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*Full Length Research Paper*

# Optimization of surface roughness in turning alloy steel by using Taguchi method

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**The surface quality of the machined parts is one of the most important product quality characteristics and one of the most frequent customer requirements. In this study the Taguchi robust parameter design for modeling and optimization of surface roughness in dry single-point turning of cold rolled alloy steel 42CrMo4/AISI 4140 using TiN-coated tungsten carbide inserts was presented. Three cutting parameters, the cutting speed (80, 110, 140 m/min), the feed rate (0.071, 0.196, 0.321 mm/rev), and the depth of cut (0.5, 1.25, 2 mm), were used in the experiment. Each of the other parameters was taken as constant. The average surface roughness ($R_a$) was chosen as a measure of surface quality. The experiment was designed and carried out on the basis of standard $L_{27}$ Taguchi orthogonal array. The data set from the experiment was employed for conducting the optimization procedures, according to the principles of the Taguchi method. The results of calculations were in good agreement with the experimental data. A certain discrepancy between the experimental results and calculations could be interpreted as the presence of measurement errors, many irregularities and deficiencies in the turning process, as well as environmental effects. The results presented in this work confirm the effectiveness of Taguchi's technique in optimization of cutting processes.**

**Key words:** turning process, surface roughness, Taguchi method, ANOVA, regression analysis.

## INTRODUCTION

The key change drivers in the case of cutting technology include: diminishing component size, enhanced surface quality, tighter tolerances and manufacturing accuracies, reduced costs, diminished component weight and reduced batch sizes (Byrne et al., 2003).

Among various cutting processes, turning process is one of the most fundamental and most applied metal removal operations in a real manufacturing environment.

The surface roughness of the machined parts is one of the most significant product quality characteristics. This characteristic refers to the deviation from the nominal surface of the third up to sixth order. The actual surface profile is the superposition of error of the form, waviness and roughness. The order of deviation is defined in international standards.

The surface roughness greatly affects the functional performance of mechanical parts such as wear resistance, fatigue strength, ability of distributing and holding a lubricant, heat generation and transmission, corrosion resistance, etc.

The perfect surface quality in turning would not be achieved even in the absence of irregularities and deficiencies of the cutting process, as well as environmental effects.

There are various parameters used to evaluate the surface roughness. In the present research, the average surface roughness ($R_a$) was selected as a characteristic of surface finish in turning operations. It is the most used standard parameter of surface roughness.

In a machining process, there are two sharp and often conflicting requirements. The first is high-quality surfaces and the second is high production rate. An extremely high quality surface can produce higher production costs and time consumption.

Therefore, the machine tool operators would not push the machine tool and/or cutting tool to its limit, rather

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**Table 1.** Cutting factors and their levels.

| Cutting factor | Factor levels | | |
|---|---|---|---|
| | Level 1 | Level 2 | Level 3 |
| Cutting speed, V (m/min) | 80 | 110 | 140 |
| Feed rate, f (mm/rev) | 0.071 | 0.196 | 0.321 |
| Depth of cut, a (mm) | 0.5 | 1.25 | 2.0 |

using less risky process factors for that reason, which neither guarantees the achievement of the desired surface quality nor attains maximum production rate or minimum production cost.

Hence, it is of great importance to exactly quantify the relationship between surface roughness and cutting conditions.

Different methodologies are employed for predicting the surface roughness in turning, such as machining theory, classical experimental design and response surface methodology (Choudhury and El-Baradie,1997; Davim, 2001; Arbizu and Pérez, 2003; Thangavel and Selladurai, 2008), artificial neural networks (Özel and Karpat, 2005; Lu, 2008; Karayel, 2009; Marinković and Tanikić, 2011), neuro-fuzzy systems (Jiao et al., 2004; Kirby and Chen, 2007; Tanikić et al., 2010), genetic algorithm (Chen and Chen, 2003; Čuš and Balič, 2003), and soft computing techniques (Samanta et al., 2008). The Taguchi method is widely used for various product and process analysis and optimization because of its relative simplicity (Kopač et al., 2002; Hasçalik and Çaydaş, 2008; Tsao and Hocheng, 2008; Yusuf et al., 2010; Mustafa and Tanju, 2011). A comprehensive review of optimization techniques in metal cutting processes is available (Mukherjee and Ray, 2006).

Mathematical modeling of cutting processes is based on well-known scientific principles. However, many theoretical models involve simplifications and approximations in relation to the real cutting process and do not take into account any imperfections in the formation of chip and surface roughness. Therefore, analytical solutions are generally not accurate enough for practical usage (Davim, 2001).

The above mentioned methods are powerful tools for systematic modeling, analysis and optimization of cutting processes. These approaches integrate experimental and mathematical (statistical) methods, thus providing sufficient accuracy of calculations for the real conditions in which the cutting process takes place.

This paper demonstrates the application of the Taguchi method for identifying the optimal cutting parameters for surface roughness in dry turning of an alloy steel.

## MATERIALS AND METHODS

### Experimental procedure

The cutting parameters (design factors) considered in the present paper were cutting speed ($V$), feed rate ($f$), and depth of cut ($a$). Other parameters were kept constant for the scope of this research. The average surface roughness ($R_a$) was chosen as the target function (response, output).

Since it was obvious that the effects of factors on the selected function were nonlinear, the experiment was set up with factors at three levels (Table 1).

The factor ranges were chosen with different criteria for each factor, in order to use the widest possible ranges of values. Also, the possibility of mechanical system and manufacturer's recommendation were taken into account.

