Detection and Diagnosis of Plant-wide Oscillations: An application study

Vinay Kariwala, M.A.A. Shoukat Choudhury, Sirish L. Shah, J. Fraser Forbes, Edward S. Meadows
Dept. of Chemical & Materials Engg., University of Alberta, Edmonton, Canada T6G 2G6
{kariwala, mdali, slshah, fforbes, emeadows}@ualberta.ca

Hisato Douke, Haruo Takada
Mitsubishi Chemical Corporation, 3-10 Ushiodori, Kurashiki, Okayama 712-8054, Japan
{3002081, 2000659}@cc.m-kagaku.co.jp

Abstract

This paper presents an overview of the emerging techniques for oscillation detection and diagnosis and investigate their efficiency through an industrial case study. The recently proposed autocorrelation function based method [15] is used for detection of multiple oscillations in process measurements and identifying signals having common oscillations. The signals having common oscillatory behavior are analyzed for the possible presence of valve stiction using the Higher Order Statistical method [1]. This method is helpful in identifying the key variables that are most likely to be the root cause of oscillations. We also present some issues pertinent to the diagnosis of oscillations, which are potential directions for future research.

1. Introduction

Oscillations are a common form of plant wide disturbance. The mass and energy integration in plants facilitates the propagation of oscillations from one process unit to another. It is important to detect and diagnose the causes of oscillations in a chemical process because a plant running close to product quality limits or operating constraints is more profitable than a plant that has to back away due to the amplitude of the oscillations [14].

The process under investigation is the plant at Mitsubishi Chemical Corporation, Mizushima, Japan. The plant personnel reported oscillations with large amplitude in the condenser level of a distillation column causing sub-optimal operation and large economic losses. Previous attempts for oscillation diagnosis by considering only the level and the variables directly affecting them were not successful. It was believed by plant personnel that the oscillations are caused due to the mismatch in the model used for the Dynamic Matrix Controller® implemented on the distillation column. Desborough and Miller (2001) [4] have pointed out that changes in operating conditions can sometimes cause the variables of model based predictive controllers to oscillate. However, a thorough analysis of the historical data revealed that the oscillatory behavior of the process variables had largely remained unchanged after the major operating condition changes ruling out this possibility. The objective of this study is to search for alternative causes and diagnose the root cause of the oscillations in the condenser level.

Before a full scale diagnosis exercise is undertaken, it is beneficial to find all signals oscillating with the common period as the root cause generally lies within this set. On the contrary, most of the available techniques for detection focus on a loop by loop analysis [5, 12, 9]. It is largely due to the efforts of Thornhill and co-workers that some detection tools are now available that consider the plant-wide nature of oscillations. To detect and cluster signals with common oscillatory behavior use of spectral principal component analysis [16] or autocorrelation functions (acf) [15] is suggested. Recently, Xia and Howell (2003) [17] have also proposed a technique that takes the interactions between control loops into account. In this paper, we use the acf based method as it reduces the effect of noise, handles multiple oscillations in the same measurement easily and also provides the time periods of the different oscillations.

In a control loop, oscillations may arise due to various reasons including poorly tuned controllers, presence of oscillatory disturbances and nonlinearities.

Generally, the oscillations arising due to poor controller tuning have a time period of the order of a few minutes [13], which is much smaller than the time period of the oscillations detected in the measurements of the present case study. With this observation, the signals having common oscillatory behavior are analyzed for possible valve problems using the Higher Order Statistical method [1]. This method is found to be helpful in identifying the key variables that are most likely to be the root cause of oscillations. We also present some insights and limitations of the available methods useful for detection and diagnosis of oscillations, as observed during this case study, showing scope for improvement.

2. Detection

In this section, the acf based method is briefly reviewed followed by the results obtained by its application to the industrial data set.

2.1. Methodology

The power spectrum (spectra) of a signal shows peaks at underlying fundamental frequencies. Where as presence of peaks in the spectra is sufficient for adjudging whether a signal is oscillatory or not, calculation of time period can be difficult due to presence of noise. For this purpose, Thornhill *et.al.* [15] proposed the use of acf. The acf oscillates at same frequency as the signal, but the effect of noise is reduced. The time period of the oscillation is easily determined by considering the zero crossings of the acf. However, the interval between successive zero crossings of acf of signals from real processes are rarely constant and statistical tests are required.

