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A Multivariate Statistical Quality Control of AISI 52100 Hardened Steel Turning

GEORGE EVANGELISTA[1], ROGÉRIO SANTANA PERUCHI[1], TARCÍSIO GONÇALVES BRITO[2], PAULO ROTELA JUNIOR[1], AND LUIZ CÉLIO SOUZA ROCHA[3]

[1]Department of Industrial Engineering, Federal University of Paraíba, João Pessoa 58051-970, Brazil
[2]Institute of Integrated Engineering, Federal University of Itajubá, Itabira 35903-087, Brazil
[3]Federal Institute of Education, Science and Technology, North of Minas Gerais, Almenara 39900-000, Brazil

Corresponding author: Paulo Rotela Junior (paulo.rotela@gmail.com)

ABSTRACT Hard turning processes have several advantages against traditional turning. Improved surface integrity and short process time are some examples. Surface integrity is one of the most important issues in modeling of machining processes. Multiple roughness parameters are observed in relation to several controllable and uncontrollable input parameters. Since these multiple roughness parameters are correlated, multivariate methods are the most suitable approach for process control. This research aims to propose a method for assessing stability and performance of multivariate processes in the presence of noise variables. A hybrid method based on design of experiment, statistical process control and principal component analysis was applied to AISI 52100 hardened steel turning. The process performance index was obtained within the range of 0.18 to 1.11. The best process performance was achieved taking cutting speed of 170m/min and lubricating fluid flow of 3 L/min.

INDEX TERMS Design of experiments, statistical process control, principal component analysis, control charts, hard turning, roughness.

I. INTRODUCTION

Hard turning is one of the most trending topics in machining studies. The process, with workpieces of hardness above 45HRC, has advantages over traditional turning [1]–[4]. The machining operation may be performed with no cutting fluid and with no additional finishing process, so that costs and setups can be reduced [5], [6].

The design of experiments (DOE) can be used for process modeling as such in hard turning [2], [7]. Generally, input parameters and their combined effects on the process outputs are of interest. Then, the best operating conditions must be determined [8]. However, some variables, the noise variables, are uncontrollable while machining workpieces. Even though, these noise variables may affect the critical-to-quality characteristics (CTQ). The tool flank wear is an example of a noise variable in hard turning studies [5], [9], [10].

In hard turning operations, the surface roughness is considered one of the most important CTQ [3], [11], [12]. In general, roughness parameters are related to input variables such as tool geometry, material properties, machinery setups, and so on [2], [4], [12]–[16]. More than often, several roughness parameters are of interest such as: arithmetic mean (R_a), maximum (R_y), quadratic mean (R_q), and maximum peak to valley (R_t) [7], [17], [18]. The presence of more than one CTQ turns the process not only more comprehensive, but also more complex. Univariate approaches may be inefficient, mainly, when conflicting results are obtained from process assessment. Therefore, multivariate methods are reasonable strategies to deal with such systems [19]–[21].

In machining, previous researches have evaluated tool wear as a noise factor in robust parameter designs (RPD). Some examples can be found at: milling of AISI 1045 steel [9], [10], [22]; turning of AISI 12L14 steel [23], [24]; hard turning of AISI 52100 steel [6], [7], [25]. Basically, these researches have applied RPD in order to remove the noise effect on CTQs. However, little attention has been paid on how the noise variable affects the stability and performance of manufacturing processes.

This research aims to develop a multivariate approach to evaluate the effect of controllable and uncontrollable variables on stability and performance of multivariate processes. A hybrid method based on DOE, Statistical Process Control (SPC) and Principal Component Analysis (PCA)

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was implemented. Initially, the correlation between noise variables and process responses had been verified. After that, factorial experiments were designed to model the CTQs as functions of controllable and uncontrollable variables. Control charts and process performance indexes, based on weighted principal component analysis, were developed to find the most stable and capable setup. In this hard turning operation, the roughness parameters $\mathbf{R_a}$ and $\mathbf{R_t}$ were evaluated taking into account the effects of control variables (cutting speed and lubricating fluid flow) and a noise variable (tool flank wear). The best multivariate process performance index was achieved at 1.11 by using cutting speed of 170 m/min and lubricating fluid flow of 3 L/min.

The remaining sessions are organized as follows. The second session details the multivariate DOE-SPC method. The third session shows univariate and multivariate methods applied to the AISI 52100 hardened steel turning operation. The last session highlights the main findings of this research and suggestions for future work.

II. STATISTICAL QUALITY CONTROL BASED ON WEIGHTED PRINCIPAL COMPONENTS

To investigate the effects of noise and controlled factors on quality characteristics, the proposed multivariate method combining SPC-DOE techniques are summarized according to Fig. 1.

The **first step** consists of stating the process problem and the *Ys* critical-to-quality characteristics. Prior knowledge is required to select *Ys* that represent quality of the process. Problem statement should be regarding process stability and performance in the multivariate context.

The **second step** consists of a correlation between the output variables. If the *Ys* have a significant correlation, the multivariate analysis is performed (step 3A), otherwise univariate (step 3B). The Pearson correlation coefficient between the *Ys* is calculated as (1):

$$\rho = \frac{\sum_{i=1}^{n} (y_{1i} - \overline{y_1})(y_{2i} - \overline{y_2})}{(n-1)s_{y_1}s_{y_2}} \tag{1}$$

where y_1 and y_2 are the average for each variable, s_{y_1} and s_{y_2} are the standard deviations of each variable, and n is the sample size.

The **Step 3A** is the calculation of the weighted principal components (**WPC**). The values of the principal components are calculated by:

$$\mathbf{PC}_i = \mathbf{e'}_i\mathbf{Y} \tag{2}$$

where e'_i is the eigenvector matrix and Y is the quality characteristic matrix that may assume a standardized form if the correlation matrix is used for the scores of the principal components. After calculating the principal components (PC_i), **WPC** is obtained as (3):

$$\mathbf{WPC} = \mathbf{W'PC} \tag{3}$$

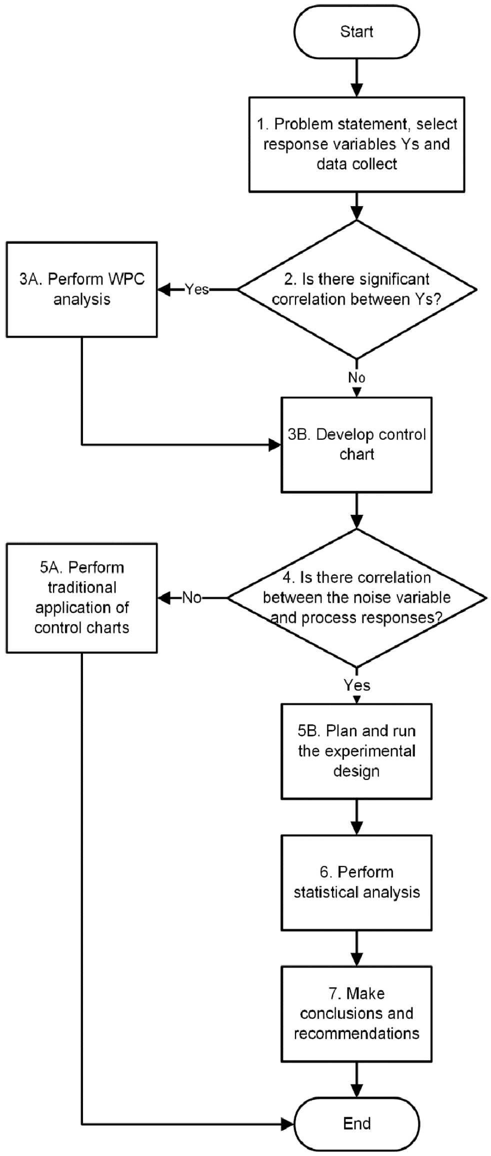

FIGURE 1. Stepwise procedure for a multivariate statistical quality control.

