DETECTING HARMONIC OSCILLATIONS IN PROCESS MEASUREMENTS USING SPECTRAL ENVELOPE

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ABSTRACT

In many industrial processes its common to observe a number of oscillating measurements. It is important to detect the source of these oscillations and rectify the situation in order to improve the overall performance of the process. The first step in detecting the source of these oscillations is to group measurements with similar harmonics together. In this paper, we make use of a technique called spectral envelope to solve this problem. We also compare this technique with other commonly used methods and present a few examples.

1. INTRODUCTION

Oscillations in process measurements are often observed due to a variety of reasons *viz*., poor controller tuning, sticky valves, disturbances etc. These oscillations generally have a source and then they propagate through the whole process making it hard to detect the source of these oscillations. In a real industrial setting, these oscillations occur due to a combination of the above reasons and hence often a number of harmonics are observed. It is important to categorize the measurements based on the type of harmonics they exhibit. This categorization helps in further analysis of the signals to find the root cause of oscillations.

In this paper we discuss how a method called spectral envelope developed by Stoffer et al. (1993) can be used in detecting oscillations and their harmonics. We also compare and contrast this method with Principal Component Analysis (PCA) and Spectral PCA (SPCA).

One of the goals of this paper is to introduce the idea of spectral envelope as an important tool in solving and giving a new perspective to the problems in the process industry. According to Stoffer et al. (1993), this method can be applied to a variety of problems. However, the emphasis in this paper is on detecting and categorizing process measurements with similar spectral characteristics.

The problem of detecting and diagonising plant-wide oscillations is an important issue facing the process industry. It has been addressed by a number of authors. In Thornhill et al., the authors utilize a spectral principal components method for detecting oscillations. The idea here is to perform principal component analysis on the spectral matrix of the data and then determine signals with similar oscillations from the score and loading plots. Kedam (1993) determine the oscillatory behavior from the zero crossings in time domain. However, this is a very difficult exercise if the process measurements have a poor signal to noise ratio.

Several authors have used autocovariance functions and the integrated absolute error to determine the period of oscillations and other useful information (Thornhill and Hagglund (1997); Thornhill et al. (2003); Miao and Seborg (1999)). These methods rely on calculating the period of oscillations from the zero crossings of the autocovariance function of each process measurement. If multiple oscillations are present in the process measurements, one may not observe any regularity in the zero crossings of autocovariance functions. Generally, this problem is resolved by filtering the data to remove oscillations at “unwanted” frequencies. Also, these methods do not automatically group all measurements with similar oscillations.

The problem of detecting and categorizing oscillations can be solved by an elegant method proposed by Stoffer et al. (1993). Spectral envelope can effectively detect the frequencies of oscillations in the measurements. This new method has the advantage of being very easy to interpret visually, unlike the loadings or scores plots of SPCA, when oscillations at multiple frequencies are present. In this paper we explain the method and outline its potential applications not only in detecting oscillations but in solving other problems in the process industry.

This paper is divided into the following sections: Section 1 describes the problem and discusses some of the literature. In section 2, the idea of spectral envelope is introduced in detail. An industrial example is included in section 3 and finally some concluding comments are provided in section 4.

2. SPECTRAL ENVELOPE

We often encounter a number of process measurements with similar spectral characteristics. Spectral envelope is an useful approach in detecting and categorizing such measurements. It was first proposed by Stoffer et al. (1993) to analyze the frequency domain characteristics of categorical time series. They assign numerical values to each of the categories in the time series and perform spectral analysis on the resulting discrete-valued time series. However, the spectrum obtained through this method depends on the values assigned to the categories. Hence, Stoffer et al. (1993) propose an approach for assigning numerical values to the categories in such a way that the periodic properties of the original categorical time series are emphasized. This is achieved by searching for the scalings that emphasize each frequency.

The idea of spectral envelope is then extended to real-valued time series in McDougall et al. (1997) and in Stoffer (1999). The spectrum of a time series depends on the transformation used. It is therefore possible to emphasize the periodic nature of a time series by choosing an appropriate transformation. Hence, the idea in McDougall et al. (1997) is to choose transformations that emphasize any periodic features that may exist in the time series.

