Applied Mathematics & Information Sciences
An International Journal

http://dx.doi.org/10.18576/amis/110227

Statistical Analysis of Surface Roughness in Hard Turning: An Optimization Approach

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Received: 98 Dec. 2016, Revised: 26 Jan. 2017, Accepted: 28 Jan. 2017
Published online: 1 Mar. 2017

Abstract: In this work, the cuttings parameters are varied to analyse the roughness of machined surface statistically during the course of hard turning of AISI 4140 steel when heat treated to 47 HRC. It uses CVD coated Ti(C, N) + Al_2O_3 carbide as cutting tool. The analysis is done on the basis of Response Surface Methodology (RSM) framed according to the design of experiments. The parameter that has the impact over roughness is measured in terms of analysis of variance. The regression and Artificial Neural Network (ANN) model to predict roughness in terms of cutting parameters are found out based on experimental data. The optimal cutting conditions to reduce roughness are also found using Response Surface Methodology (RSM). It is found out that feed rate is the most influencing parameter followed by cutting speed. The ANN model prediction ability is higher when compared to regression model.

Keywords: Analysis of variance, design of experiments, regression, ANN, response surface methodology

1 Introduction

Hardened AISI 4140 steels are widely employed in automotive, agriculture and defence industries where the problem lies in their finishing mode. Grinding process is the existing method for the purpose of finishing. It can be replaced by hard turning since it is advantageous in terms of cycle time and hazardous fluid reduction, where both soft and hard turning can be performed by the same system. [1,2,3] The cutting tools used in hard turning are CBN and ceramic. [4,5,18,19] Taguchi method was addressed by which roughness and tool wear of hardened AISI 4140 steel can be determined using Al2O3 +TiCN ceramic tools. By employing CBN, [6], formulated the hardness effect and the cutting factors that acts upon cutting forces and roughness, where X38CrMoV5-1(50HRC) steel is the material used. [7] Alike to the previous referred article, the cutting factors and harness that have the impact over AISI H11 heat treated steel are reviewed using CBN. The test procedures conducted were on the basis of RSM. [8] made the investigation over the effect of cutting factors using RSM in terms of tool wear and roughness. The sample material is the heat treated AISI4140 steel. The inserts used was coated ceramic inserts. The optimal cutting conditions and the economic viability of the inserts were also studied. [9] compared the tool life between CBN and ceramic cutting tools. The bearing steel was the work piece where the experiments were conducted on the basis of Taguchi method. The factor that affects the tool life was proved to be the cutting velocity in which the tool life of CBN was found to be better. Formulations were proposed by [10], stating how much that the hardness and spindle speed impact over surface roughness (R_a) in AISI 4140 hard turning by adopting CBN tool, that it incorporates ANOVA and ANN in modelling the regression model and surface roughness accordingly.

Even though CBN and ceramic give better performance, they are very expensive. The coated carbide is seen as a substitute in the hardness ranges 45-55 HRC, which has many industrial applications. Many authors have used the coated carbide during hard turning of heat treated steel.

[11] found out that in hard turning, carbide tools with HiPIMS coating enhanced tool life of AISI 4340 steel (55 HRC) machining. [12] While hard turning of AISI 4340 steel (47 HRC), a comparison of tool life in coated versus uncoated carbide inserts was done, where cutting forces, surface roughness, flank wear and chip structure are the parameters taken into consideration. In concerning

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performance, multilayered coated carbide inserts was far better than the uncoated carbide inserts. In [13], optimization of cutting parameters and techno economic review was conducted based on RSM and Grey relational analysis. [14] Hard turning of AISI 4340 steel (48 HRC) was performed, by employing multilayered CVD coated TiN/TiCN/Al2O3 cemented carbide, and thereby the states for lower cutting force and surface roughness were analysed.

From the referred articles, it is observed that most of the statistical analysis on the hard turning which has wide industrial applications is limited to the expensive CBN or ceramic tools. The investigations using less expensive coated carbide tool is limited to machinability study and very few formulations are carried out on the statistical aspects. In such context a detailed statistical analysis on surface roughness using less expensive coated carbide steel during the hard turning of AISI4140 steel are carried out. Along with regression and ANN models to predict the roughness by means of cutting parameters, optimal cutting conditions to determine minimal roughness are also formulated.

2 Design of Experiments (DOE)

DOE is the referred to be the scientific way to conduct any sort of experiments to fulfill the objectives and the procedures employed in them are as follows.

