

# Optimization of Surface Roughness in CNC Turning of EN36 Alloy Steel using Response Surface Methodology and Taguchi Method

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**Abstract :** *Focused on the influence of machining parameter such as spindle speed, feed rate and depth of cut. In the present study, 15 experiments have been conducted as per Box-Behnken design matrix. A mathematical model of the surface roughness was developed using response surface methodology and Taguchi method to find out the optimum machining parameters. Finally, Taguchi has been employed to find out the optimal setting of process parameters that optimize surface roughness. Main contribution of the study is to the minimum surface roughness and to find out optimum turning condition using an integration of RSM and Taguchi. RSM and Taguchi approach provide a systematic and effective methodology for the modeling and the optimization. The RSM based surface roughness model in terms of cutting speed, feed rate, and cutting environment was developed by means of the experimental database as per Box-Behnken design of experiments. The RSM based surface roughness model can be optimized using a Taguchi method to find the optimum values of independent variables.*

**Keywords** Surface Roughness, CNC turning, Response Surface Methodology, Taguchi, Cutting Speed.

## 1. Introduction:

CNC (Computer Numerical Control) turning, conventionally an operator decides and adjusts various machines parameters like feed, depth of cut etc., depending on type of job. In a CNC turning machine functions of tools are controlled by motors using computer programs. Turning is one of the most basic machining processes and it is producing the surface quality by various machining process such as spindle speed, feed rate and depth of cut in which a single-point tool remove material from the cylindrical workpiece and it give the smooth surface finish on the surface of workpiece. It is widely used in a variety of manufacturing industries including aerospace and automotive sectors. Surface roughness is an important measure of product quality since it greatly influences the performance of mechanical parts. It is an impact on the mechanical properties like fatigue behaviour, corrosion resistance, creep life, etc. It also affects other functional attributes of parts like friction, wear, light reflection, heat transmission, lubrication, electrical, conductivity.

## 2. Literature Review:

A literature review is a critical and systematic summary and evaluation of existing research, studies, and scholarly articles on a specific topic or research question. It serves as a foundation for understanding the current state of knowledge in a particular field of study and helps identify gaps, contradictions, and areas where further research is needed. The primary purpose of a literature review is to provide context for a research project, thesis, or academic paper by demonstrating the researchers. Reddy NSK et al. this paper presents an experimental investigation of the influence of tool geometry (radial rake angle and nose radius) and cutting conditions (cutting speed and feed rate) on machining performance in dry milling with four fluted solid TiAlN-coated carbide end mill cutters based on Taguchi's experimental design method. The mathematical model, in terms of machining parameters, was developed for surface roughness prediction using response surface methodology. The optimization is then carried out with genetic algorithms using the surface roughness model developed and validated in this work. This methodology helps to determine the best possible tool geometry and cutting conditions for dry milling [1]. Hau et.al. Nano-particles have been successfully and widely applied in many industrial applications.

The wet-type mechanical milling process is a popular method used to produce nano-particles. Therefore, it is very important to improve milling process capability and quality by setting the optimal milling parameters. In this research, the parameter design of the Taguchi method, response surface method (RSM) and genetic algorithm (GA) are integrated and applied to set the optimal parameters for a nano-particle milling process [2]. Killick et al. the present study focused on the influence machining parameters on the surface roughness obtained in drilling of AISI 1045. A mathematical prediction model of the surface roughness was developed using response surface methodology (RSM). The effect of drilling parameters on the surface roughness was evaluated and optimum machining conditions for minimizing the surface roughness were determined using RSM and genetic algorithm. As a result, the predicted and measured value was quite close, which indicates that the developed model can be effectively used to predict the surface roughness [3].

S. Rao et al. the present study is focused on the multi-objective optimization of performance parameters such as specific energy ( $u$ ), metal removal rate (MRR) and surface roughness ( $R_a$ ) obtained in grinding of Al-SiC35P composites. In this study non-dominated sorting genetic algorithm (NSGA -II) is used to solve this multi-objective

