# Parametric Analysis and Optimization of Cutting Parameters for Turning Operations based on Taguchi Method

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**ABSTRACT:** *Surface quality is one of the specified customer requirements for machined parts. There are many parameters that have an effect on surface roughness, but those are difficult to quantify adequately. In finish turning operation many parameters such as cutting speed, feed rate, and depth of cut are known to have a large impact on surface quality. In order to enable manufacturers to maximize their gains from utilizing hard turning, an accurate model of the process must be constructed. Several statistical modeling techniques have been used to generate models including regression and Taguchi methods. In this study, an attempt has been made to generate a surface roughness prediction model and optimize the process parameters Genetic algorithms (GA). Future directions and implications for manufacturers in regard to generation of an robust and efficient machining process model is discussed.*

***Keyword:*** *Machining operation; Surface roughness; Mathematical model; Taguchi method; Genetic Algorithm.*

## 1. 0 INTRODUCTION

Surface roughness has received serious attention for many years. It has formulated an important design feature in many situations such as parts subject to fatigue loads, precision fits, fastener holes, and aesthetic requirements. In addition to tolerances, surface roughness imposes one of the most critical constraints for the selection of machines and cutting parameters in process planning. A considerable number of studies have investigated the general effects of the speed, feed, and depth of cut on the surface roughness.

Process modelling and optimization are the two important issues in manufacturing products. The manufacturing processes are characterized by a multiplicity of dynamically interacting process variables [1, 2]. A greater attention is given to accuracy and surface roughness of product by the industry these days. Surface finish has been one of the most important considerations in determining the machinability of materials. Surface roughness and dimensional accuracy are the important factors required to predict machining performances of any machining operations [3]. The predictive modelling of machining operations requires detailed prediction of the boundary conditions for stable machining [4, 5]. The number of surface roughness prediction models available in literature is very limited [3, 5]. Most surface roughness prediction models are empirical and are generally based on experiments in the laboratory. In addition it is very difficult in practice, to keep all factors under control as required to obtain reproducible results [5]. Generally these models have a complex relationship between surface roughness and operational parameters, work materials and chip-breaker types. Optimizations of machining parameters are not only increases the utility for machining economics, but also the product quality increases to a great extent [1]. In this context, an effort has been made to estimate the surface roughness using experimental data. It has also been made an attempted to optimize the surface roughness prediction model using a Genetic Algorithmic approach.

Since turning is the primary operation in most of the production processes in the industry, surface finish of turned components has greater influence on the quality of the product. Surface finish in turning has been found to be influenced in varying amounts by a number of factors such as feed rate, work material characteristics, work hardness, unstable built-up edge, cutting speed, depth of cut, cutting time, tool nose radius and tool cutting edge angles, stability of machine tool and workpiece setup, chatter, and use of cutting fluids.

Taraman [6] used Response Surface Methodology (RSM) for predicting surface roughness of different materials. A family of mathematical models for tool life, surface roughness and cutting forces were developed in terms of cutting speed, feed, and depth of cut. Hasegawa et al., [7] conducted $3^4$ factorial designs to conduct experiments for the surface roughness prediction model. They found that the surface rough increased with an increase in cutting speed.

Sundaram and Lambert [8, 9] considered six variables i.e speed, feed, and depth of cut, time of cut, nose radius and type of tool to monitor surface roughness.

To improve the efficiency of these turning processes, it is necessary to have a complete process understanding and model. To this end, a great deal of research has been performed in order to quantify the effect of various hard turning process parameters to surface quality. These factors can be divided into a) setup variables, b) tool variables, and c) workpiece variables. In order to gain a greater understanding of the turning process it is necessary to understand the impact of the each of the variables, but also the interactions between them. It is impossible to find all the variables that impact surface roughness in turning operations. In addition, it is costly and time consuming to discern the effect of the every variable on the out put. In order to simplify the problem, one needs to eliminate or select specific variables that correspond to practical applications.

Taguchi method [10] consist of a plan of experiments with the objective of acquiring data in a controlled way, executing these experiments and analyzing data, in order to obtain information about the behaviour of a given process. It uses orthogonal arrays to define the experimental plans and the treatment of the experimental results is based on the analysis of variance (ANOVA) [2].

