APPLICATION OF DESIGN OF EXPERIMENT METHODOLOGY ON TURNING PARAMETERS OF THE SAE 52100 HARDENED STEEL

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Abstract. *This paper presents a detailed study on the application of the Design of Experiment (DOE) and Response Surface Methodology (RSM) when modeling phenomena regarding the turning process of the SAE/ABNT 52100 hardened steel. The studied input factors are: cutting speed (Vc), feed rate (fn) and depth of cut (ap). As outputs was chosen mixed ceramic tool life.*

Keywords: *Hard turning, DOE, RSM, tool life, mixed ceramic.*

1. Introduction

To establish an adequate functional relationship between the tool life and the cutting parameters (cutting speed, feed rate and depth of cut), a great number of experiments is necessary, which, usually, makes the experimentation costs prohibitive.

According to Choudhury and El-Baradie (1998), many researchers have been investigating the effects of the cutting parameters on the tool life and surface roughness, using the method of varying a single parameter per experiment. The current study, on the other hand, takes into consideration the simultaneous variation of factors to build forecasting models for the relevant outputs. This approach, of a merely statistical interest, is known as Design of Experiment method (DOE) and consists in planning experiments capable of generating appropriate data for an efficient statistical analyses, which results in valid and objective conclusions (Montgomery, 1997). From the many experimental strategies available, this study will make usage of the complete factorial and the Response Surface Methodology (RSM).

A complete factorial is an experimental arrangement in which each factor is tested and retested a same amount of times on each of its levels, which are chosen in an appropriate manner within its standard (normal, usual) range of variation. This allows the creation of a model of first order for the dependent variable y (response) from a least squares algorithm.

In an analogous manner, the RSM arrangements, such as CCD (Central Composite Design) or Box-Behnken, for instance, use a combination of a factorial arrangement (complete or fraction), average points of the factors levels (center points) and the axial points (extremes) to adjust, when it is necessary, a polynomial model of a higher order.

Many researchers have employed these methodologies to study the materials machinability. Beauchamp et al. (1996) employed a complete factorial with six factors in the investigation of the influence from the cutting parameters in the surface roughness in turning process. Noordin *et. al.* (2004) applied the RSM to describe the performance of carbide tools in AISI 1045 steel turning process. Choudhury and El-Baradie (1998) also employed the RSM to model the tool life used in the turning of high resistance steel. Allaudin *et. al.* (1997) developed a similar work. Choudhury and Bartarya (2003) employed factorials in three levels to study the influence of temperature during the tool wear. Kulkarni and Mariappan (2003), Dhavlikar et al. (2003) and Benardos and Vosniakos (2002) employed the Taguchi Methodology along with other techniques, such as Dual Optimization, Artificial Neural Networks (ANN), Monte Carlo Simulation and Fuzzy Logic. All these works have as objective the machining process optimization, from a small, but efficient amount of experiments.

2. Design of experiment

2.1 Response surface methodology

According to Montgomery (1997), the Response Surface Methodology is a collection of mathematical and statistical techniques which are used to model and analyze problems in which the answer of interest is influenced by many variables and in which the answer must achieve an optimum value.

In many problems, the relationship between the response variable and the independent ones is unknown. Therefore, a first step inside the RSM is to find a reasonable approximation to the real relationship between *y* and the set of variables. Usually, it is used, initially, a low order polynomial.

Assuming that the expected response *E(Y)* is function of *k* variables x_1, x_2, …, x_k. Coded in such a manner that the center of the region of interest is the origin (0, 0, …, 0), the relationship between *Y* and *X* variables can be written according to a expansion of the Taylor Series (Box and Draper, 1987), as follows:

$$E(Y) = \eta = \eta_0 + \sum_{i=1}^{k} \left[\frac{\partial \eta}{\partial x_i} \right]_0 x_i + \frac{1}{2} \sum_{i=1}^{k} \sum_{j=1}^{k} \left[\frac{\partial^2 \eta}{\partial x_i \partial x_j} \right] + \ldots \tag{1}$$

where the subscript zero indicates the evaluation in the origin. If the high order terms are ignored, the expansion will be simplified:

$$\eta = \beta_0 + \sum_{i=1}^{k} \beta_i x_i \tag{2}$$

If, in addition, the second order terms are maintained, the approximation will become:

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i<j} \sum \beta_{ij} x_i x_i + \varepsilon \tag{3}$$

If there is a curvature in the process, then a polynomial of a higher order must be used, such as a second order model, for instance. This way, the Eq. (3) turns into:

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \beta_{ii} x_i^2 + \sum_{i<j} \sum \beta_{ij} x_i x_{j+} \varepsilon \tag{4}$$

According to Box and Draper (1987) most of all response surface problems uses the above equations. However, it's improbable that a polynomial model is a reasonable approximation to the real model in all the experimental space covered by the independent variables. For a determined region, however, this will work fine (Montgomery, 1997).