optimization problem. Al-SiC specimens containing 8 vol. %, 10 vol. % and 12 vol. % of silicon carbide particles of mean diameter 35 $\mu$ m, feed and depth of cut were chosen as process variables. A mathematical predictive model for each of the performance parameters was developed using response surface methodology (RSM). Further, an enhanced NSGA-II algorithm is used to optimize the model developed by RSM. Finally, the experiments were carried out to validate the results obtained from RSM and enhanced NSGA-II. The results obtained were in close agreement, which indicates that the developed model can be effectively used for the prediction [4]. Antoni and Mohammad in this study, we need to minimize and to obtain as low as possible the surface roughness by determining the optimum values of the three parameters (radial rake angle, speed, feed rate and cutting condition). In this paper, we present a technique developed using hybridization of kernel principal component analysis (KPCA) based nonlinear regression and GAs to estimate the optimum values of the three parameters such that the estimated surface roughness is as low as possible. We use KPCA based regression to construct a nonlinear regression and to avoid the effect of multicollinearity in its prediction model. We show that the proposed technique gives more accurate prediction model than the ordinary linear regression's approach. Comparing with the experiment data and RSM, our technique reduces the minimum surface roughness by about 45.3% and 54.2%, respectively [5].

C. Thiagarajan et al. the Al/SiC composites have received more commercial attention than other kinds of Metal Matrix Composites (MMCs) due to their high performance. However, a continuing problem with MMCs is that they are difficult to machine, due to the hardness and abrasive nature of the SiC particles. Grinding is often the method of choice for machining Al/SiC composites to acquire high dimensional accuracy and surface finish in large scale production [6]. P. S. Sivasakthivel et al. the experiments were conducted on AL6063 by high-speed end mill cutter based on central composite rotatable designs consisting of 32 experiments. The temperature rise was measured using K-type thermocouple. The given model is utilized to analyse direct and interaction effect of the machining parameters with temperature rise. The optimization of machining process parameters to obtain minimum temperature rise was done using genetic algorithm [7]. Sunil Sheshrao et al. electrical discharge machining (EDM) is a widely used process in manufacturing industries for high-precision machining of all types of conductive materials. Material of any hardness can be machined if material can conduct electricity. Proper selection of input parameters is one of the most important aspects in the die sinking EDM, as these conditions determine important characteristics such as surface roughness and material removal rate (MRR). In the present work, empirical models have been developed for relating the surface [8]. M. Subhramaniam et al. This paper aims at developing a statistical model to predict cutting force in terms of machining parameters such as cutting speed, cutting feed rate and axial depth of cut. Response surface methodology experimental design was used for conducting experiments. The work piece material was Aluminium (Al 7075-T6) and the tool was a shoulder mill

with two carbides insert. The cutting forces were measured using three axis milling tool dynamometer [9].

P. Sivaprakasam et al. this paper investigates the influence of three different input parameters such as voltage, capacitance, and feed rate of micro-wire electrical discharge machining (micro-WEDM) performances of material removal rate (MRR), Kerf width (KW) and surface roughness (SR) using response surface methodology with central composite design (CCD). The experiments are carried out on titanium alloy (Ti6Al4V). Analysis of variance (ANOVA) was performed to find out the significant influence of each factor. The model developed can use a genetic algorithm (GA) to determine the optimal machining conditions using multi-objective optimization technique. The optimal machining performance of material removal rate, Kerf width and surface roughness are 0.01802 mm<sup>3</sup>/min, 101.5 mm and 0.789 mm, respectively, using this optimal machining conditions viz. voltage 100 V, capacitance 10 nF and feed rate 15 mm/s [10]. Jayant K et al. models have been developed using central composite design and Box-Behnken design. These two models have been tested for their statistical adequacy and prediction accuracy through analysis of variance (ANOVA) and some practical test cases, respectively. The performance of central composite design is found to be better than Box-Behnken design (BBD) for the response surface roughness and hardness, whereas the latter is found better than the former for the response porosity. The performance is adjudged based on the average absolute percent deviation in predicting the responses. The absolute percent deviation values for the responses surface roughness, hardness, and porosity are found to be equal to 5.95, 1.29, and 63.94, respectively, in central composite designs (CCD). On the other hand, corresponding values in BBD are found to be equal to 14.19, 3.04, and 4.94. Further, an attempt is made to minimize the porosity and surface roughness along with maximization of hardness of die cast component. The objective of multi-response optimization was met with a high desirability value of 0.9490 [11].

Rudrapati et al. in the present work, experiments and analyses have been made to investigate the influence of machining parameters on vibration and surface roughness in traverse cut cylindrical grinding of stainless-steel material. The experiments have been conducted as per Box-Behnken design matrix with input parameters as infeed, longitudinal feed, and work speed. Mathematical modelling has been done by response surface methodology (RSM) to develop relationships between process parameters and output response(s). The adequacy of the developed models has been tested with analysis of variance. The contour and surface plots for vibration and surface roughness have been made to reveal how output responses vary with change in the machining parameters. Finally, multi-objective genetic algorithm (MOGA) has been applied to optimize vibration and surface roughness simultaneously. And then, predicted parametric condition has been validated by confirmatory experiments. The proposed optimization methodology (RSM cum MOGA) seems to be useful for analysing and optimizing any manufacturing process where two or more input parameters influence more than one important output responses [12].