## 2.0 PLAN OF EXPERIMENT BASED ON THE TAGUCHI METHOD

For the experimental plan, the Taguchi method for three levels was used with careful understanding of the levels taken by the factors. Table 1 indicates the factors to be studied and the assignment of the corresponding levels. According to the Taguchi design concept, a $L_{27}$ orthogonal array was chosen for the experiments (Table 2). The analysis was made using the popular software, specifically used for design of experiment applications, known as MINITAB 14. The plan is made of 27 tests (array rows) in which the first column was assigned to the cutting velocity ($V_c$), the second column to the feed rate (f) and the fifth column to the depth of cut (d) and the remaining were assigned to the interactions [11-12]. The outputs to be studied are surface roughness ($R_a$) and tool life (T).

**Table 1:** Cutting parameters and their levels

| Level | Cutting velocity $V_c$ (m/min) | feed rate *f* (mm/rev) | Depth of Cut d (mm) |
|---|---|---|---|
| 1 | 135 | 0.08 | 0.60 |
| 2 | 210 | 0.20 | 1.00 |
| 3 | 285 | 0.32 | 1.60 |

## 3.0 RESULTS AND DISCUSSION

The test plan was developed with the aim of relating the influence of the cutting velocity ($V_c$), feed rate (*f* ) and depth of cut (d) on surface roughness (Ra) and tool life (T). We should mention that only one observation for a treatment is noted. The statistical treatment of the data was made in three phases. The first phase was concerned with the ANOVA and the effect of factors and the interactions. The second phase allows us to obtain the correlations betweens the parameters. Afterwards, the results were obtained through confirmation tests. In the final stage, optimization of turning parameters was carried out by using a Genetic Algorithm

### 3.1 ANOVA and the effects of factors

Analysis of Variance of the data with the surface roughness ($R_a$), and tool life (T) with the objective of the analyzing the influence of cutting velocity ($V_c$), feed rate (*f* ) and depth of cut (d) on the total variance of the results is performed. The experiments were conducted for each combination of factors (columns) as per selected orthogonal array. The number of observations under each combination of factors is one, i.e. the number of replications is one. The experimental results are shown in Table 3. Tables 4-5 show the results of the ANOVA with the surface roughness ($R_a$), and tool life (T) respectively. This analysis was undertaken for a level of significance of 5%, that is, for a level of confidence of 95%. The last column of the tables indicates that the main effects are highly significant (all have very small P-values).

**Table 2**. Orthogonal array for $L_{27}(3^{13})$ design with factor assignment to columns.

| $L_{27}(3^{13})$ | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $V_C$ | *f* | | | d | | | | | | | | |
| 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 2 | 1 | 1 | 1 | 1 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 |
| 3 | 1 | 1 | 1 | 1 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 |
| 4 | 1 | 2 | 2 | 2 | 1 | 1 | 1 | 2 | 2 | 2 | 3 | 3 | 3 |
| 5 | 1 | 2 | 2 | 2 | 2 | 2 | 2 | 3 | 3 | 3 | 1 | 1 | 1 |
| 6 | 1 | 2 | 2 | 2 | 3 | 3 | 3 | 1 | 1 | 1 | 2 | 2 | 2 |
| 7 | 1 | 3 | 3 | 3 | 1 | 1 | 1 | 3 | 3 | 3 | 2 | 2 | 2 |
| 8 | 1 | 3 | 3 | 3 | 2 | 2 | 2 | 1 | 1 | 1 | 3 | 3 | 3 |
| 9 | 1 | 3 | 3 | 3 | 3 | 3 | 3 | 2 | 2 | 2 | 1 | 1 | 1 |
| 10 | 2 | 1 | 2 | 3 | 1 | 2 | 3 | 1 | 2 | 3 | 1 | 2 | 3 |
| 11 | 2 | 1 | 2 | 3 | 2 | 3 | 1 | 2 | 3 | 1 | 2 | 3 | 1 |
| 12 | 2 | 1 | 2 | 3 | 3 | 1 | 2 | 3 | 1 | 2 | 3 | 1 | 2 |
| 13 | 2 | 2 | 3 | 1 | 1 | 2 | 3 | 2 | 3 | 1 | 3 | 1 | 2 |
| 14 | 2 | 2 | 3 | 1 | 2 | 3 | 1 | 3 | 1 | 2 | 1 | 2 | 3 |
| 15 | 2 | 2 | 3 | 1 | 3 | 1 | 2 | 1 | 2 | 3 | 2 | 3 | 1 |
| 16 | 2 | 3 | 1 | 2 | 1 | 2 | 3 | 3 | 1 | 2 | 2 | 3 | 1 |
| 17 | 2 | 3 | 1 | 2 | 2 | 3 | 1 | 1 | 2 | 3 | 3 | 1 | 2 |
| 18 | 2 | 3 | 1 | 2 | 3 | 1 | 2 | 2 | 3 | 1 | 1 | 2 | 3 |
| 19 | 3 | 1 | 3 | 2 | 1 | 3 | 2 | 1 | 3 | 2 | 1 | 3 | 2 |
| 20 | 3 | 1 | 3 | 2 | 2 | 1 | 3 | 2 | 1 | 3 | 2 | 1 | 3 |
| 21 | 3 | 1 | 3 | 2 | 3 | 2 | 1 | 3 | 2 | 1 | 3 | 2 | 1 |
| 22 | 3 | 2 | 1 | 3 | 1 | 3 | 2 | 2 | 1 | 3 | 3 | 2 | 1 |
| 23 | 3 | 2 | 1 | 3 | 2 | 1 | 3 | 3 | 2 | 1 | 1 | 3 | 2 |
| 24 | 3 | 2 | 1 | 3 | 3 | 2 | 1 | 1 | 3 | 2 | 2 | 1 | 3 |
| 25 | 3 | 3 | 2 | 1 | 1 | 3 | 2 | 3 | 2 | 1 | 2 | 1 | 3 |
| 26 | 3 | 3 | 2 | 1 | 2 | 1 | 3 | 1 | 3 | 2 | 3 | 2 | 1 |
| 27 | 3 | 3 | 2 | 1 | 3 | 2 | 1 | 2 | 1 | 3 | 1 | 3 | 2 |

