Modeling of Life Tool and Roughness in Turning Hard Steel AISI 52100 Wiper with Mixed Ceramics Using Response Surface Methodology

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Abstract

In the study of the life of tools and average roughness of the machined surfaces, the turning process, there is the influence of various process factors, such as cutting speed, feed and depth of cut. In the conventional analysis of the influence of these factors in the machining process, is usually studied the influence of each of them separately. It is in this context that the response surface methodology (RSM) through which one can establish an appropriate working relationship between the characteristics of the product or machined and the tool used (tool life, surface roughness of the part, process cost, time machining) and cutting parameters. In this case, taking into account the simultaneous variation of factors, one can build mathematical models for prediction and optimization for the responses of interest. This statistical approach to nature is to plan experiments that generate appropriate data for effective analysis, resulting in valid and objective conclusions. This paper specifically addresses the mathematical modeling tool life (T) and surface roughness (Ra, Rq) of the part in the process of turning hardened steel AISI 52100 (50 HRC) with mixed ceramic Wiper tool and its interface with the methods of optimization of nonlinear programming. Mathematical models will be obtained by response surface methodology variables were the parameters of influence cutting speed, feed rate and cutting depth.

Keywords: roughness; tool life; hard turning, ceramics mixed wiper; nonlinear programming.

1 Introduction

The hard turning technology has become an important manufacturing process and is widely used in a range of industrial applications such as gears, shafts, bearings, cams, forged parts, molds and dies This is the removal of materials whose hardness is more than 45 HRC. The turning operation is performed with tool materials mixed ceramic (Al_2O_3 + TiC) and cubic boron nitride (CBN), which induces a significant benefit, such as short-cutting time, process flexibility, low surface roughness of piece, high rate of material removal and dimensional accuracy. Referring to this process, we have the capacity utilization of modern machine tools, that will produce different contour geometries and generate complex shapes in the material being machined (ZOU, 2004).

The hard turning significantly reduces production costs, preparation time and improves the overall quality of the product in relation to the grinding process (Paiva, 2007). Especially considering their effectiveness in reducing processing time consumed in each operation, reduced power consumption, the elimination of cooling, the improvement of material properties and the ability to promote good surface finish by removing material from a single piece court, rather than a long grinding operation.

The contribution of the geometry of the tool for improvement of hard turning process, several studies show the use of wiper. (OZEL et al, 2007) investigated the influence of the edge geometry CBN tool related to the development of strain and temperature using a finite element simulation in hard turning and present a study of the effect of chamfer angle on CBN tool wear in hard turning and investigated the correlation between wear, cutting force and tool life. With this change in geometry, it is possible to double the feed rate, increasing productivity and maintaining lower surface roughness of the workpiece.

(GAITONDE et al, 2009) study the behavior of surface roughness and tool wear, using mathematical models of second order, with wiper tools. Confirm that the mixed ceramic tool presents better roughness of the part and tool performance when compared to a traditional tool in hard turning of AISI D2. (OZEL et al, 2007) indicate that AISI D2 steel with a hardness of 60 HRC piece reaches the average roughness (Ra) with wiper tools, values around 0.20 μm.

However, the potential benefits promoted by hard turning for surface quality and to increase the rate of productivity depend intrinsically an optimal setting for the process parameters such as cutting speed, feed rate and cutting depth. Some papers study the effect of these cutting conditions, the influence of the hardness of the piece, the tool geometry in roughness, cutting fluids, the tool wear and the geometric error in surface integrity (roughness and damage to the thermal layer) (SINGH, 2008).

(BOUACHA et. al, 2010) use the MSR to construct quadratic models for roughness and cutting forces in the study of hardened steel AISI 52100. Employed the response surface methodology to study the flank wear as a function of cutting speed, feed and depth of cut. (BENGA and ABRAM, 2003) study the tool life and finish of the hardened steel 100Cr6 using ceramic and PCBN inserts with response surface methodology.