The analyses of a response surface are done in terms of a fitted surface. If such a surface is adequate, its analysis will be approximately equivalent to the analysis of a real surface. Using an adequate design of experiments to collect the data of the *y* response, the parameters of the model will be efficiently forecasted.

In most of the experiments, the linear model is considered enough in terms of fitting. However, to confirm if there's a lack of adjustment it is necessary to use Center Points. Such procedure consists in adding to the full factorial design, an amount of points which are intermediaries. It will be added as much center points as the number of *k* factors from the experiment (Box et al, 1978).

2.2 Central composite design

The arrangement called *Box-Wilson Central Composite Design*, or, simply, *Central Composite Design (CCD),* is formed by three distinct experimental elements: a complete factorial or a fractional factorial design; a set of Center Points and, additionally, a set of extra levels called Axial Points or Star Points.

2.3 Model's significance test

The significance of the model is done as an ANOVA procedure. Calculating the ratio between the quadratic average of the terms in the regression and the quadratic average of error, you will find the statistic *F.* Comparing the statistic with the critical value of *F* obtained from the desired level of significance, a conclusion about the model's significance is reached. If *F* is greater than $F_{critical}$ (which is equivalent to a P-Value lower than the significance level), then the model is adequate (Montgomery, 1997).

The test for individual significance of each coefficient may lead to the optimization of the model through the elimination or/and addition of terms. As the previous item, if the P-Value of the individual test of the terms is lower than the significance level, then, the term is adequate to the model and must be maintained. If, however, the contrary occurs (Montgomery, 1997; Box & Hunter, 1978; Box and Draper, 1987), the term must be excluded if such procedure leads to an increase of the coefficient of R^2 along with a decrease of the error term *S* (this term is the square root of the mean square error). The test for the lack of fit of the reduced model must present a P-Value greater than the significance level; otherwise, the elimination of the term is unjustified. Besides that, the elimination of any term must obey the principle of Hierarchy (Montgomery, 1997), which means, if a term of a higher order is maintained in the model, the one with a lower order also must be preserved. For instance, if the interaction AB is significant, but the main effect A is not, then the model must be preserved for both.

The presence of replicates in an experiment allows that the sum of the squares of the errors be divided in two parts: the pure error and the lack of fit. When the P-Value of the test of lack of fit is superior to the significance level, then, there is no evidence that the model doesn't adequately explain the response variation (Montgomery, 1997).

3. Experimental procedure

The workpieces were made with dimensions of ϕ49 x 50mm. All of them were quenched and tempered. After this heat treatment, their hardness was between 53 and 55 HRC, up to a depth of 3 mm below the surface. The workpiece material was the AISI 52100 steel, with the chemical composition shown on Tab. 1.

Table 1. Chemical Composition of the AISI 52100 steel.

C	**Si**	**Mn**	**Cr**	**Mo**	**Ni**	**S**	**P**
1,03	0,23	0,35	1,40	0,04	0,11	0,001	0,01

The machine tool used was a CNC lathe with power of 5,5 KW in the spindle motor, with conventional roller bearings.

The mixed ceramic (AL_2O_3 + TiC) inserts used were coated with a very thin layer of titanium nitride (TiN) presenting a chamfer on the edges. Their ISO code was CNGA 120408 S01525 and they were made by Sandvik Coromant (Sandvik class CC6050). The tool holder presented negative geometry with ISO code DCLNL 1616H12 and entering angle $\chi_r = 95°$.

Tool flank wear measurements (VB_{max}) were taken through an optical microscope. It was used the end of life criteria, the tool breaking point. A full factorial experimental design was built (2^3) with three input variables each in two levels according Tab. 2.

Table 2. Three input variables in two levels.

