The Iraqi Journal For Mechanical And Material Engineering, Vol.15, No3, 2015

OPTIMIZATION AND PREDICTION OF THE OPTIMAL CUTTING CONDITIONS AFFECTING THE SURFACE ROUGHNESS OF HIGH CARBON ALLOY STEEL

Hussam Lefta Alwan*   Baraa Mohsen Hossien*   Osama sultan Muhammed*
hulefta76@yahoo.com
*Production Engineering and Metallurgy Department, University of Technology, Baghdad-Iraq.

ABSTRACT

In this research, optimization of turning cutting conditions and prediction of surface roughness has been satisfactorily accomplished. Taguchi method was applied and second – order mathematical model used for prediction has been developed. Standard L_9 Taguchi orthogonal array, S/N ratio through using the quality characteristic 'the-lower-the-better', and ANOVA technique were all adopted to determine the optimum cutting parameters and the more significant factor among them. The parameters that have considered are Spindle speed *S*, feed rate *f*, and depth of cut *a*. Nine specimens were machined according to the levels of parameters, and surface roughness (Ra) values were measured three times for each experiment. The optimum conditions obtained were 1200 rpm spindle speed, 0.12 mm/rev feed rate, and 0.7 mm depth of cut. Among them, the more significant factor is feed rate followed by spindle speed and depth of cut respectively. Based on the results of prediction by the second – order model, it can be concluded that it is a very appropriate to predict the surface roughness of high carbon steel. Confirmation results showed that the predicted values and measured values were dramatically close. This indicates that the Taguchi method and multiple regression can be effectively used to optimize and predict the surface roughness such that the coefficient of determination was found to be 99.82 % with average error not exceed 1.12 %.

Keywords: Turning, Surface Roughness, Taguchi method, Optimization, Prediction, Multiple regression.

.

الامثلية والتنبؤ بظروف القطع المثلى المؤثرة على الخشونة السطحية لفولاذ سبائكي عالي الكاربون

حسام لفتة علوان   براء محسن حسين   اسامة سلطان محمد

الخلاصة

تم في هذا البحث انجاز الامثلية لظروف القطع لعملية الخراطة والتنبؤ بالخشونة السطحية بصورة مرضية. حيث تم تطبيق طريقة تاكوجي وكذلك تم بناء موديل رياضي من الدرجة الثانية للتنبؤ بالخشونة السطحية. تم استخدام مصفوفة تاكوجي القياسية من النوع L_9 ونسبة الاشارة الى الضوضاء من خلال استخدام الخاصية "كلما كان اصغر – كلما كان افضل" وتقنية تحليل التباين لتحديد ظروف القطع المثلى والعامل الاكثر تاثيرا من بينهم. المتغيرات التي تم اعتبارها هي سرعة الدوران *S*، معدل التغذية *f*، وعمق القطع *a*. تم تشغيل تسع عينات حسب مستويات المتغيرات، وتم قياس الخشونة السطحية (Ra) بثلاث قراءات لكل تجربة. الظروف المثلى التي تم الحصول عليها كانت عند سرعة دوران 1200 دورة بالدقيقة و معدل تغذية مقداره 0.12 ملم/دورة و عمق قطع مقداره 0.7 ملم. من بين المتغيرات، كان

العامل الاكثر تاثيرا هو معدل التغذية ومن ثم سرعة الدوران ومن ثم عمق القطع على التوالي. بناءا على نتائج التنبؤ لموديل الدرجة الثانية فانه يمكن الاستنتاج بانه من المناسب جدا التنبؤ بالخشونة السطحية للفولاذ عالي الكاربون. اظهرت نتائج التاكد بان القيم المتنبأ بها والقيم التجريبية كانت متقاربة جدا. وهذا يشير الى ان طريقة تاكوجي والانحدار المتعدد يمكن استخدامها بصورة فعالة لايجاد الامثلية والتنبؤ بالخشونة السطحية بحيث ان معامل تحديد التنبؤ كان % 99.82 مع معدل خطأ لا يتجاوز % 1.12.

1. INTRODUCTION

Surface Roughness (SR) is considered as one of the most important indications to specify the quality of machined parts, since the demand for high quality and fully automated production focuses attention on the surface condition of the product, especially the roughness of the machined surface, because of its effect on product appearance, function, and reliability (Abdulkareem S. et al, 2011 and Hayajneh M.T. et al, 2007). In machining operation, the quality of surface finish is an important requirement for a lot of turned parts. Thus, the choice of cutting parameters is very important for controlling the required surface quality. Therefore, the surface roughness will be optimized if the appropriate cutting conditions are selected. The selection of cutting parameters is not that easy task, so the optimization of cutting conditions selection will lead to reduction in production cost, reduction in production time, and improvement of the product quality (Mahdavinejad R.A. and Bidgoli H.S., 2009 and Thamizhmanii S. et al, 2007).