Let $T_p^{(1)} \cdots T_p^{(k)}$ be the time elapsed for completion of each of the first k cycles of acf and $\bar{T}_p$, σ_{T_p} be their mean and standard deviation. Then the signal is considered to be oscillating with time period $\bar{T}_p$ if

$$\bar{T}_p > 3\sigma_{T_p} \tag{1}$$

The ratio $\bar{T}_p/3\sigma_{T_p}$ denotes the regularity r of the signal and a signal is consider regular, if $r > 1$. Presence of multiple oscillations can destroy the regularity of zero crossings and filtered acf is used. For every oscillation, the power spectrum of the signal is filtered using a band pass filter having zero gain outside the selected frequency range. The time period of each oscillation is determined using the filtered acf and (1).

Remark 1 *Practical considerations require that only signals with significant activity in the chosen frequency band be considered. This is taken into account by calculating the fractional power of the signal P in the frequency band $[\omega_{n_1}\ \omega_{n_2}]$ as*

$$P = \frac{\sum_{n=\omega_{n_1}}^{\omega_{n_2}} \Phi(i\omega_n)}{\sum_{n=0}^{\pi} \Phi(i\omega_n)} \tag{2}$$

where $\Phi(.)$ is the power spectrum. Thornhill et.al. *[15] suggest a threshold value of 1% for P, but higher values can used to avoid detection of insignificant oscillations.*

To ascertain the plant-wide nature of the oscillations detected in individual signals, a simple heuristic clustering algorithm is used to find all signals containing an oscillation of same period. Let the two signals under consideration have mean time periods $\bar{T}_{p,i}$, $\bar{T}_{p,j}$ and standard deviations $\sigma_{T_{p,i}}$, $\sigma_{T_{p,j}}$ respectively. These signals are considered to be oscillating with a common period if the distance metric

$$d_{i,j} = \frac{\left|\bar{T}_{p,i} - \bar{T}_{p,j}\right|}{\max(\sigma_{T_{p,i}}, \sigma_{T_{p,j}})} < 1 \tag{3}$$

The two signals satisfying (3) form a cluster and the mean time period and standard deviation of the more regular signal (with higher value of r) represents the statistics of the cluster. The process is repeated by replacing these signals with the cluster until no more changes occur. In case of a conflict, the signal is assigned to the cluster with the smallest value of the distance metric.

The acf based oscillation detection and clustering method can easily be automated. The underlying idea is to remove the non-stationary trends of the data and then detect and cluster the oscillations using the statistical tests discussed earlier. The search continues by narrowing the filter ranges around the oscillations detected in the previous step. The algorithm terminates when at most one oscillation is detected in every filter range or the filter ranges become too narrow.

Remark 2 *Presence of noise, non-stationary trends and multiple oscillations may destroy the regularity of the zero crossings of acf. Then the automated algorithm may detect (generally during first iteration) none or only one oscillation causing premature termination, despite the spectrum showing multiple distinct peaks. For the case, when a single oscillation is detected, artificially narrowing down the filter ranges around the detected oscillations is found to be helpful. This limitation of the detection algorithm is similar to the supersaturated solution, where no crystallization occurs unless seeding is done.*

2.2. Scope of analysis

There are a large number of variables in the present case study and a sequential approach is used to de-

