IJE TRANSACTIONS A: Basics Vol. 26, No. 4, (April 2013) 401-410

International Journal of Engineering

Journal Homepage: www.ije.ir

RESEARCH NOTE

Prediction Model for CNC Turning on AISI316 with Single and Multilayered Cutting tool Using Box Behnken Design

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PAPER INFO

Paper history:
Received 11 July 2012
Received in revised form 30 October 2012
Accepted 15 November 2012

Keywords:
CNC Turning
Surface Roughnesses
Tool Wear
Box Benken design
ANOVA

ABSTRACT

Austenitic stainless steel (AISI316) is used for many commercial and industrial applications owing to its high resistance to corrosion. It is too hard to machine due to its high strength and high work hardening property. Tool wear (TW) and surface roughness (SR) are broadly considered as most challenging phases, and thus causing poor results in machining. Optimization of cutting parameter is more essential at this condition for improving the results. The existing method response surface methodology (RSM) incorporating statistics as tool in design and executing experiments is proved as a standard one. In this study of modeling and optimization of a CNC turning process, RSM is adopted as an alternative methodology to replace existing conventional methods; particularly, Box Benken design (BBD) is used to build the model. This methodology not only reduces the cost and time, but also provides adequate information pertaining to the main and interaction effects with a limited attempt of experiments. SR and TW of the coated cutting tool for CNC turning of AISI 316 are taken as responses for analysis. Statistical check proves that this methodology for modeling is sufficient, lack of fit test for model is insignificant, and residual analysis and normal probability plots are also satisfied.

doi: *10.5829/idosi.ije.2013.26.04a.09*

1. INTRODUCTION

The challenges which are all felt by the modern industries in machining is mainly focused for the achievement of high quality, in terms of work piece dimensional accuracy, surface roughness (SR), high production rate, less tool wear (TW)and economy of machining, with reduced adverse impact on environment [1]. Surface integrity is an important quality measure for evaluating the productivity of the machine tools and mechanical parts. Surface quality is influenced by various factors such as tool geometry, cutting and coolant parameters, etc. Many experimental studies have been conducted to explore the effects of cutting conditions on the SR of various work piece materials. Achieving good surface finish is a hard task. Many adverse feedbacks have been reported by users during machining [2-4]. TW which results in the need for adequate replacement of tool is one of the most important Technical/Economical hurdles. Therefore, it is essential to minimize TW by optimizing the cutting parameters [5]. Normally, AISI 316 is regarded as more difficult to machine than carbon and low alloy steels due to their high strength, ductility and high work hardening property [6, 7]. Many efforts have been made to improve its machinability. Application of hard coatings on tools by physical vapor deposition (PVD) and chemical vapor deposition (CVD) is one of the efficient ways. It is proved that performance of the coated tools is better than the bare tools. Nowadays, around 70% of the tools are cemented carbide coated, used in various manufacturing industries. These hard coatings increase tool life and improve surface finish of the work [8]. Coated carbides are basically a cemented carbide insert coated with one or more layer of wear resistant materials, such as titanium nitride, titanium carbide and aluminum oxide. It is well known that the coating can reduce TW and improve the SR [9]. Therefore, most of the carbide tools used in the metal cutting industries is coated even though the costs more [10]. The effect of cutting parameters on AISI 316 was investigated with multilayer coating by TiC/TiCN/TiN and TiC/TiCN/Al_2O_3 under dry conditions [11]. Surface roughness model was developed for turning of AISI 316 with TiN/Al_2O_3/TiC coated carbide tool [12].

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Friction coefficient model was also developed between tool and work during the turning of AISI 316 with TiN coated carbide tool [13]. Kaladhar conducted a performance evaluation of coating materials and process parameter optimization for surface quality during turning of AISI 316 [14]. Thamizhmani and Hasan investigated the AISI410 by PCBN cutting tool [15]. Gutakorskis and Bonga performed the turning tests on AISI410 using non-coated cutting tool [16]. Limited research papers are only available in turning of AISI 316. More Research is needed to determine how cutting parameters affect TW and SR. Various coating materials are provided with different properties. Hence, in this work multilayer coating with Ti(C, N, B) and single layer coating with TiAlN cutting tool are taken for turning process. In order to get good SR and dimensional properties, it is necessary to employ optimization techniques to find optimal cutting parameters and theoretical models for prediction. Taguchi and response surface methodology (RSM) can be conveniently used for these purposes [17]. RSM is more practical, economical and relatively easier to apply [18]. The statistical method used in RSM has been proposed to determine the influences of individual factors and the influence of their interactions. RSM is a technique for designing experiments, building models, evaluating the effects of several factors, and achieving the optimum conditions for desirable responses with a limited number of estimated experiments [19, 20]. RSM helps to demonstrate how a particular response is affected by a given set of input variables over some specified region of interest, and what input values will yield a maximum for a specific response. The RSM was initially developed for determining optimum operating conditions in the chemical industry, but it is now used in a variety of fields and applications, not only in the physical and engineering sciences, but also in biological, clinical, and social sciences [21]. Optimization process involving one-variable-at a-time method is a time-consuming technique and it neglects the interaction between variables and it does not guarantee attaining optimal point [22]. Box-Behnken optimization design abolishes these disadvantages. Besides, it creates empirical model equations that correlate the relationship between variables and response [23]. BBD designs require fewer treatment combinations than a central composite design in cases involving 3 or 4 factors.