Taguchi method is a powerful tool for the design of high quality systems. It provides simple, efficient and systematic approach to optimize designs for performance, quality and cost. Taguchi method is especially suitable for industrial use, and it employs a special design of orthogonal array to investigate the effects of the entire machining parameters through the small number of experiments (Thamizhmanii S. et al, 2007 and Suhail A.H. et al, 2010). Each factor of the cutting parameters may have so many levels, and so a plenty of experiments will be needed. To achieve all these experiments, this demands much cost and time, so using of the orthogonal array (OA) of Taguchi method leads to reduce cost and time of implementing tests by decreasing the number of experiments according to the orthogonal array.

By applying the Taguchi technique, the time required for experimental investigations can be significantly reduced, as it is effective in the investigation of the effects of multiple factors on performance as well as to study the influence of individual factors to determine which factor has more influence (Suhail A.H. et al, 2010 and Fong T.Y., 2006).

A number of authors have researched on surface roughness with respect to machining parameters. Nalbant M. et al (2007) had used the Taguchi technique to determine the optimal cutting parameters for surface roughness in turning of AISI 1030 steel with TiN coated inserts. Three cutting parameters, insert radius, feed rate, and depth of cut, are optimized for minimum surface roughness. SINGH H. and KUMAR P. (2006) had studied obtaining of the optimal setting of turning process parameters (cutting speed, feed rate and depth of cut) resulting in an optimal value of the feed force when machining EN24 steel with TiC-coated tungsten carbide inserts. The effects of the selected turning process parameters on feed force and the subsequent optimal settings of the parameters have been accomplished using Taguchi's parameter design approach. Their results indicated that the selected process parameters significantly affect the selected machining characteristics. The results are confirmed by further experiments. Ihan Asiltürk and Akkus Harun (2011) conducted an optimization study by machining a hardened AISI 4140 (51 HRC) with coated carbide cutting tools. The statistical methods of signal to noise ratio (SNR) and the analysis of variance (ANOVA) are applied to investigate effects of cutting speed, feed rate and depth of cut on surface roughness. Results of their study indicated that the feed rate has the most significant effect on Ra and Rz. In addition, the effects of two factor interactions of the feed rate-cutting speed and depth of cut-cutting speed appear to be important. In the study of Adem Çiçek et.al (2012), the effects of deep cryogenic treatment and drilling parameters on surface roughness and roundness error were investigated in drilling of AISI 316 austenitic stainless steel with M35 HSS twist drills by using Taguchi technique.

The aim of the present research is to study the effect of the basic cutting condition factors, namely; spindle speed, feed rate, and depth of cut on the surface roughness of the high carbon alloy steel turned parts to optimize and predict the surface roughness by using Taguchi method and multiple regression.

2. MATERIAL AND CONDITIONS

In this work, high carbon alloy steel was chosen as a work piece material. The experimental tests were carried out on a traditional turning machine Harrison M300. Also, the experiments had been conducted under dry condition. The carbide insert with designation DNMG 443-15 having 1.2 mm nose radius was used as a cutting tool material. The average surface roughness (Ra) was measured using Pocket Surf III device. Three readings of Ra were taken for each experiment, and the arithmetic mean of these three values was calculated.

Three essential cutting parameters (spindle speed *S*, feed rate *f*, and depth of cut *a*) with three levels for each, were considered to optimize and predict the surface roughness. These parameters and their levels are shown in **Table 1**.

3. EXPERIMENTAL DESIGN

The traditional experimental design methods are too complex and difficult to use, and they also require large numbers of experiments to be carried out when the number of machining parameters increase (Ihan Asiltürk and Harun Akkuş, 2011 and Marinković Velibor and Madić Miloš, 2011). Therefore, the need for decreasing the number of experiments, which in turn leads to decrease the cost and the effort, is becoming a necessary demand. For that reason, Taguchi method, that is an experimental design technique, is useful in reducing the number of experiments by using orthogonal arrays (Ihan Asiltürk and Harun Akkuş 2011). Thus, for three parameters and three levels for each parameter used in this study, Taguchi orthogonal array L_9 (3^3) with nine rows had been selected. **Table 2** shows the standard Taguchi's L_9 orthogonal array.

There are three types of quality characteristic S/N ratio, such as 'the lower - the - better', 'the higher - the - better', and 'the nominal - the - better'. Since the surface roughness should be as minimum as possible, the quality characteristic 'the lower - the - better' has been used; it is calculated as follows (Ihan Asiltürk and Süleyman Neşelib, 2012):

$$ {}^{S}/_{N} = -10\log\left[\frac{1}{n}\left(y_1^2 + y_2^2 + \cdots y_n^2\right)\right] \qquad (1)$$

Where $(y_1^2 + y_2^2 + \cdots y_n^2)$ are the responses (Ra) of the machining characteristic for each experiment. In this study, the machining characteristic is the surface roughness Ra which is repeated three times (n=3). For all the 27 readings, the S/N ratios were calculated and their values along with the results of the experimental surface roughness values are reported in **Table 3**.

