DETECTION AND DIAGNOSIS OF PLANT-WIDE OSCILLATIONS USING THE SPECTRAL ENVELOPE METHOD

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Abstract: Plant-wide oscillations are common in many processes. Their effects propagate to many units and may impact the overall process performance. It is important to detect and diagnose the oscillations early in order to rectify the situation. This paper proposes a new procedure to detect and diagnose plant-wide oscillations. A technique called spectral envelope is used to detect the oscillations. Two kinds of plots - scaling and power plots - are proposed to identify the variables exhibiting common oscillation(s). These plots are also useful in isolating the key variables as the candidates of the root cause. An industrial case study is presented to demonstrate the applicability of the proposed procedure.

Keywords: Chemical industry, Oscillation, Fault Diagnosis, Power Spectrum, Control loop, Process Monitoring

1. INTRODUCTION

Detection and diagnosis of plant-wide disturbances is an important issue in many process industries (Qin, 1998). Oscillations are a common type of plant-wide disturbance whose effects propagate to many units and thus may impact the overall process performance. Increasing emphasis on plant safety and profitability strongly motivates the search for techniques to detect and diagnose plant-wide oscillations. Thornhill and Hägglund (1997) used the zero-crossings of the control error signal to calculate integral absolute error (IAE) in order to detect oscillation in a control loop. This method has poor performance for noisy error signals. Miao and Seborg (1999) suggested a method based on the auto-correlation function to detect excessively oscillatory feedback loop. The auto-covariance function (ACF) of a signal was utilized in Thornhill *et al.* (2003*a*) to detect oscillation(s) present in a signal. This method needs a minimum of five cycles in the auto-covariance function to detect oscillation, which is often hard to obtain, particularly in the case of a long oscillation (e.g., an oscillation with a period of 400 samples). Although the data set can be downsampled in such cases, downsampling may introduce aliasing in the data. Thornhill *et al.* (2002) proposed to perform spectral principal component analysis (SPCA) to detect oscillations and categorize the variables having similar oscillations. This method does not provide any diagnosis of the root cause of the oscillation which is generally the main objective of the exercise.

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In this paper, a new procedure based on the spectral envelope method for detection and diagnosis of common oscillation(s) is proposed. The spectral envelope method needs neither a minimum number of cycles to be present in the signal nor filtering of the data to detect multiple oscillations. In terms of grouping the variables with common oscillation(s), the proposed procedure is more sensitive to oscillations and has a better resolution in identifying the variables oscillating at the same frequencies than the commonly used SPCA method. Furthermore, the proposed procedure can also deliver useful information about the root cause of common oscillation(s).

2. OSCILLATION DETECTION

In this section, the concept of spectral envelope is introduced. A simulation example is presented to demonstrate its ability to detect multiple oscillations. The performance comparison with SPCA method is also included.

2.1 Definition of the Spectral Envelope

The concept of spectral envelope was first proposed by Stoffer *et al.* (1993) to explore the periodic nature of categorical time series. In 1997, McDougall *et al.* (1997) extended the concept of spectral envelope to real-valued series. Here we provide an easy interpretation of the concept of spectral envelope.

Let $X(t) = [x_1(t), x_2(t), \cdots, x_m(t)]^T, t = 0, \pm 1, ...$, be a vector-valued time series on $\Re^m$. $x_i(t), 1 \leq i \leq m$, is a univariate time series which can be a sequence of observations of a process variable. Denote the covariance matrix of $X(t)$ as V_X and the power spectral density matrix of $X(t)$ as $P_X(\omega)$. Here, ω represents frequency and is measured in cycles per unit time, for $-1/2 < \omega \leq 1/2$.

Let $g(t, \beta) = \beta^* X(t)$ be a scaled series from $\Re^m$ to $\Re$, where β is a column vector which may be real or complex. The * means complex conjugate. $g(t, \beta)$ is actually a linear combination of the rows of $X(t)$. Then the variance $V_g(\beta)$ of $g(t, \beta)$ can be expressed as $V_g(\beta) = \beta^* V_X \beta$, and the power spectral density $P_g(\omega, \beta)$ of $g(t, \beta)$ can be expressed as $P_g(\omega, \beta) = \beta^* P_X(\omega)\beta$.