2. MATERIALS AND METHODS

The work material used in the present investigation is a round bar of AISI 316. The diameter of the material is 32mm and machined length is 60mm for all trials. The chemical composition of the work material is given in Table 1.

TABLE 1. Chemical composition of AISI 316

C	Si	Mn	P	S	Ni	Cr	Mo
0.040	0.49	1.56	0.03	0.017	10.45	16.71	2.112

TABLE 2. Machining parameters and levels

Parameter	Designation	Level 1	Level 2	Level 3
Cutting speed (m/min)	V	110	160	210
Feed (mm/rev)	F	0.1	0.2	0.3
Depth of cut	D	0.7	1.4	2.1

2. 1. Response Surface Designs

Response surface designs are useful for modeling a curved quadratic surface to continuous factors. A response surface model can pinpoint the minimum and or maximum response, if one exists in the factor region. Three distinct values for each factor are necessary to fit a quadratic function, so the standard two-level designs cannot fit curved surfaces. It combines a two-level fractional factorial and two other kinds of points are center points, for which all the factor values are at the zero value and Axial points, for which all but one factors are set at zero and that one factor is set at outer values. The BBD is an alternative to central composite designs. One distinguishing feature of the BBD is that there are only three levels per factor. Another important difference between the two design types is that the BBD has no points at the vertices of the cube defined by the ranges of the factors. This is sometimes useful when it is desirable to avoid these points due to engineering considerations. The price of this characteristic is the high uncertainty of prediction near the vertices compared to the central composite design. When process factors satisfy an important assumption that they are measurable, continuous, and controllable by experiments, with negligible errors, the RSM procedure is carried out as follows:

1. A series of experiments are performing for adequate and reliable measurement of the response of interest.
2. A mathematical model of the second-order response surface with the best fit is developed.
3. The optimal set of experimental parameters producing the optimum response value is determined.
4. The direct and interactive effects of the process parameters are represented through two and three-dimensional plots.

It involves the design of experiments to achieve adequate and reliable measurements of the response of interest. BBD is a very efficient design tool for fitting second-order model is selected for use in this study.

3. EXPERIMENTAL DETAILS

The experiments were conducted on the Fanuc CNC lathe. The technical specification of the CNC machine is given in Table 3. Multilayered CNMG 120408 coated with Ti(C, N, B) of 6 µm and single layered with TiAlN of 3 µm are used as the insert for all machining operations. The range of cutting parameters was selected based on past experience, data book and available resources. SR is measured by the Mitutoyo surface roughness tester. TW is measured by an optical tool maker's microscope with image optic plus version 2.0 software designed to run under Microsoft widow's 32 bit system, which can be captured by the area of the TW.

The three cutting parameters selected for the present investigation is cutting speed, feed and depth of cut. Since the considered factors are multi-level variables and their outcome effects are not linearly related, it has been decided to use three-level tests for each factor. The machining parameters used and their levels chosen are given in Table 2. Box and Behnken derived a series of three-level second-order designs that has been very popular, especially for a small number of factors [24]. Three factors requires only 12 runs, plus a recommended 3 center point runs. The three factors chosen for this study are designated as x_1, x_2, x_3 and prescribed into three levels, coded +1, 0, −1 for high, intermediate and low value, successively. For predicting the optimal point, a second-order polynomial model is fitted to correlate relationship between independent variables and for the three factors, the Equation (1).

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_{12} x_1 x_2 + \beta_{13} x_1 x_3 + \beta_{23} x_2 x_3 + \beta_{11} x_1^2 + \beta_{22} x_2^2 + \beta_{33} x_3^2 \quad (1)$$

where Y is the predicted response; 0 is model constant; are independent variables; 1, 2 and 3 are linear coefficients; 12, 13 and 23 are cross-product coefficients; and 11, 22 and 33 are the quadratic coefficients. The quality of fit of the polynomial model equation is expressed by the coefficient of determination $R2$. Minitab14 statistical software has been used for the analysis of the experimental work.

