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# OPTIMIZATION OF SURFACE ROUGHNESS IN CNC TURNING OF EN36 ALLOY STEEL USING RESPONSE SURFACE METHODOLOGY AND TAGUCHI METHOD

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## ABSTRACT

The turning process is used in many industries ranging from large engine manufactures to small die shops. The turning process using CNC lathe is widely used because of its versatility and efficiency. Surface roughness is an important factor that affects the quality in manufacturing process. The main objective of this paper is to analysis the surface roughness in CNC turning operation by various parameters such as feed rate, cutting speed, depth of cut. Response surface methodology has been used to study the effect of the main turning parameters on the surface roughness of EN 36 alloys steel. 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 will develop 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 in order to find the optimum values of independent variables.

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

## 1. INTRODUCTION

Computer Numerical Control may be considered to be a means of operation machine through the use of discrete numerical values fed into the machine. The machine follows a predetermined sequence of machining operation at the predetermined speeds necessary to produce a work piece of the right shape and size and thus according to completely prediction results. Roughness plays an important role in determining how a real object will interact with its environment. Rough surfaces usually wear more quickly and have higher friction coefficients than smooth surfaces. Roughness is often a good predictor of the performance of a mechanical component, since irregularities in the surface may form nucleation sites for cracks or corrosion. On the other hand, roughness may promote adhesion. Roughness can be measured by manual comparison against a “surface roughness comparator”, a sample of known surface roughnesses, but more generally a surface profile measurement is made with a profilometer that can be contact (typically a diamond stylus) or optical (e.g. a white light interferometer or laser scanning confocal microscope) Reddy NSK et al. [1] 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 sur- face 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. Kilickap et al. [3] 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. S. Rao et al. [4] 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 (Ra) 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 35µm, 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. Antoni and Mohammad [5] 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. P. S. Sivasakthivel et al. [7] the experiments were conducted on AL6063 by high-speed end mill cutter based on central composite rotatable desings 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. P. Sivaprakasam et al.[10] 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 (Tie6Ale4V). 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 mm3/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. Jayant K et al. [11] 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, and63.94, 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. Rudrapati et al. [12] 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 analyzing and optimizing any manufacturing process where two or more input parameters influence more than one important output responses

## 2. METHODOLOGY

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 upto RC62 when carburized, hardened and tempered

**Table 1**: Physical properties of EN36 steel

| Density ($g/cm^3$) | Coefficient of thermal expansion | Modulus of Elasticity ($KN/mm^2$) |
|---|---|---|
| 15.7 | $11.6x10^{-6}$ | 669-696 |

**Table 2**: Chemical composition of EN36

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

## 3. 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 less 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:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots\dots\dots + \beta_n x_n + \varepsilon \qquad (1)$$

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

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

Where, y is the response surface, ε 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.

## 4. TAGUCHI METHOD

The Taguchi method involves reducing the variation in a process through robust design of experiments. The overall objective of the method is to produce high quality product at low cost to the manufacturer. The Taguchi method was developed by Dr. Genichi Taguchi of Japan who maintained that variation.

Taguchi developed a method for designing experiments to investigate how different parameters affect the mean and variance of a process performance characteristic that defines how well the process is functioning. The experimental design proposed by Taguchi involves using orthogonal arrays to organize the parameters affecting the process and the levels at which they should be varies. Instead of having to test all possible combinations like the factorial design, the Taguchi method tests pairs of combinations. This allows for the collection of the necessary data to determine which factors most affect product quality with a minimum amount of experimentation, thus saving time and resources. The Taguchi method is best used when there is an intermediate number of variables (3 to 50), few interactions between variables, and when only a few variables contribute significantly.

The Taguchi arrays can be derived or looked up. Small arrays can be drawn out manually; large arrays can be derived from deterministic algorithms. Generally, arrays can be found online. The arrays are selected by the number of parameters (variables) and the number of levels (states). This is further explained later in this article. Analysis of variance on the collected data from the Taguchi design of experiments can be used to select new parameter values to optimize the performance characteristic. The data from the arrays can be analyzed by plotting the data and performing a visual analysis, ANOVA, bin yield and Fisher's exact test, or Chi-squared test to test significance.

## 5. CONCLUSION

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. The quadratic modes develope 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.

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