Based on the selected factors and factor levels, a design matrix was constructed (Table 2) in accordance with the standard $L_{27}(3^{13})$ Taguchi orthogonal array (OA). The selected design matrix was a full factorial design consisting of 27 rows of coded factors, corresponding to the number of trials, and 13 columns at three levels. The three levels of each factor were denoted by 1, 2 and 3.

This design provided uniform distribution of experimental points within the selected experimental hyper-space and the experiment with high resolution. Likewise, this OA was chosen due to its capability to check the interactions among factors.

The cutting parameters in experiment were changed according to different cutting conditions for each trial. All of the trials were conducted on the same machine tool, with the same tool type and the same other cutting conditions.

Longitudinal dry turning of steel bars was performed on a production type PA-C-30 (Potisje Ada) lathe. The cylindrical bars, with a diameter of 45 mm and length of 250 mm, were fixed in the lathe with a three-jaw chuck.

The workpiece material used in the experiment was cold rolled alloy steel $42CrMo_4$ / AISI 4140 (1.40% C, 1,00% Cr, 0.20% Mo, 0.90% Mn, 0.25% Si, 0.03% P, 0.10% S; ultimate tensile strength 1050 N/mm$^2$, hardness 205 BHN). TiN-coated tungsten carbide inserts, type CNMG 120408 (Sandvik Coromant) of 235 grade, were used for turning. The tool holder used for experimentation was PCLNR 32 25 P12 (Sandvik Coromant).

The average surface roughness ($R_a$) of machined workpieces was measured using Surfrest SJ-301 (Mitutoyo) profilometer (Figure 1). The average surface roughness values shown in Table 2 are the arithmetical mean of three measurements.

The experiment was described in more detail in the referential literature (Tanikić, 2010; Marinković and Tanikić, 2011).

It should be noted that, throughout the entire text, the terms factors, variables, and parameters are synonymously used to refer to factors which influence the outcome of the process under research.

### Taguchi method (TM) - An overview

The Taguchi experimental design method is a well-known, unique and powerful technique for product/process quality improvement. It is widely used for analysis of experiment and product or process optimization. The application of the TM is not limited to any specific problem.

**Table 2.** Experimental design and results.

| Trial | Natural factor | | | Coded factor | | | Response, $R_a$ (µm) |
|---|---|---|---|---|---|---|---|
| | V | f | a | A | B | C | |
| 1 | 80 | 0.071 | 0.50 | 1 | 1 | 1 | 3.60 |
| 2 | 80 | 0.071 | 1.25 | 1 | 1 | 2 | 3.61 |
| 3 | 80 | 0.071 | 2.0 | 1 | 1 | 3 | 3.96 |
| 4 | 80 | 0.196 | 0.50 | 1 | 2 | 1 | 4.30 |
| 5 | 80 | 0.196 | 1.25 | 1 | 2 | 2 | 4.955 |
| 6 | 80 | 0.196 | 2.0 | 1 | 2 | 3 | 5.92 |
| 7 | 80 | 0.321 | 0.50 | 1 | 3 | 1 | 5.13 |
| 8 | 80 | 0.321 | 1.25 | 1 | 3 | 2 | 5.28 |
| 9 | 80 | 0.321 | 2.0 | 1 | 3 | 3 | 5.98 |
| 10 | 110 | 0.071 | 0.50 | 2 | 1 | 1 | 2.32 |
| 11 | 110 | 0.071 | 1.25 | 2 | 1 | 2 | 2.745 |
| 12 | 110 | 0.071 | 2.0 | 2 | 1 | 3 | 3.44 |
| 13 | 110 | 0.196 | 0.50 | 2 | 2 | 1 | 2.55 |
| 14 | 110 | 0.196 | 1.25 | 2 | 2 | 2 | 3.405 |
| 15 | 110 | 0.196 | 2.0 | 2 | 2 | 3 | 3.33 |
| 16 | 110 | 0.321 | 0.50 | 2 | 3 | 1 | 3.73 |
| 17 | 110 | 0.321 | 1.25 | 2 | 3 | 2 | 4.005 |
| 18 | 110 | 0.321 | 2.0 | 2 | 3 | 3 | 4.23 |
| 19 | 140 | 0.071 | 0.50 | 3 | 1 | 1 | 1.13 |
| 20 | 140 | 0.071 | 1.25 | 3 | 1 | 2 | 2.79 |
| 21 | 140 | 0.071 | 2.0 | 3 | 1 | 3 | 3.08 |
| 22 | 140 | 0.196 | 0.50 | 3 | 2 | 1 | 1.85 |
| 23 | 140 | 0.196 | 1.25 | 3 | 2 | 2 | 2.835 |
| 24 | 140 | 0.196 | 2.0 | 3 | 2 | 3 | 3.27 |
| 25 | 140 | 0.321 | 0.50 | 3 | 3 | 1 | 3.52 |
| 26 | 140 | 0.321 | 1.25 | 3 | 3 | 2 | 3.605 |
| 27 | 140 | 0.321 | 2.0 | 3 | 3 | 3 | 3.66 |

The TM is a more structured and efficient technique that differs from classical design of experiment (DoE), and in that sense, it is a relatively simple method.

In engineering applications, among the various DoE (factorial, fractional factorial, central composite design, Placket-Burmann etc.) the TM is the most used one (Ilzarbe et al., 2008).

Taguchi's experimental procedure and analysis consist of several steps (Phadke et al., 1989; Taguchi et al., 2005; Zhang et al., 2007). The order of these steps may be as given in Figure 2.