4. ANALYSIS OF MEANS (ANOM)

ANOM is the process of estimating the factor effects. Depending on the results of analysis of mean, optimum combination of the cutting parameters can be specified (D. Lazarević et al, 2012). The factor means effects have been analyzed according to signal to-noise ratio as well as to the response. **Tables 4** and **5** show the results of the average values for both S/N ratio and Ra. The average was calculated at each level for a factor. The level that corresponds to the highest S/N ratio value and lowest value of the mean of Ra should be chosen to be the optimum level. Therefore, the level combination of three factors that agrees with these principles is $A_3B_1C_2$, which equivalent to spindle speed of 1200 rpm, feed rate of 0.12 mm/rev, and depth of cut of 0.7mm.

The results of ANOM have been graphically represented in **Fig. 1** and **Fig. 2**. It can be seen from **Fig. 1** that the feed rate has a continuous negative relationship with the S/N results, while it has a continuous positive relationship with the mean of Ra as shown in **Fig. 2**. And this is true, since lower feed rate can make an overlapping action which will concentrate machining over very small distance of the work piece and thereby decreasing the surface roughness.

5. ANALYSIS OF VARIANCE (ANOVA)

ANOVA is widely used in the design of experiment. The purpose of analysis is to investigate the factors that affect the quality characteristics significantly (Sang-Heon Lim et al, 2006). The results of analysis of variance are summarized in **Table 6**. About the calculations of determining the terms placed in ANOVA table, it can refer to the reference (Kompan Chomsamutr and Somkiat Jongprasithporn, 2010). Based on the results shown in the table, it can be seen that the feed rate has the highest contribution of 74.124 %. This emphasizes that the feed rate has the significant effect on the process. The second factor in affecting the surface roughness is the spindle speed with contribution of 15.334 % followed by the depth of cut with contribution of 10.413 %. These results have proved the results of ANOM.

6. MULTIPLE REGRESSION ANALYSIS.

Multiple regression is a statistical technique that determines the correlation between independent and dependent variables (Ihan Asiltürk, 2012). Considering the experimental values of surface roughness as output, and cutting parameters as inputs, the second order (quadratic) model can be used to express the relationship between the output, dependent variable, Ra, and inputs, independent variables, *S*, *f* and *a* (M. Cemal Cakir et al, 2009). This model is expressed as follows (Ihan Asiltürk, 2012):

$$\tilde{R}a = \beta_0 + \beta_1.S + \beta_2.f + \beta_3.a + \beta_4.S^2 + \beta_5.f^2 + \beta_6.a^2 + \beta_7.V.f \qquad (2)$$

$$+ \beta_8.V.a + \beta_9.f.a$$

where:

$\tilde{R}a$: The value of the dependent variable (the predicted surface roughness).

S: Spindle Speed.

f: Feed Rate.

a: Depth of Cut.

β_0: The regression constant.

$\beta_1,\ldots\ \beta_9$: The coefficients of regression model for three independent variables with their squares and interactions.

By using Matlab R2011a, and by the input and output data reported in **Table 3**, the unknown coefficients of the regression model can be estimated, and the equation will be written as:

$$\tilde{R}a = 0.4074 + 0.0114\,S + 8.0242\,f - 10.78\,a - 0.00619\,S^2 - 0.0\,f^2 \qquad (3)$$

$$+ 6.3547\,a^2 - 0.00405\,S.f + 0.0012\,S.a + 3.8515\,f.a$$

The predicted values ($\tilde{R}a$) producing of applying **eq. (3)** and the experimental values (Ra) were represented in **Fig. 3** with the fitting between them.

To present the potential of multiple regression, second – order, model described in **eq. (3)**, the coefficient of determination, R^2, has been determined. The coefficient of determination is widely used as a measure of fit for regression model (Ken Black, 2013). The equations used for computing R^2 can be established below (Ken Black, 2013):

$$R^2 = 1 - \frac{SS_E}{SS_{yy}} \qquad (4)$$

where

SS_E: The sum of squares of error. It is calculated as follows:

$$SS_E = \sum (y - \tilde{y})^2 \qquad (5)$$

where y: The actual value (in this study y = Ra)

$\tilde{y}$: The predicted value ($\tilde{y} = \tilde{R}a$).

SS_{yy}: the sum of squares of dependent variable.