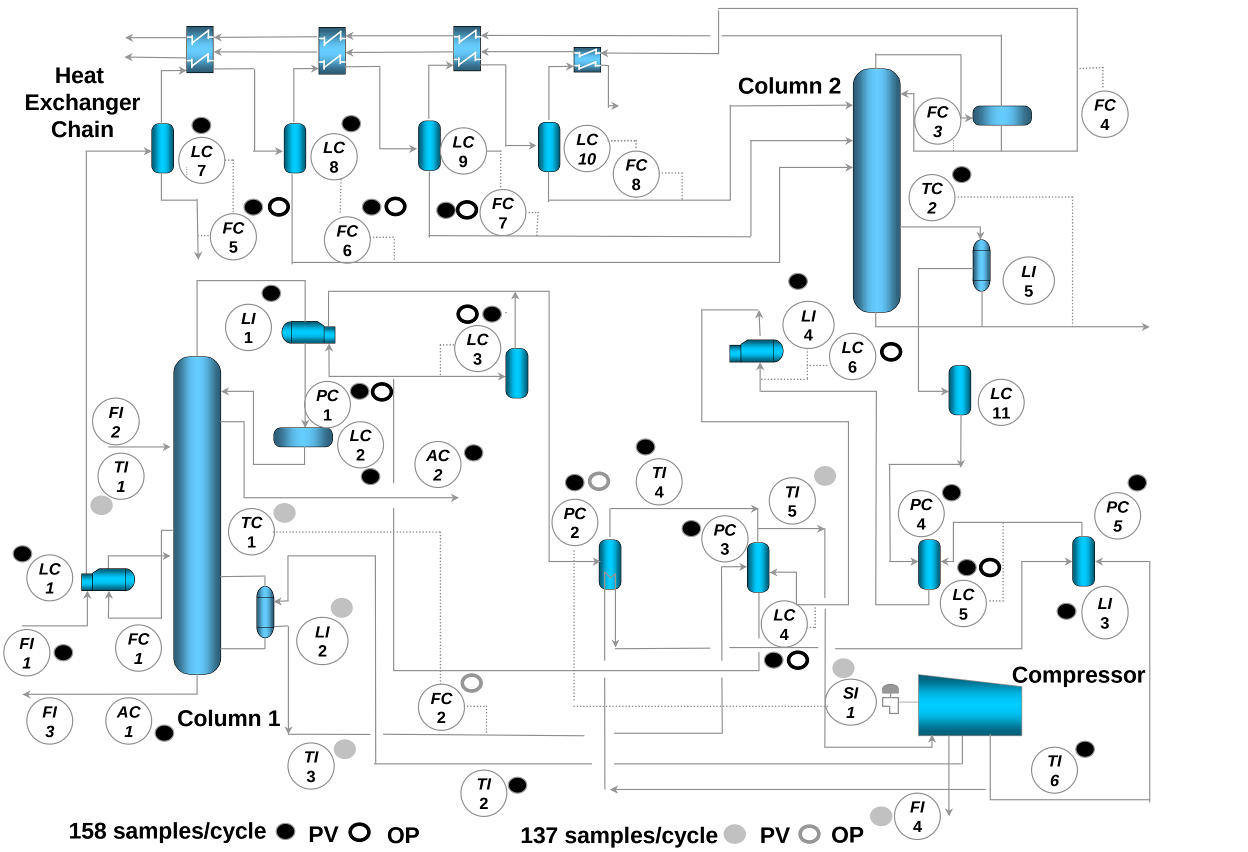

Figure 1. Process flow diagram showing detected oscillations in low frequency range (88 - 183 samples/cycle)

fine the scope of the analysis. Starting from the condenser level, the scope of the study is expanded based on mass, energy and information connectivity (based on controller structure) of the process until no more oscillations are detected. For this preliminary analysis, visual inspection of time trends and spectra are found to be sufficient. The final data set consists of 43 tags taken from various process units as shown in Figure 1. 15 of these variables are controlled using PID controllers and the controller outputs for these variables are also included in the study. In Figure 1 and ensuing discussion, the notation used for tags is standard in process industries. AC, FC, LC, PC and TC represent composition, flow, level, pressure and temperature tags respectively that are controlled. Similarly, FI, LI, SI and TI represent the flow, level, rotor speed and temperature tags respectively that are indicators only. We denote the set point, process value and controller output as *sp*, *pv* and *op* respectively.

2.3. Results

A sample data set consisting of 2880 samples is collected at the rate of 1 sample/minute. The data set is filtered to remove the low frequency non-stationary trends and the acf based method is applied on the filtered data set. The results of the detection analysis are summarized in Table 1 and the key characteristics are discussed below:

- The condenser level (LI1) oscillates with a period of approximately 158 samples/cycle with power (2) of 88% or more. Thus 158 samples/cycle is taken as the fundamental time period for the purposes of this study.
- The algorithm also detects 26 other variables that oscillate with a similar time period as the condenser level. Among these variables, 17 variables have power of 40% or more, which require immediate attention.
- 10 variables oscillate with a time period of approximately 137 samples/cycle. Note that it is difficult