The DoE is sometimes too complex, time consuming and not easy to use (Montgomery, 2001; Antony, 2003; Marinković, 1994). More trials have to be carried out when the number of process factors increases. The TM uses special, highly fractionated factorial designs and other types of fractional designs obtained from orthogonal (balanced) arrays to study the entire experimental region of interest for the experimenter, with the minimum number of trials as compared with the classical DoE, especially with a full factorial design. Fewer trials imply that time and cost are reduced. For example, for experiment with 4 factors at 3 levels, a full factorial design would require $3^4$=81 trials. Using Taguchi's experimental design, the standard OA denoted by the symbol $L_9$ ($3^4$) requires only 9 trials.

Taguchi in his off-line quality control strategy proposed that optimization of a process or product should be carried out in a three-step approach: system design, parameter (factors) design, and tolerance design.

The parameter (factors) design is the key step in the TM for achieving high quality characteristics, without increasing cost. The objective of this step is to optimize the settings of the process factor values as close as possible to the target factor values, with minimum variation. Hence, the TM belongs to the so called robust design.

The overall aim of high quality engineering is to make products and/or processes that are robust (insensitive) with respect to all various causes of variation (noise factors). Noise factors (external conditions, manufacturing imperfections, etc.) are unwanted sources of variation and can be uncontrollable or too expensive to control. These factors are usually ignored in the classical DoE approach.

The key principle of Taguchi technique lies in the fact that the reduction in variation is obtained without removing its causes.

In general, the experimental plan (matrix) in Taguchi's design consists of the inner array (control factors) and the outer array (noise factors). This type of design is also called the crossed array design. The outer array is, as a rule, much smaller than the inner array.

Although the noise factors are not controllable in the real environment, they have to be controlled during the experiment. The noise factors that cannot be controlled at all should have equal effect throughout the experiment. This is to avoid biasing the results that could lead to their misinterpretation.

The robust design containing both control and noise factors in the

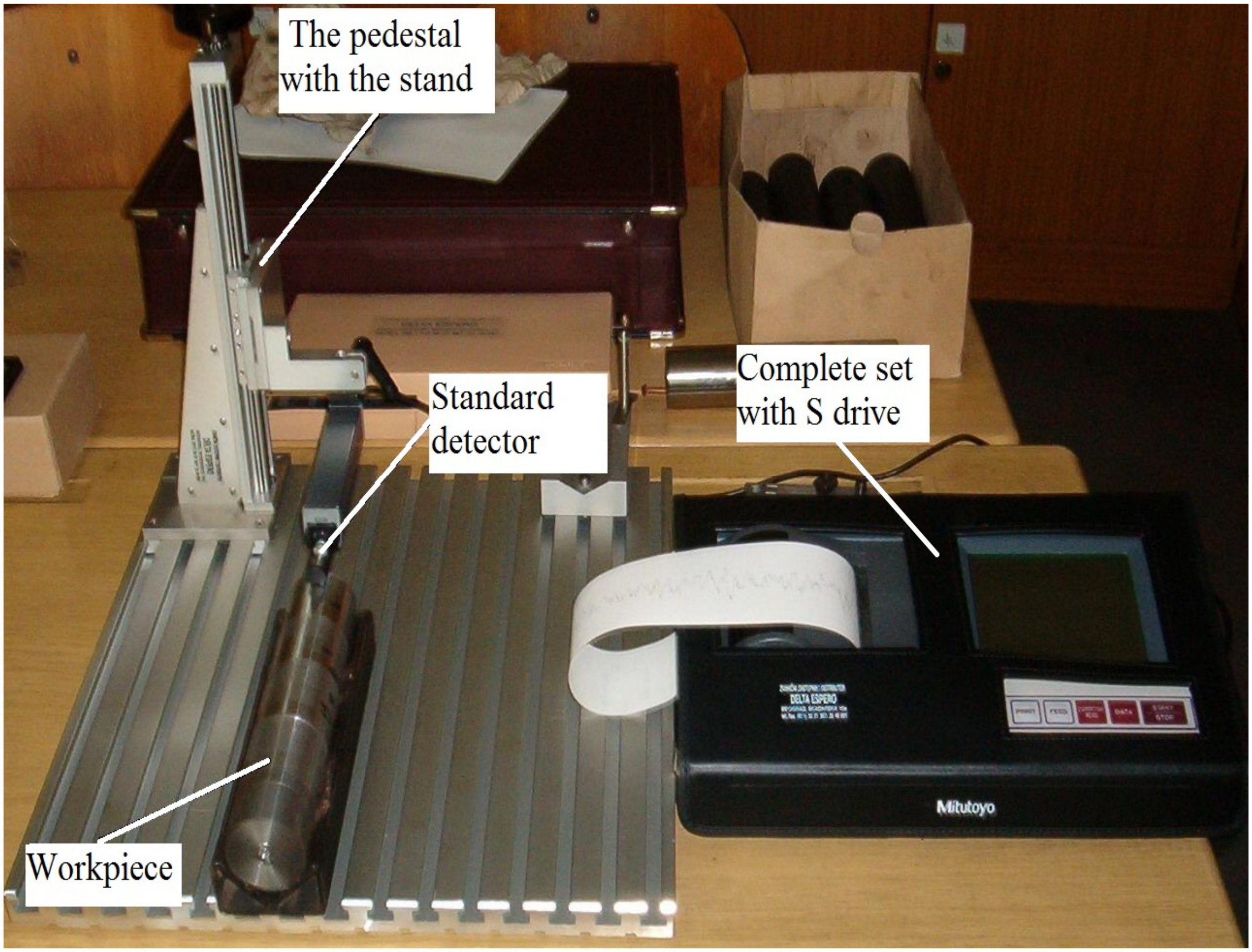


**Figure 1.** Equipment for surface roughness measurement.

same experimental matrix is called the combined array design (Montgomery, 2001).