**Table 3**. Experimental design using $L_{27}$ orthogonal array.

| Test | Cutting Speed $V_c$ (m/min) | Feed Rate $f$ (mm/rev) | Depth of Cut d (mm) | Surface Roughness $R_a$ (μm) | S/N ratio (db) | Tool Life T (Sec) | S/N ratio (db) |
|---|---|---|---|---|---|---|---|
| 1 | 135 | 0.08 | 0.60 | 2.0855 | -6.3842 | 1713.96 | 64.6800 |
| 2 | 135 | 0.08 | 1.00 | 2.3377 | -7.3758 | 1650.48 | 64.3522 |
| 3 | 135 | 0.08 | 1.60 | 2.5220 | -8.0349 | 1597.58 | 64.0693 |
| 4 | 135 | 0.20 | 0.60 | 4.3262 | -12.7221 | 1272.25 | 62.0914 |
| 5 | 135 | 0.20 | 1.00 | 4.7142 | -13.4682 | 1200.83 | 61.5896 |
| 6 | 135 | 0.20 | 1.60 | 5.0440 | -14.0555 | 1139.99 | 61.1380 |
| 7 | 135 | 0.32 | 0.60 | 6.8870 | -16.7606 | 830.53 | 58.3871 |
| 8 | 135 | 0.32 | 1.00 | 7.2362 | -17.1902 | 761.76 | 57.6364 |
| 9 | 135 | 0.32 | 1.60 | 7.4884 | -17.4878 | 708.86 | 57.0112 |
| 10 | 210 | 0.08 | 0.60 | 3.4144 | -10.6663 | 1425.66 | 63.0803 |
| 11 | 210 | 0.08 | 1.00 | 3.6181 | -11.1696 | 1385.98 | 62.8351 |
| 12 | 210 | 0.08 | 1.60 | 3.7733 | -11.5344 | 1354.24 | 62.6339 |
| 13 | 210 | 0.20 | 0.60 | 5.9655 | -15.5129 | 981.29 | 59.8359 |
| 14 | 210 | 0.20 | 1.00 | 6.1983 | -15.8455 | 938.98 | 59.4531 |
| 15 | 210 | 0.20 | 1.60 | 6.3632 | -16.0735 | 907.24 | 59.1544 |
| 16 | 210 | 0.32 | 0.60 | 8.0413 | -18.1065 | 595.13 | 55.4922 |
| 17 | 210 | 0.32 | 1.00 | 8.1965 | -18.2726 | 560.74 | 54.9752 |
| 18 | 210 | 0.32 | 1.60 | 8.3032 | -18.3849 | 534.29 | 54.5555 |
| 19 | 285 | 0.08 | 0.60 | 4.3941 | -12.8574 | 1243.15 | 61.8905 |
| 20 | 285 | 0.08 | 1.00 | 4.5202 | -13.1032 | 1219.35 | 61.7226 |
| 21 | 285 | 0.08 | 1.60 | 4.6075 | -13.2693 | 1203.48 | 61.6088 |
| 22 | 285 | 0.20 | 0.60 | 6.8676 | -16.7361 | 817.31 | 58.2477 |
| 23 | 285 | 0.20 | 1.00 | 6.9937 | -16.8941 | 793.50 | 57.9909 |
| 24 | 285 | 0.20 | 1.60 | 7.0713 | -16.9900 | 777.63 | 57.8155 |
| 25 | 285 | 0.32 | 0.60 | 8.5360 | -18.6251 | 481.39 | 53.6499 |
| 26 | 285 | 0.32 | 1.00 | 8.6039 | -18.6939 | 460.23 | 53.2595 |
| 27 | 285 | 0.32 | 1.60 | 8.6524 | -18.7427 | 447.01 | 53.0063 |