Given these considerations, the main objective of this experimental work specifically addresses the mathematical modeling of parameters of the tool life (T) and part roughness (Ra, Rt) in relation to cutting speed, feed rate and depth of cut, in the process of turning hardened steel ABNT 52100 (50 HRC) using wiper geometry.

2 Response Surface Methodology

According to (MONTGOMERY, 2005), the Response Surface Methodology, or RSM, is a collection of mathematical and statistical techniques that are useful for the modeling and analysis of problems in which a response of interest is influenced by several variables and the objective is to optimize this response. Thus, when the mathematical relationships between input parameters and responses (objective functions) are unknown, the RSM enables such functions to be determined as from experimental data, which are collected in a planned way (GOMES et al, 2011).

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \beta_{ii} x_i^2 + \sum_{i<j} \sum \beta_{ij} x_i x_j \qquad (1)$$

2.1 Multivariate Mean Square Error

The Multivariate Mean Square Error (MMSE), as presented by (PAIVA et al, 2009), is a method that combines the Response Surface Methodology (MONTGOMERY, 2005) and the Principal Component Analysis (JOHNSON and WICHERN, 2002) for the optimization of multiple correlated responses in multivariate processes.
Given that the principal component (PC), through its scores, can be modeled by RSM, the eigenvalue λ represents the variance and taking ζ_{PC} as target for the principal component, the multivariate mean square error (MMSE) is defined as:

$$MMSE = \left(PC - \zeta_{PC}\right)^2 + \lambda \qquad (2)$$

In Equation 2, PC is a second-order polynomial fitted in relation to the input variables. The target ζ_{PC} must keep a straightforward relation with the targets of the responses of interest, presenting a compatible value with the objectives of the original problem. It is established using Equation 3:

$$\zeta_{PC} = e^T \left[Z\left(Y_j \middle| \zeta_{Y_j}\right) \right] = \sum_{j=1}^{p} e_j \cdot \left[Z\left(Y_j \middle| \zeta_{Y_j}\right) \right] \tag{3}$$

with: ζ_{PC} – Target for the principal component

e – Eigenvector associated to the principal component

P – Number of responses of interest

$Z\left(Y_j \middle| \zeta_{Y_j}\right)$ – Standardization of the responses of interest in relation to their targets:

$$Z\left(Y_j \middle| \zeta_{Y_j}\right) = \frac{\zeta_{Y_j} - \mu_{Y_j}}{\sigma_{Y_j}} \tag{4}$$

with: ζ_{Y_j} – Target of the jth response

μ_{Y_j} – Mean of the jth response

σ_{Y_j} – Standard deviation of the jth response

In this approach, the optimization is given by minimizing the MMSE stated in Equation 5, which means that the principal component tends to reach the established target with minimum variance. If more than one principal component is needed, then the MMSE optimization is obtained by the following mathematical formulation:

$$\begin{aligned} &Minimize \quad MMSE_T = \left[\prod_{i=1}^{m} MMSE_i \right]^{\left(\frac{1}{m}\right)} = \left\{ \prod_{i=1}^{m} \left[\left(PC_i - \zeta_{PC_i} \right)^2 + \lambda_i \right] \right\}^{\left(\frac{1}{m}\right)}, \quad m \le p \\ &Subject\ to: \ g_n(\mathbf{x}) \le 0 \\ &\qquad \mathbf{x}^T \mathbf{x} \le \alpha^2 \end{aligned} \tag{5}$$

In Equation 5, $MMSE_T$ is the total Multivariate Mean Square Error; $MMSE_i$ is the Multivariate Mean Square Error for the ith principal component; m is the number of needed principal components; p is the number of responses of interest; PC_i is the response surface function for the ith principal component; ζ_{PC_i} is the target for the ith principal component; λi is the eigenvalue for the ith principal component g_n (x) ≤ 0 represents a constraint equation and $\mathbf{x}^T\mathbf{x} \le \alpha^2$ is the spherical constraint for the experimental region.