Tag	High (4-44)		Medium (44-88)		Low (88-183)		Tag	High (4-44)		Medium (44-88)		Low (88-183)	
	Period	P	Period	P	Period	P		Period	P	Period	P	Period	P
Process Variables:													
FI1	-	-	73 ± 18	12	168 ± 30	22	LC1	50 ± 9	9	82 ± 16	10	163 ± 32	52
FI2	-	-	62 ± 5	29	-	-	TI1	-	-	74 ± 2	6	137 ± 18	38
FC1	-	-	-	-	-	-	AC1	-	-	75 ± 2	11	157 ± 14	65
FI3	-	-	-	-	-	-	LI1	-	-	-	-	159 ± 7	90
PC1	-	-	75 ± 2	7	160 ± 13	90	LC2	-	-	75 ± 2	14	161 ± 13	56
AC2	-	-	75 ± 2	14	161 ± 12	60	TC1	41 ± 10	9	75 ± 3	42	140 ± 37	42
LI2	-	-	75 ± 4	11	141 ± 27	50	FC2	-	-	-	-	-	-
TI2	-	-	73 ± 5	17	160 ± 27	11	TI3	43 ± 5	63	73 ± 3	16	144 ± 28	18
LC3	-	-	63 ± 16	9	157 ± 26	10	PC2	-	-	-	-	160 ± 12	77
TI4	-	-	73 ± 7	9	158 ± 8	54	PC3	-	-	80 ± 8	6	159 ± 7	62
TI5	44 ± 3	48	73 ± 16	15	124 ± 36	21	LC4	-	-	63 ± 18	8	161 ± 28	31
PC4	-	-	75 ± 7	9	160 ± 19	51	LC5	-	-	63 ± 18	14	162 ± 25	56
LI3	-	-	-	-	158 ± 8	90	PC5	-	-	-	-	157 ± 7	39
TI6	-	-	73 ± 5	5	155 ± 9	28	FI4	4 ± 1	81	-	-	141 ± 45	12
SI1	-	-	75 ± 3	8	144 ± 42	28	LI4	-	-	-	-	157 ± 6	13
LC6	-	-	73 ± 23	25	-	-	LI5	-	-	63 ± 7	42	108 ± 36	31
TC2	-	-	62 ± 7	22	172 ± 34	29	FC3	-	-	-	-	-	-
FC4	-	-	86 ± 7	17	-	-	LC7	-	-	89 ± 19	7	158 ± 17	44
FC5	-	-	-	-	158 ± 44	6	LC8	-	-	65 ± 17	17	159 ± 16	19
FC6	-	-	65 ± 17	11	159 ± 13	26	LC9	-	-	-	-	-	-
FC7	-	-	-	-	159 ± 20	10	LC10	26 ± 8	86	-	-	-	-
FC8	-	-	-	-	-	-							
Controller Outputs:													
FC1	-	-	-	-	-	-	PC1	-	-	-	-	160 ± 12	77
FC2	-	-	75 ± 4	10	139 ± 19	20	LC3	-	-	75 ± 8	10	157 ± 10	37
PC2	-	-	75 ± 3	8	143 ± 41	28	LC4	-	-	63 ± 18	7	161 ± 21	65
LC5	-	-	76 ± 15	8	162 ± 20	76	LC6	-	-	69 ± 22	10	160 ± 36	26
TC2	-	-	63 ± 6	37	-	-	FC3	-	-	86 ± 23	6	-	-
FC4	44 ± 6	9	85 ± 8	17	-	-	FC5	-	-	-	-	157 ± 10	15
FC6	-	-	65 ± 20	11	159 ± 20	26	FC7	-	-	-	-	158 ± 39	15
FC8	-	-	-	-	-	-							

Table 1. Oscillation detection summary for controller outputs

to distinguish these variables with those oscillating with the time period of 158 samples/cycle through direct visualization of power spectrum.

- Considering 158 samples/cycle to be the fundamental time period, it is noted that a number of the variables exhibit harmonics (approximately 79 samples/cycle). This indicates the presence of nonlinear elements (*e.g.* valve stiction, deadband) in the process.

Remark 3 *It is pointed out that though useful, the acf based method is prone to false detections. Since the algorithm uses ideal band pass filters, the filtered data may be oscillatory misleading the algorithm. This difficulty can be overcome by using Hanning window, but this increases the complexity of the algorithm [13]. In this paper, the oscillations detected close to the filter boundaries are verified against the peaks present in the spectra. We also widen the filter range and repeat the analysis to distinguish between a false detection and a true oscillation present close to filter boundaries during every iteration.*

The variables affected by low frequency oscillations with a power of 10% or more are shown in Figure 1, where the plant wide nature of the oscillations should be noted. Due to presence of high heat integration and a multivariable controller, which acts as a supervisory controller, it is difficult to diagnose the root cause of oscillations through a cause-effect analysis and a systematic analysis is presented in the next section.