Let X_t for $t = 0, 1, \cdots$, be a multivariate real-valued stationary time series. Consider some transformation of the time series denoted by $f(X_t)$, where $f(X_t)$ is a function that belongs to a function class denoted by $\mathscr{F}$. This approach involves choosing a transformation, in the class $\mathscr{F}$, that emphasizes the frequency ω in $-\pi < \omega < \pi$. One way to determine the transformation that emphasizes a particular frequency is to maximize

$$\lambda(\omega) := \sup_{f \in \mathscr{F}} \frac{\Phi_f(\omega)}{\sigma_f^2} \tag{1}$$

where $\Phi_f(\omega)$ and σ_f^2 are the spectrum and variance of $f(X_t)$ respectively. The variance is the area under the spectrum given by

$$\sigma_f^2 = \frac{1}{2\pi} \int_{-\pi}^{\pi} \Phi_f(\omega) d\omega \tag{2}$$

$\lambda(\omega)$ can be interpreted as the maximum fraction of the total power that can be attributed to the original time series signal through any transformation in the class of functions $\mathscr{F}$.

The notion of maximal fractional power at any frequency leads to the concept of spectral envelope. The spectral envelope is formally defined below (McDougall et al. (1997)):

Definition: Let X_t, $t = 0, 1, \cdots$, be a time series on $\mathbb{R}^n$ and let $\mathscr{F}$ be a class of transformations from $\mathbb{R}^n$ to $\mathbb{R}$ such that for any $f \in \mathscr{F}$, the spectral density $\Phi_f(\omega)$ of $f(X_t)$ exists. The *spectral envelope* of X_t with respect to $\mathscr{F}$ is defined to be

$$\lambda(\omega) = \sup_{f \in \mathscr{F}} \frac{\Phi_f(\omega)}{\sigma_f^2} \qquad -\pi < \omega < \pi \tag{3}$$

The name *spectral envelope* is derived from the fact that $\lambda(\omega)$ is larger than fractional power for any function in the class $\mathscr{F}$ at frequency ω. It is important to note that the optimal transformation depends on the frequency. It turns out that this is one of the important features that distinguishes it from principal component analysis as will be seen in a later section.

In general, it is difficult to construct a spectral envelope directly from the definition as given above. However, if certain simplifying assumptions are made on the type of the function class, $\mathscr{F}$, then it is possible to reduce the above maximization problem to that of an eigenvalue problem. In the rest of this paper, we assume that the function class $\mathscr{F}$ is a k-dimensional vector space. Let us assume that $\{f_1(X_t), f_2(X_t), \cdots, f_k(X_t)\}$ is a basis set for the function class. Hence any function, $f(X_t)$, in that vector space can be represented by

$$f(X_t) = \beta_1 f_1(X_t) + \beta_2 f_2(X_t) + \cdots + \beta_k f_k(X_t) \tag{4}$$

Using compact notation, we can write it as

$$f(X_t) = \beta^T F(X_t) \tag{5}$$

where $F(X_t) = [f_1(X_t), \cdots, f_k(X_t)]^T$. It is assumed that the basis vector $F(X_t)$ has a continuous spectrum and hence the transformed time-series also has a continuous spectrum. It is easy to observe that

$$\Phi_f(\omega) = \beta^T \Phi_F(\omega) \beta \tag{6}$$

and

$$\sigma_f^2 = \beta^T \sigma_F^2 \beta \tag{7}$$

Thus, the spectral envelope defined over the function class, $\mathscr{F}$ can be evaluated using

$$\lambda(\omega) = \sup_{\beta \neq 0} \frac{\beta^T \Phi_F(\omega)\beta}{\beta^T \sigma_F^2 \beta} \tag{8}$$

The solution to this problem can be obtained by solving for the largest eigenvalue of

$$|\Phi_F(\omega) - \lambda(\omega)\sigma_F^2 \beta| = 0. \tag{9}$$

or alternatively the largest eigenvalue that satisfies

$$\Phi_F(\omega)\beta(\omega) = \lambda(\omega)\sigma_F^2 \beta(\omega) \tag{10}$$

The eigenvector, $\beta(\omega)$, corresponding to the largest eigenvalue,$\lambda(\omega)$, is the optimal transformation that emphasizes the frequency ω.

3. INDUSTRIAL EXAMPLE

In this section we present an industrial example, which highlights the usefulness of spectral envelope in detecting the source of oscillations. The example considered is an oil refinery experiencing a high degree of variation in the coil outlet temperature (COT) of the tubular reformer in their Hydrogen Generation Unit. Currently, the COT exhibits a $\pm 10^o C$ variation and is considered high. We have undertaken a performance analysis study of the hydrogen generation unit to determine the major sources of performance degradation. The main objectives of this study are :

- To evaluate the current performance levels of the existing key controllers.
- To identify the source of oscillations in coil outlet temperature of the tubular reformer.