4. RESULTS AND DISCUSSION

Fifteen responses are observed and taken to compute the model using the least square method. The two responses are associated with the three factors using the second-order polynomial. From the experimental data, quadratic regression models are obtained. Table 4 shows the BBD of experiments with three independent variables for Ti(C, N, B) and for TiAlN.

TABLE 3. Specification of the CNC machine.

Capacity	
Swing over way covers	350 mm
Admit between centre	375 mm
Maximum turning length (with chuck)	375 mm
Maximum turning diameter	220 mm
Job Holding	
Hydraulic chuck – standard	135 mm
Slide	
Cross Travel X-Axis	130 mm
Longitudinal Travel Z-Axis	375 mm
Rapid Rate X-Axis	24m/min
Rapid Rate Z-Axis	24m/min
Ball Screw X-Axis (dia & pitch)	32X10
Z-Axis (dia & pitch)	32X10
LM Guide ways X-Axis	35 HSR
LM Guide ways Z-Axis	35 HSR
Main Spindle (Standard)	
Spindle motor power	5.5/7.5 kw
Spindle bore diameter	40 mm
Spindle front bearing diameter	80 mm
Spindle nose	A2-5
Maximum bar capacity	27
Spindle speed – Standard	4000 rpm
Spindle speed – Optional	5000 rpm
Turret	
No. of stations	8 Nos
Maximum boring bar capacity	32 mm
Tool cross section	25X25 mm
Tail Stock	
Quill diameter	60 mm
Quill stroke	60 mm
Thrust maximum	350 kgf
Quill taper	MT 3
Coolant	
Tank capacity	100 ltrs.
Pump motor capacity	0.25 kw
Machine Size	
Weight (Approximate)	3300 kg
Dimension (LXBXH)	1730X2000X1500mm
Accuracy	
Positioning	± 0.010 mm
Repeatability	± 0.003 mm

4. 1. Validation of the Models for Ti(C, N, B) It is usually mandatory to ensure the adequacy in results of the fitted model while applying in real system. Unless the model shows an adequate fit, proceeding with an investigation and optimization of the fitted response surface is lead to give inappropriate results. Graphical and numerical methods are primary tool and confirmations, so graphical techniques are also applied to validate the models in this study. The graphical method characterizes the nature of residuals of the models. A residual is defined as the difference between an observed and the fitted values. The plot can be used to check the drift of the variance during the experimental process, when data are time-ordered. If the residuals are randomly distributed around zero, it means that there is no drift in the process.

Figure 1 shows the residuals versus the fitted plot of SR for Ti(C, N, B) and Figure 2 shows the residuals versus the fitted plot of TW for Ti(C, N, B). These plots indicate the SR for Ti(C, N, B) and TW for Ti(C, N, B) are randomly scattered; hence, there is no drift in the process. It is used to exam the sufficiency of the functional part of the model. Figure 3 shows the residual versus order of the SR for Ti(C, N, B) and Figure 4 shows the residual versus order of the TW for Ti(C, N, B).

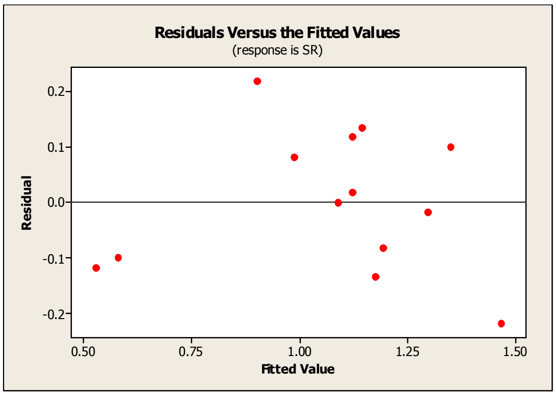

Figure 1. Residuals versus fitted values for SR of Ti(C, N, B)

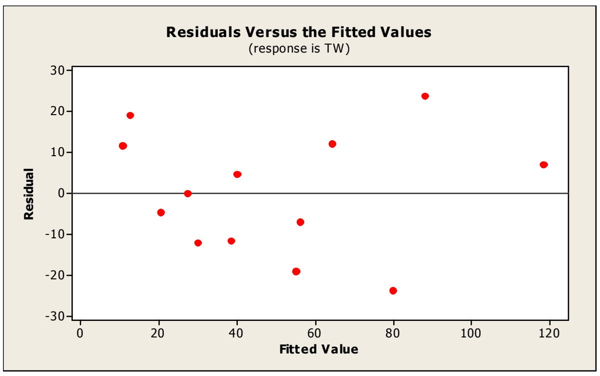

Figure 2. Residuals versus fitted values for TW of Ti (C, N, B)

