OPTIMIZATION OF CUTTING PARAMETERS FOR SURFACE ROUGHNESS IN TURNING

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ABSTRACT

The optimized cutting parameters are very important to control the required surface quality. In the present study, Taguchi method is used to find the optimal cutting parameters for surface roughness (Ra) in turning. The L-18 orthogonal array, the signal-to-noise ratio & analysis of variance are employed to study the performance characteristics in turning operations of AISI-410 steel bars using TiN coated inserts. The four cutting parameters namely, insert radius, depth of cut, feed & cutting speed are optimized with considerations of surface roughness. The analysis reveals that feed rate has the most significant effect on Ra.

Keywords: Surface Roughness, Taguchi method, DOE, L-18 array
1. INTRODUCTION

The surface roughness of machined parts is a significant design specification that is known to have considerable influence on properties such as wear resistance and fatigue strength. The quality of surface is a factor of importance in the evaluation of machine tool productivity. Hence it is important to achieve a consistent surface finish and tolerance. Turning is the most common method for cutting and especially for the finishing machined parts. In a turning operation, it is important task to select cutting parameters for achieving high cutting performance. Cutting parameters affect surface roughness, surface texture and dimensional deviations of the product.

Surface roughness is a factor that greatly influences manufacturing cost. It describes the geometry of the machined surfaces and combined with the surface texture. To select the cutting parameters properly, several mathematical models based on neural network or statistical regression techniques have been constructed to establish the relationship between the cutting performance and cutting parameters [1-5].

I.A. Choudhary et al. [6] discusses the development of surface roughness prediction models for turning EN 24T steel (290 BHN) utilizing response surface methodology. A factorial design technique was used to study the effects of the main cutting parameters such as cutting speed, feed and depth of cut, on surface roughness. The tests were carried out using uncoated carbide inserts without any cutting fluid. They reveals that response surface methodology combined with factorial design of experiments is a better alternative to the traditional one-variable-at-a-time approach for studying effects of cutting variables on responses such as surface roughness and tool life.

B.Y. Lee et al. [7] considered the use of computer vision techniques to inspect surface roughness of a workpiece under a variation of turning operations were reported in this paper. The surface image of the workpiece is first acquired using a digital camera and then the feature of the surface image is extracted. A polynomial network using a self-organizing adaptive modeling method was applied to constructing the relationships between the feature of the surface image and the actual surface roughness under a variation of turning operations. They observed that the surface roughness of the turned part can be predicted with reasonable accuracy if the image of the turned surface and turning conditions are given.

M. Thomas et al. [8] reveals that the surface can also be deteriorated by excessive tool vibrations, the built-up edge, the friction of the cut surface against the tool point, and the embedding of the particles of the materials being machined. The effects of cutting parameters, which also contribute to the variation in the tool’s modal parameters, are more useful for controlling tool vibration. This study focuses on the collection and analysis of cutting-force, tool-vibration and tool-modal-parameter data generated by lathe dry turning of mild carbon steel samples at different speeds, feeds, depths of cut, tool nose radii, tool lengths and workpiece lengths. A full factorial experimental design (288 experiments) were took into consideration the two-level interactions between the independent variables was performed. This analysis investigated the effect of each cutting parameter on tool stiffness and damping, and yielded an empirical model for predicting the behavior of the tool stiffness variation.

E. Daniel Kirby et al. [9] investigated the development of a surface roughness prediction system for a turning operation, using a fuzzy-nets modeling technique. The goal was to develop and train a fuzzy-nets-based surface roughness prediction (FN-SRP) system that can predict the surface roughness of a turned workpiece using accelerometer measurements of turning parameters and vibration data. The FN-SRP system has been developed using a computer numerical control (CNC) slant-bed lathe with a carbide cutting tool. The system was trained using feed rate, spindle speed, and tangential vibration data collected during experimental runs. A series of validation runs indicate that this system has a mean accuracy of 95%.

M. Nalbant et al. [10] considered the Taguchi method to find the optimal cutting parameters for surface roughness in turning. The orthogonal array, the signal-to-noise ratio, and analysis of
variance were employed to study the performance characteristics in turning operations of AISI 1030 steel bars using TiN coated tools. Three cutting parameters namely, insert radius, feed rate, and depth of cut, were optimized with considerations of surface roughness. The study reveals that feed rate and insert radius were the main parameters that influence the surface roughness in turning AISI 1030 carbon steel.