The spectral envelope of $X(t)$ is defined to be:

$$\lambda(\omega) \triangleq \sup_{\beta \neq 0}\{\frac{P_g(\omega, \beta)}{V_g(\beta)}\} = \sup_{\beta \neq 0}\{\frac{\beta^* P_X(\omega)\beta}{\beta^* V_X \beta}\} \quad (1)$$

where $-\frac{1}{2} < \omega \leq \frac{1}{2}$ and the relationship between $P_g(\omega, \beta)$ and $V_g(\beta)$ is $V_g(\beta) = \int_{-\frac{1}{2}}^{\frac{1}{2}} P_g(\omega, \beta) d\omega$.

The quantity $\lambda(\omega)$ represents the largest proportion of the power (or variance) that can be obtained at the frequency ω for any scaled series. The scaling vector that results in the value $\lambda(\omega)$ is called the optimal scaling vector at frequency ω, which is denoted as $\beta(\omega)$. Accordingly, the elements of the optimal scaling vector are called the optimal scalings. The optimal scaling vector $\beta(\omega)$ is not the same for all ω.

We prefer to limit β to the constraint, $\beta^* V_X \beta = 1$. Therefore the scaled series $g(t, \beta)$ is unit variance. This will make the calculated spectral envelope more interpretable and make the magnitude of the elements of $\beta(\omega)$ more comparable. Accordingly, the quantity $\lambda(\omega)$ represents the largest power(variance) that can be obtained at the frequency ω for any scaled series with unit variance.

With the optimal scaling vector $\beta(\omega)$, equation (1) can be rewritten as:

$$\lambda(\omega) V_X \beta(\omega) = P_X(\omega)\beta(\omega) \quad (2)$$

It follows that $\lambda(\omega)$ is the largest eigenvalue associated with the determinant equation:

$$|P_X(\omega) - \lambda(\omega) V_X| = 0 \quad (3)$$

$\beta(\omega)$ is the corresponding eigenvector satisfying equation (2).

2.2 Another Definition of the Spectral Envelope

Denote $V = diag(V_X)$, which only has the diagonal elements of V_X. We can use V instead of V_X in equation (1) and have a new expression for $\lambda(\omega)$:

$$\lambda(\omega) = \sup_{\beta \neq 0}\{\frac{\beta^* P_X(\omega)\beta}{\beta^* V \beta}\} \quad (4)$$

The resulting $\lambda(\omega)$ and $\beta(\omega)$ is different from those in the equation (1). Only under the condition that $\{x_1(t), x_2(t), ..., x_m(t)\}$ are mutually independent, V is equal to V_X and equation (4) is the same as equation (1).

We also prefer to limit β to the constraint such that $\beta^* V \beta = 1$, but this will not guarantee that the scaled series $g(t, \beta)$ is unit variance, except under the condition mentioned above.

2.3 Simulation Example

The following simulation example demonstrates the superiority of the performance of the spectral envelope method over the power spectrum and the SPCA method in detecting oscillation(s) in signals highly corrupted with noise.

2.3.1. Time Series Generation The example consists of 12 time series generated with various sinusoid oscillations. In these time series, $\varepsilon(t)$ is a white noise sequence with unit variance and $t = 1, ..., 512$.

The first four time series are corrupted by colored noise and have base oscillation at frequency $\omega_1 = 0.1Hz$:

$$x_1(t) = 0.8cos(2\pi\omega_1 t) + 2\varepsilon(t) + \varepsilon(t-1)$$
$$x_2(t) = 0.6cos[2\pi\omega_1(t-5)] + 2\varepsilon(t) + \varepsilon(t-1)$$
$$x_3(t) = 0.4cos[2\pi\omega_1(t-15)] + 2\varepsilon(t) + \varepsilon(t-1)$$
$$x_4(t) = 0.2cos[2\pi\omega_1(t-2)] + 2\varepsilon(t) + \varepsilon(t-1)$$