There are three types of the OAs, those that deal with two-level factors, those that deal with three-level factors, and those that deal with mixed-level factors. The TM is usable when the control and noise factors are all quantitative (continuous), all qualitative (discrete), or mixed. Moreover, this method may include qualitative (discrete) quality characteristics.

For the selection of an appropriate OA (matrix), the number of factors and levels, and their possible interactions must be taken into consideration. It should be noted that the same OA may be selected for different number of factors.

The orthogonality of a design matrix is not lost by keeping one or more columns of an OA empty. Thus, the design matrix formed by remaining columns is also an OA. There are different techniques for modifying OAs such as dummy-level technique, compound factor method, column merging method, branching design, etc (Phadke, 1989; Roy, 1990).

Each row of an OA represents one trial with the levels of different factors in that trial. The number of rows must be at least equal to the total degrees of freedom required for the experiment. Each column of an OA represents one factor and its setting levels in each trial. Some of the columns represent the interactions among the control factors. Columns for all of the OAs interactions are designated in the original design matrix, triangular interaction tables, and linear graphs. Each linear graph must be consistent with the triangular interaction table of an OA. The different linear graphs are useful for design of experiments having various requirements (Phadke, 1989; Taguchi et al., 2005; Roy, 1990).

Taguchi suggested a summary statistic that combines information about the mean and variance into a single performance measure, known as the signal-to-noise (S/N) ratio. Taguchi found out empirically that S/N ratios give the (near) optimal combination of the factor levels, where the variance is minimum, while keeping the mean close to the target value, without using any kind of model.

For that purpose, the experimental results should be transformed into the S/N ratios. There are three categories of the S/N ratio (Phadke, 1989; Taguchi et al., 2005):

(a) Smaller-the-better,

$$\eta \equiv S/N = -10\log\left(\frac{1}{n}\sum_{i=1}^{n} y_i^2\right) \tag{1a}$$

(b) Larger-the-better,

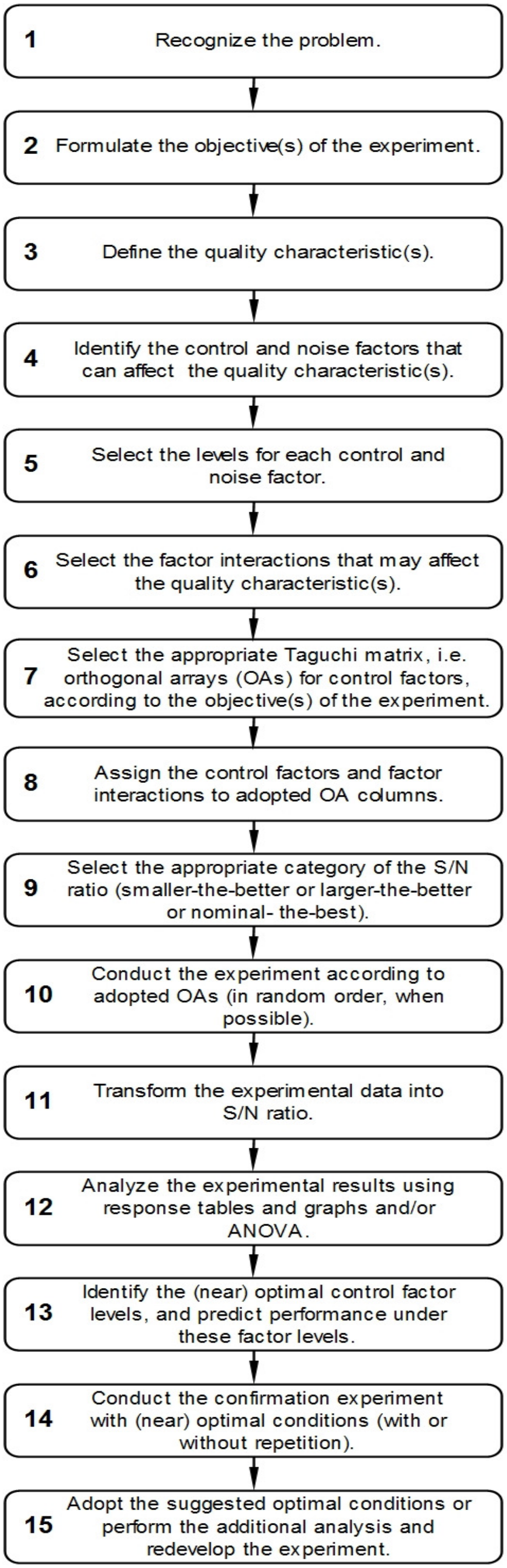


**Figure 2.** Steps in the Taguchi method.

$$\eta \equiv S/N = -10\log\left(\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_i^2}\right) \qquad (1b)$$

(c) Nominal-the-best,

$$\eta \equiv S/N = 10\log\left(\frac{\bar{y}^2}{s^2}\right) \qquad (1c)$$

Where $y_i$ is the i-th observed value of the response (quality characteristic), $n$ is the number of observations in a trial, $\bar{y}$ is the average of observed values (response) and $s$ is the variance.