The optimization of the principal components implies the optimization of the responses of interest, since these are defined as from linear combinations of the original responses.

3 Experimental Procedure

3.1 Machine tools, materials and Measuring Instruments

For the turning process developed in this study used a CNC Nardini Logic 175, with maximum power of 7.5 HP axis; maximum speed of 4000 rpm; tower with eight positions and maximum torque of 200 Kgf.m.

The inserts are of mixed ceramic (Al_2O_3 + TiC) coated with titanium nitride (TiN) manufacturer Sandvik, 6050 GC class with wiper geometry ISO CNGA S01525WH 120408. The tool holder is ISO DCLNL Model 1616H12; position angle of 95 °, rake angle of -6 °, angle of -6 ° and clearance angle of 7 degrees.

Figure 3.1 shows the geometry of rays straightening the tip of the tool and its effect combined with the advances in the roughness of the machined part. The specimens used in the tests have dimensions of 49 mm in diameter and 50 mm long, with steel AISI 52100. The high hardness is achieved in this steel for induction hardening process. This material is usually treated with pre-heating for two hours at a temperature of 500°C, heated for 40 min at 830°C, followed by a 30 min cooling (martêmpera to 180°C), cold air until 80°C, annealed for two hours at 200°C and again air-cooled to about 30°C.

This results in a microstructure of martensite up to 5% of retained austenite. The hardness of the steel AISI 52100 reached 50 HRC. This steel has the following chemical composition according to Table 3.1:

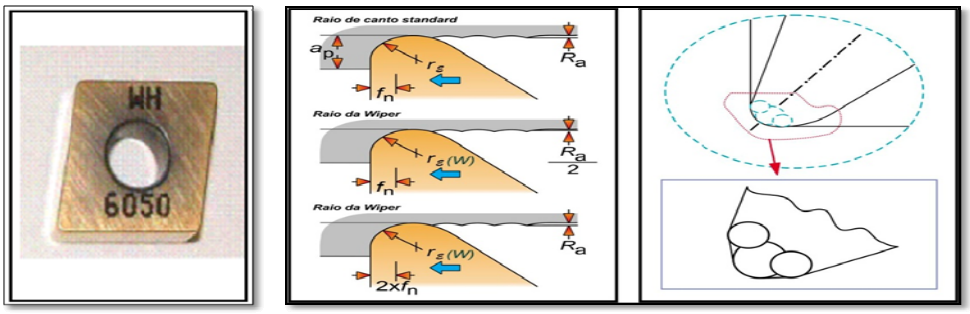


Figure 3.1. Wiper tool geometry and tool nose radius trowel.

Source: Sandvik, 2010, adapted by the author.

Table 3.1. Composition of Steel AISI 52100

Chemical composition of steel AISI 52100 (wt%)								
Element	C	Si	Mn	Cr	Mo	Ni	S	P
Content(%)	1,03	0,23	0,35	1,4	0,04	0,11	0,001	0,01

For the measurements of roughness parameters Ra and Rt used a tool tip, roughness model Mitutoyo SJ 201. The tool wear was monitored using an optical microscope Olympus SZ 61 with a digital camera with 30 x magnification. The permissible flank wear was established VBmax = 0.3 mm according to ISO 3685 (1993).