One minute snapshot data for a period of 10-days is available for the analysis. We have used Matrikon's control loop performance assessment tool, ProcessDoc^{TM}, to complete the analysis.

It is essential that the regulatory control loops deliver good performance for any process plant to operate optimally. This is especially true if advanced control schemes that communicate with the regulatory layer are in use. Minimum Variance based performance indices are obtained for selected control loops around the reformer. ProcessDoc^{TM} generates a performance index (PI) that is bounded by 0 and 1. A low performance index (i.e. close to 0) indicates potential for further improvement. Conversely, when the performance index is close to one, it can be concluded that further reduction in variance is not possible. This index also serves as a useful screening tool for identifying the key troublesome loops as controller performance changes over time. Additional analysis can then be performed on these key loops using Spectral Envelope to identify the sources of performance degradation. Table1 summarizes the performance indices generated for the selected tags. For reasons of confidentiality, we have changed the original tag names and the controller names. These indices are obtained by analyzing data for the period between 12:00am Feb 19,1999 and 12:00am Feb 21, 1999.

FC4001	LPG/Propane Flow controller	0.55
FC4004	Membrane Tail Gas Flow	0.35
FC4008	Fuel gas flow controller (to Feed vaporizer)	0.40
FC4009	Steam flow controller (to reformer)	0.61
FC4012	Process gas flow controller	0.51
FC4017	Fuel gas controller (to reformer)	0.20
FC4304	PSA off-gas controller	0.015
FC4052	HP steam temperature	0.0356
FC4054	COT controller	0.0120
LC4017	Steam drum level controller	0.1625
LC4020	1^{st} process condensate separator level controller	0.4785
LC4026	2^{nd} process condensate separator level controller	0.4035
LC4028	3^{rd} process condensate separator level controller	0.087

Table 1. Performance Indices of controllers

As mentioned earlier, the primary focus of this study is to identify the source(s) of variance in the coil outlet temperature (COT). The plant personnel believe that the $\pm 10^o C$ variation in the coil outlet temperature is unacceptably high and can potentially be reduced. Figure 1 shows the impulse response of coil outlet temperature controller TC4054. The oscillatory behaviour evident in the impulse response translates into a resonant peak in the power spectrum shown in Figure 2. The coil outlet temperature (COT) signal exhibits severe oscillations and has a '17-minute' cycle. Performance index for this controller is estimated to be 0.0120. This low performance index is mainly due to the closed-loop oscillations observed in the process variable.

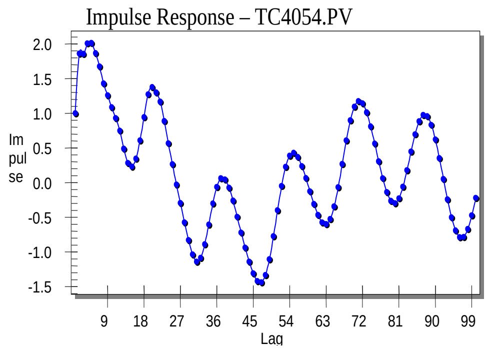

Fig. 1. *Impulse response of the temperature loop*

It is evident that any efforts to improve the COT controller performance should aim at reducing the magnitude of these oscillations. To this end, further analysis is performed to identify the source(s) of these oscillations. The main input streams entering the reformer are as follows:

a) Fuel gas (FC4017)
b) PSA off-gas (FC4304)
c) Process gas (FC4012)

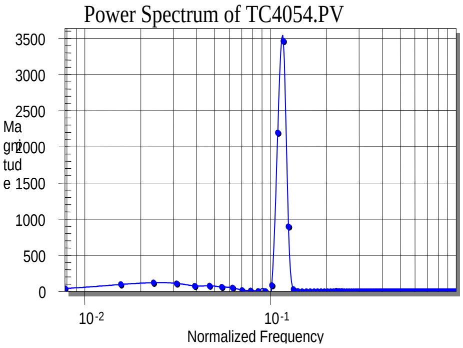

Fig. 2. *Spectrum of the temperature*

d) Combustion air (FC4018)

Cross-correlation functions are computed between the COT and each of the input streams. Figure 3 shows the cross-correlation function between the COT and the PSA off-gas flow. It can be observed that the off-gas flow is highly correlated with COT. Figure 4 shows the power spectrum of off-gas flow. Note the striking similarity between the COT spectrum and the off-gas flow spectrum. The off-gas flow exhibits a '17-minute' cycle similar to COT.