2.1 Factor and level selection

To design the regression equation, depth of cut (d), cutting speed (V) and feed rate (f) are the chosen parameters. Table 1 shows the selected levels.

Table 1: Selected levels

Level	Cutting speed(m/min)	Feed(mm/rev)	Depth of cut(mm)
1	70	0.08	0.3
2	120	0.1	0.45
3	170	0.12	0.6

2.2 Response variable measurement

The response variable considered is the roughness (R_a) of the machined surface which is assessed by means of surface roughness using mitutoyo make (SJ-210). R_a is determined by the equation,

$$R_a = \frac{1}{l}\int_0^1 |f(x)|dx \tag{1}$$

where l is the length considered and f(x) is the roughness profile function.

2.3 Experimental design

Design is based on RSM, i.e. the central composite design where the numeric factors differ by three levels namely -1, 0, and +1. In order to maintain rotatability, the value of α is calculated by the equation,

$$\alpha = [number\ of\ factors]^{\frac{1}{4}} \tag{2}$$

If the design factor equals three, then the value of is 1.68179. Total number of experimental runs required for the central composite design is less and for three factors, 20 experimental runs are conducted. Table 2 includes the details of machining parameters and its corresponding response.

2.4 Experimental analysis

The material used for investigation is AISI4140 hardened to 47 HRC. The experiments are carried out in an Industrial type Kirloskar lathe having 6.6 KW spindle power. The cutting fluids are not used. ISO designate CNMG120408, CVD coated $Ti(C,N)+Al_2O_3$ durotomic carbide tool (SECO make) is the cutting tool. The nose radius is 0.8mm.The PCLNR2525 M12 of the following specifications is the tool holder: major cutting edge angle = 95^0, back rack angle= -6^0 and negative cutting edge inclination angle= -6^0. The experiments are carried out for fixed lengths of 200mm. The input and output factors are the cutting parameters and the roughness, where the observed values are given in Table 2.

3 Analysis of variance (ANOVA)

ANOVA determines the most influencing cutting variables on roughness [17]. The following procedure is adopted for ANOVA study and the details are given in Table 4.

To calculate the sum of squares with in a factor, the relation can be,

$$Sum\ of squares = \sum_i k(x_i - \overline{x})^2 \tag{3}$$

where x_i is the factor and $\overline{x}$ is the mean value of factor considered, and k is the number of observation and to calculate the mean square value with in the factor, the following relation is used.

$$Mean\ square = \frac{\sum_i k(x_i - \overline{x})^2}{DOF} \tag{4}$$

where DOF is given as the Degree of Freedom.

$$F - Value = \frac{Mean\ square\ between\ treatments}{Mean\ square\ error} \tag{5}$$

Table 2: Experimental results

Run No.	Machining parameters			Response factor
	V(m/min)	f(mm/rev)	d(mm)	$R_a(\mu m)$
1	120	0.10	0.45	0.788
2	36	0.10	0.45	0.889
3	70	0.12	0.30	1.109
4	170	0.08	0.60	0.412
5	120	0.10	0.45	0.768
6	70	0.08	0.60	0.621
7	170	0.08	0.30	0.397
8	120	0.13	0.45	1.292
9	120	0.10	0.45	0.768
10	120	0.10	0.70	0.769
11	120	0.07	0.45	0.492
12	170	0.12	0.60	0.927
13	120	0.10	0.20	0.759
14	70	0.12	0.60	1.129
15	70	0.08	0.30	0.614
16	120	0.10	0.45	0.770
17	204	0.10	0.45	0.504
18	170	0.12	0.30	0.887
19	120	0.10	0.45	0.778
20	120	0.10	0.45	0.782

4 Design of regression model

On the basis of experimental data, estimation of roughness in AISI4140 steel is done using coated carbide tool while hard turning by employing the designed multiple regression model. Roughness depends on the process parameters, V, f and d, where, R_a is the function of them. Mathematically it can be represented as

$$R_a = \varphi(V, f, d) + \varepsilon \tag{6}$$

where ε is the error observed in response. In RSM a suitable relation between the response and the independent variable are found out using a polynomial (nonlinear quadratic). The obtained equation is the regression equation. The regression equation is formulated based on the following relation

$$y = \beta_0 + \sum_{i}^{k} \beta_i x_i + \sum_{i=1}^{k} \beta_i x_i^2 + \sum\sum_{i<j} x_i x_j + \varepsilon \tag{7}$$