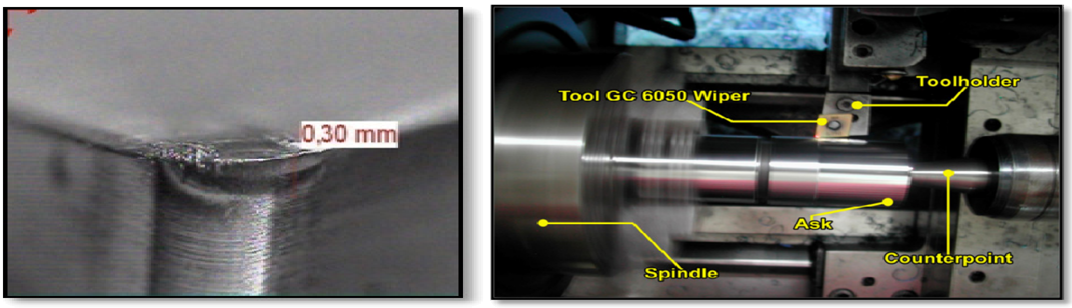
3.2 Methodology for Testing

For tests were adopted two levels of variation for each of the machining parameters studied. Table 3.2 presents the three factors: cutting speed, feed rate, machining depth and their levels of variation. The levels were specified in terms of data recommended by the manufacturer's catalog of tools (SANDVIK, 2010) and was also designed a factorial design (three parameters and two levels and a central point) for the tests.

Table 3.2– Parameters and their levels

Parameters	Unit	Notation	Levels				
			-1.682	-1	0	+1	+1.682
Cutting speed	m/min	Vc	186	200	220	240	254
Feed rate	mm/v	f	0.13	0.20	0.30	0.40	0.47
Depth of cut	mm	d	0.10	0.15	0.22	0.30	0.35

The turning tests were sized to provide an accurate way of studying the influence of cutting speed, feed and depth of the machining surface roughness (Ra, Rt) and the tool life (T) of the workpiece through the application the methodology of design of experiments (DOE) and response surface methodology (RSM). It was adopted as a criterion for tool change, especially roughness values (Ra <0.5) m is flank wear VBmax <0.3 mm (Figure 3.2 a). This criterion was adopted according to the risk of breakage of the ceramic insert. Each specimen machined, it was removed from the machine for measuring roughness. At this time the insert was also removed support for the monitoring of flank wear (VBmax). At this time the insert was also removed support for the monitoring of flank wear (VBmax). The Figure 3.2 b represents the turning process of AISI 52100 steel used in the experimental study.



a) b)

Figure 3.2 - Process of Turning Tool with Carbide Ceramics Mixed

The roughness measurements were performed four times in (A, B, and C), according to the scheme illustrated in Figure 3.3 (symmetrical sides), after roughness measurements were performed the arithmetic mean of roughness values. To monitor the tool life was measured over time and the number of passes at each value of the process parameters.

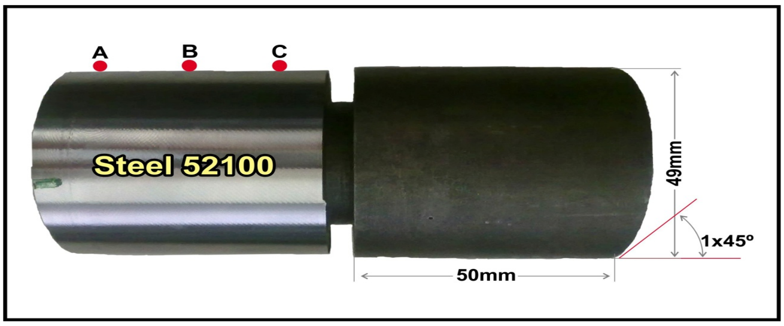


Figure 3.3 Positions reading roughness in specimens

4 Results and Discussion

Through the development of a complete factorial arrangement with five central points was made to analyze the data obtained experimentally. Table 4 presents the results of life (T) of mixed ceramic tool and the surface roughness (Ra, Rt) tested for the eight conditions required to obtain the factor scores and five central points.

From the data of Table 4 ANOVA was performed to compare the averages of three factors at two levels (23) and the focal point for both the response of tool life (T) as for the roughness (Ra, Rt).

To obtain the Central Composite Design (CCD), previously mentioned, will use the results of the factor in Table 4 and in addition only the axial points of the arrangement.

