

PLANTWIDE PERIODICAL DISTURBANCES ISOLATION AND ELIMINATION IN A PETROCHEMICAL UNIT

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Abstract - Reducing process variability is crucial to reach a more profitable operating point. Periodical disturbances, however, impose barriers to achieve this goal. Their effect can be strong since one disturbance that appears in a specific loop of a highly coupled plant can be seen in several loops. Thus, isolating their source and diagnosing their cause are essential. In this work, we describe the application of spectral independent component analysis to isolate a periodical disturbance that has a strong impact on the final variability in a polyethylene plant located in Southern Brazil. After the first analysis, the source was detected and the cause identified: valve stiction. To identify the cause (valve, bad tuning, or periodic disturbance), we used the methodology based on higher-order statistics. Once the valve problem had been overcome, the product variance was reduced by 93%.

Keywords: Fault diagnosis; Plant-wide disturbance; Oscillation; Independent Component Analysis.

INTRODUCTION

One frequent cause of poor process performance is the presence of plant-wide periodical disturbances (Thornhill and Horch, 2007) whose effect can spread through the entire plant, inhibiting the process from achieving a more profitable operating point. Nowadays, plants are more coupled and have a large number of recycles because of mass and heat integration. One oscillation that starts in a specific loop can be propagated to the entire process, increasing the product variability. Thus, it is clear that detecting and eliminating plant-wide oscillations are essential to ensure

process profitability and reduce product variability. However, the diagnostics of the loop that is the source of the disturbance and the cause of the oscillation is not straightforward.

This is the scenario seen in a petrochemical plant located in Southern Brazil. One periodical oscillation affects the product variability and, because of plant recycles, the engineers could not detect either the source or the cause. Our goal is to detect and find the source of the oscillation, eliminating it (if possible) after diagnosing the cause.

The procedure to eliminate plant wide oscillations requires three steps:

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1. Detecting the oscillation;
2. Detecting the root-cause of oscillation (i.e., the loop where the oscillation started); and
3. Diagnosing the cause of oscillation: valve stiction or poor tuning.

Initially, the disturbance should be diagnosed. In many cases, the oscillation is detected visually by engineers. In the literature, there are three groups of methods to automatically detect loop oscillations. The first is time-domain methods (e.g., based on integral of absolute error (IAE) (Hägglund, 1995) and zero crossings (Thornhill and Hägglund, 1997). The second is based on the Autocovariance Function (ACF) (Thornhill *et al.*, 2003). The third is based on spectral peak detection. A good review about plant-wide periodical disturbance detection can be found in Thornhill and Horch (2007).

The second step is to identify the root cause of the oscillation, i.e. the source of the disturbance. In the literature, there are several methods with this focus which are segmented into data-based and topology-based (Duan *et al.*, 2014). The data-based methods are based on a non-linearity test (Choudhury *et al.*, 2004; Thornhill, 2005) or spectral analysis (Jiang *et al.*, 2007; Xia and Howell, 2005; Xia *et al.*, 2007). Good reviews can be found in Thornhill and Hägglund (2007), Choudhury *et al.* (2008) and Duan *et al.* (2014). In this work, the spectral independent component method (Xia *et al.*, 2005a) will be used.

Once the source of the oscillation is isolated, the

cause should be diagnosed: valve, or poor loop tuning or external disturbances. First the hypothesis of stiction is evaluated; if the result is negative, then the cause is tuning or disturbances. In the literature, there are many methods to assess stiction (Choudhury *et al.*, 2004; Horch, 1999; Rossi and Scali, 2005; Singhal and Salsbury, 2005; Yamashita, 2006). Most of these techniques are summarized in Brásio *et al.* (2014).

The paper sums these three sets of methods to diagnose and eliminate periodic disturbances in a petrochemical plant, whose description is provided subsequently. The next section summarizes the methodologies used in this work, and the main results of the application are then discussed. Finally, the conclusions are drawn.