The next four time series are corrupted by colored noise and have base oscillation at frequency $\omega_2 = 0.3Hz$:

$$x_5(t) = 0.9cos(2\pi\omega_2 t) + 2\varepsilon(t) - \varepsilon(t-1)$$
$$x_6(t) = 0.7cos[2\pi\omega_2(t-7)] + 2\varepsilon(t) - \varepsilon(t-1)$$
$$x_7(t) = 0.5cos[2\pi\omega_2(t-10)] + 2\varepsilon(t) - \varepsilon(t-1)$$
$$x_8(t) = 0.3cos[2\pi\omega_2(t-20)] + 2\varepsilon(t) - \varepsilon(t-1)$$

The next two time series have oscillations at both frequencies $\omega_1 = 0.1Hz$ and $\omega_2 = 0.3Hz$:

$$x_9(t) = 0.4cos[2\pi\omega_1(t-6)] + 0.5cos[2\pi\omega_2(t-8)] + 2\varepsilon(t) + \varepsilon(t-1)$$
$$x_{10}(t) = 0.8cos[2\pi\omega_1(t-16)] + 0.6cos[2\pi\omega_2(t-4)] + 2\varepsilon(t) - \varepsilon(t-1)$$

The last two time series are simple colored noise sequences in a form of moving average:

$$x_{11}(t) = \varepsilon(t) + 0.5\varepsilon(t-1)$$
$$x_{12}(t) = \varepsilon(t) - 0.5\varepsilon(t-1)$$

Before doing further analysis, all the time series are normalized to be zero-mean and unit variance. Figure 1 shows the time trends and power spectra of the 12 time series. As shown in Figure 1, the signals are highly corrupted with noise. The power spectra of the time series do not highlight any oscillations at $0.1Hz$ or $0.3Hz$.

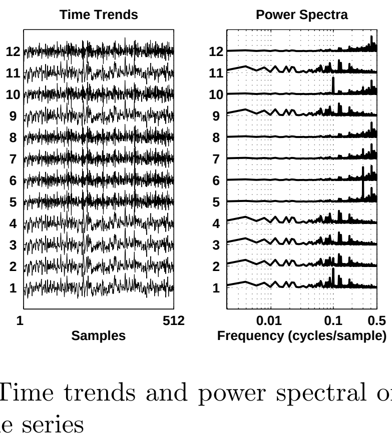

Fig. 1. Time trends and power spectral of the 12 time series

2.3.2. SPCA Analysis Figure 2 shows the first two principle components (PCs) plot. These two PCs explain over 95% of the variability of the spectra. However, these two PCs do not clearly indicate any oscillation at $0.1Hz$ or $0.3Hz$. Further clustering based on these two PCs could not give any useful information about the two oscillations as well. Therefore, SPCA fails to detect the oscillations at frequencies $0.1Hz$ and $0.3Hz$.

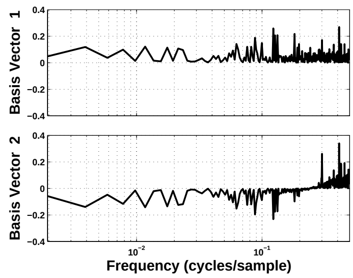

Fig. 2. SPCA PCs plot of the 12 time series

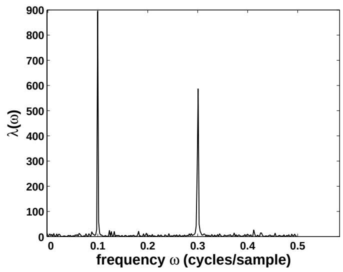

Fig. 3. Spectral Envelope of the 12 time series

2.3.3. Oscillation Detection Using the Spectral Envelope Method Figure 3 shows the spectral envelope calculated by equation (1) with the constraint $\beta^* V_X \beta = 1$. There are two significant peaks at $0.1Hz$ and $0.3Hz$, which means that the scaled series could have much more energy at these two frequencies than any other frequencies. It further implies that some of (or all of) the 12 time series may have significant energy at $0.1Hz$ and $0.3Hz$. Therefore, it can be concluded that the spectral envelope can clearly detect the multiple oscillations present in the time series.