where **PC** are the scores of principal components and $\mathbf{W'} = \left[\frac{\lambda_1}{\sum_{j=1}^{q}\lambda_j} \; \frac{\lambda_2}{\sum_{j=1}^{q}\lambda_j} \cdots \frac{\lambda_q}{\sum_{j=1}^{q}\lambda_j} \right]$ is the vector of weights.

Step 3B consists of the control chart development. The design of the control chart depends on some aspects such as: data type, autocorrelated process, sample size, and others [26]. Control charts are tools for monitoring process outputs and their behavior [27]. Out of control points due to the presence of special causes of variation can be checked by this tool [26]. Due to low production volume in this study, control charts for individuals (I-MR) are the best choice for the stability study [26-27]. Montgomery [26] determines the formulation for center line (CL), upper (UCL) and lower control (LCL) limits for individual control charts (I-MR):

$$CL = \overline{WPC}$$

TABLE 1. Analysis of variance for WPC vector.

Source of variation	Sum of squares (SS)	Degrees of freedom (DF)	Mean Square (MS)	F_0
Factor	$n\sum_{i=1}^{a}(\overline{WPC}_{i.}-\overline{WPC}_{..})^2$	$a-1$	$MS_F=\frac{SS_F}{a-1}$	$\frac{MS_F}{MS_E}$
Error	$\sum_{i=1}^{a}\sum_{j=1}^{n}(WPC_{ij}-\overline{WPC}_{.j})^2$	$a(n-1)$	$MS_E=\frac{SS_E}{a(n-1)}$	
Total	SS_F+SS_E	$an-1$		

where: a = number of terms in the model; n = number of observations; $\bar{y}_i$ = average of observations in level factor i; $\bar{y}$ = average of all observations; y_{ij} = value of the observation j in the level factor i.

$$\begin{aligned} UCL &= \overline{WPC}+3\frac{\overline{MR}}{d_2}\\ LCL &= \overline{WPC}-3\frac{\overline{MR}}{d_2}\\ CL &= \overline{MR} \end{aligned} \tag{4}$$

$$\begin{aligned} UCL &= \overline{MR}+3\overline{MR}\frac{d_3}{d_2}\\ LCL &= \overline{MR}-3\overline{MR}\frac{d_3}{d_2} \end{aligned} \tag{5}$$

where $\overline{WPC}$ is the mean of the **WPC** vector, $\overline{MR}$ is the moving range of **WPC** for 2 subsequent subgroups, d_2 and d_3 are constants that change according to the sample size.

The **fourth step** correlation between the noise variable (z) and the weighted principal component (**WPC**) must be checked. Now, Eq. (1) is applied to verify whether there is correlation between **z** and **WPC** variables. If there is no correlation, **step 5A** indicates a traditional application of control charts.

Step 5B occurs when **z** and **WPC** are correlated. It consists of developing an experimental design for understanding the effects of control (**x**) and noise (**z**) variables, as well as their interactions (x_ix_j and x_iz_l) on **WPC**. In this step, experimental designs with k controlled factors and their levels must be determined. In general, 2^k factorial designs with at least 2 factors are recommended. After that, the data referring to the noise variables and quality characteristics for each combination of controlled factors are collected.

Step 6 is the statistical analysis to investigate the effect of control (**x**) and noise (**z**) variables on weighted principal components (**WPC**). The regression model can be calculated using equations (6)-(8):

$$\mathbf{WPC} = \mathbf{X}\boldsymbol{\beta}+\boldsymbol{\varepsilon} \tag{6}$$

$$\widehat{\beta} = (\mathbf{X}'\mathbf{X})^{-1}(\mathbf{X}'\mathbf{Y}) \tag{7}$$

where:

$$\mathbf{WPC}=\begin{pmatrix} WPC_1\\ WPC_2\\ \vdots\\ WPC_n\end{pmatrix};\quad \mathbf{X}=\begin{pmatrix} 1 & X_{11} & X_{12} & \cdots & X_{1k}\\ 1 & X_{21} & X_{22} & \cdots & X_{2k}\\ \vdots & \vdots & \vdots & \ddots & \vdots\\ 1 & X_{n1} & X_{n2} & \cdots & X_{nk}\end{pmatrix};$$

$$\beta=\begin{pmatrix}\beta_1\\ \beta_2\\ \vdots\\ \beta_k\end{pmatrix};\quad \text{and } \boldsymbol{\varepsilon}=\begin{pmatrix}\varepsilon_1\\ \varepsilon_2\\ \vdots\\ \varepsilon_k\end{pmatrix} \tag{8}$$

The regression model can be evaluated by analysis of variance (ANOVA), according to the source of variation, degrees of freedom, sum of squares and F_0 as shown in Table 1 [26].

Model adequacy should be verified by the residual analysis, the coefficient of determination and lack-of-fit tests. Further details on model adequacy assessment can be found in [28].

Finally, this step is completed by evaluating process stability and performance. Control charts in Eqs. (4) and (5) are conducted in order to check process stability. In the multivariate context, process performance assessment is conducted as follows. Considering $\mathbf{Y}'=(\mathbf{Y_1},\mathbf{Y_2},\ldots,\mathbf{Y_m})$ the vector of q quality characteristics with mean vector μ and positive definite variance-covariance matrix Σ. The target, lower and upper specifications are $\mathbf{T}'=(T_1,T_2,\ldots,T_q)$, $\mathbf{LSL}'=(LSL_1,LSL_2,\ldots,LSL_q)$ and $\mathbf{USL}'=(USL_1,USL_2,\ldots,USL_q)$, respectively [17], [29]. Specification limits for $\mathbf{PC}_i$ and **WPC** are given by Eqs. (9) – (14):

$$\mathbf{LSL_{PCi}} = \mathbf{e'_iLSL} \tag{9}$$

$$\mathbf{USL_{PCi}} = \mathbf{e'USL} \tag{10}$$

$$\mathbf{T_{PCi}} = \mathbf{e'T} \tag{11}$$

$$LSL_{WPC} = \mathbf{W'LSL_{PC}} \tag{12}$$

$$USL_{WPC} = \mathbf{W'USL_{PC}} \tag{13}$$

$$T_{WPC} = \mathbf{W'T_{PC}} \tag{14}$$

The process performance (Ppk) index is estimated as follows:

$$\begin{aligned} Pp_{k;wpc} &= \min\left(Pp_{l;wpc},Pp_{u;wpc}\right)\\ &= \min\left(\frac{\overline{WPC}-LSL_{wpc}}{3s_{wpc}},\frac{USL_{wpc}-\overline{WPC}}{3s_{wpc}}\right) \end{aligned} \tag{15}$$