PLANT DESCRIPTION

The unit studied in this paper consists of four processes:

- prepolymerization;
- polymerization;
- monomer recovery;
- monomer recycle to the reaction stage.

Its process schematic is shown in Figure 1 and a list with the main loops is given in Table 1.

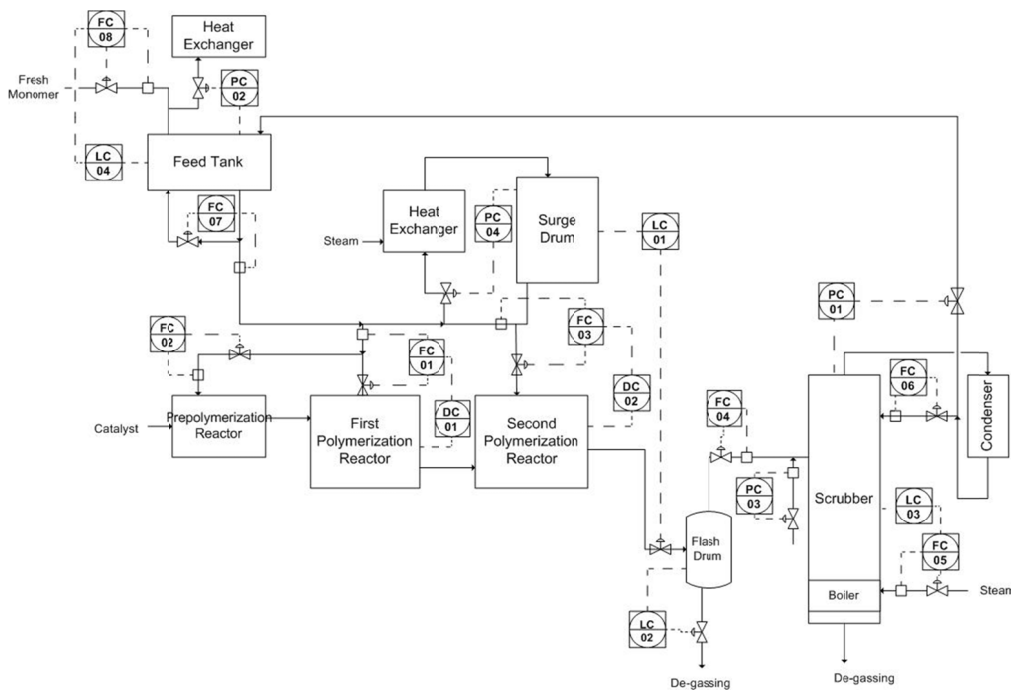


Figure 1: Petrochemical plant schematic representation.

Table 1: List of loops in the petrochemical plant.

Loop	Function
DC01	Mud Concentration in First Polymerization Reactor
DC02	Mud Concentration in Second Polymerization Reactor
FC01	Monomer Inlet Flow to First Polymerization Reactor
FC02	Monomer Inlet Flow to Prepolymerization Reactor
FC03	Monomer Inlet Flow to Second Polymerization Reactor
FC04	Top Stream of Flash Drum
FC05	Steam to Recycle Monomer Scrubber Reboiler
FC06	Reflux to Recycle Monomer Scrubber
FC07	Recirculation Flow (Minimum Flow to Pump)
FC08	Make-up of Fresh Monomer
LC01	Reactors Surge Drum Level
LC02	Flash Drum Level
LC03	Recycle Monomer Scrubber Level
LC04	Feed Tank Level
PC01	Recycle Monomer Scrubber Pressure
PC02	Feed Tank Pressure
PC03	De-gassing Stream Pressure
PC04	Reactors Surge Drum Level

Monomer and the catalytic complex, formed by catalyst and co-catalysts, are fed into the prepolymerization reactor. The mixture formed by polymer and unreacted monomer in the prepolymerization is continuously sent to polymerization reactors. The polymerization process consists of two tubular loop reactors, filled with liquid monomer, that are operated in series.

