of EN 8 Steel Using SWARM Intelligence

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## ABSTRACT

Economics is the over rider factor in all manufacturing processes. The economic optimization of the manufacturing set ups starts with the functional design that must satisfy the need of the customer and the design for production. In present work focus in on selection of optimized parameters for turning of EN 8 material in order to have enhancement in surface finish and increased material removal rate. This work deals with CNC turning of EN 8 steel using Cemented Carbide inserts (VCMT) tool for varying cutting speed, Feed and Depth of cut. The experiment is designed for Second order linear model using Response Surface Method (CCD). Mathematical formulation is carried out by correlating the values of responses Surface Roughness, Machining time and material removal rate with the contributions and correlations of cutting speed, feed and depth to develop the Empirical models for the responses. The Optimization of cutting parameters is carried out using Ant Colony Optimization.

***Keywords :*** *Response Surface Methodology (RSM), SWARM Intelligence, Ant Colony Optimization (ACO), Central Composite Design (CCD), Machining.*

## 1. Introduction

Turning is a machining process wherein material is removed from a rotating work piece by means of feeding a harder cutting tool parallel to the axis of rotation for a given depth of cut. The machining parameters in turning are speed, feed and depth of cut. In any machining operation, the main objective in general will be to minimize the cost of production or to maximize the production rate of the product. If the product is in continuous production the aim will be to maximize the overall profit over a given time period.

The work material used for the present study is mild steel EN8 of composition Carbon (0.36- 0.44) %, Silicon (0.1-0.4) %, Maganese (0.60- 1.00) %, Phosphorus (0.05) % Sulphur (0.05) %. Its hardness is (201-255) Brinell. This mild steel EN8 is suitable for shafts, Medium torque shafts, typical applications include shafts, studs, bolts, connecting rods, screws, rollers, Hydraulic rams (chromed), key steel and machinery parts. It is mostly used in Automobile parts and machine building industry.

Amiolemhen et.al [1] proposesd an optimization technique based on genetic algorithms for the determination of the cutting parameters in multi-pass machining operations by simultaneously considering multi-pass roughing and single-pass finishing operations. The optimum machining parameters are determined by minimizing the unit production cost of converting a cylindrical bar stock into a continuous finished profile involving seven machining operations; with each operation subject to many practical constraints.

The cutting model developed for each machining operation is a non-linear, constrained problem. The mathematical models used for the work presented in this paper embrace a comprehensive set of practical constraints. The optimum result obtained in fifty generations will not take much time.

In Bouzid [2] a method is described for calculating the optimum cutting conditions, in turning for objective criteria such as maximum production rate. The method uses empirical models for tool life, roughness and cutting forces. Coefficients of these models were determined based on turning experiments in high speed machining. Four types of commercially available inserts have been used to turn an AISI 4340 steel. Three chemical vapor depositions (CVD) coated inserts and one ceramic tool has been studied. In this work, the machine power and the maximum spindle speed were considered as the process constraints. The method explains the feed in relation to the roughness which depends on the cutting speed. Then, the cutting speed which gives the minimum production time was calculated. This value is then compared to the allowed values imposed by the constraints. At least, the optimal value of feed was calculated. The obtained results indicate that the described method is capable of selecting the appropriate conditions.

Cus et. al [3] represented a new hybrid multi-objective optimization technique, based on ant colony optimization algorithm (ACO), to optimize the machining parameters in turning processes. Three conflicting objectives, production cost, operation time and cutting quality are simultaneously optimized. An objective function based on maximum profit in operation has been used. The proposed approach uses adaptive neuro-fuzzy inference system (ANFIS) system to represent the manufacturer objective function and an ant colony optimization algorithm (ACO) to obtain the optimal objective value.

ACO algorithm is completely generalized and problem independent so it can be easily modified to optimize this turning operation under various economic criteria. It can obtain a near-optimal solution in an extremely large solution space within a reasonable computation time. The developed hybrid system can be also extended to other machining problems such as milling operations. An example has been presented to give a clear picture from the application of the system and its efficiency. The results are compared and analyzed using methods of other researchers and handbook recommendations. The results indicate that the proposed ant colony paradigm is effective as compared to other techniques carried out by other researchers.

Vijaykumar et.al [4] proposed a new optimization technique based on the ant colony algorithm for solving multi-pass turning optimization problems. In this paper the objective of cutting model is to determine the optimal machining parameters including cutting speed, feed, depth of cut and number of rough cuts in order to minimize the unit production cost. Researchers considered six different constraints.