3. VARIABLE CATEGORIZATION

After detecting the oscillation(s), the next step is to group the variables oscillating together at a common frequency. Here we propose two plots, a scaling plot and a power plot, to perform this task.

3.1 Scaling Plot

The first proposed plot is called the scaling plot, which is the bar plot of the magnitude of the optimal scalings calculated by equation (4) at the oscillation frequency in a descending sequence. The variables that have large scaling magnitudes at a oscillation frequency are the ones contributing most to the spectral envelope peak at that frequency, and thus are the ones participating in the oscillation. For example, Figure 4 is the scaling plot of the 12 time series (of the example in section

2.3) at the frequency $0.1Hz$. This plot clearly identifies that the time series 1, 10, 2, 9, 3 and 4 have oscillation at $0.1Hz$. The scaling plot of the 12 time series at the frequency $0.3Hz$ can also identify the variables oscillating at $0.3Hz$. Due to lack of space, we do not present it here.

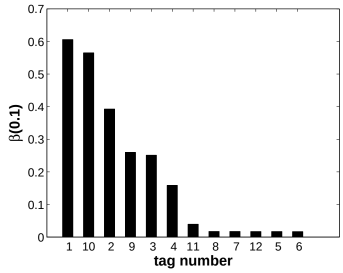

Fig. 4. Scaling plot of the 12 time series at $0.1Hz$

3.2 Power Plot

Another proposed plot is called the power plot, which is the bar plot of the power of each variable at the oscillation frequency in a descending sequence. The variables that have significant energy at the oscillation frequency are definitely the ones participating in the oscillation. For instance, Figure 5 is the power plot of the 12 time series (of the example in section 2.3) at the oscillation frequency $0.1Hz$. This plot clearly identifies that the time series 1, 10, 2, 9, 3 and 4 have oscillation at $0.1Hz$ since they have much more energy than the other time series at this frequency. The power plot of the 12 time series at the frequency $0.3Hz$ can also identify the variables oscillating at $0.3Hz$. Due to lack of space, we do not present it here.

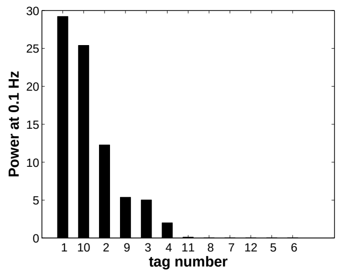

Fig. 5. Power plot of the 12 time series at $0.1Hz$

3.3 Comparison of Scaling Plot and Power Plot

Comparison between the scaling plot and the power plot reveals that the tag numbers of the variables appear in the same order in these two plots (see Figures 4 and 5). In other words, the series that has more energy at the oscillation frequency will have larger scaling magnitude in the optimal scaling vector. Therefore, these two plots are interchangeable in identifying and categorizing the variables at the oscillation frequency.

4. ROOT CAUSE DIAGNOSIS

Root cause diagnosis is a challenging problem in the area of detection and diagnosis of plant-wide oscillations. The main contribution of current data based root cause diagnosis techniques (Thornhill *et al.*, 2003*b*) is to isolate the few key variables as the candidates of the root cause, or at least identify those variables close to the root cause. This will reduce the workload and the cost of plant test to determine the real root cause.

Power plot (or scaling plot) may also be used to serve the same purpose. The main idea is to pick up the first few variables that contribute the most energy at the oscillation frequency as the key variables. The root cause probably lies within these few variables. The reason is that chemical processes are usually low pass filters. The process gain typically decreases as the frequency increases, as observed in most Bode plots. Therefore, as the oscillation propagates through different control loops, the energy at the oscillation frequency will decrease because of the low pass filtering effect of the chemical processes. The variables close to the root cause should exhibit more energy at the oscillation frequency than the other variables. Thus, we take the few variables that contribute the most energy at the oscillation frequency as the candidates of the root cause. The industrial case study in a later section will demonstrate the efficiency of using this idea to isolate the key variables.