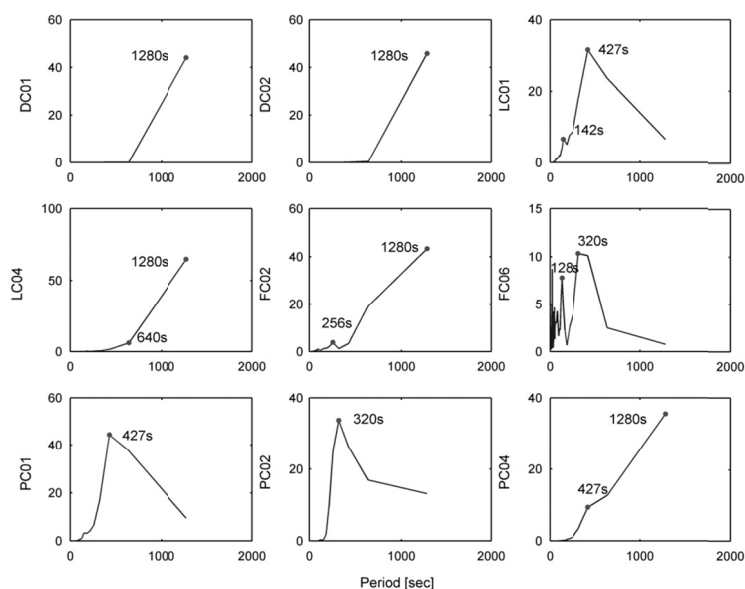
Each reactor has an independent monomer feed line with independent flow controllers, FC01 (first reactor) and FC03 (second reactor). These flow loops receive remote setpoints from concentration of slurry

(monomer + polymer) inside the reactor loop controllers, DC01 (first reactor) and DC02 (second reactor). It is important to note that low variability in slurry concentration results in a possible production increase, as it permits one to increase the concentration setpoint.

Slurry from the first polymerization reactor is continuously fed to the second reactor. In this second stage of the polymerization, the process discharge is controlled by LC01. This loop controls the level of the surge drum, which must guarantee that the polymerization reactors are filled with liquid monomer. The resulting product from the second reactor is discharged to a flash drum where the unreacted monomer is evaporated and separated from the polymer. Polymer discharged from the flash drum flows to the next stages of the production process, such as de-gassing.

Unreacted monomer, from the flash drum and from the de-gassing process, flows to a recycle monomer scrubber, where entrained polymer particles are separated from recovered monomer. The top stream of the scrubber is condensed and pumped into a monomer feed tank, which supplies the reactors. The tank level is controlled by manipulating the flow of fresh monomer, while the pressure is controlled by PC02 that vaporizes part of the fresh liquid.

The analysis in the periodogram of several variables, as shown in Figure 2, indicates that periodical disturbances can be found in the plant. Thus, it is advisable to remove some of them to achieve a smoother operation and achieve a more profitable operating point. In this work, we desire to remove the oscillations with periods 320 seconds and 427 seconds, called respectively $dist_1$ and $dist_2$.

**Figure 2: Process variable periodograms.**

METHODOLOGY

This section describes the methodologies used to automatically detect the oscillation, its root cause (source), and the cause of oscillation.

Oscillation Detection

Initially, the oscillation was automatically detected using the integral of the square error, a method proposed by Hägglund (1995).

The idea behind the method is simple: based on time trend zero-crossing, the integral of the absolute error between each zero crossing is computed (IAE_C). It is then compared with a threshold value (IAE_{LIM}). If $IAE_C > IAE_{LIM}$, then the process has an oscillatory behavior.

The oscillation detection procedure can be summarized as follows:

1. Choose an acceptable oscillation amplitude (a);
2. Compute IAE_{LIM} as $2a/\omega$. ω is $2\pi/T_i$ and T_i is the integral time of the controller.
3. Monitor IAE_C . Restart it when the control error changes its signal.
4. If IAE_C exceeds IAE_{LIM} then the oscillation has occurred.