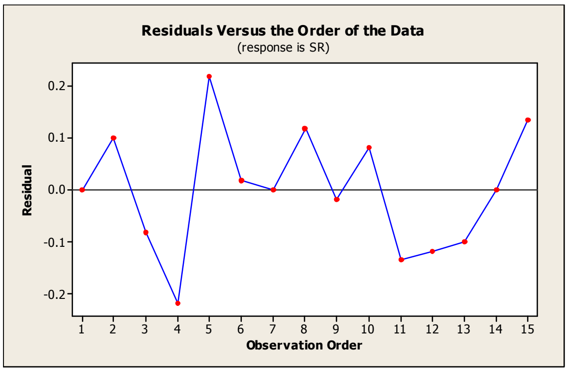

Figure 3. Residuals versus observation for SR of Ti(C, N, B)

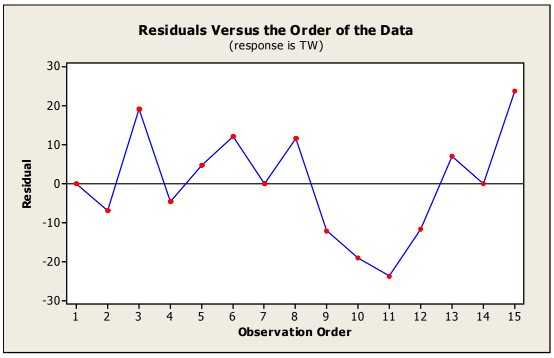

Figure 4. Residuals versus observation for TW of Ti(C, N, B)

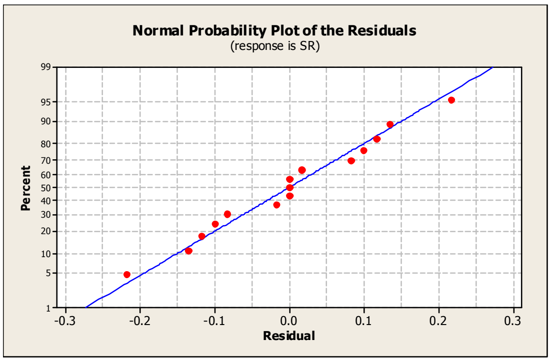

Figure 5. Normal probability plots for SR of Ti(C, N, B)

Residual is plotted against an index of observation orders of data, which is used to check for any drift in the process. The graphical residual analysis indicated no obvious pattern, implying that the residuals of the models are randomly distributed. The normal probability plots of SR for Ti(C, N, B) and TW for Ti(C, N, B) are shown in Figures 5 and 6. The data are plotted against a theoretical normal distribution in such a way that the points should form an approximate straight line. A departure from this straight line would indicate a departure from a normal distribution, which is used to check the normal distribution of the residuals. It is reasonable that the assumptions of normality are satisfied with the data.

TABLE 4. BBD of experiments for Ti(C, N, B) and TiAlN.

Experimental Design				Results for Ti(C, N, B)				Results for TiAlN			
Trial	V	F	D	SR_{exp}	SR_{pred}	TW_{exp}	TW_{pred}	SR_{exp}	SR_{pred}	TW_{exp}	TW_{pred}
1	0	0	0	1.07	1.09	27.30	27.30	1.57	1.57	40.20	40.20
2	0	1	-1	1.45	1.35	49.20	56.20	2.96	3.01	33.50	43.29
3	-1	1	0	1.11	1.19	31.70	12.52	2.80	2.32	25.07	10.18
4	1	0	-1	1.25	1.46	15.80	20.44	1.54	1.53	35.80	43.57
5	-1	0	1	1.12	0.90	44.70	40.05	1.36	1.36	44.99	37.21
6	1	0	1	1.14	1.12	76.60	64.42	1.44	1.52	55.91	50.82
7	0	0	0	1.09	1.09	27.30	27.30	1.57	1.57	40.20	40.20
8	1	1	0	1.24	1.12	22.40	10.75	2.82	2.76	31.30	13.72
9	-1	0	-1	1.28	1.29	17.90	30.07	1.62	1.53	42.76	47.84
10	1	-1	0	1.07	0.98	35.78	54.95	0.87	0.84	33.55	48.43
11	0	1	1	1.04	1.17	56.10	79.92	2.77	2.74	69.30	91.96
12	-1	-1	0	0.41	0.52	26.80	38.44	0.58	0.63	25.07	42.64
13	0	-1	1	0.48	0.58	125.24	118.24	0.93	0.87	84.98	75.18
14	0	0	0	1.09	1.09	27.30	27.30	1.57	1.57	40.20	40.20
15	0	-1	-1	1.28	1.14	111.82	88.00	0.75	0.77	149.90	127.23