Parameter	Symbol	Unit	Low Level	High Level
Cutting speed	Vc	m/min	200	240
Feed	fn	mm/rev.	0.05	0.10
Depth of cut	ap	mm	0.15	0.30

4. Results and discussion

4.1 Tool life model

According to Choudhurry and El-Baradie (1998), the relationship between tool life and the independent machining variables can be written as follows:

$$T = C\left(Vc^{l}\, fn^{m}\, ap^{n}\right)\varepsilon' \tag{5}$$

Where T is the tool life in minutes, Vc, fn and ap are the cutting parameters, shown on Tab. 2, C, l, m and n are constants and ε is the model's random error. Rewriting Eq. (5) in a logarithm form, it will result:

$$\ln T = \ln C + l \ln Vc + m \ln fn + n \ln ap + \ln \varepsilon' \tag{6}$$

The linear model of Eq. (6) is:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \varepsilon \tag{7}$$

where y is the tool life, $x_1 = \ln Vc$; $x_2 = \ln fn$; $x_3 = \mathrm{l\,n}ap$; ε=ln ε. Assuming that ε is independent (non-correlated) and normally distributed, with zero average and constant variance, $\beta_0 = \ln C$, and β_1, β_2, β_3 are parameters of the model. Hence, the estimated response can be written as follows:

$$\hat{y} = y - \varepsilon = b_0 + b_1 x_1 + b_2 x_2 + b_3 x_3 \tag{8}$$

In this paper, the parameters b_0, b_1, b_2 and b_3 will be estimated using the least square method, employing the software Minitab®. The experimental matrix with four center points and tool life results are shown on Tab. 3.

Table 3. Full factorial 2^3 with center points and tool life response.

Nº	Vc (m/min)	fn (mm/rev)	ap (mm)	Coded units			Tool life (min)
1	200	0,05	0,15	-1	-1	-1	15,8
2	240	0,05	0,15	1	-1	-1	10,9
3	200	0,1	0,15	-1	1	-1	9,2
4	240	0,1	0,15	1	1	-1	8,5
5	200	0,05	0,3	-1	-1	1	12,4
6	240	0,05	0,3	1	-1	1	7,2
7	200	0,1	0,3	-1	1	1	7,9
8	240	0,1	0,3	1	1	1	6,8
9	200	0,05	0,15	-1	-1	-1	17,7
10	240	0,05	0,15	1	-1	-1	12,1
11	200	0,1	0,15	-1	1	-1	10,5
12	240	0,1	0,15	1	1	-1	8,5
13	200	0,05	0,3	-1	-1	1	10,6
14	240	0,05	0,3	1	-1	1	7,7
15	200	0,1	0,3	-1	1	1	8,5
16	240	0,1	0,3	1	1	1	5,7
17	220	0,075	0,225	0	0	0	8,6
18	220	0,075	0,225	0	0	0	6,8
19	220	0,075	0,225	0	0	0	7,2
20	220	0,075	0,225	0	0	0	9,1

Table 4. ANOVA of the full factorial 2^3 with center points for tool life response.

Term	**Effect**	**Coeficient**	**Standard Error**	**T**	**P**
Constant		10,000	0,2327	42,98	0,000
Vc	-3,150	-1,575	0,2327	-6,77	0,000
fn	-3,600	-1,800	0,2327	-7,74	0,000
Ap	-3,300	-1,650	0,2327	-7,09	0,000
Vc x fn	1,500	0,750	0,2327	3,22	0,008
Vc x ap	0,150	0,075	0,2327	0,32	0,753
fn x ap	1,350	0,675	0,2327	2,90	0,014
Vc x fn x ap	-0,450	-0,225	0,2327	-0,97	0,354
Center Point		-2,075	0,5203	-3,99	0,002

Source	**DF**	**SEQ SS**	**ADJ SS**	**MS**	**F**	**P**
Main Effects	3	135,090	135,090	45,0300	51,99	0,000
Two-way Interactions	3	16,380	16,380	5,4600	6,30	0,010
Three-way Interactions	1	0,810	0,810	0,8100	0,94	0,354
Curvature	1	13,778	13,778	13,7780	15,91	0,002
Residual Error	11	9,527	9,527	0,8661		
Pure Error	11	9,527	9,527	0,8661		
Total	**19**	**175,585**				

Observing the results on Tab. 4, we conclude that the adopted arrangement lies within the vicinities of the optimum region once that the curvature P-Value is lower than the 5% significance level. Therefore, the response can be fitted using CCD. In this case, it will be used the results from the previous factorial, using, additionally, only the axial points of the arrangement. As the previous factorial has a replicate, it will be used the average of the responses of each experiment. To prevent a possible biasness, the experiment needs to be blocked. This way, the results obtained plus two central points will form block 1, while the axial points, followed by two central points, will form block 2. If there is no difference between the blocks, the term will be excluded from the model. That is how Tab.5 is build.