The dependent variable, Ra, being predicted in a regression model has a variation which is measured by SS_{yy}, depending on the following equation:

$$SS_{yy} = \sum (y - \bar{y})^2 \qquad (6)$$

Or by using the terms used in this work, this equation can be written as:

$$SS_{Ra} = \sum (Ra - \bar{R}a)^2 = \sum Ra^2 - \frac{\left(\sum Ra\right)^2}{n} \qquad (7)$$

where

$\bar{R}a$: The mean of surface roughness which equals to $((Ra_1 + Ra_2 + \ldots + Ra_n) / n)$

n: The number of trails (n = 9)

After substituting all the equations described above, the R2 was found to be (0.9982 or 99.82%).

Also, the mean absolute percentage error MAPE has been calculated from the equation shown below (Ihan Asiltürk, 2012):

$$MAPE = \frac{1}{n}\sum_{i}^{n}\left|\frac{Ra_i - \tilde{R}a_i}{Ra_i}\right| \times 100 \qquad (8)$$

where i = 1, 2, ..., n
The results of prediction of surface roughness along with the experimental values are showed in Table 7 with their residuals that represent the differences between the experimental values of surface roughness Ra and the predicted values, $\tilde{R}a$. Also, the results of applying eq. (8) for each trail, and the average of all of them are shown in the same table.

From the results of **Table 7**, it is clear that the values of predicted $\tilde{R}a$ are very close to those of the experimental Ra, since the differences or residuals between each one of them is so small. Thus, the average error percentage was so small too. According to these results, it can be said that the developed regression model is excellent in prediction the surface roughness.

7. CONFIRMATION TEST

The final step of the Taguchi method is the confirmation test for examining the quality characteristic and validating of the optimized condition (Adem Çiçek et al, 2012 and Nilrudra Mandal et al, 2011). The optimal levels of factor process design, obtained by analysis of S/N ratio and by the main effect of surface roughness shown in **Tables 4** and **5**, will be used to develop the confirmation experiment. The confirmation test can be applied using the regression model presented in **eq. (3)** and another model called predicted optimum surface roughness, which is computed as follows (Adem Çiçek et al, 2012 and Nilrudra Mandal et al, 2011):

$$Ra_{opt.} = \overline{Ra}_{Total} + (A_3 - \overline{Ra}_{Total}) + (B_1 - \overline{Ra}_{Total}) + (C_2 - \overline{Ra}_{Total}) \qquad (9)$$

Where $\overline{Ra}_{Total}$ is the total average of surface roughness (corresponding to all (9 x 3 = 27) readings in **Table 3**). A_3, B_1, and C_2 are the average values of the surface roughness Ra at the optimum levels of the process parameters spindle speed, feed rate, and depth of cut. This model depends directly on the resulted optimum conditions of cutting parameters and the total average of Ra ($\overline{Ra}_{Total}$). The $Ra_{opt.}$ represents the optimum predicted mean value of the surface roughness at optimum condition.

The optimum combination was found to be at levels: A_3, B_1, and C_2. The calculated value of total average Ra was ($\overline{Ra}_{Total} = 3.237\ \mu m$), and the optimum levels are ($A_3 = 2.731\ \mu m$), ($B_1 = 2.320\ \mu m$), and ($C_2 = 2.776\ \mu m$) respectively. By substituting these values in **eq. (9)**, the optimum predicted mean value of the surface roughness was found to be ($Ra_{opt.} = 1.353\ \mu m$).

Also, the confidence interval has been calculated to reveal the reliability of optimization. It was calculated by the equation below (Adem Çiçek et al, 2012 and Nilrudra Mandal et al, 2011), assuming that the reliability of the confidence interval is 95 %.

$$CI = \sqrt{F_{(\alpha,1,f_e)} * V_e * \left(\frac{1}{N_{eff}} + \frac{1}{r}\right)} \qquad (10)$$

If the reliability of the condition is assumed to be 95%, then the confidence interval can be given by using the following equation (Adem Çiçek et al, 2012 and Nilrudra Mandal et al, 2011):