J. Paulo Davim et al. [11] developed surface roughness prediction models using artificial neural network (ANN) to investigate the effects of cutting conditions during turning of free machining steel, 9SMnPb28k(DIN). The ANN model of surface roughness parameters \( R_a \) and \( R_t \) were developed with the cutting conditions such as feed rate, cutting speed and depth of cut as the affecting process parameters. The experiments were planned as per L27 orthogonal array with three levels defined for each of the factors in order to develop the knowledge base for ANN training using error back-propagation training algorithm (EBPTA). 3D surface plots were generated using ANN model to study the interaction effects of cutting conditions on surface roughness parameters. The analysis reveals that cutting speed and feed rate have significant effects in reducing the surface roughness, while the depth of cut has the least effect. The details of experimentation, ANN training and validation are presented in the paper.

Ilhan Asilturk et al. [12] focus on optimizing turning parameters based on Taguchi method to minimize surface roughness \( (R_a \) and \( R_z \)). Experiments have been conducted using L9 orthogonal array in a CNC turning machine. Dry turning tests were carried out on hardened AISI 4140 (51 HRC) with coated carbide cutting tools. As a result they observed that the feed rate has the most significant effect on \( R_a \) and \( R_z \).

In this study an alternative approach based on Taguchi method is used to determine the cutting parameters which affect the surface roughness significantly. The purpose of this research was to demonstrate a use of the Taguchi parameter design in order to identify the optimum surface roughness performance with a particular combination of cutting parameters in a turning operation.

2. TAGUCHI METHOD

Taguchi has developed a methodology for the application of designed experiments, including a practitioner’s handbook [1]. This methodology has taken the design of experiments from the exclusive world of the statistician and brought it more fully into the world of manufacturing. His contributions have also made the practitioner work simpler by advocating the use of fewer experimental designs, and providing a clearer understanding of the variation nature and the economic consequences of quality engineering in the world of manufacturing [1,2]. Taguchi introduces his approach, using experimental design for [2]:

- designing products/processes so as to be robust to environmental conditions;
- designing and developing products/processes so as to be robust to component variation;
- minimizing variation around a target value.

The philosophy of Taguchi is broadly applicable. He proposed that engineering optimization of a process or product should be carried out in a three-step approach, i.e., system design, parameter design, and tolerance design. In system design, the engineer applies scientific and engineering knowledge to produce a basic functional prototype design, this design including the product design stage and the process design stage. In the product design stage, the selection of materials, components, tentative product parameter values, etc., are involved. As to the process design stage, the analysis of processing sequences, the selections of production equipment, tentative process parameter values, etc., are involved. Since system design is an initial functional design, it may be far from optimum in terms of quality and cost.
The objective of the parameter design [13] is to optimize the settings of the process parameter values for improving performance characteristics and to identify the product parameter values under the optimal process parameter values. In addition, it is expected that the optimal process parameter values obtained from the parameter design are insensitive to the variation of environmental conditions and other noise factors. Therefore, the parameter design is the key step in the Taguchi method to achieving high quality without increasing cost.

Classical parameter design, developed by Fisher [14], is complex and not easy to use. Especially, a large number of experiments have to be carried out when the number of the process parameters increases. To solve this task, the Taguchi method uses a special design of orthogonal arrays to study the entire parameter space with a small number of experiments only. A loss function is then defined to calculate the deviation between the experimental value and the desired value. Taguchi recommends the use of the loss function to measure the performance characteristic deviating from the desired value. The value of the loss function is further transformed into a signal-to-noise (S/N) ratio $\eta$. There are three categories of the performance characteristic in the analysis of the S/N ratio, that is, the lower-the-better, the higher-the-better, and the nominal-the-better. The S/N ratio for each level of process parameters is computed based on the S/N analysis. Regardless of the category of the performance characteristic, the larger S/N ratio corresponds to the better performance characteristic. Therefore, the optimal level of the process parameters is the level with the highest S/N ratio $\eta$. Furthermore, a statistical analysis of variance (ANOVA) is performed to see which process parameters are statistically significant. With the S/N and ANOVA analyses, the optimal combination of the process parameters can be predicted. Finally, a confirmation experiment is conducted to verify the optimal process parameters obtained from the parameter design. In this paper, the cutting parameter design by the Taguchi method is adopted to obtain optimal machining performance in turning.