In these equations, USL_{wpc} and LSL_{wpc} are upper and lower specification limits; $\overline{wpc}$ is the mean of **WPC**; and s_{wpc} is the standard deviation of **WPC**. According to Dharmasena

LS, Zeephongsekul [23], Kaya and Kahraman [30] and Peruchi *et. al.* [17], the process performance can be classified as poor ($Pp_{k;wpc} < 0.67$), inadequate ($0.67 \leq Pp_{k;wpc} < 1.00$), capable ($1.00 \leq Pp_{k;wpc} < 1.33$), satisfactory ($1.33 \leq Pp_{k;wpc} < 1.67$), excellent ($1.67 \leq Pp_{k;wpc} < 2.00$) or super excellent ($Pp_{k;wpc} \geq 2.00$).

The **seventh** and **final step** is to develop conclusions and recommendations on the process setup. Assessing a shift in process level and dispersion, the multivariate performance index is the main tool for helping to draw conclusions on process setup.

III. HARDENED STEEL TURNING APPLICATION

The proposed method has been applied to the hard turning of AISI 52100 steels using interchangeable CBN inserts in hard metal with ISO code CNGA120408GA BC8020 and tip radius of 0.8 mm. A Mitsubishi tool holder ISO code DCLNR 2020K12 was used. The following tool geometry has been used: exit angle $\gamma = -8°$; inclination angle $\lambda = 0°$; and position angle $\chi r = 90°$. The manufacturing and measurement processes are shown in Figs. 2 and 3, respectively.

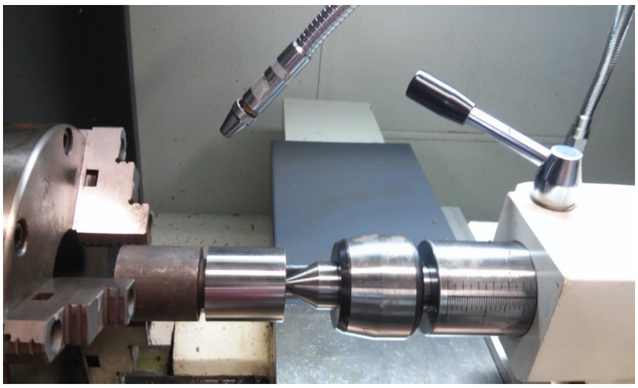

FIGURE 2. Turning operation of AISI 52100 hardened steel.

In addition, it is worth noting that the measurement of the roughness values of the workpiece was recorded by the portable surface roughness tester Mitutoyo Surftest 201, which was gauged and calibrated before the measurements started. The cut-off parameter was adjusted to 0.8 mm for all measurements.

Finally, in relation to the process, the cutting fluid ME-II from the manufacturer Tapmatic was used, being a synthetic soluble oil and concentrated (high dilution rate in water).

In hard turning, friction between the two surfaces such as workpiece and cutting tool or cutting tool and chip interfaces cause rise in temperature [1] and the thermal aspects, in conjunction with the plastic deformation strongly affects the surface integrity and the quality of the machined product. In fact, the deformation process is concentrated in a very small zone and the local high temperatures due to heat generation have important consequences on the workpiece [31]. Subsequently, surface integrity, tool life and dimension accuracy of the product deteriorated [32]. However, according to

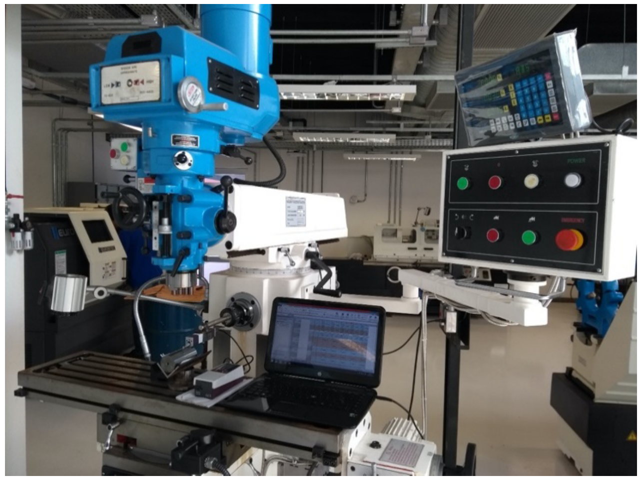

FIGURE 3. Roughness measurement process.

Liew *et al.* [1], the most important aspects in hard turning are surface roughness and tool wear. This is because the surface roughness affects corrosion resistance, fatigue strength, pace and tribological properties of machined parts meanwhile tool wear affects the dimensional accuracy of the finished products, surface finish, residual stress, the integrity of the surface (white layer) and the tool life.

In order to improve engine cooling and lubrication during operation, the cutting fluid has been used. Cutting fluid originally used to lubricate the interface chip and tool as well as tool and workpiece, remove heat from the workpiece and the cutting zone, carrying away chips from the cutting area and prevent erosion [1].

Although, cutting fluids are beneficial in the industries, today their uses has been questioned around the world, due to environmental consciousness enhanced laws and regulations [33]. The use of cutting fluids has several adverse effects such as environmental pollution, dermatitis to operators, water pollution and soil contamination during disposal [34]–[36].

However, cutting fluids play a significant role in machining areas. The complete absence of cutting fluid creates problems in chip transportation and causes an increase of the tool-chip and tool-workpiece friction affecting the tool life and quality of the machined surface. Moreover, the proper application of cutting fluid or cooling medium allows use of higher cutting speeds and higher feed rates by limiting overheating of the cutting tool and machine [37].

Before applying the proposed procedure for statistical quality control, univariate analyses for each quality characteristic are implemented (section III.A). Conflicting results for process classification is obtained by using this approach. Then, the proposed procedure is carefully conducted in section III.B to solve this issue and to come up with a final decision on process setup.

A. UNIVARIATE APPROACH

If few changes are applied, the statistical quality control, based on univariate analysis, can be conducted by the

TABLE 2. Univariate process performance analysis.

Roughness	Normality test	*USL*	$\overline{x}$	*s*	*Ppk*	Classification
R_a	0.447[a] (0.261[b])	0.85	0.6890	0.1189	0.46	Out-of-control, Poor
R_t	0.281 (0.616)	4.2	3.599	0.2350	0.85	In control, Inadequate

[a] Anderson-Darling statistic
[b] p-value for Anderson-Darling normality test

proposed method in section II. Basically, vector **WPC** should be replaced by the original quality characteristics and the steps related to principal component analysis must be neglected.

