DINCON 2017
CONFERÊNCIA BRASILEIRA DE DINÂMICA, CONTROLE E APLICAÇÕES
30 de outubro a 01 de novembro de 2017 – São José do Rio Preto/SP

# Oscillation Detection on Offshore Oil Platforms Control Loops

Celso José Munaro[1]

Departamento de Engenharia Elétrica, Centro de Tecnológico, UFES, Vitória, ES.

Vinicius Belmuds Vasconcelos[2]

Departamento de Engenharia Elétrica, Centro de Tecnológico, UFES, Vitória, ES.

Débora de Souza Martins[3]

Departamento de Engenharia Elétrica, Centro de Tecnológico, UFES, Vitória, ES.

Paulo Emílio Altoe Targa[4]

Petrobrás, Avenida Nossa Senhora da Penha, 1688, Barro Vermelho, Vitória, ES.

Abstract. The presence of oscillations in control loops results in increased product variability and hence reduction of profitability. Oscillation detection on offshore oil platforms control loops is a challenge due to the presence of high amplitude non-oscillatory disturbances, causing distortions on spectra calculated by available methods in existent literature. In this article it is shown that the use of prefilters tends to eclipse low frequency oscillatory signals. A procedure for data segmentation is proposed to select data to be used for detection of oscillations. Considering that in such plants, many different and similar oscillations may result, an important step is also proposed to cluster similar frequencies and to keep only those that cause higher impact in the variance of the original signals. The methodology is applied daily during four days to 36 signals of an offshore oil platform, resulting in a reliable and easy to use report of oscillations that persist in subsequent analyzes, categorized by their impact.

**Keywords**. Oscillation, fault detection, performance monitoring, spectral density, disturbance signals.

## 1 Introduction

Detection of oscillations is a well-known problem in industrial processes. The presence of oscillations may reduce the product quality, increase the consumption of energy, cause wear on actuators and reduce safety among others. Many approaches are available in the literature to detect oscillations. Most of them are based on spectral analysis. The use of autocorrelation function followed by calculation of power spectral density (PSD) was proposed in [6] and improved in [7]. The spectral envelope has the advantage of using a single curve that describes the spectral content of all signals [4]. The independent component analysis is a statistical technique used in the extraction of independent sources from observed data consisting of the

[1] munaro@ele.ufes.br
[2] belmuds.eng@gmail.com
[3] deborasm539@gmail.com
[4] Paulo.targa@petrobras.com.br

mixture of unknown sources [9]. Recently the discrete cosine transform has received attention to handle problems such as slowly varying trends and signals corrupted by white and colored noises [8]. In the empirical mode decomposition method, the signal is decomposed in a finite set of intrinsic mode functions that can be analysed separately [3].

The major drawback of spectral based methods is the need to apply pre-filters to eliminate low frequencies related to disturbances and slow varying signals. The failure in this step results in difficulty to detect the band of frequencies related to oscillations, which are eclipsed by low frequency components. The inclusion of a low pass-filter may prevent detection of low frequency oscillation. In addition, in some cases, the disturbance is replaced by an oscillatory signal induced by the filter's response to the disturbance when its boundaries are placed on the frequency axis such that they split a broad spectral feature across two ranges [7].

In this paper, an algorithm for data segmentation is proposed to avoid the use of a fillter. The approach also allows on line monitoring, since data segments are automatically collected from raw data for analysis. In industrial plants subject to non-oscillatory disturbances of high amplitude, the repeatability of results is also threatened. A method to cluster only significant oscillations is also presented and the coefficient of variation (CV) weighted by the oscillation energy is used for this purpose. The application of the proposed methodology to data from an offshore platform for oil and gas production highlights its advantages.

# 2 Proposed Methodology

It this section, methods for raw data segmentation and clustering of detected oscillations are presented.