Nominal is the better: 

$$S_{NT} = 10 \log \left( \frac{\bar{y}}{S^2} \right)$$

Larger-is-the better (maximize): 

$$S_{NL} = -10 \log \left( \frac{1}{n} \sum_{i=1}^{n} \frac{1}{y_i^2} \right)$$

Smaller-is-the better (minimize): 

$$S_{NS} = -10 \log \left( \frac{1}{n} \sum_{i=1}^{n} y_i^2 \right)$$

where $\bar{y}$ is the average of observed data, $S^2$ is the variance of $y$, $n$ is the number of observations and $y$ is the observed data.

Notice that these S/N ratios are expressed on a decibel scale. We would use $S_{NT}$ if the objective is to reduce variability around a specific target, $S_{NL}$ if the system is optimized when the response is as large as possible, and $S_{NS}$ if the system is optimized when the response is as small as possible. Factor levels that maximize the appropriate S/N ratio are optimal. The goal of this research was to produce minimum surface roughness (Ra) in a turning operation. Smaller Ra values represent better or improved surface roughness. Therefore, a smaller-the-better quality characteristic was implemented and introduced in this study [13].

The use of the parameter design of the Taguchi method to optimize a process with multiple performance characteristics includes the following steps [15]:

- Identify the performance characteristics and select process parameters to be evaluated.
- Determine the number of levels for the process parameters and possible interactions between the process parameters.
- Select the appropriate orthogonal array and assignment of process parameters to the orthogonal array.
- Conduct the experiments based on the arrangement of the orthogonal array.

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Calculate the total loss function and the S/N ratio.
- Analyze the experimental results using the S/N ratio and ANOVA.
- Select the optimal levels of process parameters.
- Verify the optimal process parameters through the confirmation experiment.

3. MATERIAL, METHOD AND LEVEL OF PARAMETERS

Turning is a machining process in which a single-point cutting tool removes material from the surface of a rotating cylindrical workpiece. Four cutting parameters, i.e., insert radius, depth of cut, feed rate, and cutting speed must be determined in a turning operation. Machining performance in a turning operation is based on the surface roughness. Hence, optimization of the cutting parameters based on the parameter design of the Taguchi method using L18 array is adopted in this experiment to improve surface roughness in a turning operation.

3.1. Material

In this study the workpiece made of AISI 410 grade steel was used. Its sizes were $\phi$ 25 x 100 mm. The chemical composition and mechanical properties of AISI 410 carbon steel which was used in the experiments are shown in Table 1 and 2, respectively.

Table 1 Chemical composition of AISI 410 carbon steel, % weight

<table>
<thead>
<tr>
<th>C</th>
<th>Si</th>
<th>Mn</th>
<th>P</th>
<th>S</th>
<th>Cr</th>
<th>Ni</th>
<th>Mo</th>
<th>Al</th>
<th>V</th>
<th>Co</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.117</td>
<td>0.310</td>
<td>0.516</td>
<td>0.0309</td>
<td>0.0163</td>
<td>11.80</td>
<td>0.0679</td>
<td>0.0020</td>
<td>0.0134</td>
<td>0.0348</td>
<td>0.0149</td>
</tr>
</tbody>
</table>

Table 2 Mechanical properties of AISI 410 carbon steel

<table>
<thead>
<tr>
<th>Elongation (%)</th>
<th>Hardness (HRB)</th>
<th>Tensile Strength (MPa)</th>
<th>Yield strength (MPa)</th>
<th>Thermal conductivity (W/mK)</th>
</tr>
</thead>
<tbody>
<tr>
<td>25</td>
<td>85</td>
<td>517</td>
<td>310</td>
<td>24.9</td>
</tr>
</tbody>
</table>

3.2. Method

The cutting experiments were carried out on a LMW (Laxmi Machine Works) CNC lathe (model: LL20T L5) using TiN coated inserts with the grade of P-20 and P-30 for the machining of AISI 410 steel bars. The tool holder used was model: MWLNR 2525 M08. TiN coated inserts WNMG 0800408 MT TT5100 and WNMG 0800412 RT TT3500 were used as the cutting tool material. The experiments were conducted under flooded coolant conditions. The Castrol make COOL EDGES SL (5% solution in water) were used as coolant. The Surface roughness was measured using a Mitutoyo Surf test SJ-201P Portable Surface Roughness Tester with a sampling length of 4.0 mm.

