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ROBUST PARAMETER PROJECT APPLIED TO THE OPTIMIZATION OF THE STEEL TURNING PROCESS AISI 12L14

Fabricio A. Almeida(*), José H.F. Gomes, Wesley G.M. Pinto, Vinicius R. Paula, Bruno M. Nardini
Universidade Federal de Itajuba, Brazil
(*)*Email:* fabricio.alvesdealmeida@gmail.com

ABSTRACT

The objective of this work is to determine an optimum setup for the turning process of AISI 12L14 steel, capable of eliminating the effects of tool wear on the roughness of the machined part. For this, it is proposed the use of robust optimization by the Mean Square Error (MSE), of the mean (μ) e variance (σ2), the average arithmetic roughness (Ra) measured in a set of experiments performed for the turning process of AISI 12L14 steel. An experimental study was carried out to model the responses of interest (relative to the average roughness of the machined surfaces) where an experimental arrangement was created for three process variables (cutting speed, feed rate and depth of cut) and for a noise variable (use of new and worn tool). This experimental arrangement, of the combined arrangement type, was created with the use of the response surface methodology (MSR).

Keywords: robust optimization, turning process, surface roughness.

INTRODUCTION

Inside the machining processes, turning has been characterized as a very important operation for a modern industry (DINIZ et al., 2010). In this process, input parameters are directly responsible for many of the process quality and productivity characteristics, such as tool wear, workpiece finish, and amount of material removed. (SINGH e RAO, 2007; CAMPOS et al., 2012).

The machining of the machined parts can be evaluated according to the surface roughness, which are irregularities presented on the surface of the parts, characterized by grooves made by the tool during the machining process. There are several parameters to evaluate the surface roughness, the present study makes use of only one parameter of roughness evaluation, the average arithmetic roughness (R_a), which is the arithmetic mean of the absolute values of the ordinates of the effective (measured) profile in relation to the midline in a sample length (CAMPOS, 2011).

This work focuses on the surface roughness of turned parts and how this feature is affected by the wear of the cutting tool. There are several types of wear that can occur in a tool (notch wear, edge wear, crater wear, etc.) and the combination of these wear and cutting parameters used in the process can be critical to the machined work surface finish (DINIZ et al., 2010).

The object of study of this work is the turning process of AISI 12L14 steel. An experimental study was carried out to model the responses of interest (relative to the average roughness of the machined surfaces) where an experimental arrangement was created for three process

variables (cutting speed, feed rate and depth of cut) and for a noise variable (use of new and worn tool). This experimental arrangement, of the combined arrangement type, was created with the use of the response surface methodology (MSR).

The objective of this work is to determine an optimum setup for the turning process of AISI 12L14 steel, capable of eliminating the effects of tool wear on the roughness of the machined part. For this, it is proposed the use of robust optimization by the Mean Square Error (MSE), of the mean (μ) e variance (σ^2), the average arithmetic roughness (R_a) measured in a set of experiments performed for the turning process of AISI 12L14 steel.

Robust Parameter Design (RPD) Is characterized by a collection of techniques to identify the degree of factors that reduces the sensitivity of the process to the noise (uncontrollable factors), providing a process analysis and improvement in order to find the levels of its variables, ensuring that they reach the desired mean of the responses, in addition to minimizing their variation, making the process more stable and insensitive to noise (ARDAKANI e NOOROSSANA, 2008; MONTGOMERY, 2009; YANG et al., 2013; ELSAYED e LACOR, 2014). O RPD Is a method used to reduce the time of experimentation, besides increasing the set of information that can be obtained before the data (JURKÓW e STIERNSTEDT, 2014).

In relation to the analysis and modeling of the data for the robust optimization, used Response Surface Methodology (MSR) and considering the mean and variance equations, one can then use multi-objective optimization techniques, where in this article was chosen the Mean Square Error (MSE). The formulation of this optimization is presented in Equation (1) (BRITO et al., 2014).

$$\begin{aligned} &Minimizar\ EQM(y) = \left[\mu(y) - T_y\right]^2 + \sigma^2(y) \\ &sujeito\ a: \boldsymbol{x}^T\boldsymbol{x} \leq \propto^2 \end{aligned} \tag{1}$$

Where μ is the model for the mean, T the target for mean and σ^2 the model for the variance. All related to the answer *y*. It has also been$\boldsymbol{x}^T\boldsymbol{x} \leq \propto^2$ As the spherical constraint for the sample space of the experimental arrangement.

