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ANALYSIS OF TUNDISH WEIGHT ON THE STRIP CASTING PROCESS THROUGH RESIDUES CONTROL CHARTS IN THE PRESENCE OF VOLATILITY

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ABSTRACT

The present study assesses the stability of the tundish weight that comprises the strip casting process by means of residues control charts. For monitoring purposes, the Principal Component Analysis technique was used to address the cross-correlation, while the ARIMA-GARCH model was used to address autocorrelation, with control charts being applied to residues resulting from this modeling. The study was conducted in the melt shop of a steel billets manufacturer, where, after being modeled, the selected components ($PC1_{PD}$ and $PC2_{PD}$) had its residues submitted to control charts. Thus, out-of-control points in relation to the residues of ARIMA and ARCH models were compared, leading to the conclusion that volatility influences stability changes in the process. In this sense, the procedure in use was able to represent the manufacturing process, providing an understanding of the behaviors of the variables and supporting process monitoring, in order to avoid process instability and the occurrence of scraps.

Keywords: *Principal Components, ARIMA Models, GARCH Models, Volatility, Control Charts, Strip Casting*

1. INTRODUCTION

The use of statistical procedures for quality control is becoming increasingly common. The correct use of these methods depends on the ability of the researcher to employ the most suitable method for evaluating the study. Consequently, the success of the research depends on the correct use of the methods, so that every evaluation of the production process results in proper and reliable decisions.

If the production process has correlation characteristics and if variables have autocorrelation characteristics, the work does not become trivial. Some alternative procedures for the application of multivariate control charts can be suggested, said Montgomery(2012), so that the analysis is not compromised by the correlation - which is the connection among variables - or by the linkage between the time instants within each variable, what would reveal the autocorrelation; then, making the task easier.

Thus, we try to show a univariate procedure to evaluate a set of multivariate variables. The technique of Principal Component Analysis (PCA) and Autoregressive Integrated Moving Average models - ARIMA(p,d,q) is used together with the Generalized Autoregressive Conditional models for Heterocedasticity (GARCH), in order to obtain a non biased estimate of residues that will be evaluated by means of control charts.

 ISSN: 2047 - 0398
SPECIAL ISSUE – V|4|N|5|, January | 2015

When using control charts, there's a basic assumption that the variable under analysis fulfils independence conditions and is identically distributed (*i.i.d*), what does not occur in autocorrelated processes, according to Souza et al. (2012). This justifies the adoption of a methodology addressing the autocorrelation, based on the modeling proposed by Box and Jenkins (1970), where the residue analysis of the variable under study will be investigated by control charts.

In this sense, the purpose is to find statistic modeling residues with a *White Noise* characteristic, which can also be used to represent the process under analysis. Since the Autoregressive Moving Average Models (ARIMA) analyzes and performs series forecasting, the series variability through Autoregressive Conditional Heterocedasticity models(ARCH) is also investigated.

The Heterocedasticity is revealed when the *White Noise*, in its quadratic form, is autocorrelated. Thus, there's an evidence of a serial dependence able to show the variable's volatility (BENTES et al., 2008). Thus, the quadratic residues have some kind of information that is worth to be investigated (SILVA et al., 2005). ARIMA and ARCH models enable the average level of development of the variables under analysis and study the series persistence, which is the ability to show if the variability influencing the process continues for a long period of time though ARCH (α) and GARCH (β) parameters.

The objective is to evaluate the stability of the tundish weight on the strip casting process, taking into consideration the presence of cross-correlation and autocorrelation, with residues control charts applied to the ARIMA-GARCH modeling.

The present article is structured as follows: section 1 presents an introduction of the subject under study; section 2 presents the methodology to be developed; section 3 has a practical application of theories to a dataset and also the discussion of the results included in item 4, together with the research conclusions.