The arithmetic average ($\mathbf{R_a}$) and total depth roughness ($\mathbf{R_t}$) were selected as quality characteristics. They are characteristics related to workpiece finishing and considered as critical-to-quality. $\mathbf{R_a}$ is the arithmetic average of the absolute values of the ordinates of the effective profile (measured), $\boldsymbol{y}$, in relation to the average line in a sampling set, which can be calculated by Eq. (16) [38]–[40]:

$$R_a = \frac{1}{n}\sum_{i=1}^{n}|y| \tag{16}$$

And, $\mathbf{R_t}$ is defined as the roughness corresponds to the vertical distance between the highest peak and the minimum valley in the evaluation length, regardless of the partial roughness values, given by Eq. (17) [38]–[40]:

$$R_t = \text{maximum peak - minimum valley} \tag{17}$$

The controllable variables selected were cutting speed (S) and lubricating fluid flow (L). Tool flank wear (W) was the uncontrollable variable evaluated in this study. The initial conditions were cutting speed of S = 120 m/min, lubricating fluid flow of L = 0 L/min and the cutting tool was utilized up to the tool flank wear of W = 0.3 mm. The dataset was collected and stored in Appendix A. Briefly, the I-MR control charts and the process performance for $\mathbf{R_a}$ and $\mathbf{R_t}$ using this setup are shown in Fig. 4 and Table 2, respectively.

Conflicting results were observed when assessing the process based on $\mathbf{R_a}$ and $\mathbf{R_t}$. For $\mathbf{R_a}$, the process is out-of-control and has poor performance, while for $\mathbf{R_t}$ the process is in control and the performance is inadequate. As emphasized by Peruchi et. al [17], only one of these quality characteristics is unable to describe the workpiece surface behavior. $\mathbf{R_a}$ performs an arithmetic average of the roughness. When performing this average, extreme points may not be sensible in the study. On the other hand, $\mathbf{R_t}$ measures roughness in relation to the greater range of peaks and valleys. For better decision making, if correlation among quality characteristics are significant, multivariate statistical analysis should be conducted.

B. MULTIVARIATE STATISTICAL QUALITY CONTROL BASED ON WEIGHTED PRINCIPAL COMPONENTS

Applying the proposed method, in the **first step** the process problem must be stated, CTQs should be selected and dataset

TABLE 3. Principal component analysis for R_a and R_t.

	Eigenvalues	Proportion	Cumulative	Eigenvectors	R_a	R_t
PC_1	0.0617	0.893	0.893	PC_1	0.346	0.938
PC_2	0.0074	0.107	1.000	PC_2	0.938	-0.346

TABLE 4. Full factorial design for the hard turning experiment.

	Controllable variables		Uncontrollable variable
Setup	Cutting speed (S)	Lubricant fluid flow (L)	Tool flank wear (W)
1	120 m/min (-1*)	0 L/min (-1)	from 0 (-1) to 0.3 (+1) mm
2	120 m/min (-1)	3 L/min (+1)	from 0 (-1) to 0.3 (+1) mm
3	170 m/min (+1)	0 L/min (-1)	from 0 (-1) to 0.3 (+1) mm
4	170 m/min (+1)	3 L/min (+1)	from 0 (-1) to 0.3 (+1) mm

* coded values for each factor level

is collected. As mentioned in section III.A, $\mathbf{R_a}$ and $\mathbf{R_t}$ were the CTQs selected in this study and the dataset can be seen in Appendix A. Assessing them individually, the engineer was unable to come up with a final decision on process stability and performance. If these CTQs are correlated, multivariate statistical analysis is useful and the next steps of the method can be performed.

In the **second step**, the correlation between $\mathbf{R_a}$ and $\mathbf{R_t}$ was obtained with Eq. (1). The coefficient of correlation of 0.636 was significant with p-value lower than 0.05. Then, **step 3A** is performed to calculate the **WPC** using Eqs. (2) and (3). The results for principal components analysis are in Table 3. After that, in **step 3B**, I-MR control charts, based on **WPC** vector, is built by using Eqs. (4) and (5). As shown in Fig. 5, the process is in control, however, it looks as if a downward trend is observed. This trend might be correlated with the tool flank wear.

In **step 4** the correlation between the tool flank wear (W) and the quality characteristic (**WPC**) is calculated. The correlation coefficient found was −0.808 (p-value lower than 0.05). This value indicates a significant correlation, increasing the possibility of wear effect on the process output. Due to the significant correlation, we proceeded to **step 5B**. As a result, a new experimental design and data collection were planned. The factors and levels for the full factorial design are describe in Table 4 and the dataset was also stored in Appendix A. It should also be noted that the cutting depth adopted was 0.4 mm.