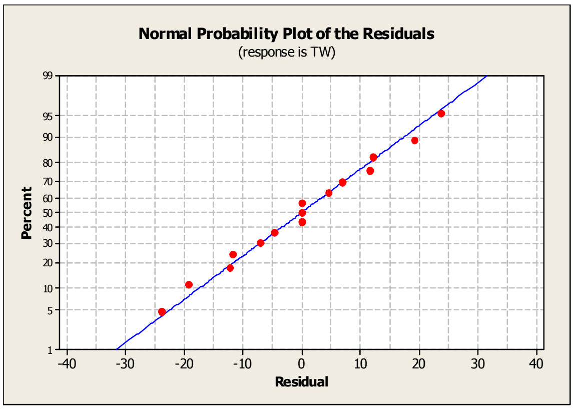

Figure 6. Normal probability plots for TW of Ti (C, N, B)

TABLE 6. Regression Coefficients for TW of Ti (C, N, B)

Term	Coef	SE coef	T	P
Constant	27.30	13.11	2.08	0.09
V	3.68	8.03	0.45	0.66
F	-17.53	8.03	-2.18	0.08
D	13.49	8.03	1.68	0.15
V*V	-22.48	11.81	-1.90	0.11
F*F	24.35	11.81	2.06	0.09
D*D	33.93	11.81	2.87	0.03
V*F	-4.57	11.35	-0.40	0.07
V*D	8.50	11.35	0.74	0.48
F*D	-1.63	11.35	-0.14	0.89

S = 22.71 R-Sq = 83.5% R-Sq(adj) = 53.8%

TABLE 5. Regression Coefficients for SR of Ti(C, N, B)

Term	Coef	SE coef	T	P
Constant	1.090	0.113	9.61	0.000
V	0.097	0.069	1.40	0.219
F	0.200	0.069	2.88	0.035
D	-0.185	0.069	-2.66	0.045
V*V	0.001	0.102	0.012	0.991
F*F	-0.133	0.102	-1.308	0.248
D*D	0.106	0.102	1.039	0.346
V*F	-0.132	0.098	-1.349	0.235
V*D	0.012	0.098	0.127	0.904
F*D	0.097	0.098	0.993	0.366

S = 0.1964 R-Sq = 82.3% R-Sq(adj) = 50.4%

Tables 5 and 6 gives an insight into the linear, quadratic and interaction effects of the parameters. These analyses are done by Fisher's 'F' and Student 'T' tests. These test are used to determine the significance of the regression coefficients of the parameters. The P value is used as a tool to check the significance of each factor and interaction between factors. Larger magnitude of T and smaller values of P are more significant in corresponding coefficient term. Regression coefficient of SR for Ti(C, N, B) is given in Table 5. It is found that the variable with the largest effect on SR is the linear effect of feed rate followed by depth of cut, having a P-value of 0.035 and 0.045. The coefficient of quadratic cutting speed is found to be insignificant with P-value of 0.991.

Regression coefficient of TW for Ti(C, N, B) is given in Table 6. It is indicate that quadratic depth of cut is the most significant factor in determining the optimum TW with P value of 0.03 followed by interaction of cutting speed and feed rate and linear feed rate with P values of 0.07 and 0.09. The coefficient of interaction between feed rate and depth of cut is found to be insignificant with P-value of 0.89.

The models are then checked using a numerical method employing the coefficient of determination (R^2), adjusted R^2 (R^2_{adj}). R^2 indicates how much of the observed variability in the data is accounted for by the model, while R^2_{adj} modifies R^2 by taking into account the number of predictors in the model. The response surface models are developed in this study with values of R^2 say 82.3% SR for Ti(C, N, B) and 83.5% for TW for Ti(C, N, B), respectively. Furthermore, an R^2_{adj} close to the R^2 values insure a satisfactory adjustment of the quadratic models to the experimental data. The Analysis of variance of SR for Ti(C, N, B) and TW for Ti(C, N, B) on these models are shown in Table 7. It demonstrates that the models are highly significant, as evident from the very low probability of P values in the regression = 0.015 and 0.133 for SR and TW. The lack of fit test describes the variation in the data around the fitted model. If the model does not fit the data well, the lack of fit will be significant. The lack of fit is not insignificant.