$$N_{eff} = \frac{N}{1 + T_{dof}} \qquad (11)$$

Where $F_{(\alpha,1,f_e)}$ is the F-ratio of significant level α, f_e is the degree of freedom of error = 20 (taken into consideration the all number of experiments 27), V_e is the error variance = 0.0341 (from ANOVA table 6), N_{eff} is the number of effective measured results, N is the total number of experiments = 27 (9 x 3), T_{dof} is the total degrees of freedom associated with optimum factor considering in determining the mean optimum characteristic = 6 (2 degrees of freedom for each effected factor *S*, *f*, and *a*), and r is the number of replications for confirmation experiment. In this study, three confirmation trails using the optimum levels ($A_3B_1C_2$) were carried out to verify the matching between the predicted and actual surface roughness. From F – standard table (Ken Black, 2013), the $F_{(0.05,1,20)} = 4.35$. Therefore, substituting the values in **eq. (10)** and **eq. (11)**, the confidence interval is ($CI = \pm 0.2965$). Hence, 95% confidence interval will lead to predict surface roughness to be ($Ra_{opt.} \pm CI$) by using **eq. (9)** and $\tilde{R}a \pm CI$ when using **eq. (3)**. Consequently, the confirmation output should be $1.053 < Ra_{opt.} < 1.647$ and $1.275 < \tilde{R}a < 1.868$. In terms of the optimum levels ($A_3B_1C_2$), three experiments were carried out to confirm the results obtained from the prediction. The measurements of these experiments are supposed to be in between the limits [1.053, 1.868] μm. The three measurements of surface roughness were 1.537, 1.391, and 1.746 respectively. **Table 8** summaries the results of confirmation experiment.

In general, it can be said that the prediction was successful in obtaining satisfactorily results for the surface roughness. Also, in most literatures the model of **eq. (9)** is used widely in prediction along with the confidence interval, while, in this study the model of **eq. (3)** was used in addition to the model of **eq. (9)**. This is to increase the reliability of prediction the surface roughness. It can be seen clearly that the limits with using **eq. (3)** is wider than that of **eq. (9)**, and it seems close to the average of experimental values of confirmation test as shown in **Table 8**. Since that may be true where there are some other cutting conditions were not considered in this study.

8. CONCLUSIONS

The results of optimization and prediction, by using Taguchi method and multiple regression model of turning high carbon alloy steel, have showed a very good matching between the experimental and predicted values. Depending on the results of this work, the following points can be drawn:

- According on the analysis the means of both signal - to - noise ratios (S/N) using the lower-the-better and surface roughness Ra, the best optimum condition of the three independent factors or parameters is $A_3B_1C_2$. That is, spindle speed of 1200 rpm, feed rate of 0.12 mm/rev, and depth of cut of 0.7 mm.
- Depending on ANOVA summary, all the process parameters were significant, but the more significant parameter was feed rate with contribution of 74.124 % followed by spindle speed with contribution of 15.334 %. Finally, the depth of cut with contribution of 10.413 %.

- The results of applying the multiple regression, second – order, model showed that the quadratic model has an excellent prediction with coefficient of determination of R^2 = 99.82 % and coefficient of correlation of R = 0.999. This indicates that the predicated values by the developed model were a very close to the actual values such that the average error MAPE equals to 1.12 %.
- The optimized value of surface roughness, by using 95% confidence interval, was predicted to be 1.353 ± 0.2965 µm based on optimum process parameter level (**eq. (9)**), while depending on regression model, the optimized Ra was predicted to be 1.572 ± 0.2965. Also, in terms of the optimum condition, the result of experimental test of confirmation using three replications was 1.558 µm, which lies between the limits of [1.053, 1.868] µm.

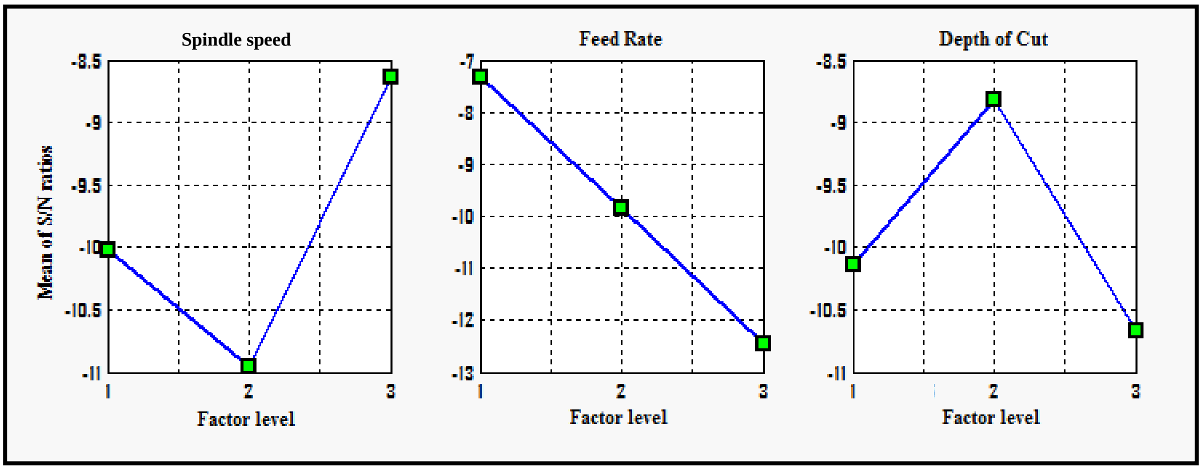

Fig. 1: The plot of mean of S/N ratio with Factor's levels.