In this paper, a cutting optimization model for multi pass turning operations has been presented and an ACO based metaheuristic has been applied to solve the machining optimization problem. The results of the proposed approach are compared with results of simulated annealing and genetic algorithm. The ACO algorithm can obtain a near-optimal solution in an extremely large solution space within a reasonable computation time. The effectiveness of the ACO algorithm has been proved through an example. The ACO algorithm developed in this project has some encouraging features:

1. The proposed ACO-based metaheuristic generates a superior solution than the simulated annealing and genetic algorithm based approaches;
2. The ACO algorithm is completely generalized and problem independent so that it can be easily modified to optimize this turning operation under various economic criteria, and numerous practical constraints; and
3. The algorithm can also be extended to other machining problems, such as milling operations and threading operations.

Pansare and Mukund [5] obtained optimum turning parameters for minimum surface roughness value by using Ant Colony Optimization (ACO) algorithm in multi-pass turning operation. The goal of experimental work was to investigate the effects of cutting parameters on surface roughness, and to establish a correlation between them for this, cutting speed, feed rate and depth of cut were chosen as process parameters feed (0.1, 0.15, 0.2 mm/rev) cutting speed (150,200,250 m/min) and depth of cut (0.5, 1, 1.5 mm). The cutting process has roughing and finishing stage. Turning operation is carried on the cutting length of 70 mm and the diameter is reduced from 50 to 44 mm in subsequent number of passes. L9 orthogonal array design of experiment is used to conduct the experiment. The work material was Oil Hardened Non shrinkable Steel (OHNS) steel in the from round of bars of 50mm diameter and 100 mm length The cutting tool used was CNMG 120408. The relationship between the parameters and the performance measures were determined using multiple linear regression, this mathematical model is used to determine optimal parameters. The experimental results show that the proposed technique is both effective and efficient. The relationship between the factors and the performance measure was modeled by multiple linear regression. Result obtained by ACO algorithm for minimization of surface roughness value shows that the minimum Ra values is obtained at minimum cutting speed with minimum feed and high depth of cut.

Kee [6] outlined constrained optimization analysis and strategies for selecting the optimum cutting conditions in multipass rough turning operations based on the minimum time criterion.

Aslan et. al. [7] mentioned that prime need of machining is use of harder tool. In this paper researcher used $Al_2O_3$ based ceramics tools due to its high hardness and wear resistant property. But their high degree of brittleness usually leads to inconsistent result and sudden catastrophic failure. This necessitates a process optimization when machining with Al2O3 based ceramic cutting tools.

In this research, researcher applied Taguchi technique. Combined effect of three cutting parameters namely cutting speed, feed and depth of cut on two performance measure like flank wear and surface roughness.

Researchers reached the conclusion that the cutting speed is the only statistically significant factor influencing the tool wear, it explains 30 % of the total variation. Although not statistically significant, the axial depth of cut has a physical influence explaining 18% of the total variation. It was found that as the cutting speed increases, the tool wear decreases. Only two interactions, cutting speed – feed rate and feed-axial depth of cut have statistically significant influence on surface roughness.

Balazinski et.al [8] proposed an idea and an implementation of a fuzzy decision support system (FDSS) based on the compositional rule of inference. Taking into account the fact that metal cutting processes are stochastic, nonlinear and ill-defined, the application of FDSS to the choice and modification of cutting parameters has been described. The results obtained in this paper show that the application of the fuzzy set theory to machining processes seems to be quite appropriate and may lead to valuable results. These results are mainly obtained using data compression. A qualitative analysis of the obtained results proves the accordance and compatibility with the results recommended in Machining Data Handbook.

Franci et.al [9] highlighted a neural network-based approach to complex optimization of cutting parameters. It describes the multi-objective technique of optimization of cutting conditions by means of the neural networks taking into consideration the technological, economic and organizational limitations. To reach higher precision of the predicted results, a neural optimization algorithm is developed and presented to ensure simple, fast and efficient optimization of all important turning parameters.

## 2. Research Approach

Firstly a broad literature review is taken for identifying the current and historical work done by other researchers. Study of different optimization technique is done, amongst which ant colony optimization algorithm is selected for finding the optimal parameters in multi pass turning. For conducting the experiment design of experiment is carried out using Response Surface Methodology (RSM). After collection of experimental data empirical mathematical model is developed by using multiple regression to find out intermediate values of response variable. A program is prepared using MATLAB to determine the optimal parameter using ACO. After obtaining the optimal parameter a confirmation run is taken for the comparison of actual and predicted values.

The turning operation is carried by using CNC turning center LMW machine tool division with 4500 RPM as its speed range. An armature shaft of electric motor of 32 mm diameter and 70mm length of designation EN-8 is selected for the experimentation which has Chemical Comosition as given in Table 1.