where y is the output (roughness) and X is the input data (V, f, d) β_0 is the constant coefficient, $(\beta_1, ..., \beta_k), (\beta_{11}, ...\beta_{kk})$ and $(\beta_{12}, \beta_{13}, ..)$ are the linear, quadratic and interacting compounds correspondingly. Equation (7) can be denoted as

$$y = X\beta + \varepsilon \tag{8}$$

where

$$y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_k \end{bmatrix}, X = \begin{bmatrix} 1 & x_{11} & x_{12} & \dots & x_{1k} \\ 1 & x_{21} & x_{22} & \dots & x_{2k} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & x_{12} & x_{12} & \dots & x_{12} \end{bmatrix}, \beta = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_k \end{bmatrix},$$

$$\varepsilon = \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_k \end{bmatrix}$$

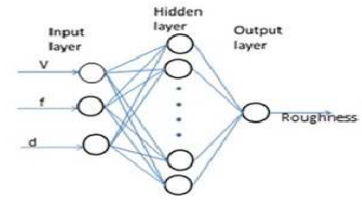

Fig. 1: Feed forward topology

The unknown β matrix is found out using Least-square estimator so that the errors are minimized. The least square estimator of β is found out as $\hat{\beta}$.

$$\hat{\beta} = (X^T X)^{-1} X^T y \tag{9}$$

5 Artificial Neural Network (ANN) model

The accuracy of regression model formulated above is based on the order of the polynomial. It is bit complicated whenever the relations are nonlinear in nature. In such cases artificial neural networks are widely used. The ANN does not take in to account the complex process involved during model formation [16]. It is purely based on the mapping of input and output data. The feed forward neural network topology is widely used one and consists of three layers as in Fig. 1. The output is calculated using the relation

$$Y = w^T x_i + b \tag{10}$$

The network is trained according to Levenberg-Marquardt (LM) back propagation algorithm based on the inputs drawn from experiments. Once the mean square error in relation to the target and network output attains minimum as specified in convergence criteria or based on the maximum iterations(epoch), the training is halted. The MSE (Mean Square Error) is calculated as below.

$$MSE = \frac{1}{N\sum_{i=1}^{k} e(k)^2} \tag{11}$$

Where, N=Total number of epochs (iterations), i=epoch number, e(k)=Error between the network output and the target output.

The input parameters considered here are, V, f and d, where roughness is the output. After the training using LM algorithm, the network finalized is 3-5-1. For this network the training is stopped based on the maximum value of iterations. The MSE plot for this network is shown in Fig. 2.

6 Optimization of cutting conditions

Optimization in RSM is achieved by means of finding the factor level values where the response is at peak or valley.

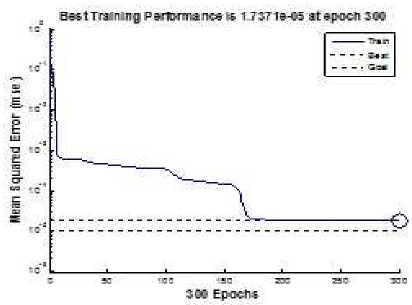

Fig. 2: The MSE plot

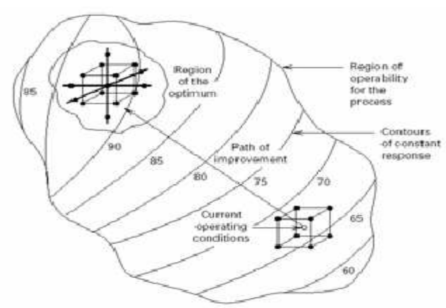

Fig. 3: Optimization using RSM

The sequential nature of RSM is depicted in the Fig. 3 [15]. The goal is to start from the current location to find the optimum spot where the response is at maximum or minimum. Steepest ascent second order model is used for optimization. It is an approach of progressing through the mode of steepest ascent and descent for maximum and minimum response. The second order model is represented by the equation (7).This equation has linear terms, cross product terms and error terms for the input values of x. y is the response. The maximum or minimum response exists at a stationary point where

$$\partial y/\partial x_1 = \partial y/\partial x_2 = ... = \partial y \partial x_k = 0 \tag{12}$$