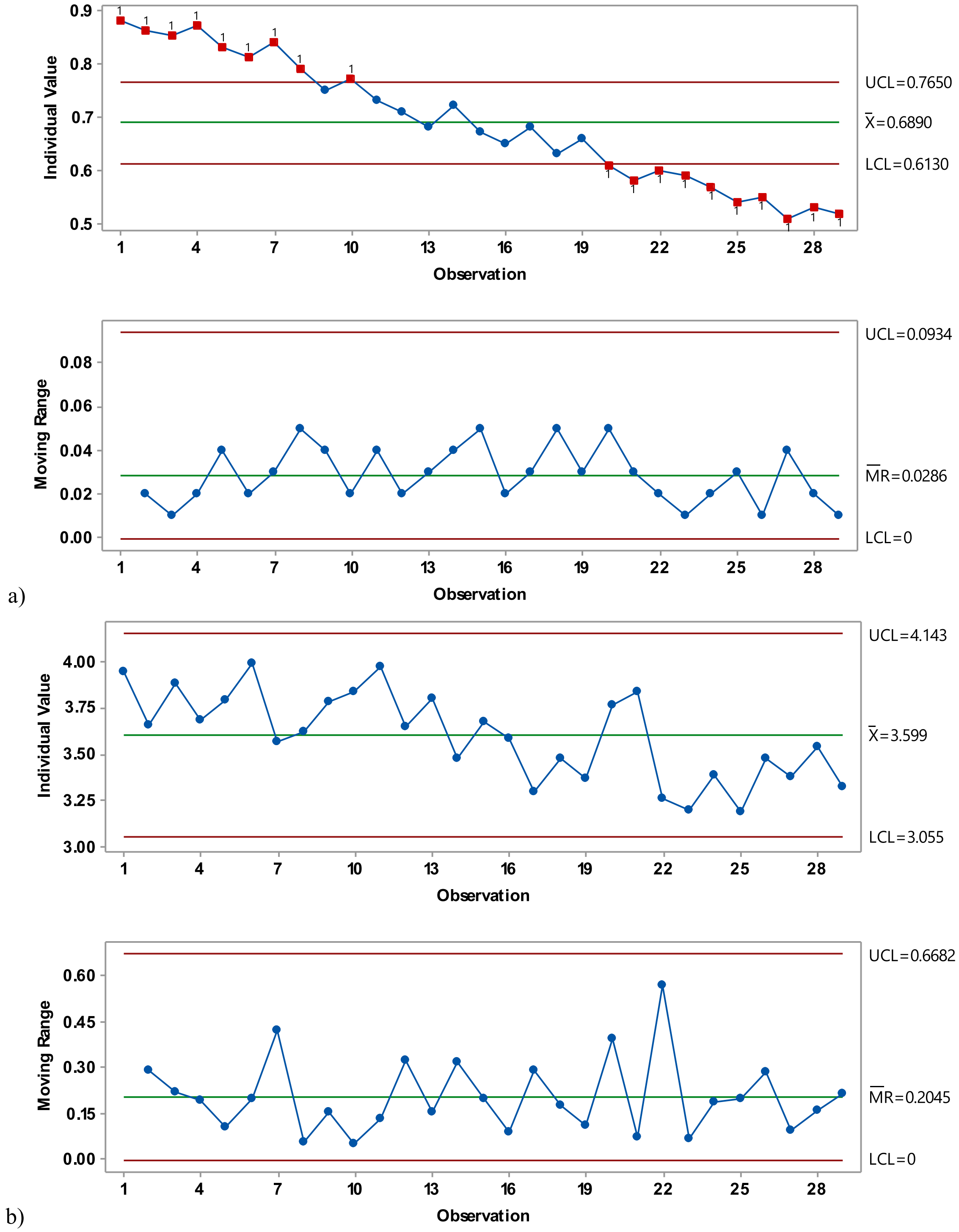

FIGURE 4. I-MR control charts of setup 1 for a) R_a and b) R_t.

In the **sixth step**, the statistical analysis is performed using Eqs. (6)-(8). The regression model was estimated with coded variables, as seen in Table 4, and it is shown in (17) below:

$$\begin{aligned} WPC = & -0.0016 - 0.6953S + 0.6335L - 1.0952W \\ & - 0.0722SL + 0.0546SW + 0.1791LW \\ & + 0.1723SLW \end{aligned} \tag{18}$$

Using equations in Table 1, the analysis of variance was performed and the sources of variation, degrees of freedom (DF), sum of squares (SS), mean squares (MS) and F value are presented in Table 5. Testing the model adequacy, the adjusted coefficient of determination (R^2_{adj}) was 92.54%, lack-of-fit test with p-value $>$ 0.05 and the normality test of the standardized residues with p-value $>$ 0.05 indicate an

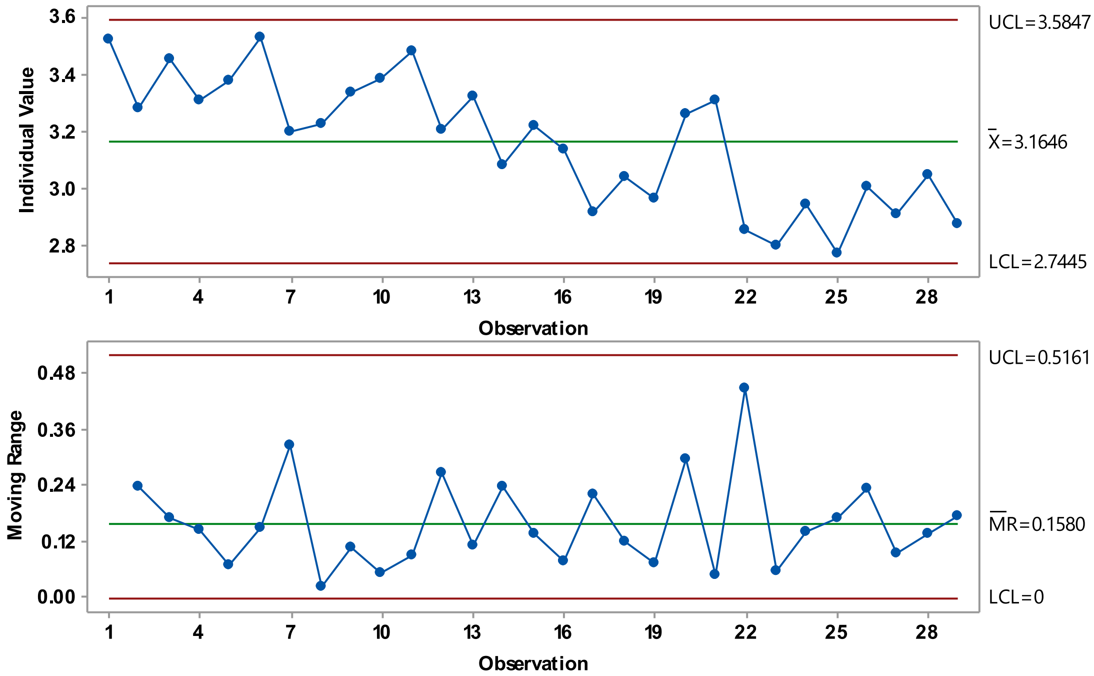

FIGURE 5. I-MR control chart of WPC for setup 1.

TABLE 5. Anova results for WPC.

Source	*DF*	*SS*	*MS*	*F-Value*	*P-Value*
Regression	7	166.046	23.7208	223.26	0.000
S	1	51.496	51.4964	484.68	0.000
L	1	42.743	42.7428	402.29	0.000
W	1	46.704	46.7037	439.57	0.000
*S*L*	1	0.555	0.5553	5.23	0.024
*S*W*	1	0.116	0.1160	1.09	0.298
*L*W*	1	1.249	1.2493	11.76	0.001
*S*L*W*	1	1.155	1.1553	10.87	0.001
Error	106	11.262	0.1062		
Lack-of-Fit	45	5.988	0.1331	1.54	0.058

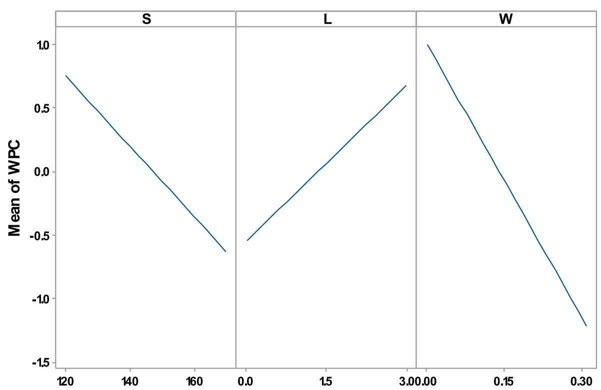

FIGURE 6. Main effects plot for WPC.

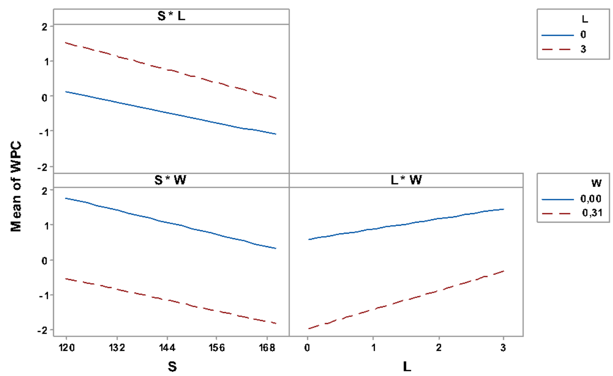

FIGURE 7. Interaction plot for WPC.

TABLE 6. Principal component analysis for each process setup.