The appropriate categories of the S/N ratio are chosen depending on the nature of the quality characteristic. For example, the S/N ratio for smaller-the-better criterion is employed when the aim is to make the response as small as possible. Ideally, the response would be equal to zero.

Regardless of the category of the quality characteristics, a greater S/N ratio corresponds to better quality characteristics, that is, to the smaller variance of the output characteristic around the desired (target) value.

The analysis of variance (ANOVA) may be used to investigate which design factors and their interactions affect the response significantly. Taguchi recommends analyzing the mean and S/N ratio using two-dimensional response graphs, instead of ANOVA.

The analysis of means (ANOM) is a statistical approach that is based on determining the mean S/N ratios for each design factor and each of its levels. For example, the mean S/N ratio of factor $Q$ at level $k$ can be calculated as:

$$\bar{\eta}_{Qk} = average\,(S/N)_{Qk} = \frac{1}{n_{Qk}}\sum_{l=1}^{n_{Qk}}\left[(S/N)_{Qk}\right]_l \qquad (2)$$

Where $n_{Qk}$ is the number of appearances of factor $Q$ at level $k$ in Taguchi's matrix, and $(S/N)_{Qk}$ is the S/N ratio related to factor $Q$ at level $k$.

Response graphs provide a simple visual identification of the quantitative and qualitative influence of main factors, within their given range. The analysis of interactions among two or more factors with two or more levels is more complicated. For example, interactions among two 2-level factors may be presented by two lines. If these lines are non-parallel, it is considered that the interaction among the two factors exists.

As it is well-known, the TM limits the optimization to the specific levels of factor values. However, some intermediate combination of factor values may exist, which would yield better results. In most cases, the optimal factor settings obtained by the TM is not the exact optimal solution, but the near optimal solution (Milani et al., 2004).

The final step in analyzing the experimental results is the verification of the improvement of the quality characteristic. For that purpose, a confirmation experiment should be carried out implying the (near) optimal levels of the design factors.

The predicted S/N ratio using the optimal levels of the design factors ( $\hat{\eta}_{opt}$ ) can be calculated as (Phadke, 1989; Taguchi et al., 2005; Roy, 1990):

**Table 3.** Experimental design, response and S/N ratio.

| Trial | Coded factor | | | Response | η=S/N ratio (dB) |
|---|---|---|---|---|---|
| | A | B | C | $R_a$ (μm) | |
| 1 | 1 | 1 | 1 | 3.60 | -11.126 |
| 2 | 1 | 1 | 2 | 3.61 | -11.150 |
| 3 | 1 | 1 | 3 | 3.96 | -11.954 |
| 4 | 1 | 2 | 1 | 4.30 | -12.669 |
| 5 | 1 | 2 | 2 | 4.955 | -13.901 |
| 6 | 1 | 2 | 3 | 5.92 | -15.446 |
| 7 | 1 | 3 | 1 | 5.13 | -14.202 |
| 8 | 1 | 3 | 2 | 5.28 | -14.453 |
| 9 | 1 | 3 | 3 | 5.98 | -15.534 |
| 10 | 2 | 1 | 1 | 2.32 | -7.310 |
| 11 | 2 | 1 | 2 | 2.745 | -8.771 |
| 12 | 2 | 1 | 3 | 3.44 | -10.731 |
| 13 | 2 | 2 | 1 | 2.55 | -8.131 |
| 14 | 2 | 2 | 2 | 3.405 | -10.642 |
| 15 | 2 | 2 | 3 | 3.33 | -10.449 |
| 16 | 2 | 3 | 1 | 3.73 | -11.434 |
| 17 | 2 | 3 | 2 | 4.005 | -12.052 |
| 18 | 2 | 3 | 3 | 4.23 | -12.527 |
| 19 | 3 | 1 | 1 | 1.13 | -1.062 |
| 20 | 3 | 1 | 2 | 2.79 | -8.912 |
| 21 | 3 | 1 | 3 | 3.08 | -9.771 |
| 22 | 3 | 2 | 1 | 1.85 | -5.343 |
| 23 | 3 | 2 | 2 | 2.835 | -9.051 |
| 24 | 3 | 2 | 3 | 3.27 | -10.291 |
| 25 | 3 | 3 | 1 | 3.52 | -10.931 |
| 26 | 3 | 3 | 2 | 3.605 | -11.138 |
| 27 | 3 | 3 | 3 | 3.66 | -11.270 |

$$\hat{\eta}_{opt} = \overline{\eta} + \sum_{i=1}^{p} (\overline{\eta}_{i,opt} - \overline{\eta}) \quad (3)$$

Where $\overline{\eta}$ is the total mean S/N ratio, $\overline{\eta}_{i,opt}$ is the mean S/N ratio for i-th design factor at the optimal level, and $p$ is the number of design factors that significantly affect the quality characteristic.

The total mean S/N ratio for an experiment is calculated by equation:

$$\overline{\eta} = \frac{1}{n_t} \sum_{i=1}^{n_t} \eta_i \quad (4)$$

Where $n_t$ is the total number of trials, and $\eta_i$ is the S/N ratio in i-th trial in the OA.

The insignificant design factors can be set to any level without affecting the product/process, i.e. they can be eliminated from consideration in any future studies.

It should be noted that TM belongs to the technique of single-criterion optimization. There are different approaches in multiple-criteria optimization using TM (Milani et al., 2004; Nian et al., 1999; Tong et al., 1997).