2. METHODOLOGICAL ASPECTS

The proposed methodology is exemplified during the strip casting process on 240 mm-square-section steel billets manufacturing. In this study, we use a set of nine measurements relating to the of tundish weight in tons. The observations are measured in batches. Each batch is of up to 65 tons, lasting about 1 hour with measurements taken every 5 minutes. Data collection took place from September 2009 to December 2010, in a total of 228 production batches. We chose for the study of Steel DIN20MnCr5 for being in the company's interest.

The methodology is based on the study of various authors, such as Kaiser (1960); Cattel (1966); Kanoa and Nakagawa (2008); Souza et al. (2011); Box and Jenkins (1970); Box et al. (1994); Gujarati (2006); Wasserman (2000); Morettin (2006); Pedrini and Caten (2008); Acquah (2010) Ehlers (2010); Montgomey and Runger (2009); Claro et al. (2007); Montgomery (2004); Crowder (1987); Lucas and Saccucci (1990ab); Montgomery et al. (1994); Bersimis et al. (2007); Souza (2000) and Casarin et al. (2012).

2.1 *Methodological steps*

The methodological steps make up the following milestones:

1. Application of descriptive statistics to characterize the study variables, such as the calculation of correlations between variables. If the variables are correlated, the Principal Component Analysis (PCA) is applied in order to eliminate the correlation effect. Studies Pearson (1901), Hotelling (1933), Morrison (1976) Seber (1984), Reinsel (1993), Jackson (1980, 1981) and Johnson and Wichern (1992, 1998) are followed. If this effect is not present, you can directly apply the Control Charts without prejudice in its interpretation.
2. Once the Principal Components (PC) are determined, the presence of autocorrelation is verified. If the autocorrelation is detected, the Autoregressive Integrated Moving Average (ARIMA) on the selected PCs in order to apply Control Charts (CC) in ARIMA modeling, then satisfying the condition imposed by the CC of *i.i.d* variables. This step applies to the methodology Box, Jenkins and Reinsel (1994). An ARIMA (p,d,q) process is represented by:

$$\phi(B)\Delta^d x_t = \theta(B)e_t \qquad (1)$$

where B is the lag operator, d is an integer positive value and represents the difference, according to the order of integration; ϕ and θ are the parameters of autoregressive processes of moving averages p and q respectively; and $e_t \sim RB(0,\sigma^2)$ and it's expected that the noise e_t is *i.i.d.*, which will be used to evaluate the process; details in MAKRIDAKIS, WHEELWRIGHT and HYNDMAN (1998), MORETTIN and TOLOI (2004) and MORETTIN (2008).

In the search for the best mathematical model that correctly represents the generating process of each series, several competing models are estimated and the model wih the lowest value for the Akaike's Information Criteria (AIC) and Bayesian Information Criteria (BIC); represented in (2) and (3), is selected.

$$AIC = T\ln(SQR) + 2n \tag{2}$$

$$BIC = T\ln(SQR) + n\ln(T) \tag{3}$$

where: T is the sample size; SQR is the sum of the squared residuals and n is the number of parameters.

2a. If residues are *White Noise* (*WN*), there's not a quadratic dependence among residues, i.e., volatility, so control charts of individual measurements ($\bar{x}$), moving rages ($\overline{MR}$) and Exponentially Weighted Moving Averages (EWMA) are drawn up in the original variables and in the residues, in order to evaluate the process' stability;

2b. If residues are *WN* and present volatility characteristics, control charts $\bar{x}$, $\overline{MR}$ and EWMA are drawn up in the original data, in the residues from ARIMA-ARCH modeling and in the volatility, being the process assessed as to its stability.

After the estimative of ARIMA model and the CC application, the volatility study is focused as an accurate tool for the decision making, SÁFADI and ANDRADE FILHO (2007).