Setup	Eigenvalues		Proportion	Cumulative	Eigenvectors	R_a	R_t
1	PC_1	0.0617	0.893	0.893	PC_1	0.346	0.938
	PC_2	0.0074	0.107	1.000	PC_2	0.938	-0.346
2	PC_1	0.1668	0.987	0.987	PC_1	0.134	0.991
	PC_2	0.0023	0.013	1.000	PC_2	0.991	-0.134
3	PC_1	0.1652	0.982	0.018	PC_1	0.241	0.971
	PC_2	0.0031	0.018	1.00	PC_2	0.971	-0.241
4	PC_1	0.0361	0.932	0.932	PC_1	0.331	0.944
	PC_2	0.0026	0.068	1.000	PC_2	0.944	-0.331

adequate regression model. Only the S^*W interaction was not statistically significant in the model considering a level of significance of 5%. Considering that the model is valid, the main effects and interactions plots can be seen in Figs. 6 and 7.

Looking at these plots, setup 3 ($S=170$ and $L=0$) in Table A seems to provide the best workpiece roughness. However, the effect of tool flank wear (W) on roughness (**WPC**) cannot

TABLE 7. Multivariate performance analysis for the hard turning process.

Setup	Normality test	USL	$\overline{WPC}$	s_{wpc}	$Pp_{k;wpc}$	Classification
1	0.381[a] (0.378[b])	3.710	3.165	0.222	0.82	In control, Inadequate
2	0.715[c] (0.054[d])	1.441	1.390	0.096	0.18	Out-of-control, Poor
3	0.472 (0.229)	4.203	3.147	0.399	0.88	Out-of-control, Inadequate
4	0.282 (0.611)	3.917	3.328	0.177	1.11	In control, Capable

[a] Anderson-Darling statistic for normality test
[b] p-value
[c] Anderson-Darling statistic for normality test after *ln* transformation
[d] p-value after *ln* transformation

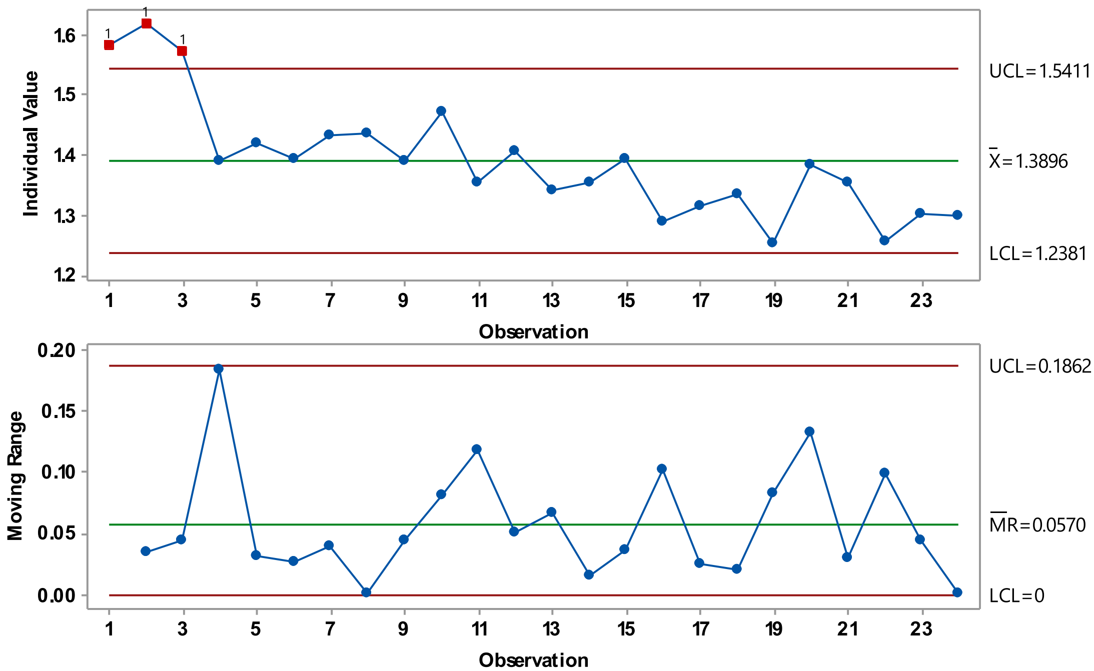

FIGURE 8. I-MR control chart of WPC for setup 2.

be neglected. The tool flank wear (W) determines a strong negative correlation with workpiece roughness (**WPC**). It is required to verify this effect for each process setup in order to come up with a final decision on process stability and performance.

Still in **sixth step**, stability and performance analyses were conducted for each process setup. Using Eqs (2) and (3), Table 6 summarizes the principal component analysis with eigenvalues and eigenvectors of each process setup. Eqs. (9)-(14) have been applied to transform original specification limits into **WPC** scores. For each setup, multivariate process performance has been estimated with Eq. (15), as seen in Table 7. Process stability for setups 1 to 4 can be evaluated by Figs. 5 and 8-10, respectively. Assessing these I-MR control charts, the tool flank wear provided the lower effect on process stability in setups 1 and 4 (in-control) than setups 2 and 3 (out-of-control). Turning now to process performance analysis, setup 4 (high cutting speed with 3 L/min of lubricant fluid flow) seems to be the best choice, since $Pp_{k;wpc} = 1.11$ classifies the process as capable.

Finally, in the **seventh step**conclusions and recommendation on process setup must be made based on the previous multivariate statistical analysis. Taking the univariate analysis in section III.A into account, the analyst was unable to come up with a final decision on process stability and performance. Through roughness $\mathbf{R_a}$, the process was classified as out-of-control with poor performance. On the other hand, $\mathbf{R_t}$ has deemed the process as in-control with inadequate performance. Since correlation among these quality characteristics had been considered significant, multivariate statistical quality control was performed. In this hardened steel turning experiment, the tool flank wear effect into roughness was significant. Thus, four setups based on a full factorial desing was planned in order to check the best process stability and performance. The setup 4 was the least sensible to effect of the uncontrollable variable tool flank wear. Therefore, high cutting speed with 3 L/min of lubricant fluid flow has been adopted as a final setup to achieve the best process stability and performance for both $\mathbf{R_a}$ and $\mathbf{R_t}$ roughness parameters.