Table 5. Cutting parameters and results for the RSM of the tool life response.

Nº	Block	Vc (m/min)	f (mm/rev.)	a_p(mm)		Coded		Life (min)
1	1	200	0,05	0,15	-1	-1	-1	16,75
2	1	240	0,05	0,15	1	-1	-1	11,50
3	1	200	0,1	0,15	-1	1	-1	9,85
4	1	240	0,1	0,15	1	1	-1	8,50
5	1	200	0,05	0,3	-1	-1	1	11,50
6	1	240	0,05	0,3	1	-1	1	7,45
7	1	200	0,1	0,3	-1	1	1	8,20
8	1	240	0,1	0,3	1	1	1	6,25
9	1	220	0,075	0,225	0	0	0	8,60
10	1	220	0,075	0,225	0	0	0	6,80
11	2	187,34	0,075	0,225	-1,633	0	0	10,10
12	2	252,66	0,075	0,225	1,633	0	0	7,60
13	2	220	0,03418	0,225	0	-1,633	0	17,50
14	2	220	0,11583	0,225	0	1,633	0	7,20
15	2	220	0,075	0,102525	0	0	-1,633	12,00
16	2	220	0,075	0,347475	0	0	1,633	6,70
17	2	220	0,075	0,225	0	0	0	7,20
18	2	220	0,075	0,225	0	0	0	9,10

4.2 Model adjustments

Using the results from Tab. 5, from the developed CCD, the first order model for the tool life is as follows:

$$\hat{y} = 9{,}600 - 1{,}251\,Vc - 2{,}341\,fn - 1{,}639\,ap \tag{9}$$

Using the transformation equation described in the paper of Alauddin *et al.* (1997) to each independent variable of this experiment, will have, respectively:

$$x_1 = \frac{\ln Vc - \ln(220)}{\ln(240) - \ln(220)};\ x_2 = \frac{\ln fn - \ln(0{,}075)}{\ln(0{,}1) - \ln(0{,}075)};\ x_3 = \frac{\ln ap - \ln(0{,}225)}{\ln(0{,}3) - \ln(0{,}225)} \tag{10}$$

Substituting these results in Eq. (5), we have:

$$T = 1{,}485.10^{25}(Vc^{-14{,}44}.fn^{-8{,}14}.ap^{-5{,}7}) \tag{11}$$

This equation shows that the tool life decrease with the increase of the cutting speed (*Vc*), feed (*fn*) and depth of cut (*ap*). This can be also noted in the factorial graph in Fig. 1. However, as Tab. 6 shows, the linear model doesn't adequately explains the phenomenon (R^2 adj = 66.7%). In this way, a higher order model must be used.

Table 6. Linear Model.

Term	COEF	SE COEF	T	P
Constant	9,600	0,4412	21,757	0,000
Vc	-1,251	0,5127	-2,440	0,029
fn	-2,341	0,5127	-4,567	0,000
ap	-1,639	0,5127	-3,197	0,006
S = 1,872	R-Sq = 72,6 %		R-Sq (adj) = 66,7 %	

Table 7 presents the ANOVA of a second order model, obtained from the CCD results. A previous analysis considered the presence of blocks. The P-Value from the block analysis (0.503) revealed the absence of differences between the experiments executed in the first round and the axial points. Therefore, eliminating the blocks from the experiment, the analyze can be more appropriate. An excellent fit is observed (R^2 adj = 85.00%), nevertheless, the interactions are not significant. According with what was shown in the item 2.3 an adjustment is needed from a reduced model, respecting, nonetheless, the hierarchy principle. Once the quadratic terms of *Vc* and *ap* are not significant, they must be dropped from the complete model. According to the P-Value in the Anova for the interaction, at least one is different from the others. Analyzing term by term, we conclude the *Vc.ap* interaction is not significant, hence, this terms can be ignored.

The reduced model, regarding only the terms shown on Tab. 7 satisfies the recommendations described on item 2.3, which means, it presents a better adjustment (R^2 adj = 87.00%), with a lower error term *S* (1.17). Moreover, there is no lack of fit evidence. For this reason, it was decided to use in this paper the following model which can be written as:

$$y = 7{,}968 - 1{,}251\,Vc - 2{,}341 fn - 1{,}639 ap + 1{,}547 fn^2 + 0{,}750 Vcfn + 0{,}675 fn.ap \quad (12)$$

Table 7. ANOVA from the response surface.