The ARCH-GARCH modeling will be used to help on the CC interpretation, mainly by the inspection of persistence parameters that show for how long a specific phenomenum or effect remains in the system. An ARCH(m) model, where m denotes the model order, expresses the conditional variance of the previous model to the conditional average, as a function of past quadratic innovations (SILVA, SÁFADI and CASTRO JÚNIOR, 2005).

$$u_t = \sigma_t^2 \varepsilon_t \tag{4}$$

It is observed that the conditional variance of error ε_t to the available information for the period (t-1) can be distributed according to Lamounier (2006), as the expression 5 demonstrates.

$$\sigma_t^2 = \alpha + \sum_{i=1}^{q} \alpha_i u_{t-i}^2 \tag{5}$$

In case of an ARCH(1) model, the conditional variance is given by:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 \tag{6}$$

It is expected that ARCH(1) model provides a residue with *i.i.d.* characteristics, as demonstrated in equation 7.

$$\varepsilon_t \sim N(0; \alpha_0 + \alpha_1 u_{t-1}^2) \tag{7}$$

According to Bollerslev (1986), when a ARCH *(m)* model is no more thrifty when using pure AR or MA models, a composite model is used, incorporating autoregressive and moving average information for describing volatility and then, reaching a GARCH *(r, m)* model.

The variance of residuals can be explained by the out-of-phase quadratic residue, as well as by the updated variance in later moments, as expressed by (8).

$$\sigma_t^2 = \omega_0 + \alpha_1 e_{t-1}^2 + \ldots + \alpha_m e_{t-m}^2 + \beta_1 \sigma_{t-1}^2 + \ldots + \beta_r \sigma_{t-r}^2 \tag{8}$$

Like in the ARCH model, there are restrictions applied the process variance to be positive and slightly stationary. To that end, ω_0, α and β constants must be positive and $\alpha + \beta \langle 1$, where $\alpha + \beta$ represents volatility persistence. If this sum is close to zero, there is indication that the shock over volatility will have rapid effects and the variance should quickly return to its historical average. Otherwise, if the sum is close to 1, the effect of persistence will be more durable and the return variance of its historical average will take longer Lamounier (2001).

3. With the definition of the ARCH-GARCH model, a diagnosis of the residues is given by verifying the model adequacy. Also, there's a verification of residues' usefulness for application of control charts.
4. In all sets of variables CC will be addressed in the original variables and in variables without the correlation effect after applying the PCA. Finally, without correlation and autocorrelation effects, after the modeling application on the PCs. Thus, it's possible to indicate the points out of control as the present effects of correlation.

 ISSN: 2047 - 0398
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The process will be considered under statistical control if all points are within the limits of control charts, emphasizing that the combination of Shewhart and EWMA charts provides a greater efficiency to detect flaws in the process. The graphics $\overline{X}$ and $\overline{MR}$ for individual measures are very sensitive to deviations from normality, but in this case they are applied to residues of estimated statistical models, if the model fitted to the data produces residues with normal distribution.

Figure 1 shows the methodology script used on the research.

