DOI: http://dx.doi.org/10.30684/etj.36.3A.1

Shaker S. Hassan
Department of Mechanical Engineering, University of Technology, Baghdad, Iraq
sakran1952_1@yahoo.com

Samir A. Amin
Department of Mechanical Engineering, University of Technology, Baghdad, Iraq
alrabiee2002@yahoo.com

Asaad. A. Dabish
Department of Mechanical Engineering, University of Technology, Baghdad-Iraq
asadabd84@gmail.com

Received on: 05/01/2016
Accepted on: 29/09/2016

Using RSM Technique for Modeling and Optimization the Influence of Cutting Parameters on Tool Wear and Cutting Forces in Turning Operation

Abstract-*This study is an attempt to investigate the effect of cutting parameters on the cutting force and tool wear during turning of AISI 304 steel using tungsten carbide tool (WC). The first aim of present work was to employ the Response Surface Methodology (RSM) technique to obtain the influence of input machining parameters, such as cutting feed, cutting speed and cutting depth on the cutting force and wear of tool. Experiments were carried out in a 20 runs experimental matrix by a CNC machine according to the design matrices established by Design of Experiment (DOE) software 'version 8' with RSM technique. Cutting force was measured using a lathe dynamometer and tool wear with the help of an optical microscope. The relationships between parameters of machining and the responses (cutting tool wear and cutting force) were modeled and analyzed by RSM technique. ANOVA analysis was applied to study the impact of machining parameters on the outputs (responses) and to establish empirical equations for these responses in terms of input machining parameters. Significant quadratic models were developed with a probability (p-value ≤ 0.05) for both tool wear and cutting force. Results showed that the depth of cut is the most significant factor affecting the cutting force, closely followed by feed and cutting speed, whereas only the important parameter influencing the tool wear was appeared to be the cutting depth. Also, the results manifested that the optimum value for minimum tool wear and minimum cutting force was found at (80 m/min) cutting speed, (0.2 mm/rev) feed and (0.4 mm) cutting depth. A good agreement was found between the experimental and predicted results with a maximum error of 8%.*

Keywords- *Cutting force, RSM, Stainless steel, Tool wear*

How to cite this article: S.S. Hassan, S.A Amin and A.A. Dabish, "Using RSM Technique for Modeling and Optimization the Influence of Cutting Parameters on Tool Wear and Cutting Forces in Turning Operation," *Engineering and Technology Journal*, Vol. 36, Part A, No. 3, pp. 234-247, 2018.

1. Introduction

Turning as a machining process is a preliminary metal cutting process that is broadly utilized in production factories dealing with cutting operations [1]. The choice of cutting input parameters for the turning process is a significant job to achieve a higher performance, which means easy to machine, good surface finish, less wear rate of cutting tool, higher rate of material removal (MMR), higher manufacturing, etc. [2].

Study the cutting forces is critically important in turning processes due to their strong correlation with the cutting performance, like dimensional accuracy of surface, wear of cutting tool, cutting tool breakage, temperature of cutting, self-excited and forced vibrations of cutting tool, etc. Awareness of the cutting forces is required to estimate the power needed to design adequate, rigid with no vibration machine tool parts, cutting tool holders and work material fixtures.

In each conventional machining process, tool wear usually occurs, and the machinists try to eliminate it for improving the life of cutting tool. Many investigations on characteristics of cutting tool wear have been performed [3]. Certain parameters that influence the wear of cutting tool and cutting force are the input machining factors, such as cutting feed, cutting speed, cutting depth, type and properties of tool material, type and properties of work material, and tool geometry of the cutting tool. Minimum variations in these parameters may cause significant variations in the quality of machined part and life of cutting tool [4].

Design of experiment (DOE) is a procedure used to indicate the relations between many input parameters and outputs (responses). It can be used to optimize the necessary resources required to conduct the experiment [5]; therefore, it is widely used in research and development investigations.

Response Surface Methodology (RSM) method is defined as a collection of mathematical and

statistical tools which are beneficial to model and analyze a problem, in which an output (response) of interest is influenced by many input parameters. The main goal of the present work is the optimization of the outputs (responses) by minimization or maximization depending upon the demand [6]. It is a technique that developed previously by Box and Wilson at the beginning of 1950s [7].

Prediction of tool wear and cutting force are important in study of metal cutting to increase the tool use and reduce the machining cost. To enhance the cutting tool life, a suitable choice of machining parameters is important prior the occurrence of machining process. The machine tool user must have knowledge on how to select the cutting parameters so to reduce the cutting tool wear and cutting force.

Mahdavinejad [8] optimized the input parameters of turning a stainless steel type AISI 304. Cutting tests were conducted at different cutting feeds (0.2, 0.3 and 0.4 mm/rev) and cutting speeds (100, 125, 150, 175 and 200 m/min) with and without using cutting fluid.

Design of experiments and ANOVA analysis were used to obtain the influence of each input parameter on the wear of cutting tool and work material surface roughness. The feed rate had the most important influence on the surface roughness and as it decreased, the surface roughness decreased. The results indicated that feed and cutting speed had greater influences on the turning quality of used steel. The flank wear of cutting tool was closely correlated with the cutting speed. The tool wear highly decreased by raising cutting speed up to 175 m/min. The cause of this cutting tool flank wear is mainly due to insufficient removal of heat because of the low conductivity of stainless steel AISI 304, size and form of the resulted chips.

Agrawalla [9] used RSM to find out the influence of input cutting variables, including feed, cutting speed and cutting depth on the work material surface roughness and tool wear. The chosen tool insert is a coated carbide tool. The results revealed that the feed rate was the highly important parameter influencing the material surface roughness followed by cutting speed and cutting depth, whereas the cutting depth was appeared to be the only important parameter influencing the wear of cutting tool.

Ameur and Elbah [10] determined the effects of cutting conditions on the surface roughness and cutting forces in hard turning of X38CrMoV5-1. This steel was hardened at 50 HRC and machined with CBN tool. The results showed how much surface roughness was mainly influenced by feed rate and cutting speed. The depth of cut exhibited maximum influence on the cutting force components as compared to the feed rate and cutting speed.

Thiyagu [11] used stainless steel in turning aiming to minimize aiming the work material surface roughness and cutting force. DOE and optimization were conducted using Box–Behnken design and RSM technique. The used factors with three levels in the experiments were cutting feed, cutting speed, cutting depth, and radius of cutting tool nose. The quadratic models established for cutting force and surface roughness were employed to predict the output (response). The experimental results obtained indicated that the feed rate and cutting speed were the most influential factors for surface roughness. Regarding the cutting force, cutting feed and nose radius were found important parameters.