Detecting the Root Cause (Source) of Oscillation

To detect the root cause of the oscillation, the methodology based on Spectral Independent Component Analysis (SICA) was used (Xia *et al.*, 2005). Initially, the time-domain ICA will be described and then the methodology to detect the root cause of oscillations will be explained.

Consider that the plant has m sensors, whose observations are x_m .

$$X = [x_1 \quad x_2 \quad \dots \quad x_m]^T \quad (1)$$

They are linear combinations of n independent, non-Gaussian source outputs. Each column is called an Independent Component (IC).

$$S = [s_1 \quad s_2 \quad \dots \quad s_n]^T \quad (2)$$

The matrix of observations (X) can be written as a linear function of the matrix of ICs (S).

$$X = AS \quad (3)$$

where A is called the mixing matrix (m by n). Each sensor can be decomposed into linear combinations of ICs.

$$x_i = a_{i,1}s_1 + a_{i,2}s_2 + \dots + a_{i,n}s_n, \quad i = 1 \dots m \quad (4)$$

The ICA problem involves the estimation of both A and S . The Fast ICA algorithm (Hyvärinen *et al.*, 2001) was used in this work.

In the spectral ICA model, the rows of X are single-sided power spectra $P(f)$ over a range of frequencies (f) of the same sensor. $P(f)$ can be estimated using Discrete Fourier Transform (DFT) (Oppenheim *et al.*, 1999). The main advantage of using power spectra instead of time series is that the first is blind to the time delays. Besides, SICA can isolate a single peak in each independent component, when multiple oscillations are present in the plant.

The procedure to apply the methodology based on SICA is described below:

1. Compute the power spectra for all measured variables (X).
2. Decompose X into independent components, obtaining A and S (using FastICA).
3. Find the sign of the dominant peak for each IC, denoted by SN_j , ($j=1 \dots n$);
4. Adjust the A and S matrixes using the following relation:

$$B = A \cdot \text{diag}(SN_1 \quad SN_2 \quad \dots \quad SN_n) \quad (5)$$

$$Y = \text{diag}(SN_1 \quad SN_2 \quad \dots \quad SN_n)S$$

Then

$$X = BY.$$

Here, the new term, based on matrix B , called the significance index is introduced. It provides the importance of the combined matrix elements. Values close to 1 represent a strong impact from an IC in a power spectrum signature. Smaller values of the significance index show a smaller impact of a given IC.

Then, each IC was adjusted to achieve a maximum significance index equal to 1.

1. Find the maximum absolute value for each column of B ($\Delta_j, j=1 \dots n$);
2. Scale the mixing matrix B and IC matrix Y ;

$$A = B \cdot \text{diag}(\Delta_1^{-1} \quad \Delta_2^{-1} \quad \dots \quad \Delta_n^{-1}) \quad (6)$$

$$C = \text{diag}(\Delta_1 \quad \Delta_2 \quad \dots \quad \Delta_n)Y$$

Then

$$X = AC.$$

Based on the new matrix A , the source of each independent component, or plant-wide disturbance, can be identified. The loop for a given IC whose significance index is close to 1 is probably the root cause of that oscillation.

In the work of Xia *et al.* (2005), the dominance of each independent component over the plant is analyzed, helping to discover which are the main plant disturbances. However, in our case, a visual analysis showed that the mentioned oscillation (see Fig. 2) appeared in several loops, causing a strong impact in the product variability.

Detecting the Cause of Oscillation

The last step is to diagnose the cause of the oscillation. In this work, we will apply the methodology based on higher-order statistics, proposed by Choudhury *et al.* (2004). To corroborate the results, the methodology to quantify stiction based on ellipsis interpolation will also be used (Choudhury *et al.*, 2008).

The method proposed by Choudhury *et al.* (2004) claims that, if the process is locally linear and a nonlinear behavior is present, then the valve is responsible for this behavior. If the loop has an oscillatory behavior and the valve is working properly, the problem can be poor loop performance or other external disturbance (e.g., a disturbance transferred from another loop with oscillatory behavior).