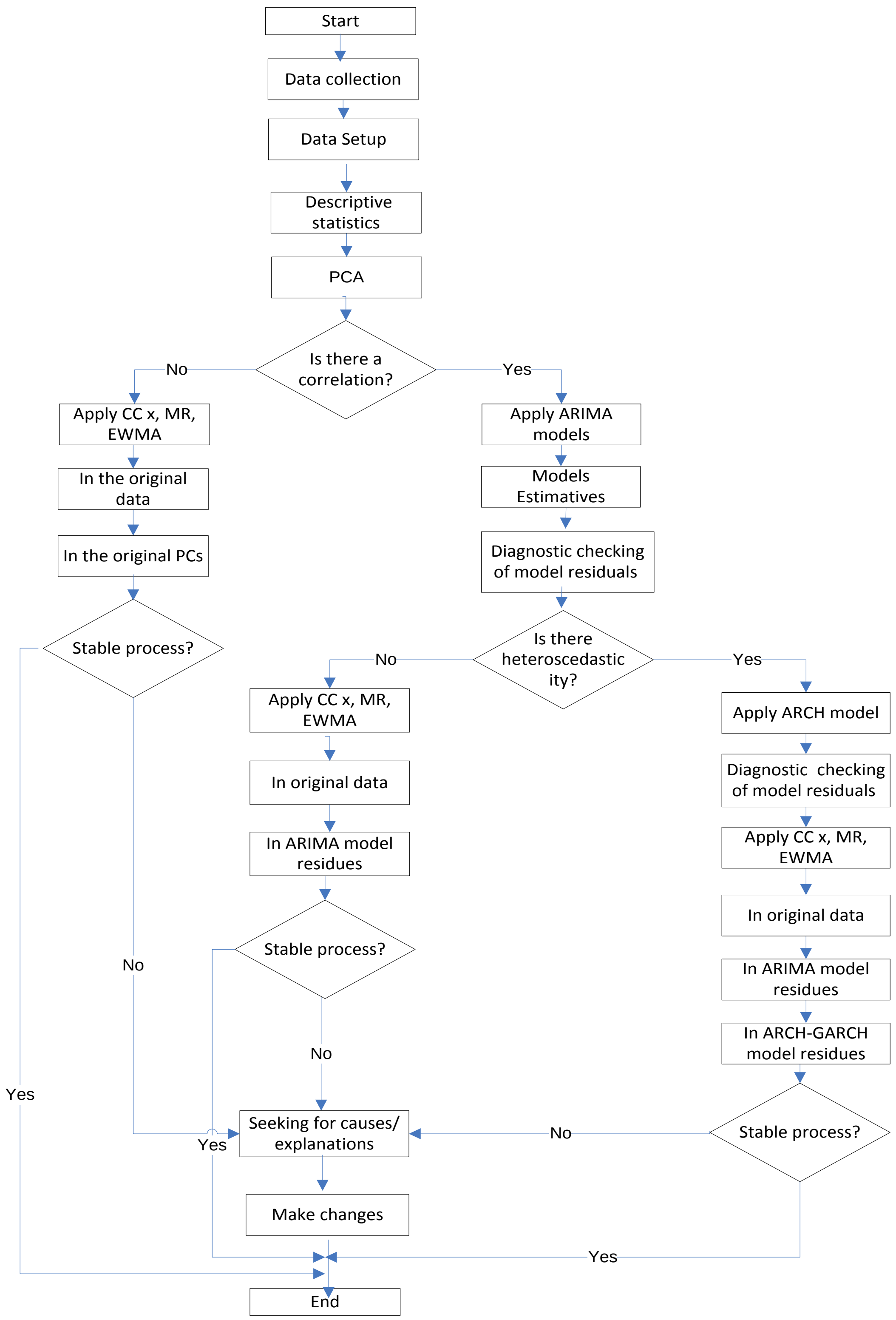

Figure 1 – Methodology script used on the research

ISSN: 2047 - 0398
SPECIAL ISSUE – V|4|N|5|, January | 2015

The procedure for evaluating a multivariate-features process will be exemplified by a case and has the ability to predict and prevent malfunctions using the knowledge on engineering and modeling methods that may provide great benefits to the casting process (ZHANG and DUDZIC, 2006). The aim of the alternative method is using alternatives for the application of univariate control charts, so the effect of correlation does not influence the detection of out of control points.

3. RESULTS AND DISCUSSIONS

By analyzing the production process, there was a strong cross-correlation between variables, providing the use of the PCA so the correlation between variables was addressed and there was no need to use multivariate control charts, therefore, an action strategy to be used is the CC application in the PCs selected for the study (TRACY et al., 1997).

Table 1 presents the estimated eigenvalues and explained variance for each component.

PC	Eigenvalues	Explaines Variance (%)	Accumulated Eigenvalue	Accumulated Variance (%)
$PC1_{PD}$	4.47	49.65	4.47	49.65
$PC2_{PD}$	1.66	18.41	6.12	68.06

Table 1 – Eigenvalues and explained variance for each component

On the eigenvalues selection, Table 1 reveals that, for the tundish weight, two PC's ($PC1_{PD}$ e $PC2_{PD}$) were selected, corresponding to 68.06%, what indicates that these two components should be investigated rather than the 9 original variables. The selection of the first two components are supported by the Selection Method Kaiser (1960) through the Cattell method (1966), exemplified by PLA (1986), where PC's selected are prior to the turning point formed by eigenvalues, by the variance explained percentage accumulated at approximately 70%, through Kwiatkowski (1992) method.