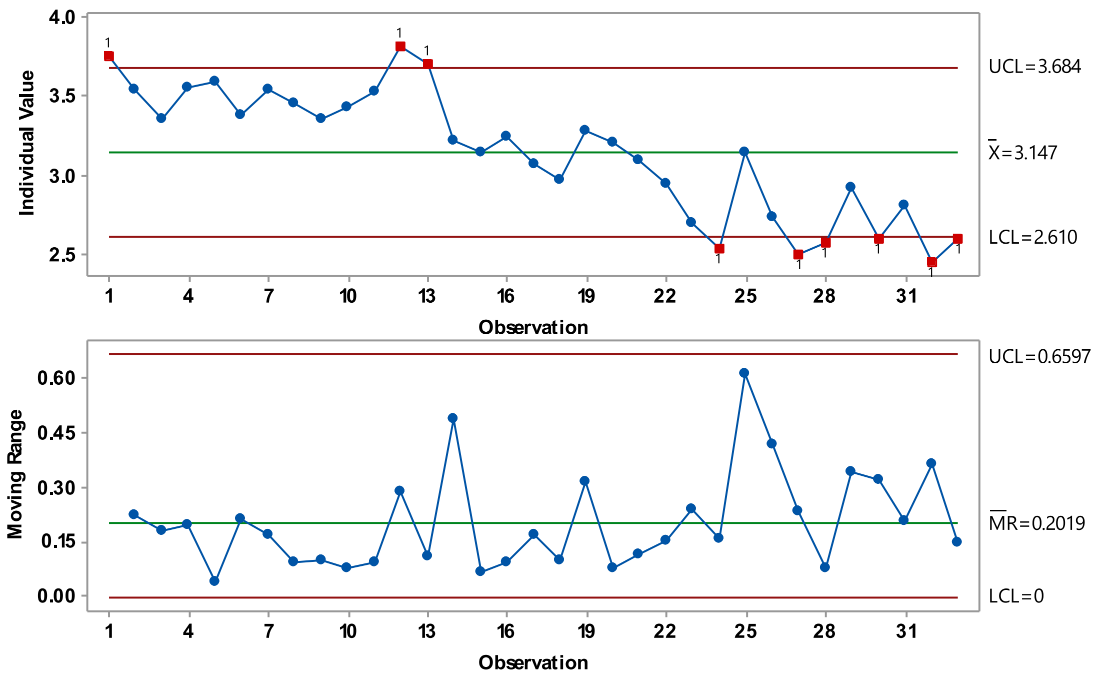

FIGURE 9. I-MR control chart of WPC for setup 3.

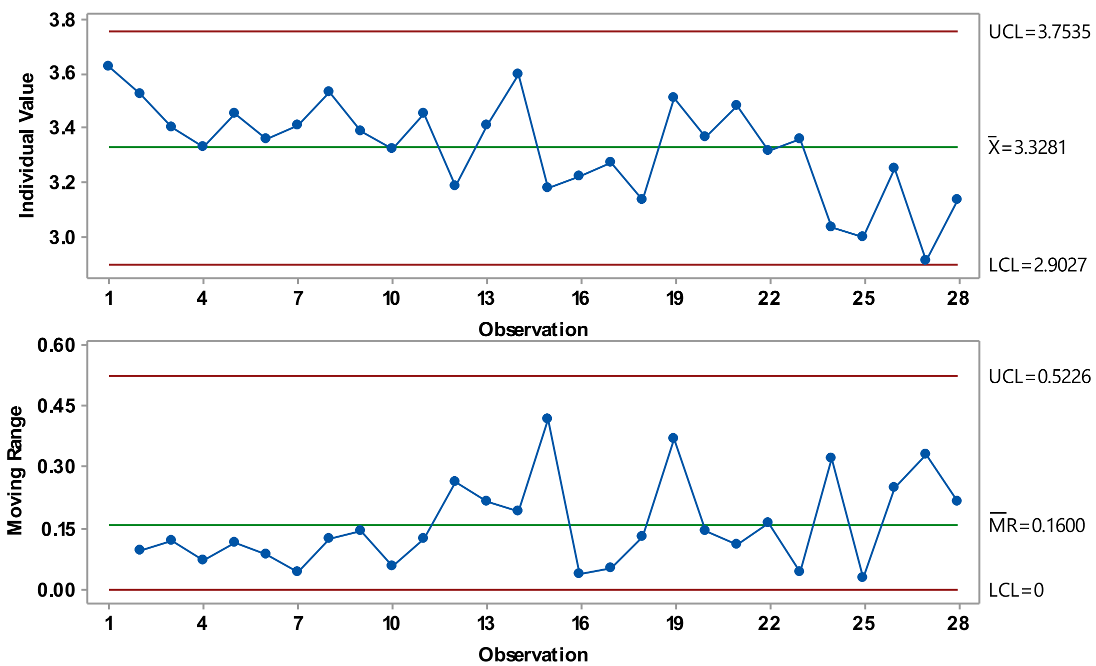

FIGURE 10. I-MR control chart of WPC for setup 4.

IV. CONCLUSION

This research has proposed a multivariate method to promote a statistical quality control on AISI 52100 hardened steel turning. Surface integrity is of pivotal relevance for quality control. This quality characteristic, which is measured by roughness parameters, is often influenced by some controllable and uncontrollable variables such as cutting speed, lubricant fluid flow, feed rate, tool flank wear, hardness, and others. Keeping the process in control in such complex environment is a tough task. Thus, statistical process control, design of experiments and principal component analysis have been utilized in order to make the process not only stable but also capable.

This proposal was able to guide the engineer into the decision making process of correcting issues of stability and performance. Since a multivariate process has been evaluated, principal component analysis has been applied to help reducing process dimension and making decisions easily. Design

TABLE 8. Experimental dataset of setups 1 to 4 for roughness R_a and R_t.

Setup	S	L	W	R_a	R_t	Setup	S	L	W	R_a	R_t
1	120	0	0	0.88	3.944	3	170	0	0	0.68	3.782
1	120	0	0	0.86	3.656	3	170	0	0	0.66	3.553
1	120	0	0.02	0.85	3.875	3	170	0	0.02	0.6	3.378
1	120	0	0.02	0.87	3.682	3	170	0	0.02	0.58	3.589
1	120	0	0.02	0.83	3.788	3	170	0	0.02	0.62	3.622
1	120	0	0.05	0.81	3.987	3	170	0	0.05	0.56	3.413
1	120	0	0.05	0.84	3.568	3	170	0	0.05	0.65	3.567
1	120	0	0.05	0.79	3.623	3	170	0	0.05	0.63	3.473
1	120	0	0.07	0.75	3.778	3	170	0	0.07	0.59	3.379
1	120	0	0.07	0.77	3.832	3	170	0	0.07	0.57	3.465
1	120	0	0.1	0.73	3.967	3	170	0	0.1	0.52	3.577
1	120	0	0.1	0.71	3.643	3	170	0	0.1	0.54	3.876
1	120	0	0.1	0.68	3.798	3	170	0	0.1	0.53	3.764
1	120	0	0.13	0.72	3.479	3	170	0	0.13	0.49	3.262
1	120	0	0.13	0.67	3.677	3	170	0	0.13	0.5	3.187
1	120	0	0.15	0.65	3.588	3	170	0	0.15	0.46	3.298
1	120	0	0.15	0.68	3.299	3	170	0	0.15	0.45	3.123
1	120	0	0.17	0.63	3.476	3	170	0	0.17	0.51	3.002
1	120	0	0.17	0.66	3.366	3	170	0	0.17	0.43	3.352
1	120	0	0.17	0.61	3.759	3	170	0	0.17	0.46	3.264
1	120	0	0.2	0.58	3.834	3	170	0	0.2	0.42	3.154
1	120	0	0.2	0.6	3.265	3	170	0	0.2	0.44	2.987
1	120	0	0.23	0.59	3.199	3	170	0	0.23	0.39	2.746
1	120	0	0.23	0.57	3.385	3	170	0	0.23	0.35	2.589
1	120	0	0.25	0.54	3.189	3	170	0	0.25	0.4	3.214
1	120	0	0.25	0.55	3.476	3	170	0	0.25	0.36	2.789
1	120	0	0.27	0.51	3.378	3	170	0	0.27	0.31	2.557
1	120	0	0.27	0.53	3.537	3	170	0	0.27	0.34	2.632
1	120	0	0.3	0.52	3.324	3	170	0	0.29	0.36	2.983
2	120	3	0	1.08	4.823	3	170	0	0.29	0.33	2.655
2	120	3	0	1	5.012	3	170	0	0.3	0.32	2.876
2	120	3	0.02	0.99	4.788	3	170	0	0.3	0.37	2.483
2	120	3	0.02	0.98	3.964	3	170	0	0.3	0.35	2.644
2	120	3	0.02	1	4.092	4	170	3	0	0.8	3.882
2	120	3	0.05	0.96	3.987	4	170	3	0	0.76	3.785
2	120	3	0.05	0.97	4.152	4	170	3	0.02	0.7	3.667
2	120	3	0.07	0.95	4.162	4	170	3	0.02	0.68	3.591
2	120	3	0.07	0.93	3.976	4	170	3	0.02	0.72	3.712
2	120	3	0.1	0.97	4.321	4	170	3	0.05	0.66	3.634
2	120	3	0.1	0.99	3.825	4	170	3	0.05	0.65	3.692
2	120	3	0.13	0.92	4.043	4	170	3	0.07	0.75	3.794
2	120	3	0.13	0.94	3.772	4	170	3	0.07	0.73	3.633