Accordingly, most of research works have mainly focused on studying the effect of turning parameters on the surface roughness with either tool wear or cutting forces applying Taguchi and RSM and DOE methods to obtain optimum factors for lowest surface roughness, tool flank wear and cutting force to improve the quality of the machined components. In addition, most of researches have used the analysis of variance (ANOVA) to analyze the influence of cutting conditions; cutting speed, feed and depth of cut.

Since, there is a few works on studying the influence of turning parameters on the tool wear and cutting forces, therefore the aim of the present work is first to use DOE with RSM technique for building empirical mathematical models suitable for predicting the tool wear and cutting forces over a used range of cutting parameters (cutting speed, feed rate and depth of cut) and then to optimize these parameters for the purpose of minimizing the tool wear and cutting forces during longitudinal CNC turning stainless steel by a tungsten carbide tool.

2. Experimental Work

I. Cutting Insert

In this work, a turning tool which was coated with Titanium Carbonitride (TiCN) has been used. The insert has identical geometry designated according to the American National Standard Institute (ANSI), and the type of used inserts is SNMG0903 has been adopted in this work.

II. Cutting Tool Holders

For turning operations, a Sandvik Coromant Coro Turn ® RC tool holder was used. This tool is used for turning and facing applications where cutting

loads are heavy. A tool holder was used with the insert (SNMG0903).

III. Used Material

AISI 316 austenitic stainless steel was used in this work containing 16-18 % Cr, 10-14 % Ni and Mo, which imparts more resistance to corrosion. This type of stainless steel is frequently utilized in welding applications due to less problem of corrosion, pitting and cracking in the sea water, equipment for producing chemicals, acids, fertilizers, foods, coastal constructions, ropes, and mechanical fasteners, such as nuts, studs and bolts.

IV. Specimens Preparation and Machine Setup

The supplied stainless steel AISI 316 was in the form of bar with 200 mm length and 40 mm diameter. Before turning experiments, samples from this bar were taken to conduct the chemical composition analysis, and the results are given in Table 1 for comparison with the standard type (ASTM A240) [12]. This table indicates that the used material is in conformity with the standard steel type. The chemical analysis was carried out in the Central Organization for Standardization and Quality Control. In order to support the workpiece at the tailstock of machine tool, a small hole was first machined on the workpiece face. Then, before starting the first cutting test, all rusty layers on the outer surface of workpiece were machined by turning with a new tool insert so to reduce influence of inhomogeneity on the experimental data.

V. Experimental Tests

According to DOE software 'Design Expert 8', the number of cutting tests that carried out in this study was 20 tests. These tests were randomly done under three different cutting parameters (cutting speed, feed and depth pf cut) to build a mathematical model to the tool wear and cutting force, as well as optimize the cutting conditions to minimize the tool wear and cutting force. The values of these cutting conditions were used according to previous machining data [13], as shown in the Table 2, with two levels of input parameters to find out their influence on the tool wear and cutting force induced by the turning tests. The design matrix established by the Design of Experiment (DOE) software for these models are given in terms of actual input factors, in Table 3.

Table 1: Chemical Compositions of the used and standard stainless steel

Materials	C (%)	Si (%)	Mn (%)	Cr (%)	Mo (%)	Ni (%)	S (%)	P (%)	Fe (%)
Used material (AISI 316)	0.045	0.422	1.84	17.1	2.07	11.1	0.028	0.036	Bal.
Standard [12]	0.08 Max	0.75 Max	2.00 Max	16-18	2.3 Max	10-14	0.03 Max	0.045 Max	Bal.

Table 2: Levels of input factors used in respective coding using machining data

Input factor	Levels			
	- 1	+ 1	- alpha	+ alpha
Cutting speed (m/min)	40	80	20	100
Feed (mm/rev)	0.2	0.4	0.1	0.5
Depth of cut (mm)	0.4	0.8	0.2	1.0

Table 3: Design matrix for actual input factors

Std. No.	Number of runs	Cutting speed (m/min)	Feed (mm/rev)	Depth of cut (mm)
1	15	40	0.2	0.4
2	8	80	0.2	0.4
3	16	40	0.4	0.4
4	6	80	0.4	0.4
5	1	40	0.2	0.8
6	20	80	0.2	0.8
9	17	20	0.3	0.6
10	3	100	0.3	0.6
11	12	60	0.1	0.6
12	9	60	0.5	0.6
13	18	60	0.3	0.2
14	18	60	0.3	1.0
15	2	60	0.3	0.6
16	19	60	0.3	0.6
17	4	60	0.3	0.6
18	14	60	0.3	0.6
19	13	60	0.3	0.6
20	7	60	0.3	0.6

3. Tool Wear Measurement

In each cutting test, a new cutting tool edge was utilized. The resulted wear of cutting tool after each test was then measured by a low magnification (X40) Optical Microscope. The tool after machining is placed on the working table with the flank face under side, and the width of the flank is measured from the projected image on the screen, Figure 1. A view of the flank wear in tool insert through the microscope is also shown in Figure 2, depicting some measured lengths in order to obtain the average flank wear width VBB formed by the turning test.

4. Measurement of Cutting Force

Cutting forces during the tests were measured with a strain gauge 3-components dynamometer (IEICOS Lathe Tool dynamometer-Model 620B: 200 Kgf) mounted on the lathe. This dynamometer was fist calibrated, and its readings in three axial indicators (X, Y, and Z) were set to zero prior to conduct any cutting test. Three cutting force components (vertical, horizontal and radial) were measured due to the oblique arrangement. The dynamometer was connected to a charge amplifier (IEICOS Multi-component Digital Force Indicator 3-channel Model 652) used to display the sensed force. Figure 3 manifests the dynamometer and multi-component digital force indicator during turning AISI 316 stainless steel. The resultant cutting force was then calculated for each cutting test.