Initially the non-Gaussianity index (NGI) is computed, using the bicoherence (bic^2) concept.

$$bic^2 = \frac{|B(f_1, f_2)|^2}{E\left[|X(f_1)X(f_2)|^2\right]E\left[|X(f_1 + f_2)|^2\right]} \quad (7)$$

where $X(f)$ is the discrete Fourier transform of any time series $x(k)$ and $B(f_1, f_2)$ is called the bispectrum in the frequencies f_1 and f_2 . The bispectrum is the third order cumulant in the frequency domain. It is defined as:

$$B(f_1, f_2) = E\left[X(f_1)X(f_2)X^*(f_1 + f_2)\right] \quad (8)$$

where $*$ denotes the complex conjugate. One positive feature of bic^2 is that it is bounded between 0 and 1.

Assuming that bic^2 at each frequency is a chi-squared (χ^2) distributed variable with 2 degrees of freedom, a modified test formulated by averaging the squared bicoherence over the triangle of the principal domain with better statistical properties will be used to verify signal Gaussianity. The test can be summarized as follows:

- Null hypothesis: the signal is Gaussian,
- Alternate hypothesis: the signal is non-Gaussian.

Under the null hypothesis, the test can be based on the following equation:

$$P\left(2KL\overline{bic}^2 > c_\alpha^{\chi^2}\right) = \alpha \quad (9)$$

where $c_\alpha^{\chi^2}$ the critical calculated from the central χ^2 distribution table for a significance of α and $2L$ degrees of freedom, K is the number of data segmentation during the bicoherence computation, L is the number of bifrequencies inside the principal domain of the bispectrum, and $\overline{bic}^2 = \sum_{i=1}^L bic^2$.

If the signal is Gaussian, the process is assumed to be linear. If the signal is non-Gaussian, the process nonlinearity should be tested. To evaluate the nonlinearity, the constancy of the squared bicoherence should be evaluated. In this work, the maximum squared bicoherence can be compared with the average squared bicoherence plus two standard deviations. At 95% confidence level, if the maximum bicoherence (bic_{max}^2) is less than $(\overline{bic}^2 + 2\sigma_{bic^2})$, the bicoherence curve is assumed to be constant. The index to evaluate the nonlinearity is defined as:

$$NLI \triangleq \left| bic_{max}^2 - \left(\overline{bic}^2 + 2\sigma_{bic^2} \right) \right| \quad (10)$$

Where σ_{bic^2} is the standard deviation of the squared bicoherence and \overline{bic}^2 is the average of the squared bicoherence. If $NLI = 0$, the process is linear; otherwise the process is nonlinear. If the loop is nonlinear, then the valve “suffers from” stiction.

To corroborate the diagnostics provided by the method based on higher-order statistics, the method based on ellipsis interpolation (Choudhury *et al.*, 2006) will also be used to diagnose and quantify valve stiction. If the process variable (pv) and control output (op) plot has an ellipsis pattern, as shown in Figure 3, then the stiction is confirmed. The apparent stiction can be quantified as the length of the horizontal ellipsis axis (sb).

RESULTS

This section describes the application of the methodologies in the petrochemical plant previously described.

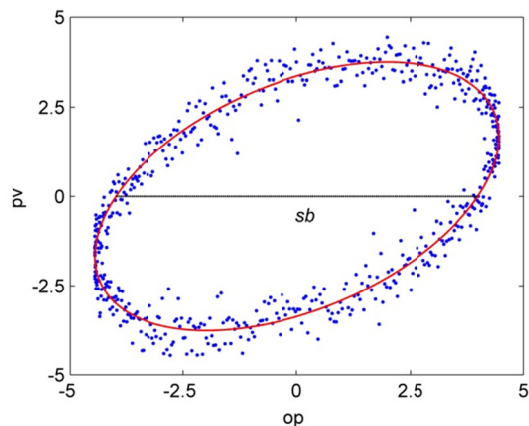


Figure 3: pv versus op plot for a sticky valve.