The obtained stationary point gives values of maxima or minima or saddle point. Neglecting error, and replacing y by $\hat{y}$ the equation (8) can be written as

$$\hat{y} = \hat{\beta}_0 + X^T b + X^T BX \tag{13}$$

where

$$x = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_k \end{bmatrix}, b = \begin{bmatrix} \hat{\beta}_1 \\ \hat{\beta}_2 \\ \vdots \\ \hat{\beta}_k \end{bmatrix}, B = \begin{bmatrix} \hat{\beta}_{11} & \hat{\beta}_{12}/2 \ldots\ldots & \hat{\beta}_{1k}/2 \\ . & \hat{\beta}_{22} \ldots\ldots & \hat{\beta}_{2k}/2 \\ . & . & . \\ . & . & \hat{\beta} \quad kk \end{bmatrix}$$

$$\partial \hat{y}/\partial x = b + 2Bx = 0 \tag{14}$$

The stationary point is given by

$$X_s = -1/2B^{-1}b \tag{15}$$

Substituting the above equation in equation (10), we can find the predicted response.

$$\hat{y}_s = \hat{\beta}_0 + 1/2_{Xs}{}^T b \tag{16}$$

Once the stationary point is obtained, a contour plot of fitted model determines the maxima or maximum condition. Here objective function is to minimize the roughness function given by equation (6). The constraints for the cutting conditions are given in Table 3.

Table 3: Optimization ranges

Variable	Goal	Lower Bound	Upper Bound
V (m/min)	Within	70	170
f (mm/rev)	Within	0.08	0.12
d (mm)	Within	0.3	0.6
Ra (m)	Minimize	0.397	1.292

7 Results and discussion

7.1 ANOVA for RSM

Analyse of variance formulated for roughness based on the data given in Table 2 is given in Table 4.

Table 4: ANOVA for roughness

Factors	Sum of squares	Degree of freedom	Mean Square	F Value	p-value Prob> F	Significance
Model	1.03	9	0.11	383.22	< 0.0001	significant
V	0.16	1	0.16	550.80	< 0.0001	Yes
F	0.82	1	0.82	2762.16	< 0.0001	Yes
D	$7.150x10^{-4}$	1	$7.150x10^{-4}$	2.40	0.1525	No
Vxf	$5.000x10^{-7}$	1	$5.000x10^{-7}$	$1.677x10^{-3}$	0.9681	No
Vxd	$9.800x10^{-5}$	1	$9.800x10^{-5}$	0.33	0.5791	No
Fxd	$1.805x10^{-4}$	1	$1.805x10^{-4}$	0.61	0.4545	No
Residual	$2.98x10^{-3}$	10	$2.98x10^{-4}$			
Total	1.03	19				

Indication of p-value < 0.005 (95% confidence level) means the variable is significant. p-value is calculated based on F-Value. It is evident from Table 4, which the model for roughness is significant where feed contributes more for surface roughness and cutting speed comes next in the order. The factor, depth of cut does not have any influence. The experimental results and this result inference have good correlation. The authors of [8,12] have expressed a similar view.

7.2 Regression model

Based on the experimentation data the coefficients (unknown) are evaluated using the least square estimator

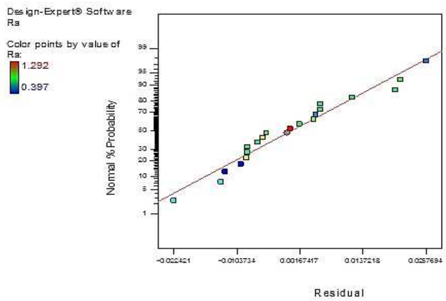

Fig. 4: Normal residual plot

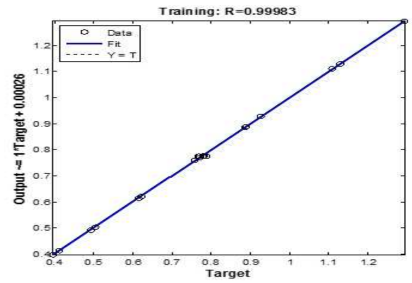

Fig. 5: Overall regression plot

given in equation (9). After deriving the various coefficients, the final regression equation is given by

$$Ra = +0.52915 + +7.18487E - 004 * V - 6.63679 * f + 0.19036 * d + 2.50000E - 004 * V * f + 4.66667E - 004 * V * d + 1.58333 * f * d - 1.31105E - 005 * V^2 + 90.85885 * f^2 + -0.39606 * d^2 \quad (17)$$