## 2.1 Segmentation of Raw Data

To motivate the proposed method, let's consider the raw data $x$ with 2000 samples collected each 10s. At time instant 10660s a disturbance affects data which is clearly oscillatory. Applying the pre-filter suggested in [5] (band pass filter [0.02 0.99]Hz/Hz), one gets the filtered signal $x_f$. One can see that the disturbance was replaced by an oscillatory signal due to the poles close to unit circle, resulting from the lower frequency bound of the filter. This signals in the time domain can be seen in Figure 1 (a). The good performance of the filter to eliminate the low frequency around 10 thousand seconds can be seen on Figure 1 (b) (top and middle): the low frequency band was completely removed. However, the oscillation induced by the filter has an important contribution, and would certainly be indicated as an oscillation, which is a misleading result pointing a main oscillation of 930,9 seconds. The bottom PSD in Figure 1 (b) of the segment $x_s$ from instant 0 to 10660s (before the disturbance) shows correctly the frequency band associated with the oscillatory signal (period around 500s). The analysis of Figure 1 (a) shows that signal values related to the oscillation are those with amplitude between 30 and 40. An histogram of this signal $x$ is shown in Figure 1 (c). Clustering data around the peak with the highest number of occurrences results in the data related to oscillations. Several steps are required to assure that most of data is selected and also that data is not corrupted. The algorithm for data segmentation is now described.

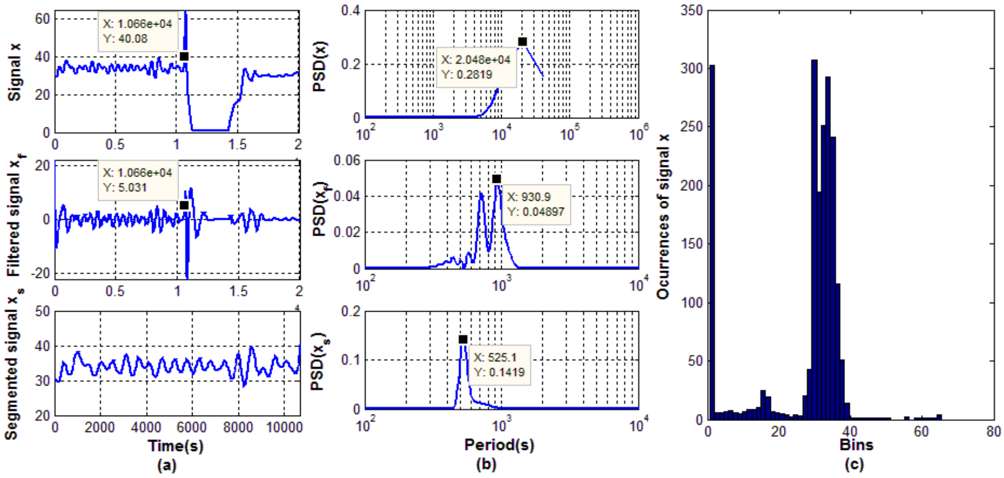


Figure 1. (a) Raw oscillatory data, filtered data and segmented data. (b) Power spectral density of original signal, filtered signal and a selected segment. (c) Histogram of raw signal $x$.

*Data segmentation algorithm – DSA*

Step 1: Compute the histogram of the raw data $x$.

Step 2: Select the bin that contains the highest number of samples.

Step 3: Select the bins in the neighborhood with a number of occurrences higher than a given threshold, given by $t_b$ as a percentage of the count of values in the bin selected on step 2.

Step 4: Define $x_{min}$ and $x_{max}$ associated to the selected bins and select the set $\{x_s = x | x_{min} \leq x \leq x_{max}\}$.

Step 5: Calculate $\mu_{x_s}$ and $\sigma_{x_s}$ , the mean and standard deviation of $x_s$, respectively.

Step 6: Recalculate $x_{min} = \mu_{x_s} - p\sigma_{x_s}$ and $x_{max} = \mu_{x_s} + p\sigma_{x_s}$ , where $p$ plays a role similar to confidence interval.

Step 7: Recalculate $\{x_s = x | x_{min} \leq x \leq x_{max}\}$

Step 8: Find discontinuities in samples of $x_s$ and keep only the largest segment in $x_s$ without discontinuities (missing samples not included in step 7).

Steps 1 to 4 allow selection of data with similar mean value, this happens if data is oscillatory. Steps 5 to 7 are very important to include samples with similar mean but larger variance, increasing the number of samples retained in $x_s$. The selected data segment must contain a sequence of samples with only one time delay between consecutive samples. Step 8 assures that the largest data segment with this feature is selected.