Term	Coeficients	Standard Error	T	P
Constant	8,5280	0,3700	23,046	0,000
Vc	-1,2512	0,3205	-3,904	0,002
fn	-2,3415	0,3205	-7,307	0,000
ap	-1,6391	0,3205	-5,115	0,000
fn x fn	1,4472	0,3330	4,346	0,001
Vc x fn	0,7500	0,4137	1,813	0,097
fn x ap	0,6750	0,4137	1,632	0,131
S = 1,17	R-Sq = 91,6 %		R-Sq (adj) = 87,0 %	

Source	DF	SEQ SS	ADJ SS	MS	F	P
Regression	9	163,798	163,798	27,300	19,940	0,000
Linear	3	129,796	129,796	43,265	31,600	0,000
Quadratic	3	25,857	25,857	25,857	18,880	0,001
Interaction	3	8,145	8,145	4,072	2,970	0,093
Residual Error	8	11,000	15,062	15,062	1,369	
Lack of fit	5	11,434	11,434	1,429	1,180	0,494
Pure Error	3	3,000	3,627	3,627	1,209	
Total	17	178,860				

As it was shown on Fig 1, the tool life increases when it is employed the control variables lower levels. Analyzing the contour plot from Fig. 2, the same conclusion is evident. For this specific material with depth of cut around 0.15 mm, lower cutting speed of 200 m/min and feed lower than 0.05 mm/rev., it is obtained tool life greater than 20 minutes. These levels for the cutting parameters optimize the mixed ceramic tool life used in the turning operation of the SAE 52100 Steel – 55 HRC.

It can be noted that the stationary point in the surface plot of Fig. 1, which is generally called minimal point, do not represent the optimal machining condition. Otherwise, as far as we walk from this point higher is the tool life. This can be noted in the nature of the response; tool life is a larger-is-better response type.

Although the present statistical conclusions are so strong, they can only be used for this specific case. It is not correct to make generalizations or extrapolations from these conclusions for other materials or tools; nonetheless, the experimental procedure used in this paper can be used in any machining process or desired material. Nevertheless, the experience of the researcher is imperative in the process of choosing the levels for the parameters.

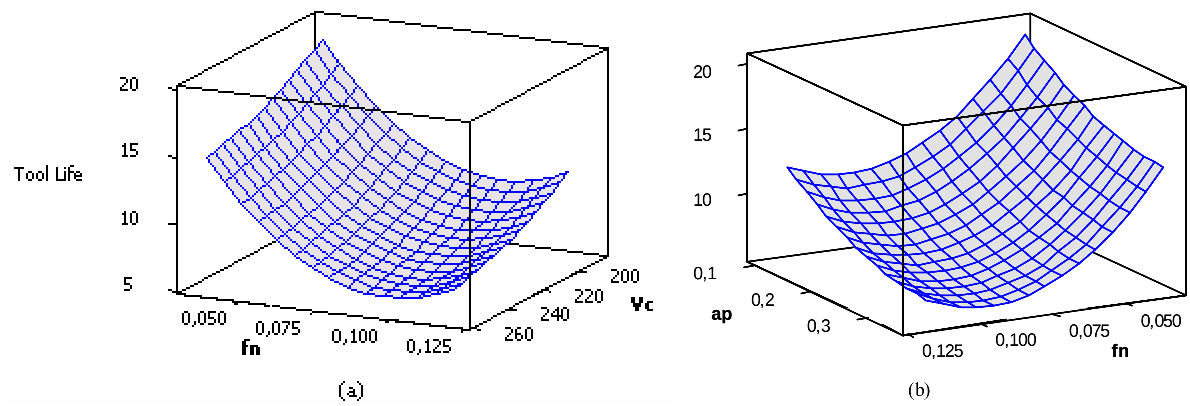

Figure 1. Response Surface of Tool Life in minutes. (a): Hold Value = ap:0,225; (b):Hold Value = Vc:200