5. NEW PROCEDURE TO DETECT AND DIAGNOSE PLANT-WIDE OSCILLATIONS

The following steps in a new procedure to detect and diagnose plant-wide oscillation are proposed:

- I. Normalize the data matrix that each variable is zero-mean and unit variance;
- II. Calculate the spectral envelope using equation (1) or (4) to find out the major oscillation frequencies;
- III. Use power plot (or scaling plot) at those oscillation frequencies identified in step II to categorize the variables having similar oscillations.
- IV. Use power plot (or scaling plot) to isolate the key variables having significant oscillations. The root cause probably lies within these variables.

6. AN INDUSTRIAL CASE STUDY

An industrial data set was provided courtesy of the Advanced Controls Technology group of Eastman Chemical Company. Figure 6 shows the process schematic of the plant. The Advanced Controls Technology group had identified a need

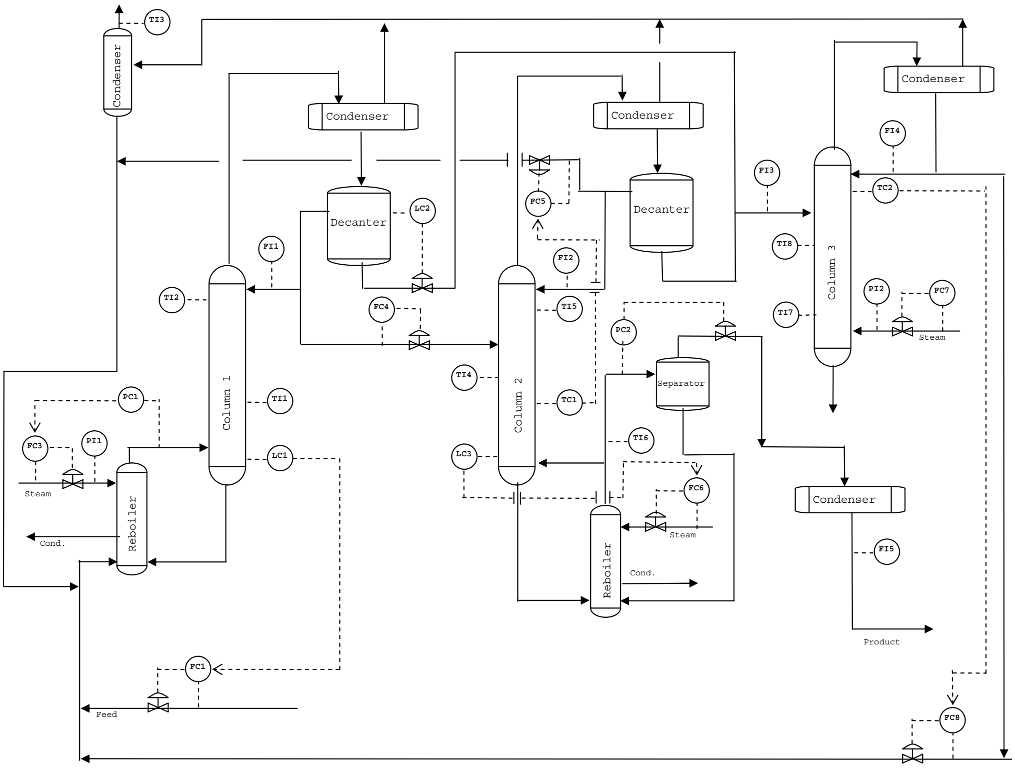

Fig. 6. Process schematic

for diagnosis of a common disturbance with an oscillation period of about 2 hours. In this section, the newly proposed procedure is applied to this data set to demonstrate its efficiency in detection and diagnosis of the plant-wide disturbance.

6.1 Data Description

The provided data set contains 48 variables: 14 process variables (*pv*'s), 14 controller outputs (*op*'s), 15 indicator variables and 5 cascade loop setpoints (*sp*'s). Each variable has 8640 observations with a sample interval 20s, which corresponds to data over 2 days of operation.