Once PC's are selected, each variable's contribution on the PCs composition is verified and a correlation is made between selected PC's and original variables. Correlations above 0.7 were considered as the ones with a greater contribution to the PC, being the most representative. The higher the degree of correlation between measurements, the greater is its influence on the component formation (KOURTI and MacGREGOR, 1996). Table 2 present the correlations between original variables and each PC's.

PC	Factorial load values
$PC1_{PD}$	PD2: -0.888105; PD3: -0.911001; PD4: -0.921266; PD5: -0.804628; PD6: -0.866267
$PC2_{PD}$	PD8:-0.890507; PD9: -0.855248

Table 2 – Main components factorial loads

PC1 and PC2 are the process' most representative components and must be investigated. In PC1 the PD4, which value is -0.92 is the most influencing variable, followed by the PD3, PD2, PD6 and PD5. In PC2, the most influencing variable is PD8, followed by PD9.

PC1 and PC2 were considered autocorrelated, so the CC application directly on the PC's is not possible, for violating the principle of independence among the observations. Thus, a ARIMA (*p*,*d*,*q*) statistical model is adjusted on the PC's, where, based on their residues, control charts will be plotted for $\bar{x}, \overline{MR}$ *and EWMA*. Table 3 presents competing models for the PCs being tested, evaluated and producing residues with RB characteristics.

Model	Parameter	AIC	BIC
$PC1_{PD}$ d=0			
AR(1)	0.371	3.925	3.956
AR(2)	0.300		
$PC2_{PD}$ d=1			
Model	**Parameter**	**AIC**	**BIC**
AR(1)	-0.317	3.349	3.409
AR(2)	-0.249		
AR(3)	-0.154		
MA(1)	-0.807		

Table 3 - Estimation of the best ARIMA model for PC1 and PC2 variables representing the tundish weight

ISSN: 2047 - 0398
SPECIAL ISSUE – V|4|N|5|, January | 2015

Table 3 present two models addressing serial correlation and having a *White Noise* characteristic; and residues from AR(2) and ARIMA(3,1,1) models were not autocorrelated. AR(2) and ARIMA(3,1,1) initial models were used for the analysis of quadratic residues, through *F* and ARCH-LM (BENTES et al., 2008) tests, detecting the presence of conditional heterocedasticity in residues. So a joint estimation is performed on ARIMA-GARCH models for the initial models on Table 3, which is shown in Table 4.

Method: ML – ARCH (Marquardt) – Normal Distribution				
$PC1_{PD}$ d=0				
Model	**Coefficient**	**Standard error**	**Statistics z**	***Prob***
AR(1)	0.315805	0.089512	3.528072	0.0004
AR(2)	0.158536	0.089995	1.761601	0.0781
Conditional variance equation				
C	0.489001	0.262230	1.864776	0.0622
ARCH(1)	0.235714	0.104077	2.264806	0.0235
GARCH(1)	0.574856	0.172603	3.330509	0.0009
$PC2_{PD}$ d=1				
Model	**Coefficient**	**Standard error**	**Statistics z**	***Prob***
AR(1)	-0.689511	0.090181	-7.645868	0.0000
AR(2)	-0.594493	0.094938	-6.261923	0.0000
AR(3)	-0.468873	0.074229	-6.316544	0.0000
MA(1)	-0.395483	0.114700	-3.447965	0.0006
Conditional variance equation				
	0.105209	0.047398	2.219691	0.0264
ARCH(1)	0.086669	0.048193	1.798372	0.0721
GARCH(1)	0.848420	0.061777	13.73362	0.0000