From Table 4, one can observe that the cutting velocity (p= 0.001) and feed rate (p=0.000) have great influence on surface roughness. The interactions of cutting velocity/feed rate (p=0.000) and cutting velocity/depth of cut (p=0.001). But The factor depth of cut (p=0.028) and the feed rate/ depth of cut (p=0.300) have present less significant contribution on the surface roughness.

From Table 5, one can observe that the cutting velocity (p=0.000) and feed rate (p=0.000) have great influence on the tool life. The interactions cutting velocity/ feed rate (p=0.000) and cutting velocity/ depth of cut (p=0.000), shows significance of contribution on the tool life. Whereas, depth of cut (p=0.030) and the interaction feed rate/depth of cut (p=0.003) have less significant effect as compare to the other factors and interactions on tool life.

**Table 4**. ANOVA table for surface roughness ($R_a$)

| Source | DF | SS | MS | F | P |
|---|---|---|---|---|---|
| A | 2 | 17.6570 | 8.8285 | 41.10 | 0.001 |
| B | 2 | 92.1785 | 46.0892 | 247.64 | 0.000 |
| C | 2 | 0.6124 | 0.3062 | 9.40 | 0.028 |
| A*B | 4 | 0.7407 | 0.1852 | 91.66 | 0.000 |
| B*C | 4 | 0.0118 | 0.0030 | 1.46 | 0.300 |
| A*C | 4 | 0.1266 | 0.0317 | 15.67 | 0.001 |
| Error | 8 | 0.0162 | 0.0020 | | |
| Total | 26 | 111.3432 | | | |

**Table 5**. ANOVA table for the tool life (T)

| Source | DF | SS | MS | F | P |
|---|---|---|---|---|---|
| A | 2 | 671614 | 335807 | 68.71 | 0.000 |
| B | 2 | 3058621 | 1529311 | 437.32 | 0.000 |
| C | 2 | 26618 | 13309 | 9.37 | 0.030 |
| A*B | 4 | 13942 | 3486 | 512.40 | 0.000 |
| B*C | 4 | 73 | 18 | 2.69 | 0.109 |
| A*C | 4 | 5633 | 1408 | 207.04 | 0.000 |
| Error | 8 | 54 | 7 | | |
| Total | 26 | 3776556 | | | |

## 3.2. CORRELATIONS

The correlations between the factors (cutting velocity, feed rate and depth of cut) and the measured surface roughness, and tool life were obtained by multiple linear regression analysis. The mathematical model suggested was in the following form.

$$Y=P_0 + P_1*V_c + P_2 * f + P_3 *d+P_4*V_c*f+P_5*f*d +P_6*V_c*d \qquad (1)$$

Here, Y is the performance output terms and $P_i$ (i=0, 1, 6) are the model constants. The constants were calculated using linear regression analysis with the help of SYSTAT 7 software, and the following relations were obtained. The calculated coefficients from SYSTAT 7 software were substituted in Eq. (1).

$$R_a= -0.309+ 0.675V_c + 0.870f + 0.175d-0.234V_c.f - 0.002f.d - 0.143Vcd \qquad r^2=0.99 \qquad (2)$$

$$T = 1.511- 0.646V_c - 0.783f - 0.186d + 0.189V_c.f + 0.004 f.d + 0.152Vcd \qquad r^2=0.99 \qquad (3)$$

The higher correlation coefficients ($r^2$) confirm the suitability of the models and the correctness of the calculated constants. In this study, a weighting method is used for the optimization of the process with multi-machining performance outputs. Since surface roughness ($R_a$) and tool life (T) are the two objectives, in order to overcome the large differences in numerical values between the objectives, the function corresponding to each machining performance output is normalized first.