3.3. Level of parameters

The level of cutting parameter ranges and the initial parameter values were chosen from the manufacturer’s handbook recommended for the tested material. The levels of cutting parameters that were selected for this study are shown in Table 3.
Table 3 Cutting parameters and their levels

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Cutting Parameter</th>
<th>Level1</th>
<th>Level2</th>
<th>Level3</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>Insert radius (mm)</td>
<td>0.8</td>
<td>1.2</td>
<td>---</td>
</tr>
<tr>
<td>B</td>
<td>Depth of cut (mm)</td>
<td>0.2</td>
<td>0.6</td>
<td>1.00</td>
</tr>
<tr>
<td>C</td>
<td>Feed (mm/rev.)</td>
<td>0.14</td>
<td>0.22</td>
<td>0.30</td>
</tr>
<tr>
<td>D</td>
<td>Cutting Speed (m/min.)</td>
<td>55</td>
<td>90</td>
<td>125</td>
</tr>
</tbody>
</table>

4. DETERMINATION OF OPTIMAL CUTTING PARAMETERS

In this section, the use of an orthogonal array to reduce the number of cutting experiments for determining the optimal cutting parameters is reported. Results of the cutting experiments are studied by using the S/N and ANOVA analyses. Based on the results of the S/N and ANOVA analyses, optimal cutting parameters for surface roughness are obtained and verified.

4.1. Orthogonal array experiment

To select an appropriate orthogonal array for experiments, the total degrees of freedom need to be computed. The degrees of freedom are defined as the number of comparisons between process parameters that need to be made to determine which level is better and specifically how much better it is. For example, a three-level process parameter counts for two degrees of freedom. The degrees of freedom associated with interaction between two process parameters are given by the product of the degrees of freedom for the two process parameters. In the present study, the interaction between the cutting parameters is neglected. Once the degrees of freedom required are known, the next step is to select an appropriate orthogonal array to fit the specific task. Basically, the degrees of freedom for the orthogonal array should be greater than or at least equal to those for the process parameters. In this study, an L18 orthogonal array was used. This array has fifty three degrees of freedom and it can handle mixed-level process parameters. The first parameter of two level and other three parameters of three level. Each cutting parameter is assigned to a column and eighteen cutting parameter combinations are available. Therefore, only eighteen experiments are required to study the entire parameter space using the L18 orthogonal array. The experimental layout for the four cutting parameters using the L18 orthogonal array along with the experimental results and S/N ratio of surface roughness is shown in Table 4.

4.2. Analysis of the signal-to-noise (S/N) ratio

As mentioned earlier, there are three categories of performance characteristics, i.e., the lower-the-better, the higher-the-better, and the nominal-the-better. To obtain optimal machining performance, the lower-the-better performance characteristic for surface roughness should be taken for obtaining optimal machining performance.
Table 4 Cutting parameters and their levels

Table 4 shows the experimental results for surface roughness and the corresponding S/N ratio using Eq. (3). Since the experimental design is orthogonal, it is then possible to separate out the effect of each cutting parameter at different levels. For example, the mean S/N ratio for the insert radius at levels 1 and 2 can be calculated by averaging the S/N ratios for the experiments 1–9, 10–18, respectively. The mean S/N ratio for each level of the other cutting parameters can be computed in the similar manner. The mean S/N ratio for each level of the cutting parameters is summarized and called the mean S/N response table for surface roughness (Table 5). In addition, the total mean S/N ratio for the nine experiments is also calculated and listed in Table 5. Fig. 1 shows the mean S/N ratio graph for surface roughness. The S/N ratio corresponds to the smaller variance of the output characteristics around the desired value.