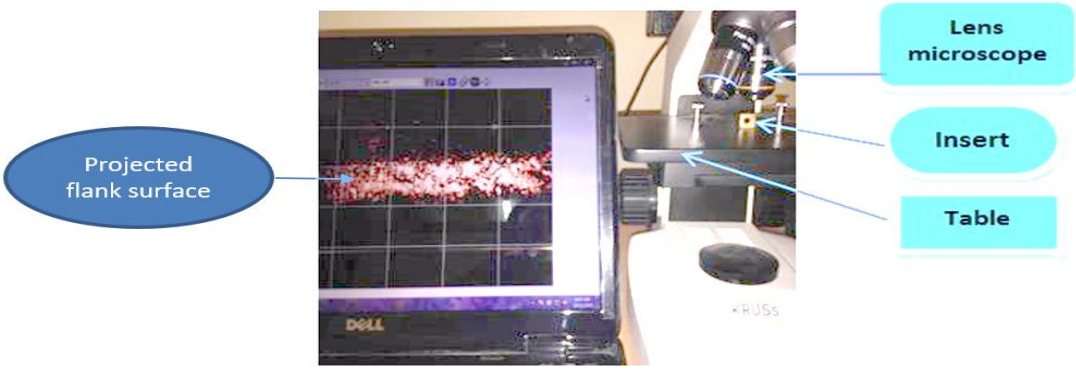

Figure 1: Measurement flank wear to (SNMG0903) insert

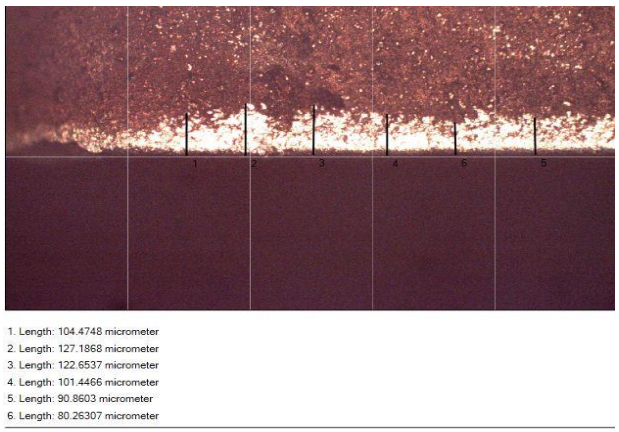

Figure 2: A view of the flank wear in tool insert showing some measured lengths

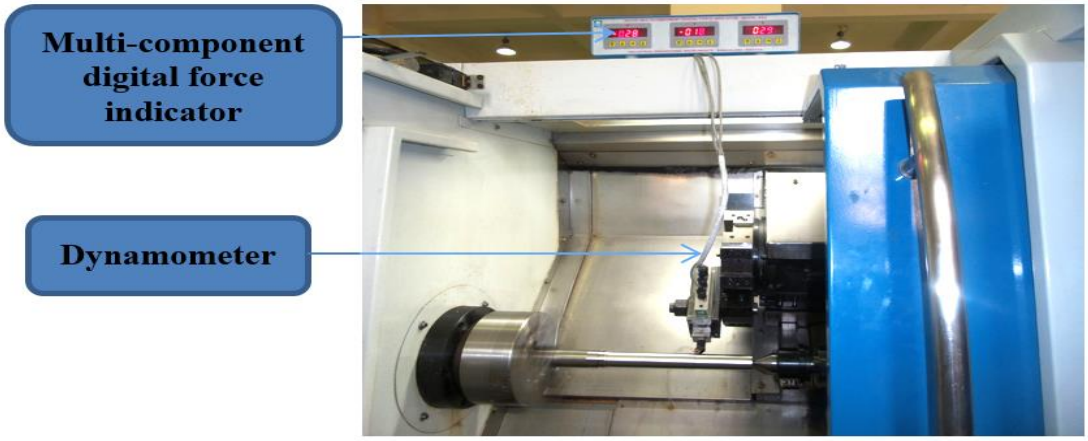

Figure 3: Machine setup showing the use of the dynamometer and multi-component digital force indicator during turning AISA 316 stainless steel

5. Modeling and Optimization

I. Experimental Design Matrices

In this work, mathematical models have been developed using response surface methodology (RSM) based on the experimental data for two responses (tool wear and cutting force). The curvature in the normal operating ranges is inadequately modeled by the first-order function, often occur. Thus, the quadratic response surface functions should be considered. A response surface methodology (RSM) using a central composite rotatable design (CCD) for 2^3 factors with 6 central points and $\alpha^* = \pm 2$ approach was undertaken. A total of 20 experiments (runs) were performed according to the experimental design matrix obtained by DOE software. The runs were performed at random using the run order for three cases depending on cutting tool angles (approach angle and rake angle). Each parameter was used at different code levels of -2, -1, 0, +1, and +2, whereby each level used conformed to an actual value equivalent to the coded value. Thus, the input parameters studied are cutting speed, feed rate and depth of cut. The experimental design matrices used for the input parameters in terms of actual factors with the experimental measured values of tool wear and cutting force were used, respectively. The software DESIGN EXPERT 8 was used to develop the prediction model within a 95% confidence level.

II. Modeling of Tool Wear and Cutting Force

The selection of appropriate model and the development of response surface models have been carried out by using the RSM technique. The regression equations for the selected model were obtained for the response characteristics. These regression equations were developed using the experimental data and were plotted to variables in order to investigate the effect of process on various response characteristics. Modeling and optimization were performed for the tool wear and cutting force at three input levels, depending on the angles of cutting tool as follows:

III. Modeling of Tool Wear

The experimental design matrix used for input parameters in terms of actual factors with the

experimental measured values of tool wear is given in Table 4. The analysis of variance (ANOVA) for response surface quadratic model for tool wear was performed statistically, as shown in Table 5. The model F-value of 90.72 in this table implies the model significance. The values of 'Prob > F' less than 0.0500 indicate model terms are significant. In this case, A, B, C, BC and B^2 are significant model terms. Therefore, this model indicates that the cutting speed (A), feed (B) and the depth of cut (C) are the more important factors affecting tool wear. Since the lack of fit is insignificant (with P-value higher than 0.05), therefore this model is good with 95 % confidence. Thus, the empirical quadratic predicted model developed for the tool wear induced by the turning of AISI316 is given as follows:

$$\text{Tool wear} = -295.64338 - 1.47813 \times A + 2519.44853 \times B + 574.06250 \times C - 1231.25000 \times B \times C - 2752.20588 \times B^2 \quad (1)$$

The diagnostic checking of the model was carried out using residual analysis, and the results are presented in Figures 4 and 5. The normal probability plot is presented in Figure 4. This figure reveals that the residuals fall on a straight line implying that the errors are distributed normally. Figure 5 shows the standardized residuals with respect to the predicted values. The residuals do not show any obvious unusual pattern and are distributed in both positive and negative directions. This implies that the model is adequate, and there is no reason to suspect any violation of the independence or constant variance assumption. Figure 6 manifests the predicted tool wear data versus the actual ones for comparison reason. This figure illustrates that predicted values of tool wear are close to actual ones measured in the experiments, indicating a good agreement between the experimental and predicted results.