TABLE 8. ***(Continued.)*** **Experimental dataset of setups 1 to 4 for roughness R_a and R_t**

2	120	3	0.15	0.86	3.844	4	170	3	0.07	0.77	3.547
2	120	3	0.15	0.91	3.987	4	170	3	0.07	0.69	3.732
2	120	3	0.17	0.89	3.589	4	170	3	0.1	0.66	3.435
2	120	3	0.17	0.86	3.687	4	170	3	0.1	0.64	3.696
2	120	3	0.2	0.87	3.765	4	170	3	0.12	0.74	3.876
2	120	3	0.23	0.88	3.457	4	170	3	0.12	0.56	3.468
2	120	3	0.23	0.83	3.968	4	170	3	0.12	0.6	3.497
2	120	3	0.25	0.85	3.846	4	170	3	0.15	0.59	3.563
2	120	3	0.25	0.82	3.477	4	170	3	0.15	0.64	3.387
2	120	3	0.28	0.79	3.645	4	170	3	0.17	0.66	3.812
2	120	3	0.3	0.83	3.633	4	170	3	0.17	0.63	3.654
						4	170	3	0.2	0.65	3.777
						4	170	3	0.2	0.62	3.598
						4	170	3	0.23	0.59	3.664
						4	170	3	0.23	0.56	3.298
						4	170	3	0.25	0.55	3.264
						4	170	3	0.25	0.53	3.564
						4	170	3	0.27	0.5	3.189
						4	170	3	0.31	0.54	3.425

of experiments was essential to promote changes in process setup. After that, control charts and performance indices have been performed to come up with final decision on the final process setup.

The result analysis has shown how ineffective the univariate approach was. The engineer was unable to make a final decision on process stability and performance. Assessing $\mathbf{R_a}$, the process was deemed out-of-control and with poor performance. On the other hand, $\mathbf{R_t}$ determined that the process was in control and with an inadequate performance. Applying the proposed multivariate approach, the engineer was able to find the best process setup for stability and performance. Setup 4 with high cutting speed and 3 L/min of lubricant fluid flow has been adopted as a final setup. Taking this process adjustment, the operation was classified as in control and with capable performance (Ppk = 1.11).

Additional study for ongoing process monitoring of future production is suggested. In this case, the engineer might use the control charts' limits in Fig. 10 to make an online monitoring and take actions as soon as an out-of-control point shows up. Another interesting work would implement optimization methods, such as robust parameter design, in order to reduce even more the effect of tool flank wear into roughness parameters.

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GEORGE EVANGELISTA received the degree from the Federal University of Piauí, in 2015, and the master's degree in production engineering from the Federal University of Paraíba, in 2019. He is currently a Production Engineer. He works in the area of design and experiment analysis, multivariate statistics, and optimization methods. His research interest includes manufacturing process optimization.

ROGÉRIO SANTANA PERUCHI received the degree in mechanical production engineering, and the master's degree in production engineering from the Federal University of Itajubá, in 2009 and 2011, respectively, and the Ph.D. degree in production engineering from the Federal University of Itajubá, in 2014, with a sandwich period at the University of Tennessee at Knoxville, in 2013. He was a Postdoctoral Researcher of production engineering with the Federal University of Itajubá, in 2015. He has served as an Associate Professor at the Faculty of Engineering, Federal University of Goiás - Regional Catalão, in 2016. He is currently an Associate Professor with the Department of Production Engineering, Technology Center, Federal University of Parabaí. He has experience in Process Engineering in the automotive sector. He has worked with scientific research in the areas of six sigma, quality management, statistical quality control, statistical process modeling, and multiobjective optimization. He is also a Level 2 Researcher of the National Council for Scientific and Technological Development.

TARCÍSIO GONÇALVES BRITO received the degree in mechanical engineering, specialization in environmental engineering, the master's degree in mechanical engineering, and the Ph.D. degree in production engineering from the Federal University of Itajubá, Brazil, in 2015. He is currently an Adjunct Professor C1 with the Federal University of Itajubá. He has experience in mechanical engineering and production, acting on the following subjects, such as manufacturing processes, technical drawing I and II, machine elements, machine dynamics, and quality control. He works in the area of design and analysis of experiments. His research interest includes operational research.

PAULO ROTELA JUNIOR received the B.Sc. degree in production engineering, and computer information systems from the Centro Universitário de Itajubá (FEPI), and the M.B.A. degree and the M.Sc. and D.Sc. degrees in production engineering from the Federal University of Itajubá (UNIFEI), in 2010, 2012, and 2015, respectively. He was a Postdoctoral Researcher with UNIFEI, from 2016 to 2018. He is currently an Assistant Professor with the Department of Production Engineering, Federal University of Paraíba (UFPB). He is also a Lead Researcher with the Applied Quantitative Methods Study Group, UFPB. He is also the Coordinator of the Laboratory of Applied Quantitative Methods (LabMeQA), UFPB. He has expertise in modeling and optimization for portfolio analysis. His research interests include economic engineering and investment analysis in renewable energy, accounting, finance, and operations research.

LUIZ CÉLIO SOUZA ROCHA received the degree in business administration and the master's degree in business administration from the Federal University of Rio Grande do Norte, in 2007 and 2010, respectively, and the Ph.D. degree in production engineering from the Federal University of Itajubá, in 2017. He is currently a Professor of management under exclusive dedication with the Federal Institute of Education, Science and Technology, Northern Minas Gerais (IFNMG), Almenara. He has experience in experimental planning, optimization, feasibility and finance analysis and economic analysis of renewable energy projects.