### 3. Experimental Details:

The physical properties of EN36 steel used for the analysis are shown in the Table 1 The EN-36 alloy steel (Bars having diameter 28 mm and length 100 mm) was used as work piece for turning operation and its chemical compositions is shown in Table 2. It is generally used in aeroplane, gears, crane shafts and gear shafts etc. EN-36 steel is a low carbon and high alloy content alloy steel. Characteristics of steel are toughness arising from the use of nickel, generally available in the annealed condition with a maximum brinell hardness of 255, characterized by high core strength, excellent toughness, and fatigue resistance in relatively large sections with case hardness up to RC62 when carburized, hardened, and tempered

**3.1 Experimental methodology:** In this optimization of control factor two methodologies are used. One is Response Surface Methodology for analysis and second is Genetic Algorithm for optimization. These two methodologies are explained below.

**Response surface methodology:** Response surface methodology (RSM) is a collection of mathematical and statistical techniques for empirical model building. It is useful for modeling and analysis of problem in which output or response is influenced by several variables and the objective is to optimize a response function (output variable). It provides more information with a smaller number of experimental.

In this study, RSM's Box-Behnken experimental design with three factors, three levels, and 15 runs are selected. The machining parameters used and their levels of CNC turning machine are depicted in Table 3 and using the Minitab software for develop the Box Behnken design matrix is shown in Table 4.

In the RSM, the true relationship between y and the independent variables is generally approximated by the lower-order polynomial model such as:

$$y = \beta_0 + \beta_1x_1 + \beta_2x_2 + \dots + \beta_nx_n + \epsilon \quad (1)$$

If there is curvature in the system, then polynomial of higher degree must be used, such as the second order model.

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

Where, y is the response surface,  $\epsilon$  represent the statistical error term,  $x_i$  and  $x_j$  are the input variables,  $x_i^2$  and  $x_i$  and  $x_j$  are quadratic and interaction terms of input variables, respectively. The  $a_i$ ,  $a_{ii}$  and  $a_{ij}$  are unknown regression coefficients The Coated Tungsten Carbide cutting tool (TNMG160404) is used for turning operation and noise radius of cutting tool is 0.8 shown in Figure 1.



Figure 1 Tungsten carbide cutting tool

Tungsten carbide is an inorganic chemical compound (specifically, a carbide) containing equal parts of tungsten and carbon atoms. Sintered tungsten carbide cutting tools are very abrasion resistant and can also withstand higher temperatures than standard high speed steel tools. Its density is around 15.7 gm/cm<sup>3</sup>. Hardness is 90 on Rockwell Scale. Its Young's Modulus is 670 GPa. Nose Radius is 0.8 mm. Machining can be performed with six tips.

Table 1: Physical properties of EN36 steel

Density (g/cm <sup>3</sup> )	Coefficient of thermal expansion	Modulus of Elasticity (KN/mm <sup>2</sup> )
15.7	11.6x10 <sup>-6</sup>	669-696

Table 2: Chemical composition of EN36

C	Ni	Cr	Si	Mn	S	P	Mo	Fe
0.700	3.200	1.050	0.250	0.420	0.01	0.012	0.140	94.358

Table 3: Input parameters and their levels of CNC turning machine

Symbol	Parameter	Levels		
		-1	0	1
X <sub>1</sub>	Spindle speed (rpm)	750	1000	1250
X <sub>2</sub>	feed rate (mm/rev)	10	20	30
X <sub>3</sub>	depth off cut (mm)	0.1	0.2	0.3

Table 4: Experimental Design-Box Behnken design matrix

Specimen no.	Spindle speed X <sub>1</sub>	Feed rate X <sub>2</sub>	Depth of cut X <sub>3</sub>	Surface roughness (Ra)
1	1250	30	0.2	6.50
2	750	10	0.2	1.64
3	1250	10	0.2	5.06
4	1000	20	0.2	2.96
5	1000	30	0.1	5.13
6	1250	20	0.1	6.78
7	750	20	0.1	2.66
8	1000	20	0.2	2.96
9	1250	20	0.3	5.60
10	1000	10	0.1	2.62
11	1000	30	0.3	5.50
12	1000	20	0.2	2.96
13	750	30	0.2	2.10
14	1000	10	0.3	2.11
15	1250	20	0.3	2.68