## RESULTS AND DISCUSSION

The design matrix in Table 3 is equivalent to a segment of the standard OA denoted by the symbol $L_{27}$ ($3^3$). Each row of the matrix represents one trial.

In the original design matrix, the first column was assigned to the cutting speed (Factor A), the second to the feed rate (Factor B), and the fifth to the depth of cut (Factor C). The empty Columns 3, 6, and 8 were assigned to the factor interactions (Taguchi et al., 2005). The S/N ratio given in Table 3 was calculated using Equation 1a.

Since the design matrix is orthogonal, it is possible to analyze the influence of each cutting factors at different levels.

On the basis of data given in Table 4, the effects of main cutting factors on mean S/N ratio are presented in graphical form (Figure 3).

The response graphs show the change in the response when a given factor goes from lower level to higher level. The slope of the line determines the power of the control factors influence on surface roughness. Graphs from

**Table 4.** Response table for mean S/N ratios.

| Cutting parameter | Mean S/N ratio (dB) | | | | |
|---|---|---|---|---|---|
| | Level 1 | Level 2 | Level 3 | $\Delta_{max\text{-}min}$ | Rank |
| Cutting speed: A | -13.382 | -10.227 | -8.641 | 4.741 | 1 |
| Feed rate: B | -8.976 | -10.658 | -12.616 | 3.640 | 2 |
| Depth of cut: C | -9.134 | -11.119 | -11.997 | 2.863 | 3 |
| Interaction: A×B | -10.548 | -11.352 | -10.351 | 1.001 | 6 |
| Interaction: B×C | -10.370 | -10.479 | -11.402 | 1.032 | 4 |
| Interaction: A×C | -11.201 | -10.857 | -10.193 | 1.008 | 5 |

The total mean S/N ratio= -10.75

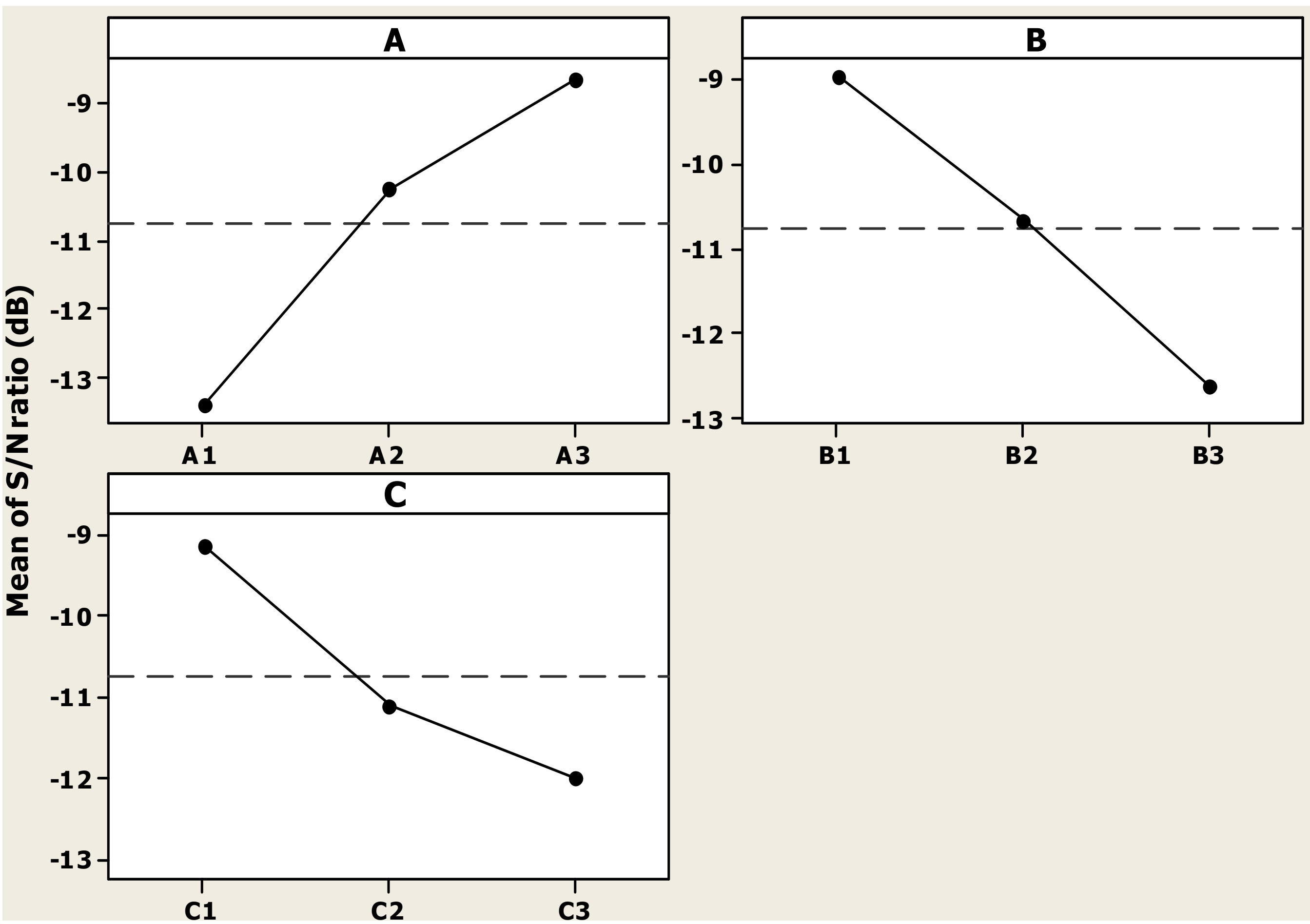


**Figure 3.** Main effects plot for S/N ratios.

Figure 3 clearly suggest a dominant influence, in a quantitative sense, of cutting speed on surface roughness.