We used an array of response surface of the CCD for three factors. With this experimental arrangement, 19 trials were conducted under controlled conditions. For each experimental condition were observed tool life and surface roughness (Ra, Rt) of the machined part. Considering the values obtained, this research sought to study a model using Response Surface Methodology for the life of the tool part number and the roughness (Ra, Rt).

Table 4 shows the calculation of roughness (Ra, Rt) and the tool life (T) for the response surface model with 19 experiments.

Table 4. Experimental matrix

	Parameters			**Responses**		
Test	***Vc***	***f***	***d***	***T***	***Ra***	***Rt***
	m/min	mm/rev	mm	min	μm	μm
1	-1	-1	-1	17.21	0.25	1.41
2	+1	-1	-1	11.37	0.27	1.72
3	-1	+1	-1	5.96	0.31	2.12
4	+1	+1	-1	4.48	0.30	2.15
5	-1	-1	+1	9.42	0.25	1.45
6	+1	-1	+1	7.37	0.25	1.58
7	-1	+1	+1	4.03	0.34	2.01
8	+1	+1	+1	6.10	0.29	1.99
9	-1.682	0	0	9.51	0.29	1.69
10	+1.682	0	0	6.86	0.26	1.81
11	0	-1.682	0	14.18	0.21	1.54
12	0	+1.682	0	4.12	0.31	2.54
13	0	0	-1.628	9.42	0.31	1.94
14	0	0	+1.682	4.92	0.31	1.74
15	0	0	0	4.89	0.26	1.81
16	0	0	0	5.00	0.26	1.71
17	0	0	0	4.77	0.26	1.71
18	0	0	0	5.01	0.26	1.71
19	0	0	0	5.12	0.26	1.71

With the aim of verifying the behavior of AISI 52100 hardened steel turning outputs during the optimization process, all responses were modeled according to RSM. So, writing the generic model stated in Equation (8) for the three input parameters considered in this work, the following expression is obtained:

$$
\begin{aligned}
y = \beta_0 + \beta_1 Vc + \beta_2 f + \beta_3 d + \beta_{11} Vc^2 + \beta_{22} f^2 + \beta_{33} d^2 + \beta_{12} Vc \cdot f + \beta_{13} Vc \cdot d \\
+ \beta_{23} f \cdot d
\end{aligned}
\tag{8}
$$

In Equation 8, Vc, f and d are expressed in their coded form. The Ordinary Least Squares algorithm, through software Minitab, was employed to determine the coefficients β0, βi, βii, βij of the models. Then, it was used the ANOVA procedure, also by Minitab, to check their statistical significance and to remove the non significant terms. Table 5 presents the developed coefficients for the final quadratic models. The results of ANOVA are presented in Table 5, showing regression p-values less than 5% of significance and adjustments above 90% for all responses. These results indicate that the models are statistically significant and, therefore, can be used in prediction and control of the turning outputs.

Table 5 – Final response surface models for the tool life and roughness

Coeff.	**Responses**		
	T	***Ra***	***Rt***
β_0	4.963	0.260	1.724
β_1	-0.861	-0.007	0.048
β_2	-3.055	0.028	0.278
β_3	-1.440	0.000	-0.052
β_{11}	1.115	0.005	-
β_{22}	1.456	-	0.094
β_{33}	0.756	0.018	0.023
β_{12}	1.060	-0.010	-0.054
β_{13}	0.918	-0.008	-0.029
β_{23}	1.435	0.005	-
R^2*(adj.)*	99.74%	98.79%	94.75%
p-value	0.000	0.000	0.000