This algorithm was applied to 8000 samples of 36 signals from an offshore oil and gas platform sampled each 10s. The result is shown in Figure 2, where the blue samples are the original signals and the red dots are the retained samples. The average of selected data was 71.5%. No data was selected on signal 4, since it is constant. No data segments with disturbances (sudden changes) in the signals were included in the selection. When trends span all range of the signals (e.g., signals 15 and 16), the whole segment is retained. These signals will be detrended before application of algorithms for oscillation detection. When there are two data segments with samples with similar features (e.g., signal 5), only the largest segment is retained. Since the non-oscillatory disturbances are removed, the application of filters for pre-treatment is no longer required.

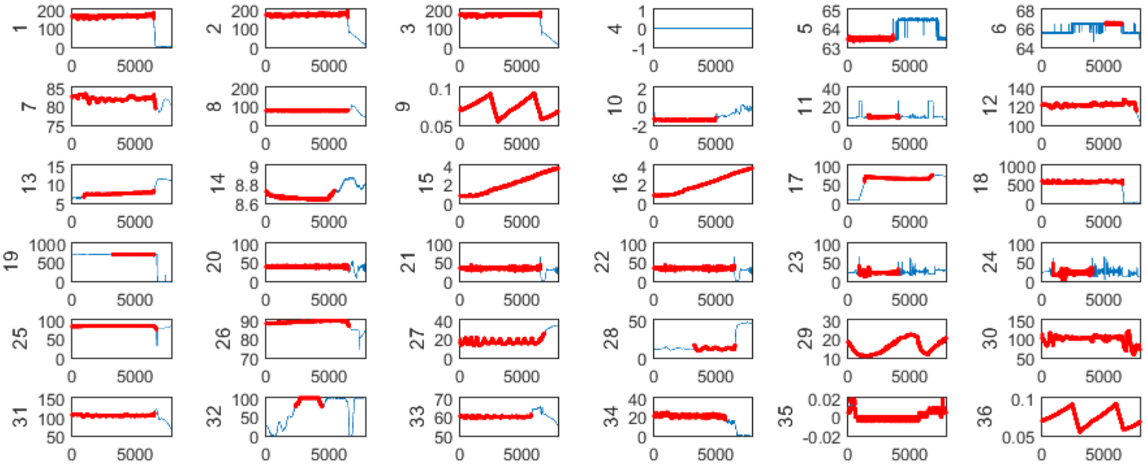


Figure 2. Selected data (red) on the 36 signals

## 2.2 Clustering of Detected Oscillations

The application of algorithms for detecting oscillations in industrial plants may result in many detections. When an oscillation propagates plant-wide, the detected oscillation may have periods that vary from one signal to another. The presence of harmonic components may multiply the number of detected frequencies. Finally, since normalization is performed on signals and PSD plots, oscillations are detected no matter the amplitude of the original signal. These spurious results need to be eliminated in order to present only the oscillatory disturbances that increase the variance in the corresponding control loops. To illustrate this situation, the algorithm described in [7] is applied to the 36 signals shown in Figure 2, resulting in 14 different detected oscillations, shown in the Figure 3. Grouping the close frequencies is required since they are probably associated to the same problem. Many clustering algorithms are available in the literature (see [1] for a good review). Most of the techniques require the user's specification of the number of clusters, which is hard to select in our case. Again, histograms will be used here to cluster similar frequencies and to investigate oscillations according to their impact in the process. This clustering phase plays a very important role to check the repeatability of the results in subsequent analysis.

## 2.3 Selection of Oscillation Using the Coefficient of Variation

To consider only oscillations that increase significantly the variability of the signals, the coefficient of variation (CV) is calculated to each signal after data segmentation algorithm . First the CV of the selected data segment is calculated using $\frac{100\sigma}{\mu}$, where $\sigma$ and $\mu$ are the standard deviation and average of the detrended data segment obtained in Step 8 of DSA. This quantity is then multiplied by the energy of the oscillation found in the respectively signal, resulting in CVE, the CV weighted by the energy. Similarly to CVE, the energy ranges from 0 to 100% and is calculated integrating the normalized PSD in the band of frequencies associated with the corresponding period (see [2] for details). The result for oscillations of signals of Figure *2* is shown in Figure 3 (a).