**Table 1. Chemical Comosition of EN-8**

| Carbon | Silicon | Manganese | Phosphorus | Sulphure |
|---|---|---|---|---|
| 0.36 | 0.1 | 0.6 | 0.05 | 0.005 |

**Table 2. Process Parameters**

| Process Parameter | Level-1 | Level-2 | Level-3 | Level-4 | Level-5 |
|---|---|---|---|---|---|
| Feed Rate ( mm/rev) | 0.07 | 0.1 | 0.2 | 0.3 | 0.37 |
| Cutting Speed (m/min) | 190 | 200 | 210 | 220 | 230 |
| Depth of Cut (mm) | 0.25 | 0.5 | 1.0 | 1.5 | 1.85 |

Five levels were specified for each process parameter. The parameter levels were selected according to the manufacturer's catalogue as given in Table 2.

## 3. Analysis of collected Data

The proposed plan of the experiment was developed to obtain values of surface roughness according to the predefined levels. This data was used to develop mathematical model which could predict the surface roughness for intermittent (cutting speed. Feed and depth of cut) values. Surface roughness is measured by using roughness tester, surftest SJ 210 of make MITUTOYA. Sampling length for measurement is 0.8 mm, cut-off length 0.8x5 = 4 mm and probe velocity 0.5 mm/sec. The method followed for the measurement is as per ISO 1997.

**3.1 Mathematical Modelling:** The correlation between the input factors i.e. cutting speed, feed, depth of cut and responses were modelled by multiple linear regression. The mathematical model incorporates interaction of cutting parameters such as cutting speed and depth of cut, cutting speed and feed rate and depth of cut. The mathematical model with regression analysis is as follows:

$$Ra = 10.7 - 0.0407\,Speed - 35.6\,feed$$
$$-1.14doc + 0.1530VF + 0.0136Vdoc + 2.00Fdoc$$

Coefficient of determinant i.e. $R^2 = 95.27\%$

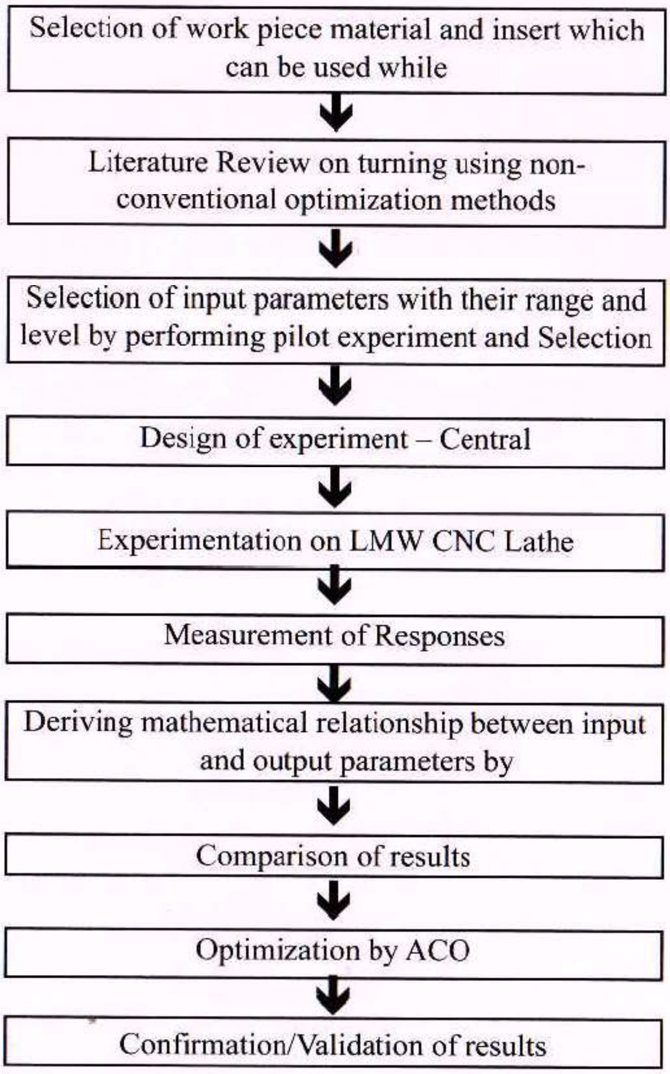


**Fig.1. Flow Chart Represents Scope of Work**

The value of coefficient of determinant $R^2$ is high enough to obtain reliable estimates. The Mathematical model used to obtain the minimum surface roughness values as given in Table 3.:

**3.2. Optimization** : The objective function is to minimize surface roughness value.

Min Ra = F (v,d,f)