Table 5 Response table mean S/N ratio for surface roughness factor

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Cutting Parameter</th>
<th>Mean S/N ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Level 1</td>
</tr>
<tr>
<td>A</td>
<td>Insert radius</td>
<td>-3.1747</td>
</tr>
<tr>
<td>B</td>
<td>Depth of cut</td>
<td>-2.9290</td>
</tr>
<tr>
<td>C</td>
<td>Feed</td>
<td>1.0264</td>
</tr>
<tr>
<td>D</td>
<td>Cutting Speed</td>
<td>-2.6981</td>
</tr>
</tbody>
</table>

Total mean S/N ratio = -2.7637
4.3. Analysis of variance

The purpose of the ANOVA is to investigate which of the process parameters significantly affect the performance characteristics. This is accomplished by separating the total variability of the S/N ratios, which is measured by the sum of the squared deviations from the total mean of the S/N ratio, into contributions by each of the process parameters and the error. First, the total sum of the squared deviations $SS_T$ from the total mean of the S/N ratio $\bar{\eta}$ can be calculated as [15].

$$SS_T = \sum_{i=1}^{m}(\eta_i - \bar{\eta})^2 = \sum_{i=1}^{m} \eta_i^2 - \frac{1}{m} \left[\sum_{i=1}^{m} \eta_i\right]^2$$  \hspace{1cm} (4)

where $m$ is the number of experiments in the orthogonal array, e.g., $m = 18$ and $\eta_i$ is the mean S/N ratio for the $i$th experiment.

The total sum of the squared deviations $SST$ is decomposed into two sources: the sum of the squared deviations $SS_p$ due to each process parameter and the sum of the squared error $SS_e$. $SS_p$ can be calculated as:

$$SS_p = \sum_{j=1}^{t} \left(\frac{s_{\eta_j}}{t}\right)^2 - \frac{1}{m} \left[\sum_{i=1}^{m} \eta_i\right]^2$$  \hspace{1cm} (5)

where $p$ represent one of the experiment parameters, $j$ the level number of this parameter $p$, $t$ the repetition of each level of the parameter $p$, $s_{\eta_j}$ the sum of the S/N ratio involving this parameter $p$ and level $j$.

The sum of squares from error parameters $SS_e$ is

$$SS_e = SS_T - SS_A - SS_B - SS_C$$  \hspace{1cm} (6)

The total degrees of freedom is $D_T = m - 1$, where the degrees of freedom of the tested parameter $D_p = t - 1$. The variance of the parameter tested is $V_p = SS_p/D_p$. Then, the F-value for each design parameter is simply the ratio of the mean of squares deviations to the mean of the squared error ($F_p = V_p/V_e$). The corrected sum of squares $S_p$ can be calculated as:

$$S_p = SS_p - D_p V_e$$  \hspace{1cm} (7)

The percentage contribution $\rho$ can be calculated as:

$$\rho = \frac{S_p}{SS_T}$$  \hspace{1cm} (8)

Statistically, there is a tool called the F-test named after Fisher [14] to see which process parameters have a significant effect on the performance characteristic. In performing the F-test, the mean of the
squared deviations \( S_{Sm} \) due to each process parameter needs to be calculated. The mean of the squared deviations \( S_{Sm} \) is equal to the sum of the squared deviations \( S_{Sd} \) divided by the number of degrees of freedom associated with the process parameter. Then, the F-value for each process parameter is simply a ratio of the mean of the squared deviations \( S_{Sm} \) to the mean of the squared error \( S_{Se} \). Usually the larger the F-value, the greater the effect on the performance characteristic due to the change of the process parameter.

Table 6 shows the results of ANOVA for surface roughness. It can be found that the insert radius is the significant cutting parameters for affecting the surface roughness. The change of the depth of cut and cutting speed in the range given by Table 3 has an insignificant effect on surface roughness. Therefore, based on the S/N and ANOVA analyses, the optimal cutting parameters for surface roughness are the insert radius at level 2, the depth of cut at level 3 the feed rate at level 1, and cutting speed at level 3.