Table 4 – Estimation of GARCH models for PC1 and PC2 variables representing the tundish weight (PD)

At the time of the joint ARIMA-ARCH estimation for PC's, Table 4, the model for the PC1 is represented by AR(2)-GARCH(1,1) with statistically significant parameters. The volatility is shown by a GARCH model, the sum of the parameters is close to 1, i.e., 0.235714 + 0.574856 = 0.81057, indicating that the conditional variance has a prolonged effect or a large persistence. This means that the tundish weight oscillates and will present this characteristic in other periods of time, producing an unstable process. The most important variable in this PC is PD4, with factor loadings equal to -0.921266. This type of modeling, although well-established in the literature, when applied to industrial processes, provides an increased quality on estimated parameters and therefore, increases the quality of residues later used by the control charts.

For $CP2_{PD}$, the model found for the volatility is a mixed model ARIMA(3,1,1)-GARCH(1,1). The step of volatility verification becomes important, since the variables with greatest importance in each PC composition are known and a high volatility is verified on the analyzed PC's, it is important to pay attention to these variables, because this great variability behavior will propagate along the production process, causing enlargement of the control limits and decreasing the efficiency of CC.

After the variables modeling, if these are free of autocorrelation and have independent and normally distributed residues, it is possible to analyze the stability of the process by means of $\bar{x}$, $\overline{MR}$ e $EWMA$ charts. Table 5 shows the points that are out of the control limits of residues from ARIMA-ARCH modeling applied to the PC's.

$PC1_{PD}$					
CC	Original Values	Main Component	Residues	Quadratic Residues	Volatility
$\bar{x}$	97	12	6	7	20
$\overline{MR}$		11	8	9	14
EWMA		22	0	0	36
$PC2_{PD}$					
CC	Original Values	Main Component	Residues	Quadratic Residues	Volatility
$\bar{x}$	97	5	5	5	150
$\overline{MR}$		3	5	8	10
EWMA		0	0	0	29

Table 5 – Sample points out of the control limits

 ISSN: 2047 - 0398
SPECIAL ISSUE – V|4|N|5|, January | 2015

Figures 2, 3, 4 show the $\overline{X}$ charts for the PC1 of the tundish weight and Figure 5 show the conditional volatility for the PC1.

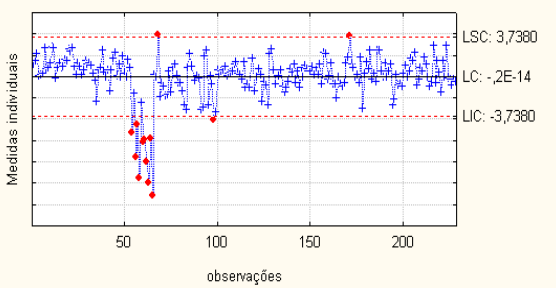

Figure 2 - Chart $\overline{X}$ for the $PC1_{PD}$

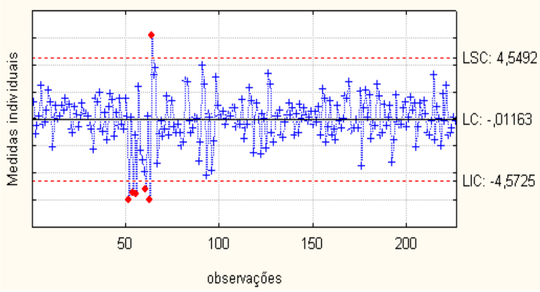

Figure 3 - Chart $\overline{X}$ of $PC1_{PD}$ residues of AR(2) model

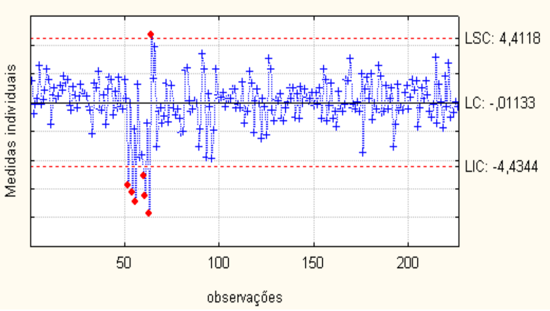

Figure 4 - Chart $\overline{X}$ of $PC1_{PD}$ residues, using AR(2)-GARCH(1,1) model