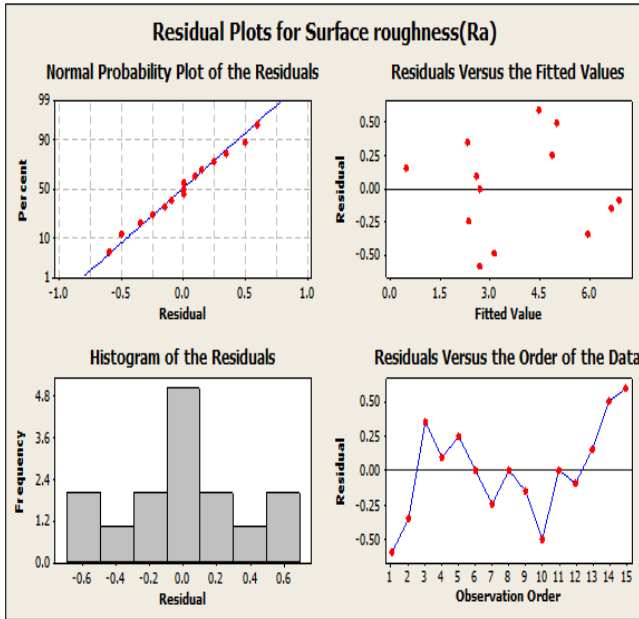


Figure 2 Residual plots for surface roughness

Measure the surface roughness (Ra) of workpiece was done using a portable stylus-type profilometer, Mursurfld 130 shown in Fig. 2. The profilometer was set to a cut-off length is 0.33 mm. The average roughness (Ra) parameter was measured only one time along the tool path and measured value of surface roughness are shown in Table 4.

#### 4. Results and Discussion:

##### 4.1 Modelling of surface roughness

The complete result from the 15 machining trials for EN36 performed as per the experiments plan are shown in Table 5 along with the run order selected at random. The second-order response surface equations have been using Minitab software for one response variables (Ra). The equations can be given in terms of the un-coded value of the dependence variables as the following: The regression equation is:

$$Ra = 0.12 - 0.0000 X1 - 0.076 X2 - 6.6 X3 + 0.000005 x1 * x1 + 0.00239 x2 * x2 + 49.4 x3 * x3 + 0.000021 x1 * x2 - 0.0137 x1 * x3 + 0.044 x2 * x3 \quad (3)$$

Table 5: ANOVA for surface roughness (Ra)

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	9	47.2200	47.22003	5.24667	15.89	0.004
Linear	3	41.3337	1.60721	0.53574	1.62	0.296
Square	3	5.3326	5.33263	1.77754	5.38	0.050
Interaction	3	0.5537	0.55370	0.18457	0.56	0.665
Residual Error	5	1.6511	1.65110	0.33022		
Lack-of-Fit	3	1.6511	1.65110	0.55037		
Pure Error	2	0.0000	0.00000	0.0000		
total	14	48.8711				

##### 4.2 Analysis of variance for surface roughness (Ra)

ANOVA has been carried out, with the use of MINITAB 14 software. The results of this analysis are shown in Table. It is known that if p value (significance probability value) is less 0.05, the corresponding parameter or variable is considered to be “significance” in influence the output response, at 95% confidence level. The coefficient of determination (R<sup>2</sup>) and Adj. R<sup>2</sup> are found to be 96.6% and 90.5%, respectively. As a further check, the normality test of residuals is carried out. It is evidence from Table 5. That residuals are distributed as per normal distribution. The normality of the data was assessed by means of the normal probability plot. The normal probability plot of the residuals for, Ra is shown in Figure 2. The normal probability plot for the responses reveals that the residuals fall in a straight line. This means the errors are distributed normally. The Independence of the data was tested, by plotting a graph between the residuals, and the run order for the responses confirms that there was no predictable pattern observed, because all the run residues lay on or between the levels

##### 4.3 SURFACE PLOT OF SURFACE ROUGHNESS

As show in Figure 3, the 3D surface graph for the surface roughness, as the spindle speed and the feed rate vary and depth of cut kept at 0.2 mm. From Figure 3, the surface roughness increasing for all the three feed rates as the spindle speed is increased from 750 to 1250 rpm. Hence the interaction effect of spindle speed and feed rate is most significant. Low level spindle speed combined with low level feed rate gives optimum surface roughness