Table 6 Results of analysis of variance for surface roughness

<table>
<thead>
<tr>
<th>Source of variation</th>
<th>Degree of freedom</th>
<th>Sum of squares</th>
<th>Mean square</th>
<th>F ratio</th>
<th>P Value</th>
<th>Contribution (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Insert radius</td>
<td>1</td>
<td>3.0412</td>
<td>3.0412</td>
<td>3.85</td>
<td>0.0782</td>
<td>1.91</td>
</tr>
<tr>
<td>Depth of cut</td>
<td>2</td>
<td>0.4465</td>
<td>0.2232</td>
<td>0.28</td>
<td>0.7615</td>
<td>0.28</td>
</tr>
<tr>
<td>Feed</td>
<td>2</td>
<td>147.9759</td>
<td>73.9880</td>
<td>93.58</td>
<td>0.0001</td>
<td>92.74</td>
</tr>
<tr>
<td>Cutting Speed</td>
<td>2</td>
<td>0.1876</td>
<td>0.0938</td>
<td>0.12</td>
<td>0.8882</td>
<td>0.12</td>
</tr>
<tr>
<td>Error</td>
<td>10</td>
<td>7.9066</td>
<td>0.7907</td>
<td>4.96</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>17</td>
<td>159.5578</td>
<td>9.3858</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

4.4. Confirmation tests

Once the optimal level of the process parameters is selected, the final step is to predict and verify the improvement of the performance characteristic using the optimal level of the process parameters. The estimated S/N ratio \( \bar{\eta} \) using the optimal level of the process parameters can be calculated as [5]

\[
\bar{\eta} = \eta_m + \sum_{i=1}^{q}(\bar{\eta}_i - \eta_m)
\]  

(9)

Where \( \eta_m \) is the total mean of the S/N ratio, \( \bar{\eta}_i \) is the mean S/N ratio at the optimal level, and \( q \) is the number of the process parameters that significantly affect the performance characteristic.

Table 7 Results of the conformation experiment for surface roughness

<table>
<thead>
<tr>
<th>Optimal cutting parameters</th>
<th>Prediction</th>
<th>Experiment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Level</td>
<td>A2B3C1D3</td>
<td>A2B3C1D3</td>
</tr>
<tr>
<td>Surface roughness (µm)</td>
<td>0.92</td>
<td>0.83</td>
</tr>
<tr>
<td>S/N ratio (dB)</td>
<td>1.7279</td>
<td>1.6533</td>
</tr>
<tr>
<td>Improvement of S/N ratio</td>
<td>0.0746</td>
<td></td>
</tr>
</tbody>
</table>

The estimated S/N ratio using the optimal cutting parameters for surface roughness can then be obtained and the corresponding surface roughness can also be calculated by using Eq. (3). Table 7 shows the results of the confirmation experiment using the optimal cutting parameters of surface roughness. Good agreement between the predicted machining performance and actual machining performance were seen. The 0.0746 dB improvement of the S/N ratio for the individual performance characteristic is shown in Table 7. Based on the result of the confirmation test, the surface roughness
is decreased by 4.31 %, the conformation experiment results confirm the optimal cutting parameters with the multiple performance characteristics in turning operations.

5. CONCLUSIONS

This paper has presented an application of the parameter design of the Taguchi method in the optimization of turning operations. The following conclusions can be drawn based on the experimental results of this study:

- It is found that the parameter design of the Taguchi method provides a simple, systematic, and efficient methodology for the optimization of the cutting parameters.
- The experimental results demonstrate that the insert radius and feed rate are the main parameters among the four controllable factors (insert radius, depth of cut, feed rate and cutting speed) that influence the surface roughness in turning AISI 410 steel.
- The confirmation experiments were conducted to verify the optimal cutting parameters. The percentage contributions of insert radius, depth of cut, feed rate and cutting speed are 1.91, 0.28, 92.74 and 0.12 respectively.
- In turning, use of greater insert radius (1.2 mm), high depth of cut (1.0 mm), low feed rate (0.14 mm/rev) and high cutting speed (125 m/min.) are recommended to obtain better surface roughness for the specific test range.
- It is found that the insert radius has the significant effect on the surface roughness.
- The improvement of S/N ratio from optimal cutting parameters to the experimental cutting parameters is about 0.0746 dB.
- the surface roughness is decreased by 4.31 %

Further study could consider more factors (e.g., tool vibrations, materials, lubricant etc.) in the research to see how the factors would affect surface roughness.

REFERENCES