A weighting method is adopted to formulate a single objective function involving surface roughness (Ra) and tool life (T).

Table 6 shows the cutting conditions and cutting time used in turning operations during confirmation experiments, a new set of data was taken out, and conducted a new set of experiments. In Table 7, a comparison was made between the values obtained from the models developed in the present work, Eqs.2-3, with the values obtained experimentally. From the analysis of the table, we can observe that the estimated error is greater especially for surface roughness ($R_a$) (maximum value 7.0% and minimum 3.33%) and for tool life (T) (maximum value 3.71% and minimum 3.00%). Therefore, it can be concluded that the evolution of correlation equations for the surface roughness and tool life with the cutting conditions (cutting velocity, feed rate and depth of cut) satisfies a reasonable degree of approximation.

**Table 6**. Cutting conditions in confirmation tests.

| Test | $V_c$ (m/min) | $f$ (mm/rev) | d (mm) |
|---|---|---|---|
| **1c** | **140** | **0.16** | **1.3** |
| **2c** | **220** | **0.12** | **1.5** |
| **3c** | **300** | **0.18** | **0.9** |

**Table 7**. Experimental plan confirmation drilling tests and their comparison with the results.

| Test | Surface Roughness $R_a$ (μm) | | | Tool life T (Sec) | | |
|---|---|---|---|---|---|---|
| | Expt. | Model(Eq.(3)) | Error(%) | Expt. | Model(Eq.(4)) | Error(%) |
| 1c | 7.56322 | 6.66851 | 10.448 | 985.45 | 858.95 | 12.83 |
| 2c | 6.78941 | 6.19235 | 8.793 | 1043.25 | 924.68 | 11.36 |
| 3c | 9.1258 | 8.82544 | 3.291 | 849.38 | 756.61 | 10.92 |

## 5. Multi-objective Optimization of turning Parameters

The aim of the proposed numerical procedure is to search for the optimal cutting conditions in drilling. A numerical model based on a genetic algorithm (GA) is proposed. Considering the design variables as the cutting speed (*V*c ), the feed rate (*f*) and the cutting time (T), a search was made over the design space defined by the experimental values. The design variables take the following discrete values.

*V*c = {140,220, 300} (m/min); *f* = {0.16, 0.12, 0.18} (mm/rev); T = {1.3, 1.5, 0.9} (Sec)

An appropriate genetic code is considered. Each chromosome has three genes identifying a given solution in the design space, and each gene represents a variable code value on the machining operation as defined in (6). The multi-objective optimization quantitatively determines the relationship between surface roughness (Ra), and tool life (T) with optimal combination of machining parameters. Here, the resultant weighted objective function to be maximized as:

$$\text{Max. } Z = (w_1 \times F1 + w_2 \times 1/F_2)(1 - K \times C) \quad (4)$$

$F_1$ Normalized function for tool life

$F_2$ Normalized function for surface roughness.

C violation coefficient

K a penalty parameter, usually the value is 1 0

Subjected to constraints:

$$V_{cmin} \leq V_c \leq V_{cmax} \quad (5)$$

$$f_{min} \leq f \leq f_{max} \quad (6)$$

$$d_{min} \leq d \leq d_{max} \quad (7)$$

where $w_1$ and $w_2$ are the weighting factors for normalized surface roughness (Ra) and tool life (T) respectively. The weighting factors are selected in such a manner that their sum is equal to one. A higher weighting factor indicates more emphasis on that particular objective. The min and max from Eqs.5-7 show control factor settings in between the lowest and highest machining parameters used in this study (Table 1).

A genetic algorithm (GA) was used to obtain the optimum machining parameters for multi-objective outputs by using several combinations of the weight. The values of the weights are assigned depending on degree of emphasis on improvement in the machining performance outputs. To optimize the multi-objective function, the GA parameters used are summarized in Table 8. The computational algorithm was implemented in $C^{++}$ code.