Oscillation Detection

The oscillation is detected by the application of the IAE method previously described, considering the following IAE_{LIM} :

- 191 for DC01 and DC02 ($a = 1$, $T_i = 600$ seconds);
- 20 for PC01 and PC02 ($a = 0.5$, $T_i = 120$ seconds);

The IAE_C values have been computed for the whole dataset and the two largest values (1st IAE_C and 2nd IAE_C) are shown in Table 2 for these four controllers, as well as their limits (IAE_{LIM}).

Table 2: Largest IAE_C values (1st IAE_C and 2nd IAE_C) for DC01, DC02, PC01, and PC02.

Loop	1 st IAE_C	2 nd IAE_C	IAE_{LIM}
DC01	1900	1400	191
DC02	1730	1700	191
PC01	117	103	20
PC02	215	147	20

Based on Table 2, we can see that all values exceed the limiting IAE_{LIM} value and conclude that the process is strongly affected by periodical load disturbances.

Diagnosing the Oscillation Source

Initially, the data were collected and all measured variables had the same sampling period (5 seconds). Moreover, we ensured that the data was collected without compression. Then, each power spectrum was computed using the *pwelch* function in Matlab® (version R11, signal processing toolbox version 4.2). We collected 1024 point for each variable and the

window size in the Fourier Transform used in this work was 256.

The periodical disturbances that we want to eliminate have periods equal to 320 seconds and 427 seconds. Using the FastICA algorithm (Hyvärinen *et al.*, 2001), the matrices A and S were obtained. Figure 4 shows the independent power spectra. We limited the number of ICs in 5.

Based on Figure 4, the independent disturbance that should be eliminated is IC1. Based on ICA decomposition, the significance matrix was then computed (see Table 3). The sources of IC1 were identified as PC01 and PC02, as assessed by the significance index. The impact of each IC over each control loop is shown in Figure 5.

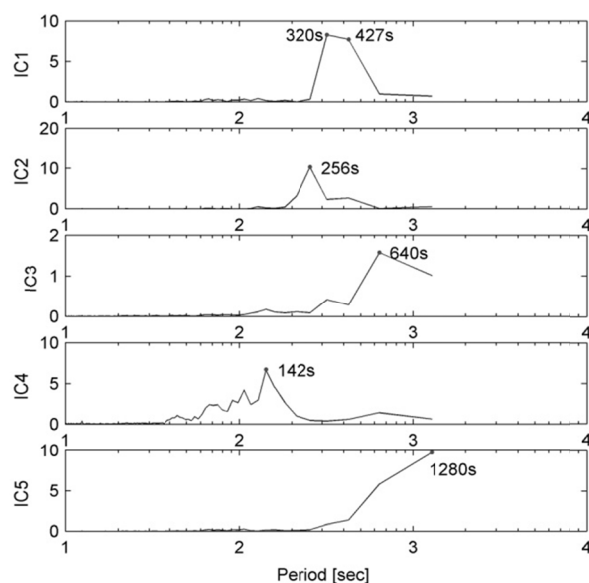


Figure 4: Spectral independent component analysis – each plot shows one independent component.

Table 3: Significance matrix for the ICA analysis – the sources of IC1 are highlighted.

	IC1	IC2	IC3	IC4	IC5
FC01	0.07	0.01	0.07	1.00	0.19
FC02	0.11	0.05	0.55	0.05	0.82
FC03	0.02	0.01	0.00	0.02	0.01
FC06	0.08	0.01	0.01	0.09	0.00
FC08	0.00	0.03	0.21	0.32	0.22
DC01	0.02	0.03	1.00	0.12	0.51
DC02	0.01	0.02	0.98	0.12	0.52
LC01	0.73	0.21	0.00	0.57	0.13
LC02	0.67	1.00	0.00	0.21	0.04
LC03	0.02	0.02	0.89	0.17	0.72
LC04	0.02	0.00	0.77	0.19	0.91
PC01	1.00	0.29	0.01	0.25	0.18
PC02	0.95	0.47	0.10	0.07	0.15
PC04	0.54	0.07	0.10	0.01	1.00