TABLE 7. Analysis of Variance for SR and TW of Ti (C, N, B)

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Surface Roughness						
Regression	9	0.895	0.895	0.099	2.58	0.155
Linear	3	0.669	0.669	0.223	5.79	0.044
Square	3	0.116	0.116	0.038	1.01	0.462
Interaction	3	0.108	0.108	0.036	0.94	0.487
Residual Error	5	0.192	0.192	0.038		
Lack of Fit	3	0.192	0.192	0.064	*	*
Pure Error	2	0.000	0.000	0.000		
Total	14	1.088				
Tool Wear						
Regression	9	13065	13065	1451	2.8	0.13
Linear	3	4022	4022	1340	2.6	0.16
Square	3	8659	8659	2886	5.60	0.047
Interaction	3	383.2	383.17	127.72	0.2	0.86
Residual	5	2579.0	2578.97	515.79		
Lack of Fit	3	2579.0	2578.97	859.66	*	*
Pure Error	2	0.0	0.00	0.00		
Total	14	15644				

4. 2. Validation of the Models for TiAlN The residual versus the fitted plot of SR and TW for TiAlN are shown in Figures 7 and 8, respectively. In this plot residuals are randomly distributed around zero. There is no drift in the experimental process. It is used to test the adequacy of the functional part of the model.

Figures 9 and 10, respectively show the residual versus order of the SR and TW for TiAlN. These plots indicate no obvious pattern, implying that the residuals of the models are randomly distributed.