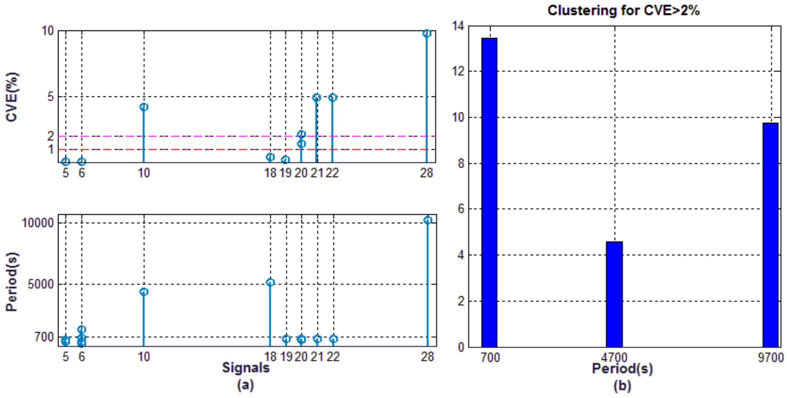


Figure 3. (a) CVE, period of oscillation detected in the 36 signals. (b) clustering results from $CVE > 2\%$

In the bottom plot the oscillation periods detected in the oscillatory signals are shown. In the top plot the CVE corresponding to each oscillation is shown. More than one circle in the stem represents the existence of more than a frequency of oscillation in the signal, each of them with the associated CVE. One can see that only six of the detected oscillations have CVE>1% (signals 10, 20, 21, 22 and 28). Since the oscillations are clustered before this selection phase, the CVE is computed for all oscillations in the group. The result for a threshold of CVE> 2% is show in Figure 3 (b). Three oscillations should be investigated: period of 700s with CVE=13.7% in the signals 20, 21 and 22; 4.700s with CVE=4.8% in signal 10 and 9.700s with CVE=9.7% in signal 28. Thus, 14 outputs were reduced to only 3 with this analysis.

# 3 Online Applications of the Algorithms

In order to be accepted in an industrial environment, the algorithms to detect oscillations should have at least the following requirements: (1) to run in unsupervised manner; (2) to yield the same result for tests with different data but with the same oscillatory behavior and (3) to produce straightforward results requiring no expertise to use them. We now show that the proposed methodology fulfills these requirements, with its applied to raw data collected during 4 days. The considerations about the application are:

- Data is provide by a process information management system (PIMS), with sample time of 10s and linear interpolation between samples.
- Each analysis is performed using 8640 daily samples.
- The DSA presented is performed before oscillation detection
- The algorithm to detect oscillation (from [7]) is applied to data of each day.

The algorithms were run daily and the result of the last four days is presented, for comparison purposes. The following parameters were used: CVE minimum of 5%, 10 bins to the cluster of frequencies, $t_b = 2{,}5\%$ (step 3 of DSA) and $p = 5$ (step 6 of DSA). The percentage of selected data using DSA is always shown, since the amount of samples retained depends on the presence of non-oscillatory disturbances. It this application, more than 65% of data was retained in each of the four days. A low retention may cause distinct results so may be useful to set a minimum data retention threshold. Also, the shorter the data segment the lower the period of the oscillation that can be detected, since at least four periods of oscillation should be detected to assure its regularity [7]. The oscillations are detected using the algorithm described in [7]. A total of 75 different oscillations were detected in the 36 signals during the four days. We now extract the important information of this large amount of outputs. The CVE of the clustered oscillations are added up, to represent the CVE of the group shown in Figure 4 (a). Oscillations with CVE greater than 5% with average period of 600s were detected during the four days. Other oscillations, with period 10.000s, around 3.000 and 4.000s are also present, but they change from one day to the other. The results show clearly that oscillations are present and should be investigated, since some of them appear every day.

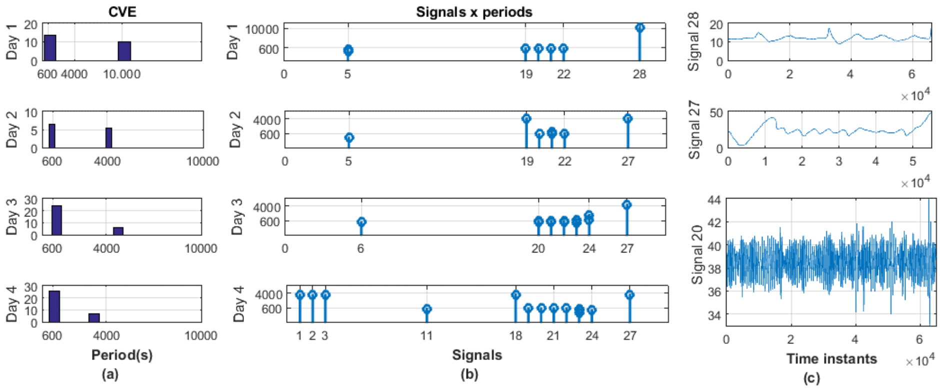


Figure 4. CVE for clustered oscillations in the 4 days, oscillations detected in the 36 signals and three selected signals to illustrate the results