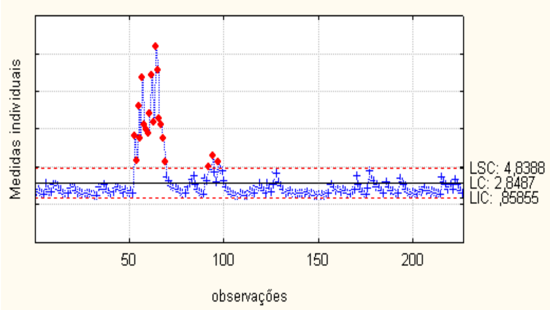

Figure 5 - Chart $\overline{X}$ for conditional volatility revealed by AR(2)-GARCH(1,1) model for the $PC1_{PD}$

Figures 6, 7 and 8 show charts $\overline{X}$ for the PC2 of the tundish weight and Figure 9 shows the conditional volatility for PC2.

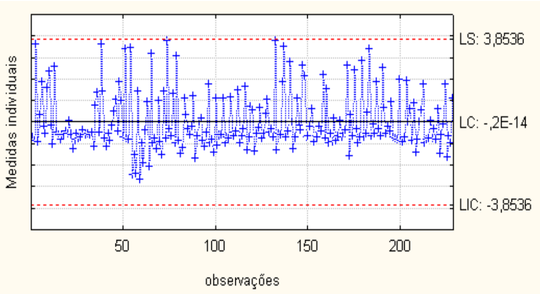

Figure 6 - Chart $\overline{X}$ for the $PC2_{PD}$

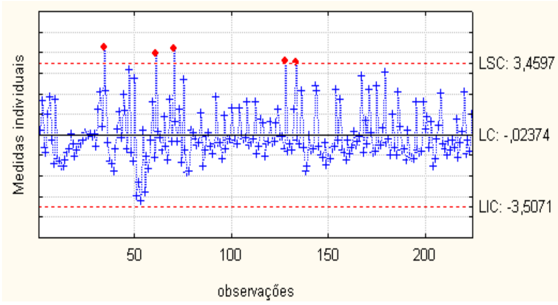

Figure 7 – Chart $\overline{X}$ of $PC2_{PD}$ residues of ARIMA(3,1,1) model

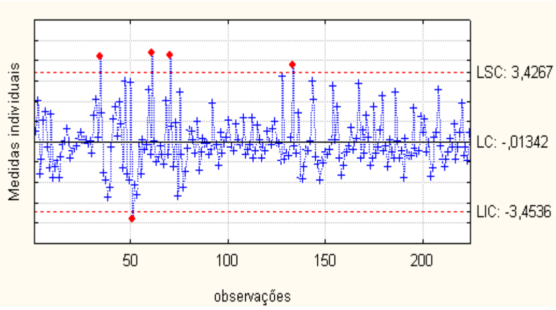

Figure 8 – Chart $\overline{X}$ of $PC2_{PD}$ residues using ARIMA(3,1,1)-GARCH(1,1) model

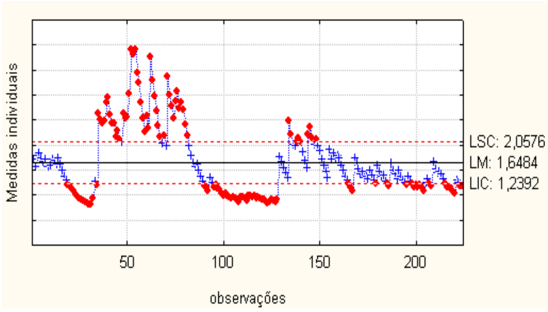

Figure 9 - Chart $\overline{X}$ for conditional volatility revealed by ARIMA(3,1,1)-GARCH(1,1) model for $PC2_{PD}$

It is observed, based on Figures 5 and 9 - which represent the respective volatility behaviors persistent over time - a wide amplitude affecting the production process, since the autovariability is the opposite path from high quality achievement.