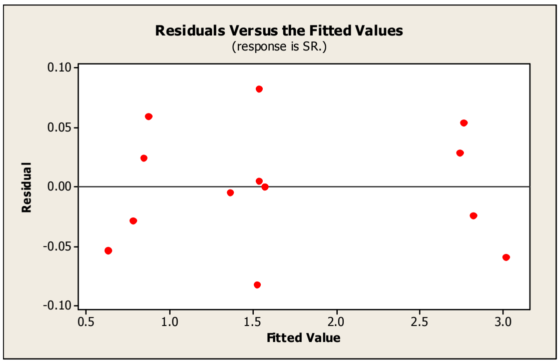

Figure 7. Residuals versus fitted values for SR of TiAlN

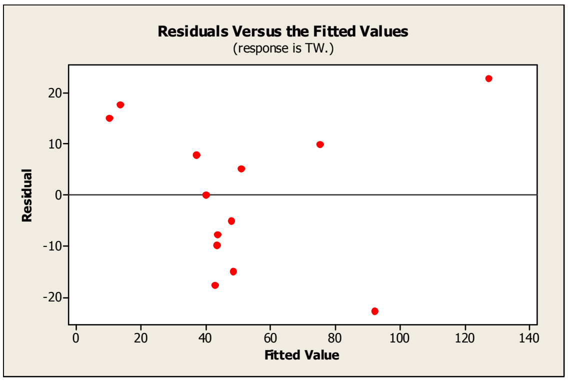

Figure 8. Residuals versus fitted values for TW of TiAlN

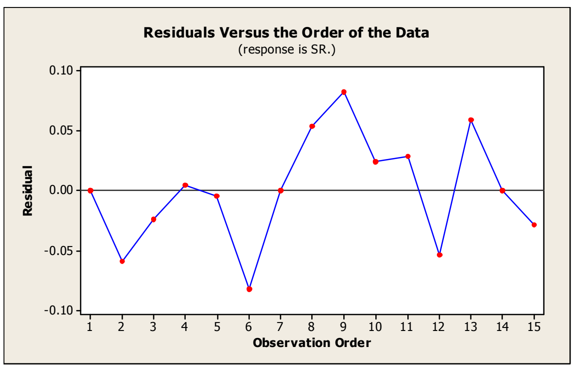

Figure 9. Residuals versus observation data for SR of TiAlN

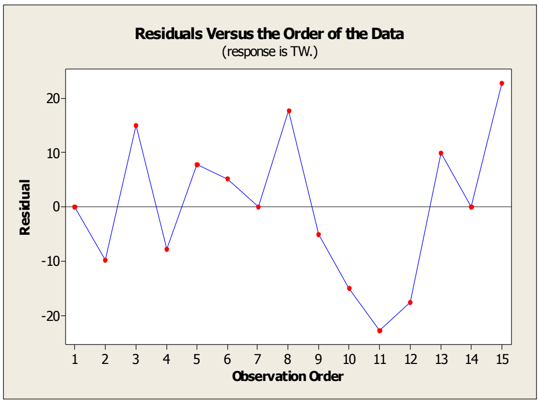

Figure 10. Residuals versus observation data for TW of TiAlN

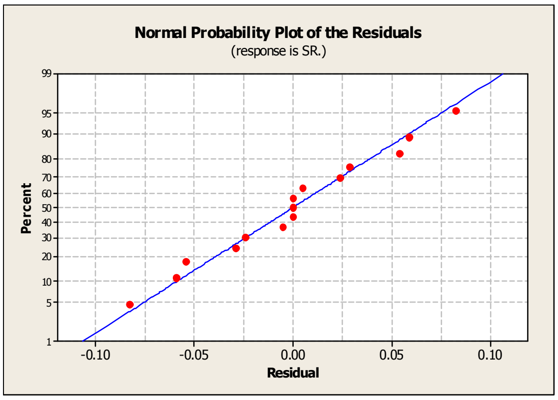

Figure 11. Normal probability plots for SR of TiAlN

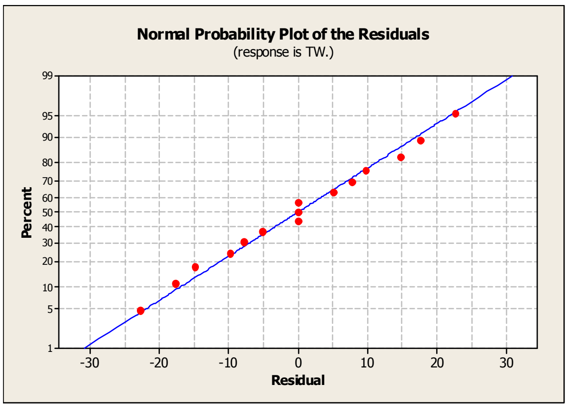

Figure 12. Normal probability plots for TW of TiAlN

The normal probability plots of SR and TW for TiAlN are shown in Figures 11 and 12. A departure from this straight line would indicate a departure from a normal distribution. These plots satisfy the data.

Regression coefficient of SR for TiAlN is given in Table 8. It is found that the variable with the largest effect on SR is the linear effect of feed rate and followed by interaction between feed rate and depth of cut, having a P-value of 0.000 and 0.060. The coefficient of quadratic depth of cut is found to be insignificant with P-value of 0.952.

Regression coefficient of TW for TiAlN is given in Table 9. It indicates that quadratic depth of cut is the most significant factor in determining the optimum TW with P value of 0.047 followed by interaction of cutting speed and feed rate and linear feed rate with P values of 0.07 and 0.09, respectively. The coefficient of interaction between feed rate and depth of cut is found to be insignificant with P-value of 0.961. The response surface models are developed in this study with values of R_2 say 99.7% SR and 82.9% for TW for TiAlN, respectively.

The analyses of variance of SR for TiAlN and TW for TiAlN on these models are shown in Table 10. It demonstrates that the models are highly significant, as evident from the very low probability of P values in the regression = 0.000 and 0.144 for SR and TW. The lack of fit is not insignificant.

TABLE 8. Estimated Regression Coefficients for SR of TiAlN

Term	Coef	SE coef	T	P
Constant	1.570	0.044	35.630	0.000
V	0.038	0.026	1.436	0.210
F	1.027	0.026	38.078	0.000
D	-0.046	0.026	-1.714	0.147
V*V	-0.082	0.039	-2.077	0.092
F*F	0.280	0.039	7.050	0.001
D*D	0.002	0.039	0.063	0.952
V*F	-0.067	0.038	-1.769	0.137
V*D	0.040	0.038	1.048	0.343
F*D	-0.092	0.038	-2.424	0.060

S = 0.07632 R-Sq = 99.7% R-Sq(adj) = 99.1%

TABLE 9. Estimated Regression Coefficients for TW of TiAlN

Term	Coef	SE coef	T	P
Constant	40.200	12.78	3.14	0.026
V	2.333	7.83	0.29	0.778
F	-16.79	7.83	-2.14	0.085
D	-0.84	7.83	-0.10	0.918
V*V	-25.50	11.52	-2.21	0.078
F*F	14.05	11.52	1.21	0.277
D*D	30.16	11.07	2.61	0.047
V*F	-0.56	11.07	-0.05	0.961
V*D	4.47	11.07	0.404	0.703
F*D	25.18	11.07	2.27	0.072