Proceeding to the analysis of the data in Table 5, we can get the model of second order (Full Quadratic Model) for the life of the tool and the surface roughness (Ra, Rt), as shown in Table 5 the coefficient of determination models of R-Sq (adj) provides excellent fits with values of R-Sq (adj) = 99.74% for (T), R-Sq (adj) = 98.79% for Ra and R-Sq (adj) = 94.75 % for Rt, which means that the models adequately explain the phenomena. For this reason it was decided to use this work the full quadratic model, which can be written in their decoded form, for the tool life (T) and surface roughness (Ra, Rt) as shown by equations 3.1, 3.2 and 3.3 in turn:

$$T=4{,}963-0{,}861Vc-3{,}055f-1{,}440ap+1{,}115Vc*Vc+1{,}456f*f+0{,}756ap*ap+1{,}060Vc*f+0{,}918Vc*ap+1{,}435*f*ap \quad (3.1)$$

$$Ra=0{,}260-0{,}007Vc+0{,}028f+0{,}000ap+0{,}005Vc*Vc+0{,}018ap*ap-0{,}010Vc*f-0{,}008Vc*ap+0{,}005f*ap \quad (3.2)$$

$$Rt=1{,}724+0{,}048Vc+0{,}278f-0{,}052ap+0{,}094f*f+0{,}023ap*ap-0{,}054Vc*f-0{,}0029*Vc*ap \quad (3.3)$$

4.1 MMSE optimization

The correlation structure between the responses to be optimized is showed in Table 6. As can be observed, these data are highly correlated, which makes of Multivariate Mean Square Error an appropriate approach to this problem. Applying the Principal Component Analysis on the responses of Table 7, it was found the results presented in Table 7, which identified that 95.1% of the data are explained by three principal components. These new uncorrelated variables were then used to represent the original correlated responses during the optimization.

Table 6 – Correlation between the responses

	T	***Ra***
Ra	-0.497	
	0.031	
Rt	-0.585	0.720
	0.009	0.001

Cells: *Pearson correlation*
p-value

Applying the Principal Component Analysis on the responses of Table 7, it was found the results presented in Table 7, which identified that 95.1% of the data are explained by three principal components. These new uncorrelated variables were then used to represent the original correlated responses during the optimization.

Table 7 – Principal Component Analysis

Eigenvalue	2.206	0.526	0.268
Proportion	0.735	0.175	0.090
Cumulative	0.735	**0.910**	1.000
Eigenvector	*PC*1	*PC*2	*PC*3
T	-0.536	-0.823	0.186
Ra	0.584	-0.521	-0.622
Rt	0.609	-0.225	0.760

The next step consist in determine de quadratic models for the significant principal components. Thus, taking the scores calculated in the PCA and modeling these data according to RSM, the following expressions were obtained:

$$PC1 = -0.128 + 0.110Vc + 1.603f + 0.094d - 0.088Vc^2 + 0.267d^2 - 0.463Vc \cdot f - 0.339Vc \cdot d - 0.165f \cdot d \quad (3)$$

$$PC2 = 0.871 + 0.264Vc - 0.017f + 0.367d - 0.329Vc^2 - 0.403f^2 - 0.480d^2 - 0.058Vc \cdot d - 0.388f \cdot d \quad (4)$$

The results of ANOVA for these models identified p-values less than 5% of significance for all of them. In relation to their adjustments, PC1 presented an R2 (adj.) of 98.85% and 98.19% for PC2. The targets for the principal components were established based on the targets of the original responses. These latter were specified by the experts involved in the process and took into account that the AISI 52100 hardened steel turning could operate with good economic and productive factors, combined with the good surface finishing characteristic of the wiper inserts. The data contained in Table 7, through Equations 3 and 4, were then used to these calculations. It resulted in targets of -3.613 and -0.763 for PC1, PC2 respectively.