Regarding of the individual effect of each input parameter deviated from the center point of the selected level; Figure 7 reveals the perturbation of tool wear in this model. It shows that the cutting depth (C) increased greatly the tool wear over the whole selected input levels (0.4-0.8 mm). While, cutting speed (A) has an adverse effect, and the tool wear value decreased largely at high cutting speed (80 m/min). However, the feed (B) first increased the tool wear to the highest value at the center of the level (0.3 mm/rev) and then decreased slightly at the higher level. This means that the feed has less impact on the tool wear than cutting speed and depth of cut. This result is also confirmed by the 2D contour plot and 3D surface plot depicted in Figures 8 and 9, respectively as a function of cutting speed and feed, showing that the maximum tool wear occurred at (0.8) mm cutting depth. It can be observed from these figures that increasing the cutting speed leads to a decrease in the tool wear, whereas increasing the feed rate results in the maximum tool wear value (up to 315 µm) at (0.3) rev/min and at low cutting speed (40 m/min).This could be attributed to more material removed with feed increase and due to higher cutting force caused by the lower speed, thus leading to more tool wear.

In order to investigate the effect of depth of cut on the tool wear in this model, Figures 10 and 11 illustrate the 2D and 3D plots, respectively as a function of feed and depth of cut, showing the minimum tool wear occurred at (80) m/min cutting speed. It can be seen from both figures that the decrease in both depth of cut and feed leads to decrease the tool wear (down to 125 µm) at lower feed (0.2) mm/rev, lower depth of cut (0.4) mm and at higher cutting speed (80 m/min). This could be ascribed to the combined influence of the decrease of these two parameters that caused less material removal and lower cutting force at higher speed despite of the thermal effect of cutting speed increase, since the austenitic stainless steel has less thermal conductivity with the cutting tool even at higher cutting speed [14]. Therefore, the heat induced by the increase of the cutting speed will mostly be carried away by the removed chips. Therefore, the depth of cut and feed have the dominant influence on the tool wear due to their combined effect. Also, it can be seen that increasing both feed up to (0.3) mm/rev and depth of cut up to (0.8) mm increases the tool wear to a higher value at (80) m/min cutting speed. The increase of tool wear is more likely due to higher material removal resulted from the increase of feed and cutting depth and to lower cutting force at higher speeds.

Finally, it can be concluded that the cutting speed and depth of cut have the greater influence on the tool wear in this model than feed. This conclusion is confirmed by the cube shape of tool wear in terms of cutting speed, feed rate and depth of cut as shown in Figure 12, and the optimum value of the tool wear at the optimum cutting parameters will be given in the numerical optimization section.

Table 4: Design matrix for actual input and output factors

Std. No.	Number of runs	Cutting speed (m/min)	Feed (mm/rev)	Depth of cut (mm)	Tool wear (µm)	Cutting Force (N)
1	15	40	0.2	0.4	152	345
2	8	80	0.2	0.4	117	324
3	16	40	0.4	0.4	234	599
4	6	80	0.4	0.4	193	550
5	1	40	0.2	0.8	290	578
6	20	80	0.2	0.8	240	530
7	5	40	0.4	0.8	271	1140
8	10	80	0.4	0.8	220	1015
9	17	20	0.3	0.6	320	760
10	3	100	0.3	0.6	172	589
11	12	60	0.1	0.6	119	255
12	9	60	0.5	0.6	163	950
13	18	60	0.3	0.2	177	241
14	11	60	0.3	1.0	342	1165
15	2	60	0.3	0.6	260	653
16	19	60	0.3	0.6	237	715
17	4	60	0.3	0.6	252	700
18	14	60	0.3	0.6	243	675
19	13	60	0.3	0.6	256	612
20	7	60	0.3	0.6	234	689

Table 5: ANOVA for Response Surface Reduced Quadratic Model for Tool wear

Source	Sum of Squares	Degress of freedom	Mean Square	F Value	p-value Prob> F	
Model	68929.33	5	13785.87	90.72	< 0.0001	significant
A-Cutting speed	13983.06	1	13983.06	92.02	< 0.0001	
B-Feed	2678.06	1	2678.06	17.62	0.0009	
C-Depth of cut	26814.06	1	26814.06	176.45	< 0.0001	
BC	4851.12	1	4851.12	31.92	< 0.0001	
B^2	20603.01	1	20603.01	135.58	< 0.0001	
Residual	2127.47	14	151.96	90.72	< 0.0001	
Lack of Fit	1567.47	9	174.16	1.56	0.326	not significant
Pure Error	560.00	5	112.00			
Cor Total	71056.80	19	13785.87			
Std. Dev.	12.33			R-Squared	0.9701	
Mean	224.60			Adj R-Squared	0.9594	
C.V.	5.49			Pred R-Squared	0.9325	
PRESS	4799.29			Adeq Precision	32.263	