S = 22.15 R-Sq = 82.9% R-Sq(adj) = 52.0%

TABLE 10. Analysis of Variance for SR and TW of TiAlN

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Surface Roughness						
Regression	9	8.864	8.864	0.984	169	0.00
Linear	3	8.475	8.475	2.825	484	0.00
Square	3	0.330	0.330	0.110	18	0.004
Interaction	3	0.058	0.058	0.019	3.37	0.112
Residual Error	5	0.029	0.029	0.005		
Lack of Fit	3	0.029	0.029	0.009	*	*
Pure Error	2	0.000	0.000	0.000		
Total	14	8.893				
Tool Wear						
Regression	9	11860	11860	1317.88	2.69	0.144
Linear	3	2304.9	2304.8	768.30	1.57	0.308
Square	3	6938.7	6938.7	2312.91	4.72	0.064
Interaction	3	2617.3	2617.3	872.44	1.78	0.267
Residual Error	5	2452.4	2452.4	490.49		
Lack of Fit	3	2452.4	2452.4	817.48	*	*
Pure Error	2	0.0	0.00	0.00		
Total	14	1431				

5. CONCLUSIONS

This investigation is focused on prediction and analysis of CNC turning AISI 316 with multilayer coated with Ti(C, N, B) and single layer coated with TiAlN cutting tool during change of cutting parameters. From the study of a result in turning is using BBD. The following can be concluded from the present study.

1. The response surface model for SR and TW are developed from the observed data the predicted and measured values are fairly close, which indicates that the developed model can be effectively used to predict the SR and TW for both Ti (C, N, B) and TiAlN.
2. The response surface models are developed for the SR and TW of multilayered Ti (C, N, B) with $R2$ values are 82.3% and 83.5% and single layered TiAlN with $R2$ values of 99.7% and 82.9%.
3. Feed rate, followed by the depth of cut are the most significant factors for the SR of Ti (C, N, B) with P-values of 0.035 and 0.045, respectively. Quadratic depth of cut, followed by linear feed rate are the most significant factors for TW of Ti (C, N, B) with P values of 0.03 and 0.07, respectively.
4. Feed rate, followed by interaction between feed rate and depth of cut are the most significant factors for the SR of TiAlN with P-values of 0.000 and 0.060, respectively. Quadratic depth of cut, followed by interaction of feed rate and depth of cut are the most significant factor for TW of TiAlN with P-values of 0.047 and 0.072, respectively.
5. The lack of fit test describes the variation in the data around the fitted model. The lack of fit is not insignificant for both Ti (C, N, B) and TiAlN.
6. Departure from straight line normal probability plots would indicate a departure from a normal distribution, which is used to check the normality distribution of the residuals for both Ti (C, N, B) and TiAlN.

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Prediction Model for CNC Turning on AISI316 with Single and Multilayered Cutting tool Using Box Behnken Design

RESEARCH NOTE

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PAPER INFO

Paper history:
Received 11 July 2012
Received in revised form 30 October 2012
Accepted 15 November 2012

Keywords:
CNC Turning
Surface Roughnesses
Tool Wear
Box Benken design
ANOVA

چکیده

فولاد زنگ‌نزن سخت شده (AlSl316) به علت مقاومت به خوردگی بالای برای چندین کاربرد صنعتی و تجاری استفاده شده است. به علت استحکام بالا و خاصیت کار سخت شوندگی آن به سختی قابل ماشین‌کاری و تراش‌کاری می باشد. ابزار سایش (TW) و زبری سطحی (SR) به صورت گسترده به عنوان جنبه‌های مشکل کار بررسی شده است، که بخشی از دلایل نتایج نامطلوب در ماشین کاری است. بهینه سازی پارامترهای برش در این شرایط برای بهبود نتایج بسیار ضرروی است. روش حاضر، روش سطح پاسخ (RSM) آماری به عنوان ابزار طراحی و آزمایش‌های اجرایی با استاندارد ۱ تایید شده است. در تحقیق مدل سازی و بهینه سازی فرایند تراش‌کاری CNC، RSM به عنوان روش جایگزین برای روش‌های متداول موجود پذیرفته شده است، به خصوص طراحی Box Benken (BBD) برای ساخت مدل استفاده شده است. این روش نه تنها به منظور کاهش زمان و هزینه است، بلکه اطلاعات کافی مربوط به تاثیرات اصلی و متقابل که با آزمایش‌های محدود به دست می آید را تهیه می کند. SR و TW ابزار برش پوشش تراشکاری ALSL 316 به عنوان پاسخ آنالیزها اتخاذ شده‌اند. بررسی‌های آماری ثابت می‌کند که این شیوه برای مدل سازی کافی بوده و فقدان ازمایش‌های مناسب برای مدل بی اهمیت است اگرچه انالیزهای باقی‌مانده و نمودارهای احتمال معمولی هم برای این مدل کافی می‌باشد.

doi: *10.5829/idosi.ije.2013.26.04a.09*