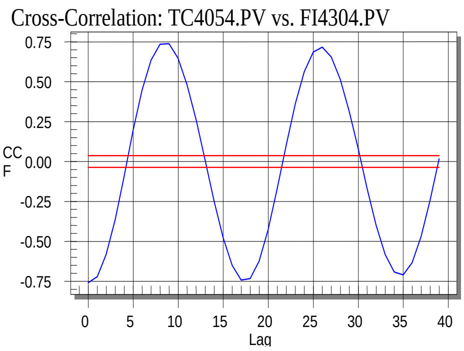

Fig. 3. *Cross-correlation function between COT and PSA Off-gas flow*

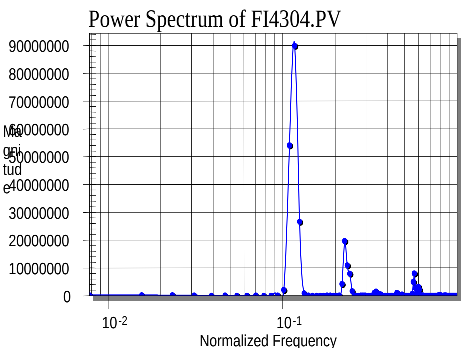

Fig. 4. *Power spectrum of PSA off-gas flow*

In order to find the source of the oscillations, each process variable is analyzed using both time domain and spectral techniques. The spectral envelope of all the tags available in this unit is shown in Figure 5. It clearly indicates three peaks at frequencies 0.06, 0.12, 0.301 and their respective periods 16.67 min, 8.33 min, 3.32 min. The eigenvectors corresponding to the above frequencies provide the weights associated with each tag used. The larger the weight, the stronger is that particular frequency in the tag. Using the spectral envelope approach all the variables exhibiting the 17-minute cycle are quickly identified. The 17-minute cycle can be regarded as a 'signature' indicating performance deterioration in the reformer unit. Some of the important variables exhibiting the 17-minute cycle are marked with a diamond (◇) in the Figure 6 below (e.g. TC4054).

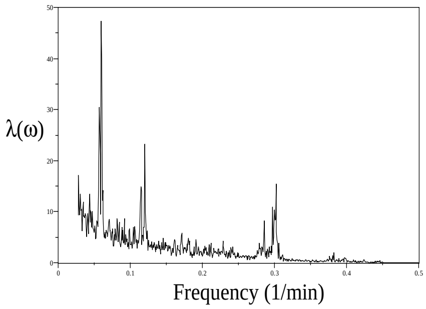

Fig. 5. *Spectral Envelope of all the available process measurements*

The results obtained using spectral envelope can easily be corroborated by plotting the cross-correlation functions of some of these tags. Under normal operation, process feed is comprised of membrane tail gas, light naphtha and LPG/Propane. There is a very significant correlation between membrane tail gas flow and the coil inlet temperature as shown in Figure 7. The cross-correlation plots between other feed streams (Light Naphtha, LPG/Propane) show no significant correlation with COT and are not shown here. It is interesting to note that the membrane tail gas flow controller exhibits a 17-minute cycle that is similar to the cycle observed in COT.

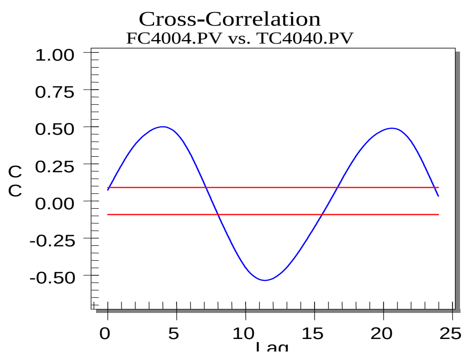

Fig. 7. *Cross-correlation function between Membrane tail gas flow and CIT*

Figure 8 shows the cross-correlation plot between fuel gas density and coil inlet temperature. Fuel gas is used