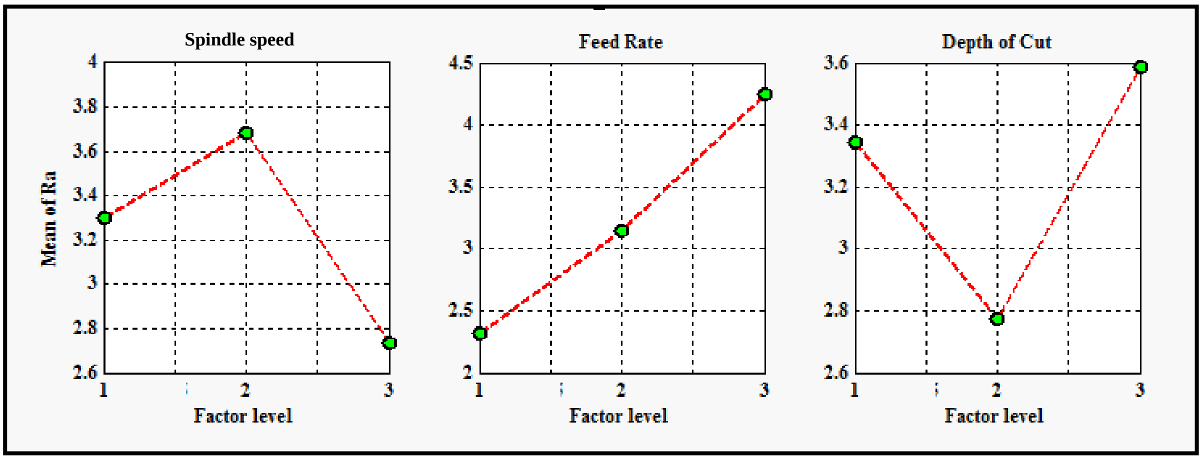

Fig. 2: The plot of mean of Ra with factor's levels.

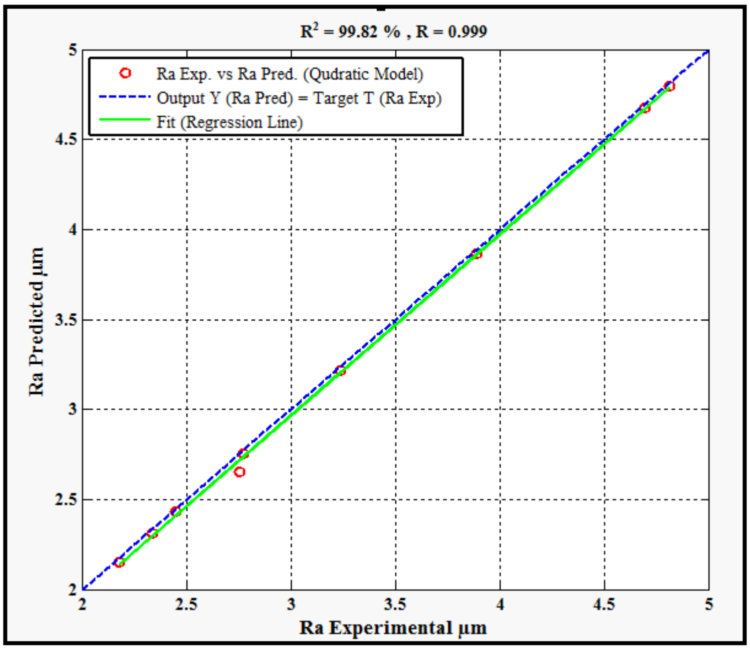

Fig. 3: Fitting between experimental and prediction Ra.

Table 1: Cutting parameters and their levels

Parameter or Factor	Unit	Symbol	Factor levels		
			Level 1	Level 2	Level 3
Spindle Speed (*S*)	rpm	A	540	800	1200
Feed Rate (*f*)	mm/rev	B	0.12	0.25	0.40
Depth of Cut (*a*)	mm	C	0.4	0.7	1.0

Table 2: Standard Taguchi's orthogonal array L_9 (Domnita Fratila and C. Caizar, 2011).