Since the category smaller-the-better is adopted, it is evident from Figure 3 that the optimal combination of factor levels, which gives the lowest value of the average surface roughness, is A3B1C1.

The interpretation of effects of factor interactions may be much more complex. In this case, certain influence of factor interactions on surface roughness exists, but in a much smaller amount.

The results from Table 4 suggest that the best combination of factor interactions, in terms of minimizing surface roughness, is (A×B)3 (A×C)3 (B×C)1.

Since Factor A is the dominant factor in relation to Factors B and C, it can be concluded, on the basis of the above mentioned interactions, that the optimal level for this factor is A3. The interaction of Factors B and C

**Table 5.** Analysis of variance for S/N ratio.

| Source | DF | Seq sum of square | Adj sum of square | Adj mean square | F | p | ρ (%) |
|---|---|---|---|---|---|---|---|
| Cutting speed: A | 2 | 104.820 | 104.820 | 52.410 | 28.81 | 0.000 | 42.79 |
| Feed rate: B | 2 | 59.715 | 59.715 | 29.858 | 16.41 | 0.001 | 24.38 |
| Depth of cut: C | 2 | 38.716 | 38.716 | 19.358 | 10.64 | 0.006 | 15.81 |
| Interaction: A×B | 4 | 5.307 | 5.307 | 1.327 | 0.73 | 0.597 | 2.17 |
| Interaction: A×C | 4 | 11.335 | 11.335 | 2.834 | 1.56 | 0.275 | 4.63 |
| Interaction: B×C | 4 | 10.497 | 10.497 | 2.624 | 1.44 | 0.305 | 4.29 |
| Error | 8 | 14.553 | 14.553 | 1.819 | | | 5.93 |
| Total | 26 | 244.943 | | | | | |

The standard tabulated value of F-ratio: $F_{0.01,2,8} = 8.65$ ; $F_{0.01,4,8} = 7.01$ .

**Table 6.** Confirmation experiment.

| | Natural factors | | | Coded factors | | | | |
|---|---|---|---|---|---|---|---|---|
| Trial | v | f | a | A | B | C | $R_a$ (μm) | S/N (dB) |
| 1 | 140 | 0.085 | 0.5 | 3 | 1.112 | 1 | 1.14 | -1.138 |
| 2 | 140 | 0.150 | 0.5 | 3 | 1.633 | 1 | 1.57 | -3.918 |
| 3 | 130 | 0.071 | 1.0 | 2.666 | 1 | 1.666 | 2.18 | -6.769 |

The mean S/N ratio = -3.942.

confirms the above mentioned statement that the optimal levels of these factors are B1 and C1.

Therefore, it is not necessary to perform the revision of the original solution to the optimal arrangement of factor levels.

The statistical analysis was also performed by using ANOVA. This analysis was prepared using software MINITAB. The ANOVA results for S/N ratio are shown in Table 5. These results fully support the conclusions derived earlier. Namely, Factors A, B, and C are identified as the significant control factors at the 99% confidence level.

The percentage contribution of source to the total variation defines parameter sensitivity. It can be proven from Table 5 that changing the factor levels of A, B, and C contributes to nearly 83 % of the total variation.

Furthermore, based on Equation (3) $\hat{\eta}_{opt} = -5.251$ was obtained, while the optimum value of the average surface roughness $\hat{R}_{alopt} = 1.3\ \mu\text{m}$ was obtained using Equation 1a.

Therefore, for the purpose of confirmation, three new trials were conducted, with factor levels close to the optimal point. Table 6 gives the chosen factor levels used for the confirmation experiment.

On the basis of the calculated mean S/N ratio (Table 6), using Equation 1a, a correspondent value of surface roughness $R_a = 1.574\ (\mu\text{m})$ is determined. The comparison of the predicted $\hat{R}_{alopt}$ with the actual $R_a$ from the confirmation experiment showed good agreement.

The surface roughness was most affected by cutting speed. The impact of feed rate was somewhat smaller, while the influence of depth of cut was least pronounced. On the other side, in qualitative terms, the influence of feed rate and depth of cut on the surface quality was opposite in relation to cutting speed. In fact, while the increase of cutting speed caused better surface quality, the increase of feed rate and depth of cut led to the decrease of surface quality. Similar conclusions can be found in the literature (Aslan et al., 2007; Davim, 2001; Jiao et al., 2004; Thangavel and Selladurai, 2008).

The influence of cutting parameters on the surface quality should be analyzed considering cutting parameter(s) ranges. The analysis developed by Jiao et al. (2004) shows that, in a narrower range of feed rate, the influence of this cutting parameter can be neglected.

In some cases, for technical-technological and/or other reasons, it is not possible to use the optimal values of cutting parameters, for the chosen optimization criteria.

The selected quality characteristic may be determined in an indirect way from the multiple regression equation, which establishes the dependency between the corresponding category of S/N ratio and cutting parameters.