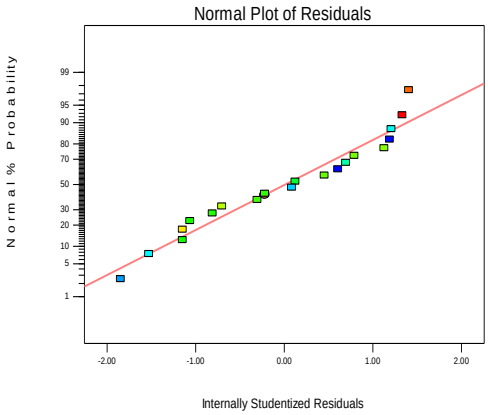

Figure 4: Normal probability plot for tool wear data

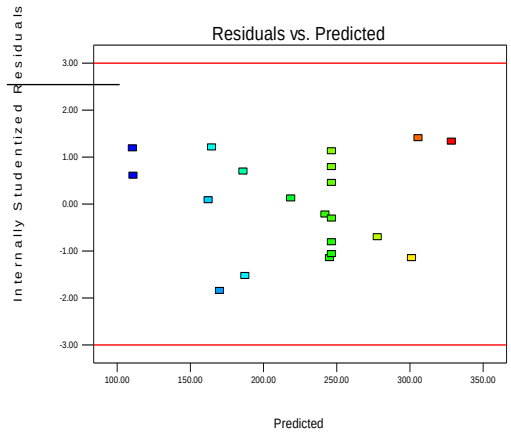

Figure 5: Residual versus predicted responses for tool wear data

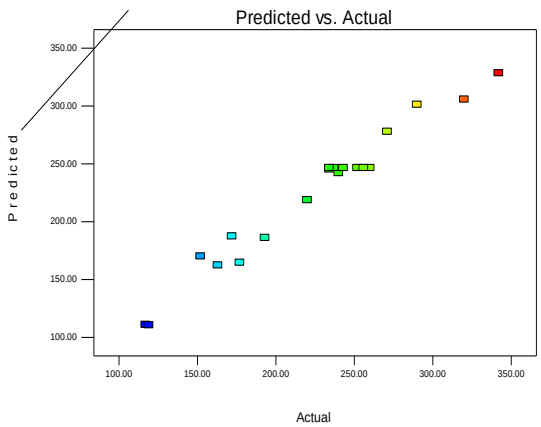

Figure 6: Predicted versus actual tool showing wear data for comparison

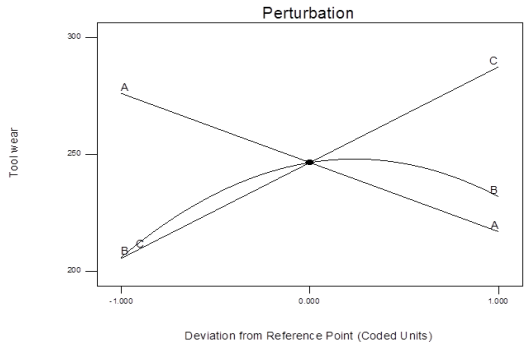

Figure 7: Perturbation of tool wear showing the effect of each input parameter over the selected level

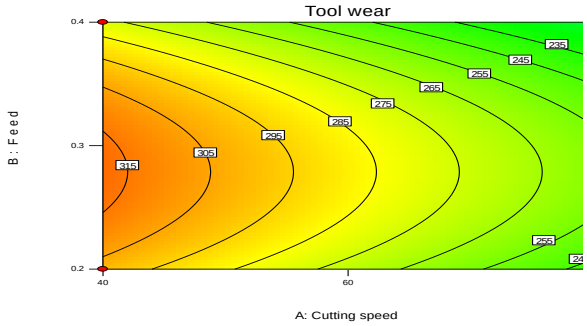

Figure 8: 2D plot showing the maximum minimum tool wear at 0.8 mm depth of cut

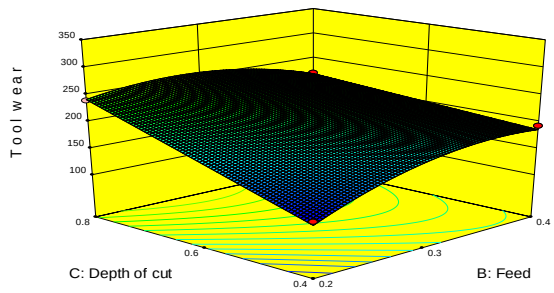

Figure 9: 3D plot showing the tool wear at 80 m/min cutting speed

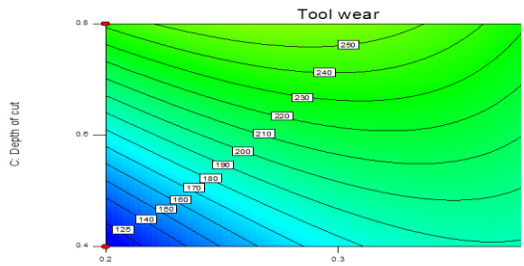

Figure 10: 2D plot showing the minimum minimum tool wear at 80 m/min cutting

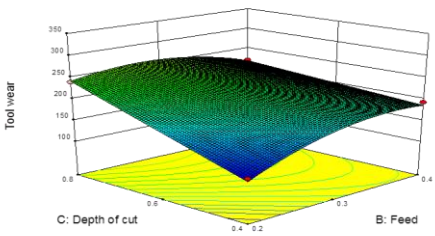

Figure 11: 3D plot showing the wear at 80 m/min cutting speed

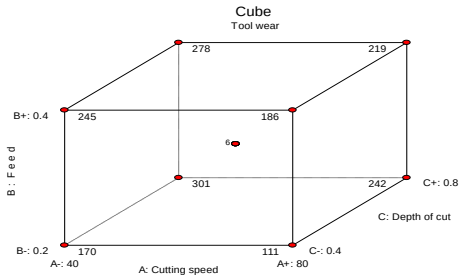

Figure 12: Cube shape for tool wear in terms of cutting speed (m/min), feed (mm/rev) and depth of cut (mm)

IV. Modeling of Cutting Force

The experimental data given in Table 4 were used to develop the quadratic response surface model for cutting force. From Table 6, model F-value of 137.19 implies the model is significant. Values of " Prob > F " less than 0.0500 indicate model terms are significant. In this case A, B, C, BC and B^2 are significant model terms. Therefore, this model indicates that the cutting speed (A), feed (B) and the depth of cut (C) had the impact on the cutting force. The determination coefficient "R-Squared" is a measure of the degree of fit. When "R-Squared" reaches unity, the better response model fits the actual data. Also from Table 4, the "R-Squared" value for fit is 0.9800. "Pred R-Squared" 0.9553 is reasonably in agreement with the "Adj R-Squared" 0.9729. Since the lack of fit is insignificant (with P-value higher than 0.05), therefore this model is good with 95 % confidence level. Thus, the empirical quadratic predicted model developed for the cutting force induced by the turning of AISI316 is given as follows:

$$\text{Cutting Force (R)} == +66.50368 - 1.82813 \times A + 947.61029 \times B - 34.06250 \times C + 3543.75000 \times B \times C - 2084.55882 \times B^2 \ldots (2)$$

Table 6: ANOVA for Response Surface Reduced Quadratic Model for cutting Force

Source	Sum of Squares	Degrees of freedom	Mean squares	Fp-value	Prob > F	
Model	1.283E+006	5	2.566E+005	137.19	< 0.0001	significant
A-Cutting speed	21389.06	1	21389.06	11.44	0.0045	
B-Feed	5.318E+005	1	5.318E+005	284.33	< 0.0001	
C-Depth of cut	6.777E+005	1	6.777E+005	362.36	< 0.0001	
BC	40186.13	1	40186.13	21.49	0.0004	
B2	11819.45	1	11819.45	6.32	0.0248	
Residual	26184.99	14	1870.36			
Lack of Fit	19316.99	9	2146.33	1.56	0.3242	not significant
Pure Error	6868.00	5	1373.60			
Cor Total	1.309E+006	19				

Std. Dev	43.25	R-Squared	0.9800
Mean	654.25	Adj R-Squared	0.9729
C.V.	6.61	Pred R-Squared	0.9535
PRESS	1.319E+005	Adeq Precision	38.954