Constraints,

$$V_{max} > V > V_{min}$$
$$f_{max} > f > f_{min}$$
$$d_{max} > d > d_{min}$$

### 3.3. Ant Colony Optimization

The ant colony optimization algorithm (ACO) is a probabilistic technique for solving computational problems which can be reduced to finding good paths through graphs and other data. This algorithm is a member of ant colony

**Table 3. Surfess roughness result**

| Sr. No. | V (m/min) | F (mm/rev) | D (mm) | Ra (µm) |
|---|---|---|---|---|
| 1 | 220 | 0.1 | 1.5 | 4.62 |
| 2 | 190 | 0.2 | 1 | 3.672 |
| 3 | 210 | 0.2 | 1 | 3.667 |
| 4 | 200 | 0.3 | 0.5 | 2.145 |
| 5 | 210 | 0.3 | 1 | 3.758 |
| 6 | 200 | 0.1 | 1.5 | 4.945 |
| 7 | 210 | 0.2 | 1 | 3.667 |
| 8 | 220 | 0.3 | 1.5 | 4.968 |
| 9 | 200 | 0.07 | 0.5 | 2.609 |
| 10 | 210 | 0.2 | 1 | 3.667 |
| 11 | 220 | 0.1 | 0.5 | 2.812 |
| 12 | 210 | 0.2 | 1 | 3.667 |
| 13 | 210 | 0.2 | 0.25 | 1.672 |
| 14 | 210 | 0.37 | 1 | 3.577 |
| 15 | 200 | 0.3 | 1.5 | 4.081 |
| 16 | 220 | 0.3 | 0.5 | 2.16 |
| 17 | 230 | 0.2 | 1 | 3.663 |
| 18 | 210 | 0.2 | 1 | 3.667 |
| 19 | 210 | 0.2 | 1 | 3.667 |
| 20 | 210 | 0.2 | 1.85 | 4.962 |

algorithms family, in swarm intelligence methods, and it constitutes some metaheuristic optimizations. Initially it was proposed by Dorigo (1996). Near-blind ants are establishing the shortest route from their nest to the food source and back. These ants secrete a substance, called pheromone, and use its trails as medium of communicating information. The probability of the trail being followed by other ants is enhanced by further deposition of pheromone by other ants moving on that same path. This cooperative behavior of ants inspired the new computational paradigm for optimizing real life systems, which are suited for solving large scale problems with a lot of different data, mentioned by Socha and Dorigo (2008). There are different variants of ant colony optimization algorithms. These algorithms carry out three operations:

- ant-based solution construction,
- pheromone update,
- daemon actions.

Solutions are chosen probabilistically based on pheromone level. Thus, this operation forces the algorithm to search in the area of better solutions. The aim of pheromone update is to increase the pheromone values associated with good or promising solutions and decrease those that are associated with bad ones. Usually this is achieved by increasing the pheromone levels associated with chosen good solutions and by decreasing the pheromone values through pheromone evaporation, which basically reduces the pheromone level [3,4,6].

### 3.4. Method of Global Search:

**Step 1 : Reproduction:** This step is used to repair the inferior solutions. Reproduction consists of three part named; crossover, mutation and trail diffusion. Crossover and mutation is applied on 75 % of inferior solutions and remaining solutions will be repaired by trail diffusion.

**Step 2: Crossover:** This is the starting stage of reproduction. This is used to repair the solutions from inferior region. Hence it is applied on the solutions from 13 to 18 only. Procedure of crossover is completed in three sections. In first section two parent chromes are selected randomly from superior region. To pick these chrome two random numbers between 1 to 12 are generated and corresponding chrome are selected and named as parent 1 and parent 2. Two parents are shown in fig. 17

**Step 3: Mutation:** Mutation is the process whereby randomly adding or subtracting a value is done to each variable of newly created solutions in the inferior region with mutation probability. Probability of mutation is taken equal to 0.45. A random number in the range of 0 to 1 is selected as a level of mutation. Condition for application of mutation is decided as "level of mutation is greater than the probability of mutation". Mutation in ACO is done by the swapping of the two sets of single chrome to get new chrome. Fig 2 shows the chrome obtained by mutation.