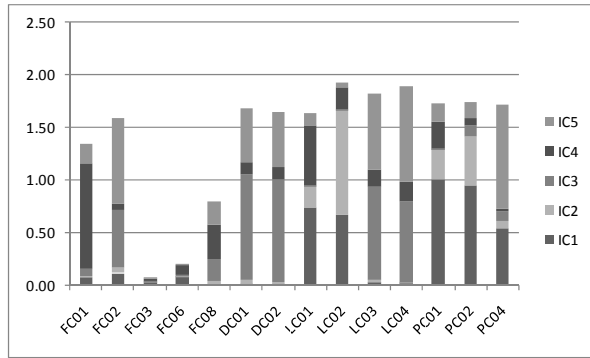


Figure 5: Histogram with the impact of each independent component (IC) (significance) over each variable.

Figure 5 shows that the impact of IC1 is not restricted to PC01 and PC02. It spreads its effect in all observed loops.

Determining the Oscillation Cause

Subsequent to determining the source of oscillation, its cause should be diagnosed. We suspect that both valves suffer from stiction.

First, the PC02 loop will be analyzed. The methodology based on higher-order statistics shows that this loop is non-Gaussian and nonlinear, confirming the hypothesis of a sticky valve. To corroborate this result and quantify the stiction (sb), the pv versus op plot was drawn, as shown in Figure 6.

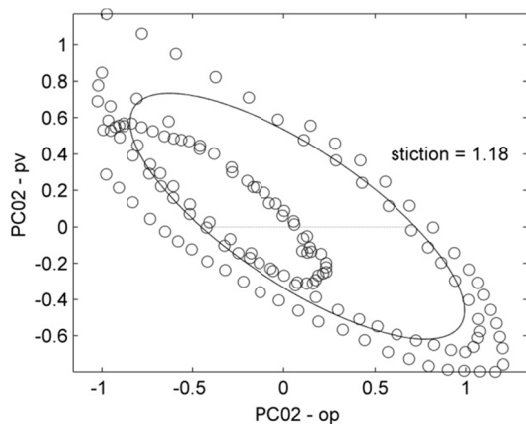


Figure 6: pv versus op for PC02.

Figure 6 clearly indicates that the valve has visible stiction. The sb is 1.18% of the valve span. In this case, the valve should be replaced.

In the case of PC01, the same analysis is made. Again, the loop is also non-Gaussian and nonlinear, which indicates another sticky valve. Figure 7 shows the ellipsis interpolation for the pv versus op curve.

Based on Figure 7, the hypothesis of valve stiction is again confirmed. The sb for PC01 is equal to 0.90.

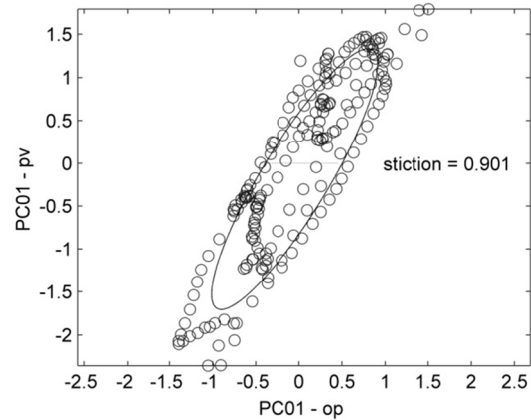


Figure 7: pv versus op for PC01.

Applying the Solution in a Real Plant

Finally, after we diagnosed that the source of IC1 was PC01 and PC02, and the cause in both cases was valve stiction, we should then corroborate (or not) this hypothesis through a test in a real plant.

The maintenance group does not allow replacing any valve, because there is no bypass available for them. However, we open each loop for a period to verify if the oscillation disappears.

In the first test (Test₁), the loop PC01 was open. Then the data was collected and decomposed into spectral independent components. Figure 8 shows the histogram with the significance indices for the plant when PC01 was open.