Table 8 – Data used in the establishment of targets for the principal components

	T	*Ra*	*Rt*
Mean	7.355	0.276	1.807
Standard deviation	3.661	0.031	0.270
Target	17.185	0.210	1.392
Standardization	2.685	-2.117	-1.537
Eigenvector *PC*1	-0.536	0.584	0.609
Eigenvector *PC*2	-0.823	-0.521	-0.225

Having developed the RSM models for the significant principal components and taking their calculated targets, the MMSE formulation was built, considering equal weights for all responses and equal weights for all principal components. It resulted in:

$$Min \quad MMSE_T = \left\{\left[(PC1 + 3.613)^2 + 2.206\right]\cdot\left[(PC2 + 0.763)^2 + 0.526\right]\right\}^{\left(\frac{1}{2}\right)} \tag{5}$$

$$St: \mathbf{x}^T\mathbf{x} \leq 2.829$$

with: $PC1,\ PC2$ – RSM models described in Equations 3 and 4

$\mathbf{x}^T\mathbf{x}$ – Spherical constraint for the experimental region

As previously presented, the material removal rate was treated in this problem as a constraint, looking for ensuring a minimum productivity of the turning process. The Generalized Reduced Gradient was applied in the MMSE formulation, after it was programmed in a Microsoft Excel worksheet. By employing the Solver supplement the optimal point was identified (Table 9).

Table 9 – Optimal results

	Parameters			Responses		
	Vc	***f***	***d***	***T***	***Ra***	***Rt***
Optimal point	205	0.15	0.20	16.58	0.22	1.44
Targets	-	-	-	17.19	0.21	1.39
Units	m/min	mm/v	mm	min	µm	µm

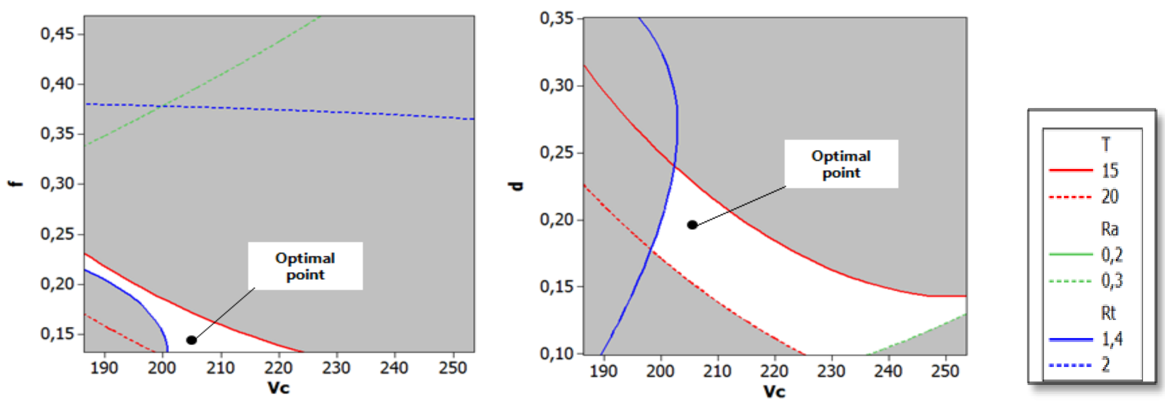


Figure 4.1 – Overlaid contour plots

Good solutions were achieved for all the answers. The production times were better than their targets and the optimal values for surface roughness (Ra, Rt) and life of the tool set, smaller than their desired values.

5 Conclusions

- The analysis of machining parameters using the MSR technique has the advantage of investigating the influence of each of the machining parameters and their interactions;

- All models developed for both turning and outputs to the main components, can be used for prediction and process control, since they showed values of P less than 5% significance and settings above 90%.

- The complete models obtained by MSR showed excellent explanation of the adjustment parameters of the tool life and surface roughness Ra and Rt, which demonstrates that the breakthrough factors, speed and depth of cut, as well as their interactions have significant influence on tool life and the roughness Ra and Rt;

- The analysis of variance indicated that the levels of the variables are experienced in a region of great for the life of the tool and the surface roughness Ra and Rt, because the value of P of curvature are less than 5%.

- The principal component analysis reduced the dimensionality of the problem in half, since two principal components were needed to represent the six optimized responses.

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