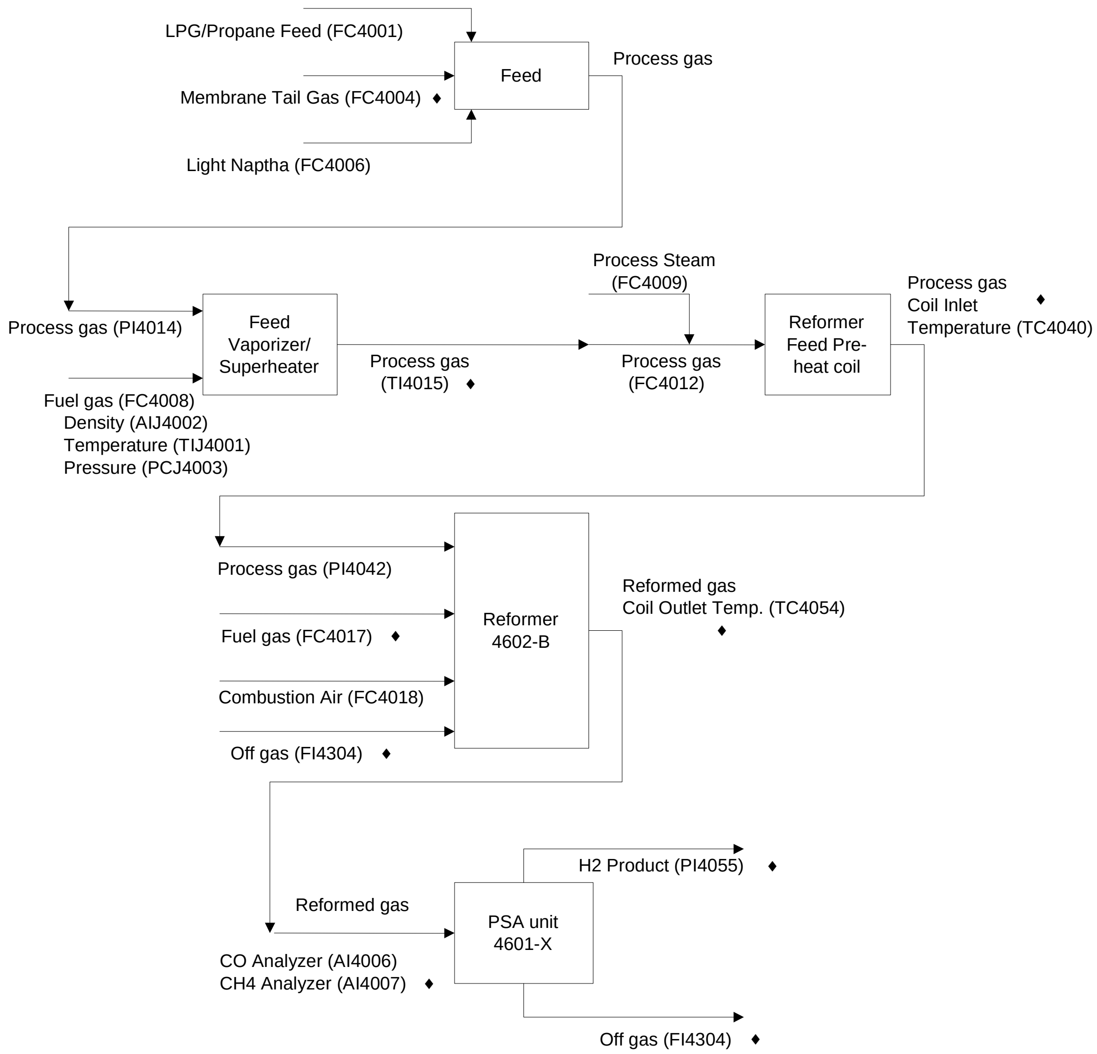

Fig. 6. *Simplified process flow diagram of Hydrogen Generation Unit*

in the Feed Vaporizer/Superheater, which is upstream to the reformer and affects the coil inlet temperature. The cross-correlation between fuel gas temperature and CIT is insignificant and is not shown here.

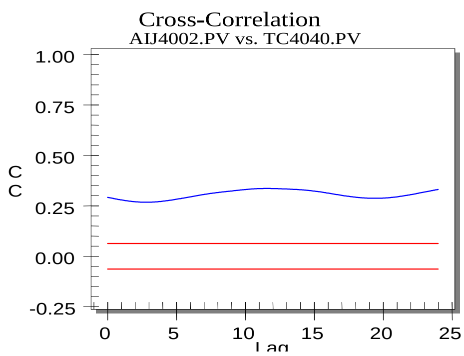

Fig. 8. *Cross-correlation between fuel gas density and coil outlet temperature (COT)*

To Summarize:

- CIT exhibits a 17-minute cycle.
- These variations are definitely induced from upstream processes (Process feed, Fuel gas to feed vaporizer).
- Spectral envelope has revealed a strong correlation between CIT and membrane tail gas flow.
- In addition, correlation between fuel gas density and CIT was also observed.

These are the most likely sources of oscillation in the CIT and COT.

4. CONCLUSIONS

The idea of spectral envelope is successfully used on a real industrial problem to isolate process variables with similar oscillations. These variables are then used in isolating the problem causing process variables. Spectral envelope is very useful when the oscillations propagate through a large number of controllers and process variables.

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