So far, the requirements (1) and (2) where satisfied. Next step is to find the signals more affected by the oscillations. According to Figure 4 (b) the oscillation with period around 600s affects signals 20, 21, 22 at least in three of the four days. An oscillation with period around 4.000s affects signal 27 on days 2, 3, 4. The oscillation with period of 10.000s affects signal 28 on first day. Signals 20, 27 and 28 are shown in Figure 4 (c). Although the variance in signal 20 is smaller than variance in signals 27 and 28, the oscillation present in signal 20 is also present in 6 and 7 more signals on days 3 and 4 respectively. Thus, the sum of the CVE of these signals result in CVE of almost 30% as shown. The oscillation detected on signal 27 is present in 4 more signals on day 4 and the sum of the CVE of these 5 signals result in CVE of approximately 7%. The oscillation present on signal 28 is detected only on day 1 and is not detected in other signals. However, the impact of the (distorted) oscillation on this signal is worthy of attention.

To sum up, a persistent oscillation of period around 600s (10min) should be investigated, and the search should start on signals 20, 21, 22 where the oscillation was detected in the analysis of the four days. This is the expected straightforward result (requirement (3)) that can be easily utilized by the operating staff.

# 4 Conclusions

An approach to detect oscillations in industrial plants subject to strong non oscillatory disturbances was proposed. An algorithm for data segmentation allows an unsupervised selection of raw data, very important for any algorithm for oscillation detection. An algorithm from literature is used to detect the oscillations, which are clustered and categorized by their impact according to the proposed methodology. The signals from an oil and gas platform are suitable to test the methods, since disturbances are very common in such plants. The results from this application show that a large amount of detected frequencies can be summarized to only three frequencies that should be investigated, prioritizing the oscillation that appears in the daily analysis. The proposed methods can be executed in an unsupervised manner, showing first the presence or not of oscillations that cause a significant impact in the plant, and then, indicating the signals affected by these oscillations.

## Acknowledgements

The authors thank Petroleo Brasileiro S.A. for the financial support and for providing the data and information necessary for the development of this work and for CENPES/PETROBRAS for the technical support.

## References

[1] C. Aldrich, and L. Auret, Unsupervised process monitoring and fault diagnosis with machine learning methods. Springer, (2013).

[2] C.F. Depizzol and C.J. Munaro, On frequency detection and root cause analysis of plant-wide oscillations via acf method. In 2011 9th IEEE International Conference on Control and Automation (ICCA), (2011), 1279-1286. IEEE.

[3] N.E. Huang, Z. Shen, S.R. Long, M.C.Wu, H.H. Shih, Q. Zheng, N.C. Yen, C.C. Tung, and H.H. Liu, The empirical mode decomposition and the hilbert spectrum for nonlinear and non-stationary time series analysis. In Proceedings of the Royal Society of London A: Mathematical, Physical and Engineering Sciences, volume 454, 903-995, (1998).

[4] H. Jiang, M.S. Choudhury, and S.L. Shah, Detection and diagnosis of plant-wide oscillations from industrial data using the spectral envelope method. Journal of Process Control, 17(2), 143-155, (2007).

[5] S. Karra, and M.N. Karim, Comprehensive methodology for detection and diagnosis of oscillatory control loops. Control Engineering Practice, 17(8), 939-956, (2009).

[6] N.F. Thornhill and T. Hagglund, Detection and diagnosis of oscillation in control loops. Control Engineering Practice, 5(10), 1343-1354, (1997).

[7] N.F. Thornhill, B. Huang and H. Zhang, Detection of multiple oscillations in control loops. Journal of Process Control, 13(1), 91-100, (2003).

[8] J. Wang, B. Huang and S. Lu, Improved dctbased method for online detection of oscillations in univariate time series. Control Engineering Practice, 21(5), 622-630, (2013).

[9] C. Xia and J. Howell, Isolating multiple sources of plant-wide oscillations via independent component analysis. Control Engineering Practice, 13(8), 1027-1035, (2005).