**Table 8**. Genetic algorithm parameters

| | |
|---|---|
| Population size | 50 |
| Maximum number of generation | 500 |
| Number of problem variables | 3 |
| Probability of crossover | 75% |
| Probability of mutation | 5% |

Genetic algorithms (GAs) are mathematical optimization techniques that simulate a natural evolution process. They are based on the Darwinian theory, in which the fittest species survive and propagate while the less successful tend to disappear. The genetic algorithm concept is based on the evolution process, introduced by Holland [13] and depends on operators such as reproduction, crossover and mutation. Reproduction is accomplished by copying the best individuals from one generation to the next, in what is often called an elistic strategy. The best solution is monotonically improving from one generation to the next. The selected parents are submitted to the crossover operator to produce one or two children. The crossover is carried out with an assigned probability, which is generally rather high. If a number randomly sampled is inferior to the probability, the crossover is performed. The genetic mutation introduces diversity in the population by an occasional random replacement of the individuals. The mutation is performed based on an assigned probability. A random number is used to determine if a new individual will be produced to substitute the one generated by crossover. The mutation procedure consists of replacing one of the decision variable values of an individual, while keeping the remaining variables unchanged. The replaced variable is randomly chosen, and its value is calculated by randomly sampling within its specific range. The pseudo-code for a standard genetic algorithm is presented below. Where $S_a$ is initial population

**The standard genetic algorithm**

{
Generate initial population. $S_a$
Evaluate population $S_a$
While stopping criteria not satisfied repeat

Select elements from Sa to put into $S_{a+1}$
Crossover elements of $S_a$ and put into $S_{a+1}$
Mutate elements of $S_a$ and put into $S_{a+1}$
Evaluate new population $S_{a+1}$
$S_a = S_{a+1}$
{
{

Table 9 shows the optimum conditions of the machining parameters for multi-performance outputs with different combinations of the replacing one of the decision variable values of an individual, while keeping the remaining variables crossover. The mutation procedure consists of weighting factors. From this study, Case-3 gives optimal machining performance with maximum will be produced to substitute the one generated by surface roughness (Ra), and tool life (T) and Case-3 is recommended for optimal combination of the cutting parameters

**Table 9.** Optimal machining conditions for multi-performance with different weighting factors.

| | Optimum machining conditions | | |
|---|---|---|---|
| Cutting parameters | Case-1 ($w_1$= 0.9 & $w_2$= 0.19) | Case-2 ($w_1$=0. 50 & $w_2$=0.50) | Case-3 ($w_1$=0.10 & $w_2$=0.90) |
| Cutting velocity | 133.65 | 0.038 | 0.281 |
| Feed rate | 205.38 | 0.134 | 0.677 |
| Depth of cut | 171.57 | 0.1948 | 0.965 |
| Surface roughness (µm) | 0.677954 | 0.798807 | 0.59302 |
| Tool life (Sec) | 0.572051 | 0.454417 | 0.69539 |

## 5. Conclusions

The results outlined in this study lead to conclusions for turning of S45C after conducting the experiments and analyzing the resulting data.

1. Cutting velocity (0.001) and feed rate (0.000) have greater influence on the surface roughness followed by feed rate.
2. Cutting velocity (0.000) and Feed rate (0.000) have greater influence on the tool life.

3. The interaction between cutting velocity / feed rate (0.000) has a significant effect on surface roughness.
4. Similarly, for tool life, the interaction between cutting velocity / feed rate and cutting velocity / depth of cut has greater significant effect.
5. The confirmation tests showed that the error associated with surface roughness (maximum value 10.448 % and minimum 3.291%) is lesser than the error associated with tool life (maximum value 12.83 % and minimum 10.92 %).
6. Using experimental data, a multiple linear regression model is developed and proves to be effective in optimizing the cutting conditions in turning operations.
7. The search for optimal turning conditions is based on mathematical formulation of the multi-objective optimization problem, and the contribution of each machining parameter is studied. The algorithm is tested to find optimal values of parameters with varying weighting factors for different objectives.
8. It can be concluded from this preliminary study that the turning were carried out on an engine lathe using tungsten carbide with the grade of P-10 for the machining of S45C steel bar is a very difficult operation, and much more work remains to be done to establish effective turning operation for such materials through improvement of tooling and process parameters.
9. In this study, the Taguchi method gives effective methodology in order to find out the effective performance out put and machining conditions.

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