The diagnostic checking of the model was carried out using residual analysis, and the results are presented in Figures 13 and 14. In Figure 13, the normal probability plot of residuals for cutting force is a straight line indicating that the errors (residuals) were normally independently distributed. The standardized residuals versus the predicted values are depicted in Figure 14. The residuals do not reveal any clear unusual form and are spreading in both positive and negative sides. This means that this model is adequate, and there is no reason to suspect any violation of the independence or constant variance assumption. Figure 15 manifests predicted actual cutting force data versus the actual ones for comparison purposes. This figure illustrates the predicted values of cutting force are close to actual ones measured in the experiments, revealing that there is a good agreement between the experimental and predicted results. Figure 16 depicts the perturbation of tool wear, showing the effect of each input parameter over the selected level. It can be observed that increasing both feed (B) and depth of cut (C) individually increases largely the cutting force with increasing their levels, whereas increasing the cutting speed (A) level decreases slightly the cutting force. This means that both feed and depth of cut have greater impact on the cutting force than cutting speed. This result is also confirmed by the 2D contour plot and 3D surface plot depicted in Figures 17 and 18, respectively as a function of cutting speed and feed, showing that the maximum cutting force occurred at (0.8) mm cutting depth. Also, these figures reveal that the feed rate is more effective on the cutting force than cutting speed. This means that increasing the cutting speed leads to a decrease in the cutting force, whereas increasing the feed rate results in the maximum cutting force value (up to 1100 N) at (0.4) rev/min, low cutting speed (40) m/min and (0.8) mm depth of cut. This could be ascribed to more material removed with the feed increase that requires higher cutting force to be applied at the lower cutting speed, thus leading to higher cutting force and higher tool wear as explained in earlier section. The high forces at lower cutting speed causes the chips remain, for long time, in contact with the tool rake face yielding an increase in the tool-chip contact length. This implies an increase in the friction between the tool and chip that resulted in higher forces.

To investigate the effect of depth of cut on the tool wear in this model, Figures 19 and 20 illustrate the 2D and 3D plots, respectively as a function of feed and depth of cut, showing the minimum cutting force occurred at (80) m/min cutting speed. It can be seen from both figures that the decrease in both depth of cut and feed leads to decrease the cutting force (down to 310 N) at lower feed (0.2) mm/rev, lower depth of cut (0.4) mm and higher cutting speed (80) m/min. This could be attributed to the combined influence of the decrease of these two parameters that resulted in less material removal and that needs lower cutting force at higher cutting speed, thus leading to minimum tool wear. Also, these figures show that increasing both feed up to (0.4) mm/rev and depth of cut up to (0.8) mm increases the cutting force to a higher value at (80) m/min cutting speed. The increase of cutting force is more likely due to higher material removal resulted by the increase of feed and cutting depth that necessitates using higher cutting force at higher speeds, leading to higher tool wear.

Finally, it can be concluded that in this model, the feed and depth of cut have a greater influence on the cutting force in this model than cutting speed. This conclusion is confirmed by the cube shape for cutting force in terms of cutting speed, feed rate and depth of cut as shown in Figure 21. The optimum value of the cutting force at the optimum cutting parameters will be given in the next section.

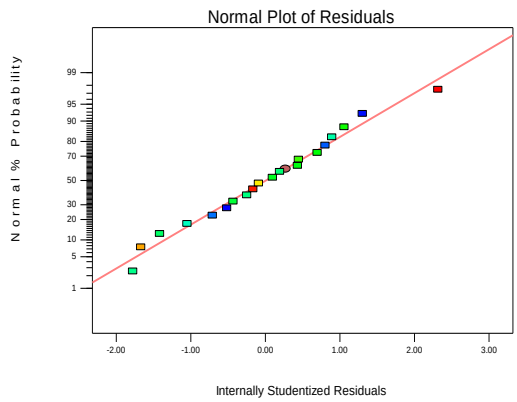

Figure 13: Normal probability plot for cutting force data

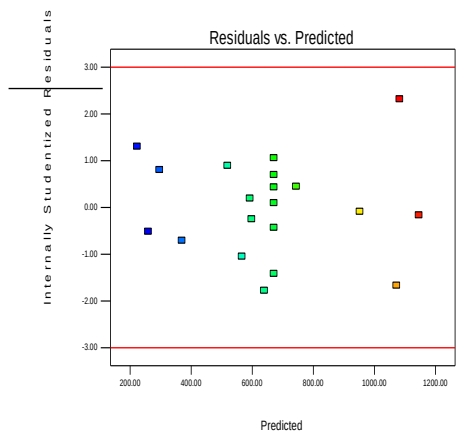

Figure 14: Residual versus predicted cutting responses for cutting force data

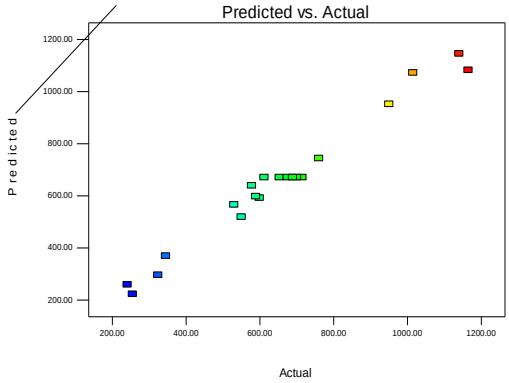

Figure 15: Predicted versus actual cutting force data for comparison

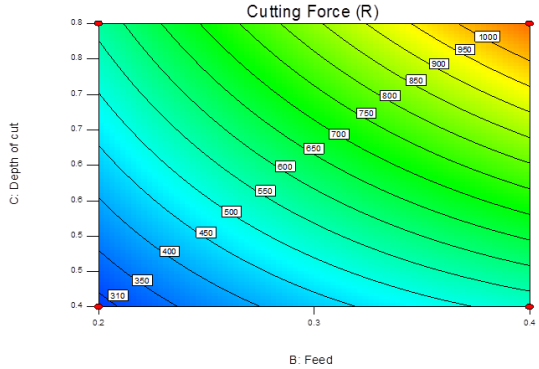

Figure 19: 2D plot showing the minmum cutting force at 0.8 mm depth of cut

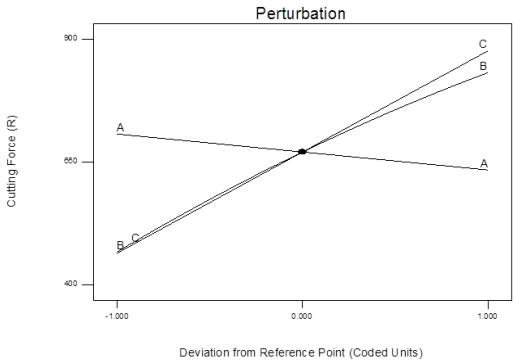

Figure 16: Perturbation of cutting force maximum showing the effect of each input parameter over the selected level