Experiment no.	A	B	C	Ra		
				R_1	R_2	R_3
1	1	1	1	$T_{1,1}$	$T_{1,2}$	$T_{1,3}$
2	1	2	2	$T_{2,1}$	$T_{2,2}$	$T_{2,3}$
3	1	3	3	$T_{3,1}$	$T_{3,2}$	$T_{3,3}$
4	2	1	2	$T_{4,1}$	$T_{4,2}$	$T_{4,3}$
5	2	2	3	$T_{5,1}$	$T_{5,2}$	$T_{5,3}$
6	2	3	1	$T_{6,1}$	$T_{6,2}$	$T_{6,3}$
7	3	1	3	$T_{7,1}$	$T_{7,2}$	$T_{7,3}$
8	3	2	1	$T_{8,1}$	$T_{8,2}$	$T_{8,3}$
9	3	3	2	$T_{9,1}$	$T_{9,2}$	$T_{9,3}$

A, B, and C are the parameters.
Ra is the surface roughness repeated three times R_1, R_2, and R_3.

Table 3: Experimental results and S/N calculated values

Exp. No.	Combinations			Surface Roughness (Ra µm)			Average (Ra) (µm)	S/N ratio (dB)
	A	B	C					
	Spindle Speed (rpm)	Feed Rate (mm/rev)	Depth of Cut (mm)	First reading R_1	Second reading R_2	Third reading R_3		
1	540	0.12	0.4	2.516	2.121	2.707	2.448	-7.819
2	540	0.25	0.7	2.534	3.003	2.721	2.753	-8.816
3	540	0.40	1.0	4.727	4.559	4.801	4.696	-13.436
4	800	0.12	0.7	2.487	2.149	2.371	2.336	-7.384
5	800	0.25	1.0	3.647	4.109	3.921	3.892	-11.815
6	800	0.40	0.4	4.447	5.129	4.871	4.816	-13.668
7	1200	0.12	1.0	2.023	2.339	2.171	2.178	-6.775
8	1200	0.25	0.4	2.817	2.389	3.121	2.776	-8.918
9	1200	0.40	0.7	3.467	2.909	3.341	3.239	-10.232

Table 4: Mean S/N ratio for each factor level

Factor	Symbol	Average of levels for S/N ratio			Delta Max-Min	Rank
		Level 1	Level 2	Level 3		
Spindle Speed (rpm)	A	-10.024	-10.955	**-8.642**	2.314	2
Feed Rate (mm/rev)	B	**-7.326**	-9.850	-12.445	5.119	**1**
Depth of cut (mm)	C	-10.135	**-8.811**	-10.675	1.865	3

Underlined value represents the optimum level.

Table 5: Mean Surface roughness Ra for each factor level

Factor	Symbol	Average of levels for Ra			Delta Max-Min	Rank
		Level 1	Level 2	Level 3		
Spindle Speed (rpm)	A	3.299	3.681	**2.731**	0.950	2
Feed Rate (mm/rev)	B	**2.320**	3.140	4.250	1.930	**1**
Depth of cut (mm)	C	3.346	**2.776**	3.589	0.813	3

Underlined value represents the optimum level.

Table 6: ANOVA table for Surface roughness Ra

Source	Sumof Squares SS	Degreeof Freedom d.f.	Mean Squares MS	F(value) (MS/error)	Contribution (%)
Spindle Speed	8.1331	2	4.0666	119.16	15.334
Feed Rate	39.314	2	19.657	576.01	74.124
Depth of Cut	5.5228	2	2.7614	80.92	10.413
Error	0.0683	2	0.0341		0.1287
Total	53.0381	8			100

Table 7: Experimental and prediction of Ra and error %

No.	Ra	$\tilde{Ra}$	Residuals (Ra - $\tilde{Ra}$)	Error %
1	2.448	2.4286	0.0194	0.7925
2	2.753	2.6528	0.1002	3.6397
3	4.696	4.6757	0.0203	0.4323
4	2.336	2.3107	0.0253	1.0830
5	3.892	3.866	0.026	0.6680
6	4.816	4.7928	0.0232	0.4817
7	2.178	2.1489	0.0291	1.3361
8	2.776	2.7511	0.0249	0.8970
9	3.239	3.2132	0.0258	0.7965
Average				1.12 %

Table 8: Confirmation experiment and prediction comparison

Machining characteristic	Best initial combination	Confirmation results		
		Experimental	Predication (Equation 9)	Predication (Regression model)
	S = 1200 rpm *f*= 0.12 mm/rev, *a*= 1.0mm	Optimum process parameter Level *S*= 1200rpm, *f*= 0.12mm/rev, *a*= 0.7mm		
	$A_3B_1C_3$	$A_3B_1C_2$	$A_3B_1C_2$	$A_3B_1C_2$
Ra (µm)	2.178	1.558	1.353	1.572
S/N (dB)	-6.761	-3.851	-2.626	-3.929

REFERENCES :-

Abdulkareem S., Rumah U.J., Adaokoma A., (2011), Optimizing Machining Parameters during Turning Process, *International Journal of Integrated Engineering*, Vol.3, No.1, pp. 23-27.