The same procedure was made for PC02 (Test₂). We open this loop for a period to verify if dist₂ disappears. Figure 9 shows the histogram with the significance indices for the plant when PC02 was opened.

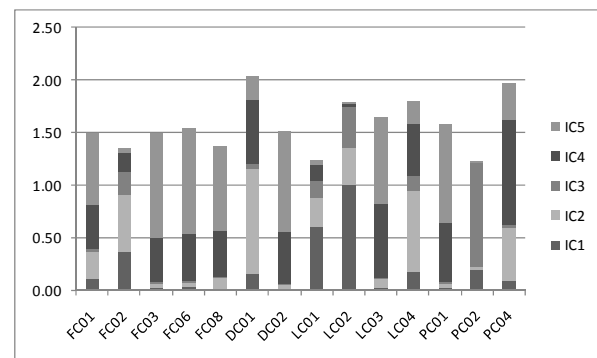


Figure 8: Histogram with the impact of each independent component (IC) (significance) on each variable with PC01 open (Test₁).

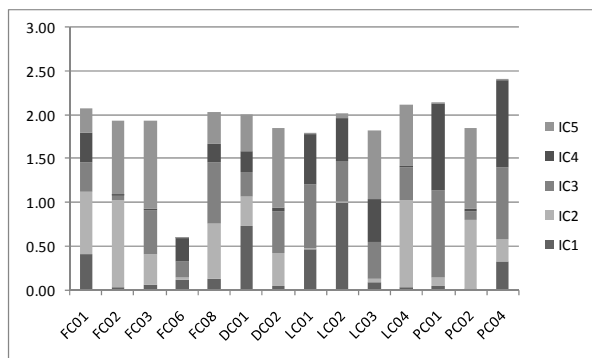


Figure 9: Histogram with the impact of each independent component (IC) (significance) on each variable with PC02 open (Test₂).

Based on Figure 8 and Figure 9, we can verify that, in each case, the disturbance vanished. The positive impact on loop variability is corroborated by the comparison between the ratio of the original (when all loops were closed) and the new variance when PC01 and PC02 were opened, as shown in Table 4.

Table 4 summarizes the strong impact caused by IC1. Its elimination can reduce the product and the whole plant variability, achieving a more profitable operating point.

Table 4: Ratio between the original and the new variance, when PC01 and PC02 were opened (see that the variance of same loop was normalized using the same parameter, for the three cases).

Loop	Normalized original variance	Relative variance - PC01 open	Relative variance - PC02 open
DC01	1	-78%	-48%
DC02	1	-88%	-93%
FC01	1	-98%	-94%
FC02	1	-83%	-84%
FC03	1	-30%	-91%
FC06	1	1724%	2%
FC08	1	86%	-78%
LC01	1	-26%	-15%
LC02	1	-1%	3%
LC03	1	1400%	2035%
PC01	1	171%	-67%
PC02	1	-51%	6867%
PC04	1	98%	-29%

CONCLUSIONS

In plants with a high number of recycles, periodical disturbances can strongly affect loop variability, because one oscillating loop can have a widespread effect in the whole plant. Thus, isolating its source and diagnosing its cause are essential to ensure a

highly efficient operation. In this work, we illustrate this scenario in a petrochemical plant located in Southern Brazil, where periodical disturbances have a strong influence on product variability.

The procedure followed three steps. Initially, we detected loop oscillation using the methodology based on IAE (Hägglund, 1995). Then, each disturbance was isolated using Spectral Independent Component Analysis (Xia *et al.*, 2005). We identified the disturbance whose period we want to isolate and its sources, which were PC01 and PC02. Finally, we diagnosed the cause of the fault in both loops as valve stiction using the methodology based on higher-order statistics (Choudhury *et al.*, 2004).

To verify the theoretical predictions in the industrial plant, each loop was opened for a period, because the valves could not be replaced. The impact was visible: the reduction in the variability of almost all loops was verified and the reduction in product variability was up to 93%.

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