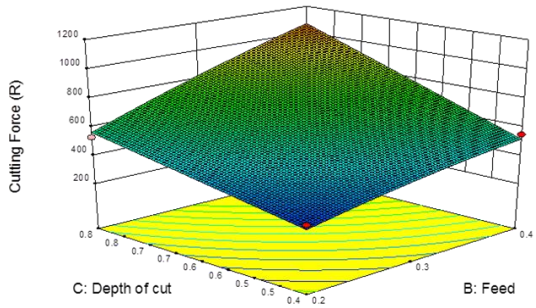

Figure 20: 3D plot showing the minimum cutting force at 0.8 mm depth of cut (mm)

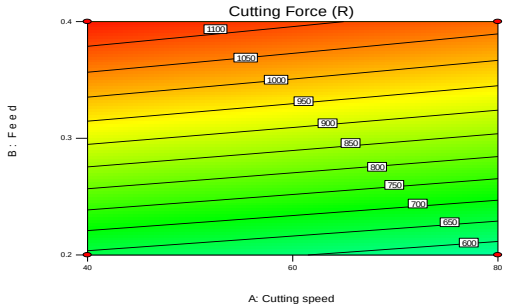

Figure 17: 2D plot showing the maximum cutting force at 0.8 mm depth of cut

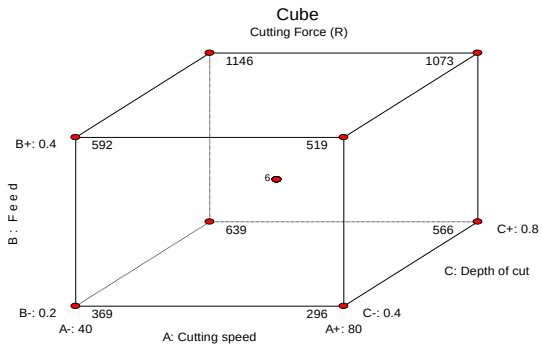

Figure 21: Cube shape for cutting force in terms of cutting speed (m/min), feed (mm/rev) and depth of cut (mm)

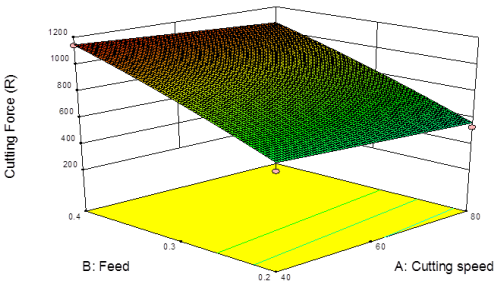

Figure 18: 3D plot showing the maximum cutting force at 80 m/min cutting speed

V. Numerical optimization of tool wear and cutting force

The numerical optimization was provided by the design of experiment software to find out the optimum combinations of parameters in order to fulfill the requirements as desired. Therefore, this software was used for optimization depending upon the results of the predicted models of two responses, tool wear and cutting force, as a function of three input factors (cutting speed, feed and depth of cut) and as follows:

To modify the new predicted model, a new objective function, called "desirability", which permits for appropriate combination of all goals, was found. Desirability is an objective function required to be maximized by a numerical optimization, it takes a value from 0 to 1 at the goal. By adjusting the desirability weight or importance, the goal characteristics may change, and the optimization objective is to determine a proper set of conditions that will satisfy all the goals. Normally, the weights are utilized to evaluate the goal's 3D importance in maximizing the desirability function. In the present work, weights were not changed, since the two outputs (tool wear and cutting force) have the main importance. The ultimate objective of optimization was to find the minimum output that simultaneously met all the parameter characteristics with a maximum desirability. Table 7 lists the required constrains for each parameter for conducting the numerical optimization of tool wear and cutting force. According to this table, one possible run fulfilled these specified constrains to obtain the minimum value for tool wear and cutting force, as given in Table 8. It can be seen that for this run, the maximum selected desirability is (0.970). Figure 22 depicts the optimum value of the minimum tool wear in 3D surface plot (111 µm), while Figure 23 illustrates the optimum value of the minimum cutting force in 3D surface plot (296 N).

Table 7: Constraints of the optimization of tool wear and cutting force

Name	Goal	Lower Limit	Upper Limit	Lower Weight	Upper Weight	Importance
A:Cutting speed	is in range	40	80	1	1	1
B:Feed	is in range	0.2	0.4	1	1	1
C:Depth of cut	is in range	0.4	0.8	1	1	1
Tool wear	minimize	117	342	1	1	1
Cutting force	minimize	241	1165	1	1	1

Table 8: Optimum solution for minimum tool wear and cutting force

Cutting speed (m/min)	Feed (mm/rev)	Depth of cut (mm)	Exp. Tool wear (µm)	Pred. Tool wear (µm)	Exp. Cutting force (N)	Pred. Cutting force (N)	Max. error (%)
80	0.2	0.4	117	111	324	296	8

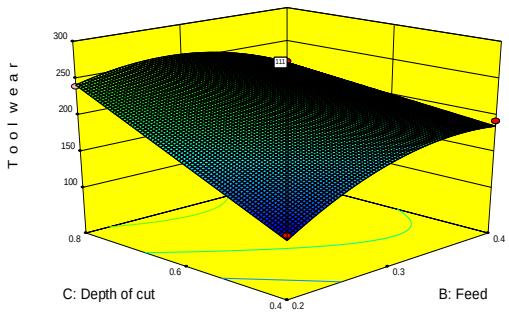

Figure 22: The minimum tool wear at the optimum cutting parameters (cutting speed= 80 m/min, feed= 0.2 mm/rev and depth of cut= 0.4 mm)

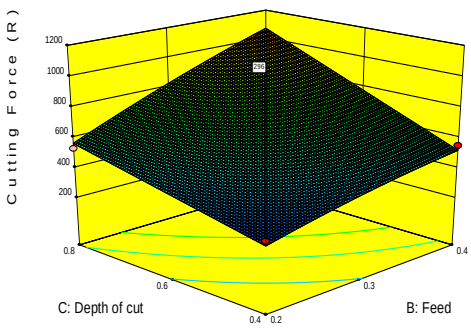

Figure 23: The minimum cutting force at the optimum cutting parameters (cutting speed= 80 m/min, feed= 0.2 m/min, feed =0.2 mm/rev and depth of cut= 0.4 mm)

VI. Confirmation tests

In order to check the validity of this model, confirmation tests were carried out with the optimum conditions of the input parameters obtained in this model to measure the tool wear and cutting force. The experimental results of these measurements are given together with the predicted results in Table (9) for comparison purposes. This table indicates that there is a good agreement between the experimental and predicted results with a maximum error of 8%.