In this case, from the data in Tables 2 and 3, the

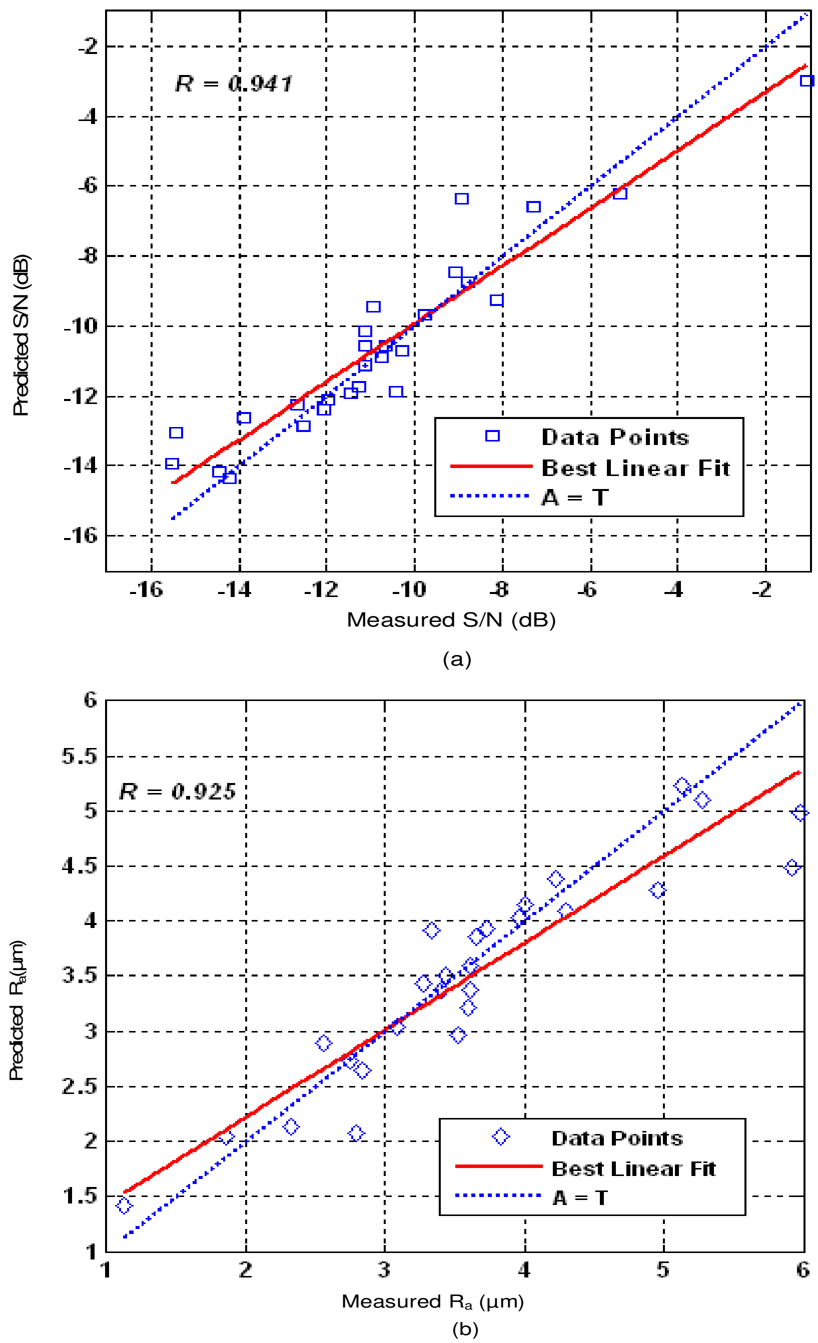


**Figure 4.** Comparison of measured and predicted values :(a) for S/N ratio ;(b) for $R_a$

following equation was obtained:

$$\eta \equiv S/N = -20.6772 + 0.1581\,V - 5.06\,f + 2.8491\,a - \\ -0.1893\,V\,f - 0.058\,V\,a - 0.4894\,f\,a + 0.0868\,V\,f\,a \quad (5a)$$

In the present study, the parameters of equation (5a) were estimated by the method of least-squares.

The average surface roughness was then determined from the simple relation:

$$R_a = 10^{-\frac{\eta}{20}} \quad (5b)$$

Figure 4a shows good agreement of the results obtained by using Equation 5a and the results given in Table 3. Also, Figure 4b shows a satisfactory accuracy of calculation by applying Equation 5b, compared with the experimental values of average surface roughness, which are given in Table 2. In addition, the absolute percentage errors were found to be $\delta_{max} = 25.65\%$, $\delta_{min} = 0.24\%$, $\bar{\delta} = 8.69\%$.

Thus, Equations 5 can be used to determine average surface roughness for arbitrarily chosen values of cutting parameters.

It should also be noted that the non-linear (quadratic) mathematical model does not guarantee a better prediction than the above-mentioned quasi-linear regression Equation 5a.

## Conclusion

This study presents the Taguchi method for optimization of surface roughness in dry single-point turning of an alloy steel using coated tungsten carbide inserts.

On the basis of the experimental results and derived analysis, one can conclude that cutting speed has the most dominant effect on the observed surface roughness, followed by feed rate and depth of cut, whose influences on surface roughness are smaller. The surface roughness is continuously improved with the increase in cutting speed, but increase in feed rate and depth of cut causes a significant deterioration of surface roughness.

The results obtained using the Taguchi optimization method revealed that cutting speed should be kept at the highest level, while both feed rate and depth of cut should be kept at the lowest level.

The response graphs and ANOVA results show that the effects of two-way interactions of these cutting parameters are statistically insignificant, that is, can be neglected.

As shown in this study, the Taguchi method provides a systematic, efficient and easy-to-use approach for the cutting process optimization.

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