**Step 4: Trail Diffusion:** This is last step to be performed for completion of reproduction. Trail diffusion is applied to the inferior solutions that were not considered during the crossover and mutation. Here two parents are selected at random from the present superior solutions region. The child can have:

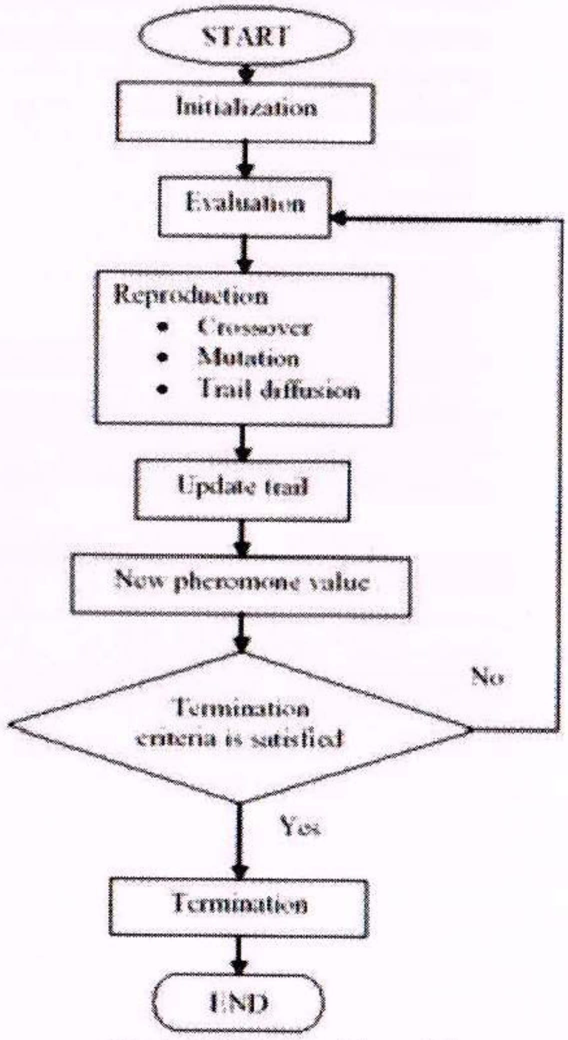


**Fig.2. ACO algorithms [4]**

i. The value of the corresponding variables of the first parent or
ii. The value of the corresponding variables of the second parent or
iii. A combination arrived from the weighted average of the parent1 and parent 2

**3.5. Method of Local Search**: In this section the improvement is made in the solutions from superior region.

$$x(child) = \alpha \times x(parent1) + (1-\alpha) \times x(parent\ 2)$$

Present code of the solutions in superior region are converted into decimal number. Then for update trail value of limiting step is determined.

### 4. Results of optimization

A MATLAB code is generated and executed for 500 iterations to (Fig.2) obtain the optimum cutting parameter for minimum surface roughness (Table 4 and Fig.3). In similar fashion the program prepared for getting maximization of material removal rate (Table5).

**Table 4 : Optimum cutting parameter for minimum Ra**

| Optimum Parameters | | | |
|---|---|---|---|
| Cutting Speed (m/min) | Feed (mm/rev) | Depth of Cut (mm) | Roughness Value (µm) |
| 190 | 0.37 | 0.25 | 1.096 |

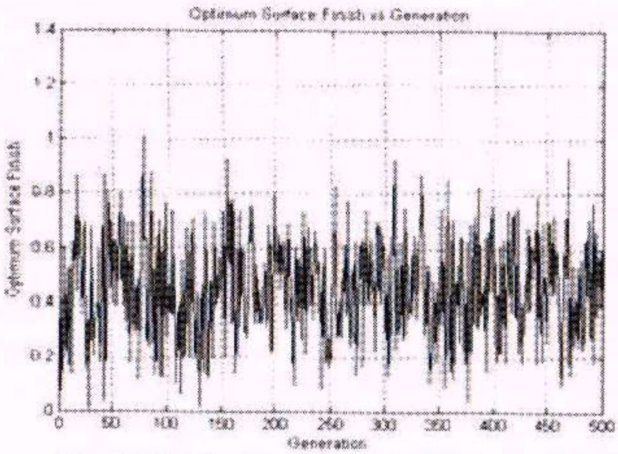


**Fig. 3: Optimum Surface Roughness Vs Iterations**

**Table 5: Optimum cutting parameter for maximum MRR**

| Optimum parameters | | | |
|---|---|---|---|
| Cutting Speed (m/min) | Feed (mm/rev) (mm) | Depth of Cut (mm) | MRP Value ($mm^3$/min) |
| 214-1935 | 0.3 | 1.467 | 89616 |

## 5. Conclusion:

The findings of an experimental investigation into the effect of feed, cutting speed, and depth of cut on the surface roughness when turning EN8 Material. ACO is best modeling as it learns the best fit of linear & non Linear models. It shows better performance in enhancement of surface finish in ACO. The minimum value surface roughness (Ra) obtained from ACO is 1.09. It is easily predictable that ACO algorithm search to find optimal cutting parameters.

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