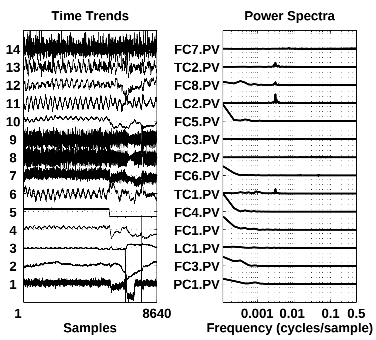

Fig. 7. Time trend and power spectra of 14 *pv*'s

Figure 7 shows the time trends and power spectra of the first 14 *pv* variables. The power spectra indicate the presence of oscillation at the frequency 0.003 cycles/sample (or about 333 samples/cycle, nearly a period of 2 hours). This oscillation affects many variables in the process and is considered as a plant-wide oscillation.

6.2 SPCA Analysis

The first two principle components (PCs) explained 87.47% variability of the spectra. The second PC has a small peak around the frequency 0.003 cycles/sample which indicates the interesting oscillation. However, the two-dimensional scores plot has no meaningful clustering. It is hard to analyze the frequency features of each variable. To save space, we do not present the PC and score plots here.

6.3 New Analysis Procedure

6.3.1. Oscillation Detection Figure 8 shows the spectral envelope (from equation (4)) of the 48 variables. In the spectral envelope, there is clear low frequency features. This is probably because the data is from a long term operation and there exists extremely long period influences like diurnal weather effects that impact the process. Beside the low frequency feature, there is a clear peak at the frequency of 0.0031 cycles/sample, indicating a oscillation with a period of 320 samples/cycle, or approximately 1.78 hours/cycle. This is exactly the oscillation that the Advanced Controls Technology group of Eastman Chemical Company wanted to detect and diagnose.

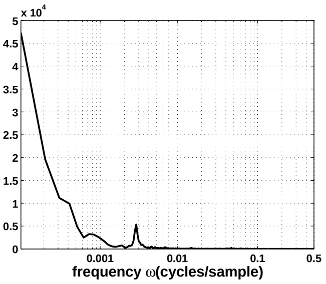

Fig. 8. Spectral Envelope of the 48 variables

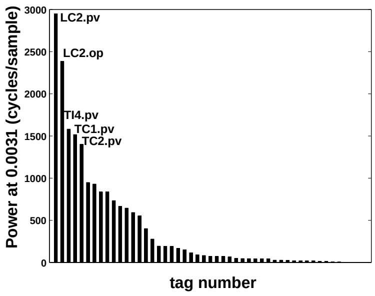

Fig. 9. Power plot of the 48 variables at the oscillation frequency 0.0031 cycles/sample

6.3.2. Variable Categorization

Figure 9 is the power plot of the 48 variables at the frequency 0.0031 cycles/sample. To make the figure clear, we only show the tag numbers of the five variables that contribute the highest energy at this frequency. They are the key variables that can be taken as the candidates of the root cause. Besides these five variables, the plot also clearly shows that many other variables are affected by this oscillation.

6.3.3. Oscillation Diagnosis Among all the variables, the *pv* and *op* of the control loop LC2 have the biggest energy at the oscillation frequency. This result indicates that the oscillation in loop LC2 is most severe and we should take this loop as the first candidate of the root cause.

Actually, the control loop LC2 was exactly the root cause found out by Thornhill *et al.* (2003*b*). It was reported that the control valve of the loop LC2 had a deadband of 4% and it was the root cause. For more information, refer to Thornhill *et al.* (2003*b*).

7. CONCLUSIONS

In this paper, the concept of spectral envelope is modified such that it is easy to apply for detecting plant-wide oscillations. This method is good at detecting oscillations whether single or multiple. Also the calculation of the spectral envelope is straightforward and no calculation parameter needs to be specified. In comparison to the ACF based method, the spectral envelope method does not suffer any limitation on minimum number of oscillation cycles and it does not require designing any filter. It can detect all oscillations in one step.

Scaling and power plots have been proposed for the purpose of grouping the variables participating in the common oscillation(s). The proposed plots can also deliver useful information about the root cause of a plant-wide oscillation.

Finally, an industrial case study was presented to demonstrate the efficacy of the method.

8. ACKNOWLEDGEMENT

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