Adem Çiçek, Turgary Kıvak and Samtaş G., (2012), Application of Taguchi Method for Surface Roughness and Roundness Error in Drilling of AISI 316 Stainless Steel, *Journal of Mechanical Engineering*, Vol. 58, No. 3, pp.165-174.

D. Lazarević, M. Madić, P. Janković and A. Lazarević, (2012), Cutting Parameters Optimization for Surface Roughness in Turning Operation of Polyethylene (PE) Using Taguchi Method, *Tribology in Industry*, Vol. 34, No. 2, pp. 68-73.

Domnita Fratila and C. Caizar, (2011), Application of Taguchi method to selection of optimal lubrication and cutting conditions in face milling of AlMg3, *Journal of Cleaner Production*, Vol. 19, Issues 6–7, pp. 640–645.

Fong T.Y., (2006), Parameter design optimization of computerized numerical control turning tool steels for high dimensional precision and accuracy, *Materials and Design*, Vol. 27, pp. 665–675.

Hayajneh M.T., Tahat M.S., Bluhm J., (2007), A Study of the Effects of Machining Parameters on the Surface Roughness in the End-Milling Process, *Jordan Journal of Mechanical and Industrial Engineering*, Vol.1, No.1, pp.1 – 5.

Ihan Asiltürk and Akkus Harun, (2011), Determining the effect of cutting parameters on surface roughness in hard turning using the Taguchi method, *Measurement*, Vol. 44, pp.1697–1704.
Ihan Asiltürk and Harun Akkuş, (2011), Determining the effect of cutting parameters on surface roughness in hard turning using the Taguchi method, *Journal of Measurement*, Vol. 44, Issue: 9, pp. 1697-1704.

Ihan Asiltürk, (2012), Predicting surface roughness of hardened AISI 1040 based on cutting parameters using neural networks and multiple regression, *International Journal of Advanced Manufacturing Technology*, Vol. 63 Issue: 1, pp. 249-257.

Ihan Asiltürk and Süleyman Neşelib, (2012), Multi response optimization of CNC Turning Parameters via Taguchi Method-Based Response Surface Analysis, *Journal of Measurement*, Vol. 45, Issue: 4, pp. 785-794.

Ken Black, (2013), Applied Business Statistics, 7th edition, *John Wiley and Sons, Inc*.

Kompan Chomsamutr and Somkiat Jongprasithporn, (2010), The Cutting for Product Quality Improvement in Turning Operations: Optimization and Validation with Taguchi Method, *Journal: The 40th International Conference on Computers & amp; Indutrial Engineering*, Pages: 1-6.

M. Cemal Cakir, Cihat Ensarioglu and Ilker Demirayak, (2009), Mathematical modeling of surface roughness for evaluating the effects of cutting parameters and coating material, *Journal of Materials Processing Technology*, Vol. 209, Issue 1, pp. 102–109.

Mahdavinejad R.A. and Bidgoli H.S., (2009), Optimization of surface roughness parameters in dry turning, *Journal of Achievements in Materials and Manufacturing Engineering*, Vol. 37, Issue 2, pp.571-577.

Marinković Velibor and Madić Miloš, (2011), Optimization of surface roughness in turning alloy steel by using Taguchi method, *Scientific Research and Essays*, Vol. 6 (16), pp. 3474-3484.

Nalbant M., Gokkaya H., Sur G, (2007), Application of Taguchi method in the optimization of cutting parameters for surface roughness in turning, *Materials and Design*, Vol. 28, pp. 1379-1385.

Nilrudra Mandal, B. Doloi, B. Mondal, Reeta Das, (2011), Optimization of flank wear using Zirconia Toughened Alumina (ZTA) cutting tool: Taguchi method and Regression analysis, *Journal of Measurement*, Vol. 44, Issue: 10, pp.2149-2155.

Sang-Heon Lim, Choon-Man Lee and Won Jee Chung, (2006), A Study On The Optimal Cutting Condition of a High Speed Feeding Type Laser Cutting Machine by

Using Taguchi Method, *International Journal of Precision Engineering and Manufacturing*, Vol. 7, (1), Pages: 18-23.

SINGH H., KUMAR P., (2006), Optimizing feed force for turned parts through the Taguchi technique, *Sadhana*, Vol.31, Part 6, pp. 671–681.

Suhail A.H., Ismail N., Wong S.V., Abdul Jalil N.A., (2010), Optimization of Cutting Parameters Based on Surface Roughness and Assistance of Workpiece Surface Temperature in Turning Process, *American J. of Engineering and Applied Sciences*, Vol. 3, No. 1, pp. 102-108.

Thamizhmanii S., Saparudin S., Hasan S., (2007), Analyses of surface roughness by turning process using Taguchi method, *Journal of Achievements in Materials and Manufacturing Engineering*, Vol.20, Issues 1-2, pp.503-506.