Finally, for modeling of the wear and cutting force for the tungsten carbide tool with approach angle (45°) and rake angle (-6°) for turning of AISI316, the optimum cutting conditions are found to give the minimum tool wear and minimum cutting force within predetermined values. In conclusion, the optimum values of these conditions are cutting speed of 80 m/min, feed rate of 0.2 m/min and depth of cut of 0.4 mm with a minimum tool wear of (111 µm) and minimum cutting force (296 N).

Table 8: Optimum solution for minimum tool wear and cutting force

Cutting speed (m/min)	Feed (mm/rev)	Depth of cut (mm)	Tool wear (µm)	Cutting force (N)	Desirability	
80	0.2	0.4	111	296	0.970	Selected

Table 9: Comparison between experimental and predicted tool wear and cutting force

Cutting speed (m/min)	Feed (mm/rev)	Depth of cut (mm)	Exp. Tool wear (µm)	Pred. Tool wear (µm)	Exp. Cutting force (N)	Pred. Cutting force (N)	Max. error (%)
80	0.2	0.4	117	111	324	296	8

6. Conclusion

a) Quadratic equations for tool wear and cutting force models were developed by using DOE with RSM technique to relate both tool wear and cutting force (as responses) with the input cutting conditions (cutting speed, feed rate and depth of cut).

b) The results revealed that the optimum value for minimum tool wear and minimum cutting force was found at (80 m/min) cutting speed, (0.2 mm/rev) feed and (0.4 mm) depth of cut.

c) Generally, the minimum tool wear and cutting force values were obtained at higher cutting speed, and lower feed and depth of cut, whereas the maximum tool wear and cutting force values were found at lower cutting speed, and higher feed and depth of cut during turning AISI 316 stainless steel.

d) Good agreement was obtained between the experimental results and predicted ones for tool wear and cutting force with a maximum error of 8%.

e) DOE and RSM proved to be good tools to predict the tool wear and cutting force for all given values of input parameters in present work.

References

[1] G. Kumar, "Multi Objective Optimization of Cutting and Geometric parameters in turning operation to Reduce Cutting forces and Surface Roughness," B. Tech. Thesis, Dept. of Mechanical Eng., National Institute of Technology, Rourkela, 2013.

[2] W.H. Yang and Y.S. Tarng, "Design optimization of cutting parameters for turning operations based on Taguchi method," Journal of Materials Processing Technology, 84 (1) pp.112–129, 1998.

[3] M.F.B.M. Faisal, "Tool Wear Characterization of Carbide Cutting Tool Inserts coated with Titanium Nitride (TiN) in a Single Point Turning Operation of AISI D2 Steel," B.Tech. Thesis, Dept. of Manufacturing Eng., Univ. Teknikal Malaysia Mekala, 2008.

[4] A.J. Makadia and J.I. Nanavati, "Optimization of machining parameters for turning operations based on response surface methodology," Measurement, 46 (4) pp.1521-1529, 2013.

[5] M.S.B. Halim, "Tool Wear Characterization of Carbide Cutting Tool Insert in a Single Point Turning Operation of AISI D2 Steel," B.Tech. Thesis, Dept. of Manufacturing Eng., Univ. Technical Malaysia Mekala, 2008.

[6] D.C. Montgomery, "Design and Analysis of Experiments," Wiley, 4th ed., New York, 1997.

[7] V.K. Sharma, Q. Murtaza and S.K. Garg, "Response Surface Methodology and Taguchi Techniques to

Optimization of C.N.C Turning Process," International Journal of Production Technology, 1 (1), pp. 13-31, 2010.

[8] R.A. Mahdavinejad, "Investigation of influential Parameters of Machining of AISI 304 Stainless steel" Qc. Indian Academy of Sciences, Vol. 36, Part 6, pp. 963-970, 2011.

[9] Y. Agrawalla, "Optimization of Machining Parameters in a Turning Operation of Austenitic Stainless Steel to Minimize Surface Roughness and Tool Wear", MSc Thesis of Technology in Mechanical Eng., 2014.

[10] M.F. Ameur and M. Elbah, "Experimental Investigation of Cutting Parameters Influence on Surface Roughness and Cutting Forces in Hard Turning of X38CrMoV5-1 with CBN Tool," Qc. Indian Academy of Sciences, Vol. 38, Part 3, pp. 429-445, 2013.

[11] M. Tjiyagu, "Experimental Studies in Machining Duplex Stainless Steel Using Response Surface Methodology," International Journal of Mechanical and Mechatronics Engineering IMME-IJENS, Vol. 14, No. 03, pp. 48-61, 2014.

[12] Stainless Steel Selection Guide (ASTM-A240).

[13] S. Kalpakjian and S. Schmid, "Manufacturing Processes for Engineering Materials," Pearson Edcation, 5th ed. Book, Illinois Institute of Technology, 2007.

[14] R.A. Mahdavinejad, (2011), "Investigation of the Influential Parameters of Machining of AISI 304 Stainless Steel," Qc. Indian Academy of Sciences, Vol. 36, Part 6, pp. 963–970.

Author's biography

Prof. Dr. Shaker S. Hassan has Ph.D. degree in applied Mechanics from university of Leeds, U.K. in 1988. He has published more than 45 articles, supervised on 40 Ph.D. and M.Sc. students. He has been consultant in Iraqi engineers union since 1976, a membership in Federation of Arab Engineers since 2011, a membership of the Public Authority of General union of cooperation. His research are is Tribology, Biomechanics and Biomedics.

Assistant professor Dr. Samir Ali Amin has a PhD degree in Engineering Metallurgy from University of Bradford, United Kingdom, 1985. He has published more than 40 papers concerning personal researches, MSc. and PhD students. He has been a member of the Iraqi Engineers, Arab Engineers Federation, SME and ASME. His research field is in the properties of materials, powder metallurgy of HSS and manufacturing processes. Assistant professor Amin is currently supervising research works on creep property, FSW welding processes and shape memory alloys.

A.A. Dabish received MSc. in Mechanical Engineering in Applied mechanics from University of Technology/Iraq in 2016. His interest is mainly in Tribology of cutting tools. Mr. Dabish is currently a mechanical engineer in Ministry of Oil.