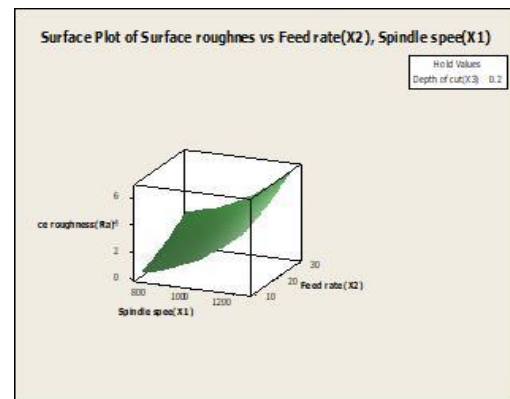


Figure 3 Surface plot of surface roughness vs Feed rate (X2), Spindle speed (X1)

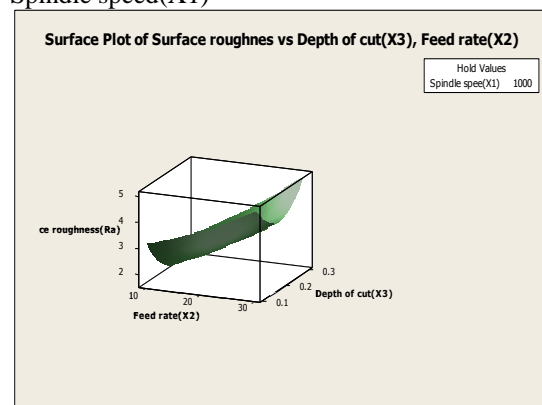


Figure 4 Surface plot of surface roughness vs Feed rate (X2), Depth of cut (X3)



As show in Figure 4, the 3D surface graph for the surface roughness, as the feed rate and the depth of cut and spindle speed kept at 1000 rpm. FromFigure 4, the surface roughness increasing for all three depths of cut as the feed rate is increased from 10 to 30 m/min. Hence the interaction effect of spindle speed and feed rate is most significant. Low level spindle speed combined with low level depth of cut gives optimum surface roughness.

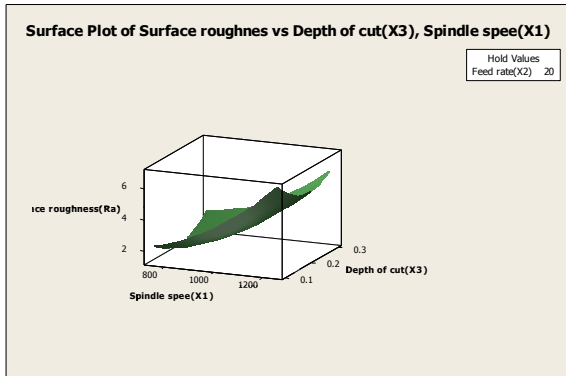


Figure 5 Surface plot of surface roughness vs Depth of cut(X3), Spindle speed(X1)

As show in Figure 5, the 3D surface graph for the surface roughness, as the spindle speed and depth of cut varies and feed rate kept at 20 m/min. FromFigure 5, the surface roughness increasing for all the three feed rates as the spindle speed is increased from 750 to 1250 rpm. Hence the interaction effect of spindle speed and feed rate is most significant. Low level spindle speed combined with low level feed rate gives optimum surface roughness.

**Table 6** Best individuals for minimum Surface Roughness (Ra)

Process parameter	Value
Spindle speed ( $X_1$ )	751 rpm
Feed rate ( $X_2$ )	11 m/min
Depth of cut ( $X_3$ )	0.1 mm

### 5 Conclusions:

Experiments were conducted on CNC turning machine using tungsten coated carbide tool, the data surface roughness was collected under different turning conditions for various combination of cutting speed, feed rate and depth of cut.

In this study is to the minimum surface roughness and to find out optimum cutting condition using an integration of RSM and Taguchi. RSM and Taguchi approach provide a systematic and effective methodology for the modelling and the optimization.

RSM provides a large amount of information with a small amount of experimentation. The RSM based surface roughness model in terms of cutting speed, feed rate, and cutting environment was developed by means of the experimental database as per Box-Behnken design of experiments. The quadratic modes developed using RSM were reasonable accurate and can be used for prediction within the limits of the factors investigated. Taguchi method have been very useful in optimisation of the response variable and also in multi-response cases. The RSM based surface roughness model can be optimized using a Taguchi

method in order to find the optimum values of independent variables.

For the surface roughness, the feed rate and spindle speed are the main influencing factor. Depths of cut have no significant effect on the surface roughness.

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