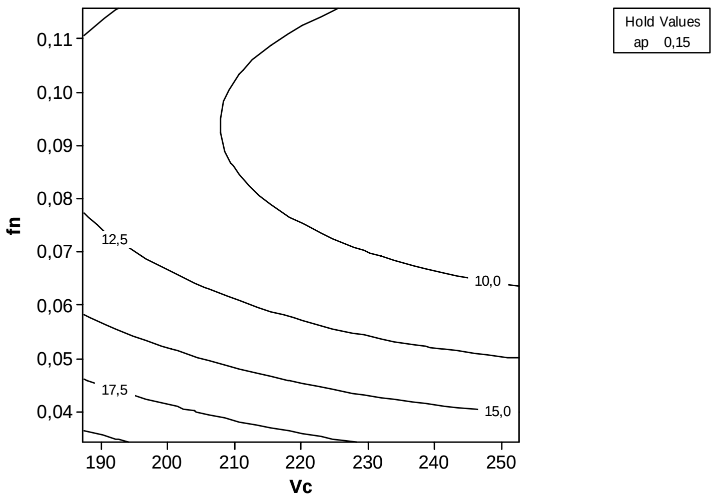

Figure 2. Contour plot for tool life response.

According with the recommendations of several authors (Montgomery, 1997; Box & Hunter, 1978; Noordin et. al, 2004), in every DOE a residual analysis of experimental response is necessary. Residuals are differences between two or more observations and the average formed by these observations (Montgomery, 1997). Therefore, every time the chosen design uses experiments replicates, there will be residuals.

The residual analysis aims to evaluate the quality of the results; in other terms, show if the results are real or if they are nothing but mere coincidence. Furthermore, they can identify discrepancies or errors, such as: value inversion, incorrect typing, inadequate experiment results, and so on.

According to Montgomery (1997), the residues must be normal, independent (non-correlated) and normally distributed. Figure 3 evaluates the normality of the obtained resides with the CCD used in this study. The good fit of the points to the theoretical curve (straight), as well as the value of P-Value from the test of Anderson-Darling (0.805) well above the significance level adopted 5%, indicate the normality of the residuals.

It is very important to verify the independence of the residues in relation to the order in which the experiments were done. Once there can not be noticed the existence of a correlation between the magnitude of the residues and the experiment which originated it, it can be stated that the residues are independent. It was observed that, there is no correlation between the residues and their respective fitted value. The fitted value is the response found for an experiment when the specific levels from the original design in the statistical model developed are replaced (in here, the complete quadratic model).

As there are no abnormality patterns shown within the residues, the results described in this paper can be taken as valid.

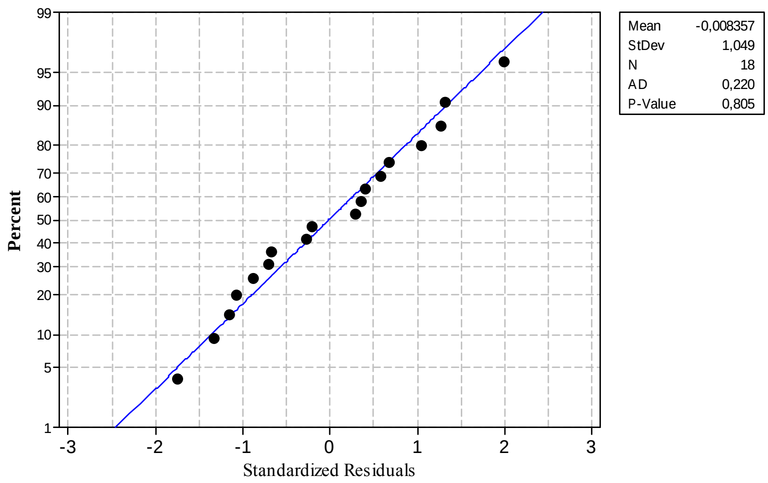

Figure 3 – Residual Analyses of the RSM from tool life response.

5. Conclusions

This paper shows the conclusions obtained from the experimental investigation over the influence of the cutting parameters over the ceramic tool life.

It was possible to state that the response surface methodology combined with full factorial experiments are very useful techniques when modeling and creating equations to forecast dependent variables from machining process. Regarding other approaches, a small number of experiments were necessary to generate useful data pool for those interested in the turning process of the 52100 hardened steel using mixed ceramic tools. For the tool life, a second order model proved to be more appropriate. Besides, it was possible to find the best levels for the parameters.

From the study, it can be extracted that the best machining conditions in question are those which maximize the tool life. The optimum levels for the response of interest were: cutting speed equal or lower than 200 m/min, feed equal or lower than 0.05 mm/rev. and depth of cut equal or lower than 0.15 mm.

These conclusions can not be extrapolated to different materials, tools, or machine tools and they are only valid in the adopted level range. Nonetheless, it can be recommended to fit the methodology to any production processes.

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5. Responsability notice

The authors are the only responsible for the printed material included in this paper.