Based on the above equation roughness values are predicted. The R^2 value of above model is 98.01%.The R^2 value determines the prediction ability. When R^2 is near to one, the predicted response data fits the measured value. The R^2 value of 0.9801 indicates the regression model is adequate and the occurrence of similarities between the predicted and measured the value is high. The normal probability graph of residual (error) based on equation (17) is shown in Fig. 4.

$$Residual = Measuredvalue - predictedvalue \quad (18)$$

From Fig. 4, it is understood that the residuals are distributed almost nearer to the straight line indicating normal distribution. Then a comparison is made with the predicted values from regression and the experimental outputs and the readings are shown in Table 5. The data drawn from the random cutting conditions confirms the results and the percentage error of the obtained readings from the predicted one are also calculated. Thus the average error of regression model is 5.7925%,

$$Error = \frac{Ra_{Exp} - Ra_{predicted}}{Ra_{Exp}} * 100 \quad (19)$$

where
R_{aExp}=Experimental Roughness
$Ra_{predicted}$=Predicted Roughness

7.3 ANN based prediction

Fig. 5 shows the overall regression plot for ANN based prediction indicating maximum correlation with respect to the predicted and the resulted value. Training with more data can make the prediction ability higher. By comparing the predicted values from ANN and the experimental values, Table 6 is drawn that are confirmed by the data obtained from random cutting conditions. The percentage error that occurred between the estimated and obtained values is analysed, where the mean error of regression model is 3.94%, The ANN model prediction ability is higher compared to the regression.

7.4 Optimal cutting conditions

Optimal conditions for minimizing the roughness are found out based on the data available in Table 7 and constraints given in Table 3. Optimal results obtained for minimization of roughness are shown in Table 7. Integration of higher V (velocity) and lower f (feed) and d (depth of cut) results in minimum roughness. These optimal levels can be considered in hard turning of AISI4140steel.

Table 7: Optimization results for roughness

Number	(V)m/min	(F)mm/rev	(d)mm	$(R_a)\mu m$	Desirability
1	170.00	0.08	0.30	0.409629	0.986
2	169.25	0.08	0.30	0.412297	0.983
3	170.00	0.08	0.35	0.416136	0.979
4	170.00	0.08	0.60	0.421674	0.972
5	170.00	0.08	0.42	0.423047	0.971

8 Conclusion

This work proposes an extensive study on the statistical analysis while hard turning of 47 HRC (AISI4140 steel) by employing less expensive carbide coating. The optimal cutting conditions for minimizing the roughness of machined surface are also suggested. Based on the investigations, it can be concluded that.

Table 5: Validation data and predicted values-regression model

S.No	Input Parameters			Roughness		
				Exp.	**Predicted**	**Error**
	V (m/min)	f (mm/rev)	d (mm)	Ra (m)	Ra (m)	(%)
1	120	0.08	0.30	0.519	0.546	5.20
2	70	0.10	0.30	0.863	0.847	1.85
3	170	0.10	0.30	0.638	0.599	6.11
4	70	0.08	0.45	0.618	0.572	7.44
5	120	0.08	0.45	0.528	0.536	1.52
6	170	0.08	0.45	0.404	0.328	18.81
7	120	0.12	0.60	1.022	1.042	1.96
8	170	0.12	0.60	0.927	0.895	3.45
					Average Error:	5.7925

Table 6: Validation data and predicted values-ANN model

S.No	Input Parameters			Surface Roughness		
				Exp.	**Predicted**	**Error**
	V (m/min)	f (mm/rev)	d (mm)	Ra (m)	Ra (m)	(%)
1	120	0.08	0.3	0.519	0.525	1.17
2	70	0.1	0.3	0.863	0.761	11.82
3	170	0.1	0.30	0.638	0.592	7.21
4	70	0.08	0.45	0.618	0.610	1.29
5	120	0.08	0.45	0.528	0.544	3.03
6	170	0.08	0.45	0.404	0.408	0.99
7	120	0.12	0.6	1.022	1.083	5.97
8	170	0.12	0.6	0.927	0.927	0
					Average Error:	3.94

The factor that impacts more on roughness is the feed (f), followed by velocity (V) where cutting depth (d) does not have influence. The regression model to predict roughness based on cutting factors is found to be vital and the error percentage is 5.79% The ANN prediction model gives superior results, when compared to regression model and the error is as low as 3.94%. The optimal condition reveal f and V of lower and higher values respectively, thus ending in minimum R_a.

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