The algorithm OLS was applied to the mean and variance data of R_a, to obtain the quadratic models of these functions. The models presented high values of R^2 indicating that the models adopted are adequate. These models are presented in Table 1. We opted for the use of the complete quadratic models.

Table 1 - Experimental matrix (combined arrangement) and values obtained for the answer

Terms	$\mu(R_a)$		$\sigma^2(Ra)$	
	Coefficients	p-value	Coefficients	p-value
Constant	2,174	0,000	0,417	0,000
V_c	0,035	0,300	0,017	0,459
f	0,118	0,005	-0,059	0,270
a_p	0,041	0,228	-0,099	0,002
V_c^2	-0,199	0,000	-0,137	0,000
f^2	-0,123	0,004	-0,108	0,001
a_p^2	-1,232	0,004	-0,060	0,025
V_c*f	0,023	0,591	-0,023	0,450
V_c*a_p	-0,078	0,092	-0,034	0,281
$f*a_p$	0,170	0,003	0,085	0,017
R^2Adj (%)	82,30		82,25	

According to the quadratic model described in Table 1, the equation of the mean (μ) and the variance (σ^2) for R_a can be described as in Equations. (2) e (3). The graphs of these response surfaces are shown in Figure 1, where the value of a_p was maintained as 0,45.

$$\mu(R_a) = 2{,}174 + 0{,}035V_c + 0{,}118f + 0{,}041a_p - 0{,}199V_c^2 - 0{,}123f^2 - 1{,}232a_p^2 + 0{,}023V_c f - 0{,}078V_c a_p + 0{,}170fa_p \quad (2)$$

$$\sigma^2(R_a) = 0{,}417 + 0{,}017V_c - 0{,}059f - 0{,}099a_p - 0{,}137V_c^2 - 0{,}108f^2 - 0{,}060a_p^2 - 0{,}023V_c f - 0{,}034V_c a_p + 0{,}085fa_p \quad (3)$$

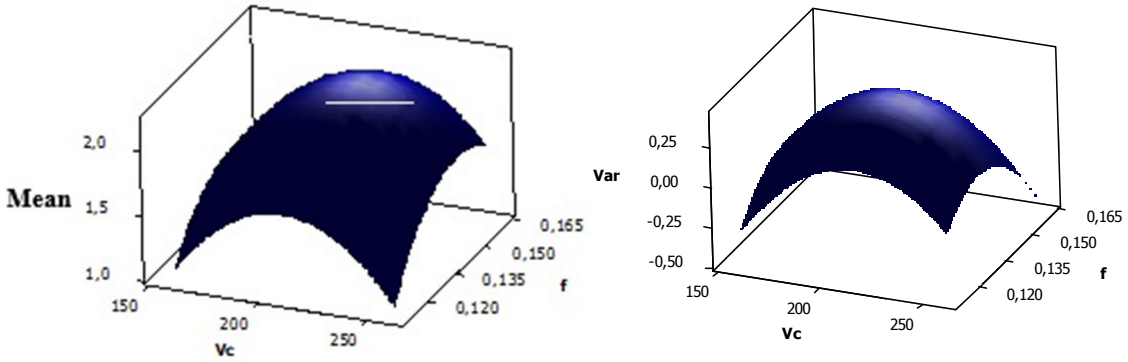

Fig. 1 - Response surface graphs for mean and variance of R_a.

Different optimizations were made for each of the points determined by the arrangement *Simplex-Lattice.* The lowest value of MSE was obtained for the combination of weights w_1 = 0,03 e w_2 = 0,97. The balance determined by these weights corresponds to the values of V_c = 240,3 m/min; f = 0,124 mm/rot. and a_p = 0,619 mm providing an average roughness of 1,4965 µm with variance of 0,001 (MSE = 0,0011).

For the test of confirmation of the results, with the setup found in the optimization, 5 experiments were performed with each tool (new and worn).

The confirmatory experiments proved that, when using the optimum setup determined through the methodology proposed in this work, the noise variable is not significant for the process, since the roughness averages using the new tool is statistically equal to the average using the worn tool.

Finally, it is important to highlight the importance of process knowledge and the establishment of decision variable values so that the desired result is optimized. Many companies use non-optimal parameters (decision variables) for their processes, resulting in considerable financial waste. In addition, the tool catalogs and machine manuals themselves often indicate non-optimal parameters in order to stimulate tool consumption. In this context, optimizing processes is a decisive action to guarantee competitiveness and market leadership.

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