According to the control charts, it was possible to see the numerous sample points outside the control limits and also the influence of process volatility in the performance of the production process, once the sampling points of ARIMA model residues coincide with out of control points represented by the GARCH models.

The production process of steel DIN20MnCr5, square section 240 mm, presents volatility, shown by the high standard deviations values. The tundish weight variable feeding the continuous casting machine has out-of-control points in relation to the process average in concomitant periods with high volatility, which is considered unstable. The wide variation in the volume of loaded steel is not kept constant and therefore the tundish weight is also not constant. When this occurs, a dead space is formed inside the pot (container transporting the liquid steel) filled with oxygen, being one of the root causes for poor quality steel production, responsible for the oxidation and for the occurrence of out-of-the-limits points, revealed by the CC when assessing this variable.

When the pot is not fully charged, it provokes chemical reactions between the liquid metal and the excessive oxygen in the pot free area that is not fully populated. Another factor that influences the instability and variability of the tundish weight is that, once the pot is not fulfilled, there is a need of extra/not totally filled loads, which will help keeping the production flow. And these additional charges, over short periods of time, are the ones which will provide the process autocorrelation and volatility.

4. CONCLUSIONS

The purpose of the study was to analyze the production process stability through control charts, applied to the residues resulting from a mixed modeling called ARIMA-ARCH, applied to the main components derived from the original data.

Thus, the gain from this alternative procedure is the use of PCA to obtain uncorrelated variables and the possible identification of variables causing the process instability. Besides contributing to address the autocorrelation in the Principal Components (PC's), when present; and providing a non-biased estimate of the ARIMA parameters, the ARIMA-GARCH modeling applied to selected components also provides information about the process variability through GARCH models (SOUZA et al. 2012).

Thus, with the use of PCA in selected variables it was possible to assess the existing cross-correlation among variables, showing the appropriateness of the proposed procedure, removing the correlation between variables. In a second step, the autocorrelation was treated by means of Box & Jenkins models, because the PCs showed autocorrelation.

The residues found in the ARIMA model on the PCs were tested for the presence of conditional volatility and, once such features were found, GARCH general class models were used. With the application of ARIMA-GARCH models, it was possible to estimate the process average as well as the conditioned variability to that average at that given instant. Moreover, the GARCH models provided the possibility of checking whether the variability effect is durable or not.

Control charts $\bar{x}$, $\overline{MR}$ and EWMA were applied at series free of autocorrelation, through the ARIMA-GARCH models for $PC1_{PD}$ and $PC2_{PD}$. Based on the comparison of these charts, the original data showed more out-of-the-control sample points on model derived from residues and quadratic residues, thus revealing the effect of autocorrelation. Only for $PC2_{PD}$, the original values have less out-of-the-control points than on the volatility.

As for the process with volatility, the $PC1_{PD}$ components have a highest number of out-of-the-control points in relation to residues from the linear and non-linear model; and $PC2_{PD}$ components have fewer out-of-the-control points in relation to the models residuals. Therefore, it is concluded that the volatility found by ARCH models influences the process and produces changes in its stability.

Analyzing the control charts, it is possible to see that both the linear and nonlinear models were effective in the treating the serial autocorrelation, since they captured the variations in the variables related to the continuous casting process.

A constraint faced in this study is the monitoring based on ACP. However, this approach does not always provide an optimization for process separation, though this research has taken care of using constraints so that PCs were orthogonal and therefore independent. Also, this study did not aim to examine the ARL (*Average Run Length*) performance where PCA is used in conjunction with X-bar charts $\overline{MR}$ and EWMA, which would run out of the scope of the research.

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