3. Diagnosis

There are several reasons that may cause a control loop to oscillate, for example poorly tuned controllers, presence of oscillatory disturbances and nonlinearities. Closed Loop Performance Assessment (CLPA) [3] is a convenient method to assess the *goodness* of controller tuning. A controller is termed as well tuned if the controller error signal has little or no predictable component and *vice versa*. For the present case study, use of CLPA provides no clear indications that the oscillations are caused due to poorly tuned controllers. This is also expected as generally the oscillations arising due to poor controller tuning have a time period of the order of a few minutes [13], which is much smaller than the fundamental time period of the oscillations detected in the condenser level. In the remaining discussion, we discuss methods aimed at detecting nonlinearities in the control valves and show their application.

3.1. Nonlinearity Detection

Oscillations produced by the nonlinearities present in control valves (*e.g.*, deadband, backlash, stiction) are often responsible for plant wide oscillations. Recently, Thornhill *et.al.*(2003) [14] showed that a deadband in the process valve can give rise to severe process oscillations. Therefore, all the control valves, that oscillate with a time period similar to the condenser level, were tested for possible presence of nonlinearities using the higher order statistics based method [1].

The method uses the sensitivity of the normalized bispectrum or bicoherence to the presence of nonlinear interactions in a signal. A distinctive characteristic of a non-linear time series is the presence of phase coupling such that the phase of one frequency component is determined by the phases of others. These phase couplings lead to higher order spectral features which can be detected in the bicoherence of a signal defined as:

$$bic^2(f_1, f_2) \triangleq \frac{|B(f_1, f_2)|^2}{E[|X(f_1)X(f_2)|^2]E[|X(f_1+f_2)|^2]} \quad (4)$$

where $B(f_1, f_2)$ is the bispectrum calculated at frequencies (f_1, f_2) and is given by

$$B(f_1, f_2) \triangleq E[X(f_1)X(f_2)X^*(f_1+f_2)], \quad (5)$$

Here, $X(f_1)$ is the discrete fourier transform of the time series $x(k)$ calculated at the frequency f_1, $X^*(f_1)$ is the complex conjugate and E is the expectation operator. A key feature of the bispectrum is that it has a non-zero value if there is significant phase coupling in the signal x between frequency components at f_1 and f_2. The bicoherence gives the same information but is normalized as a value between 0 and 1.

In [1], two indices - the Non-Gaussianity Index (NGI) and the Non-Linearity Index (NLI) - have been defined as

$$NGI \triangleq \overline{\hat{bic}^2} - \overline{bic^2}_{crit} \quad (6)$$

$$NLI \triangleq |\, \hat{bic}^2_{max} - (\overline{\hat{bic}^2} + 2\sigma_{\hat{bic}^2}) \,| \quad (7)$$

where $\overline{\hat{bic}^2}$ is the average squared bicoherence and $\hat{bic}^2_{max}$ is the maximum squared bicoherence, $\sigma_{\hat{bic}^2}$ is the standard deviation of the squared bicoherence and $\overline{bic^2}_{crit}$ is the statistical threshold/critical value obtained from the central χ^2-distribution of squared bicoherence. When both NGI and NLI are greater than zero, the signal is described as non-Gaussian and nonlinear and it is inferred that the loop in question exhibits significant non-linearity. For a control loop, this test is applied on the error signal (*sp-pv*) to the controller because the error signal is often more stationary than *pv* or *op* signal, which is specially true for cascaded loops.

Assuming that the process is linear and no nonlinear disturbance is entering the loop, the nonlinearity can be attributed to the control valve. If the disturbance is measurable, the test can also be applied to check the linearity of the disturbance.

Remark 4 *One may argue that the valve itself may have a nonlinear characteristic, e.g., a square-root or equal percentage characteristic, which is definitely not a fault. A careful observation of the nonlinear valve characteristic curves reveals that the characteristics curves can safely be assumed linear if the movement of the valve stem or the change in input signal to valve is within 10% of the full span (0 to 100%) of the valve travel.*

3.2. Use of *pv-op* Plot

The long time practice in industrial studies has been the use of *pv-op* plots for the detection of valve problems, especially stiction. But experience shows that this type of method is successful only for a handful cases of flow control loops. The use of *pv-op* plot for detecting valve problems was not successful because it only takes into account the qualitative trend information of the time series which can be destroyed due to the presence of process dynamics, noise dynamics, disturbances and tightly tuned controllers.

In our method, the *pv-op* plot is used as a second step to diagnose the valve nonlinearity problem. The detection of valve or process nonlinearity is first carried out using higher statistical method-based NGI and NLI indices. Once a nonlinearity is detected, only

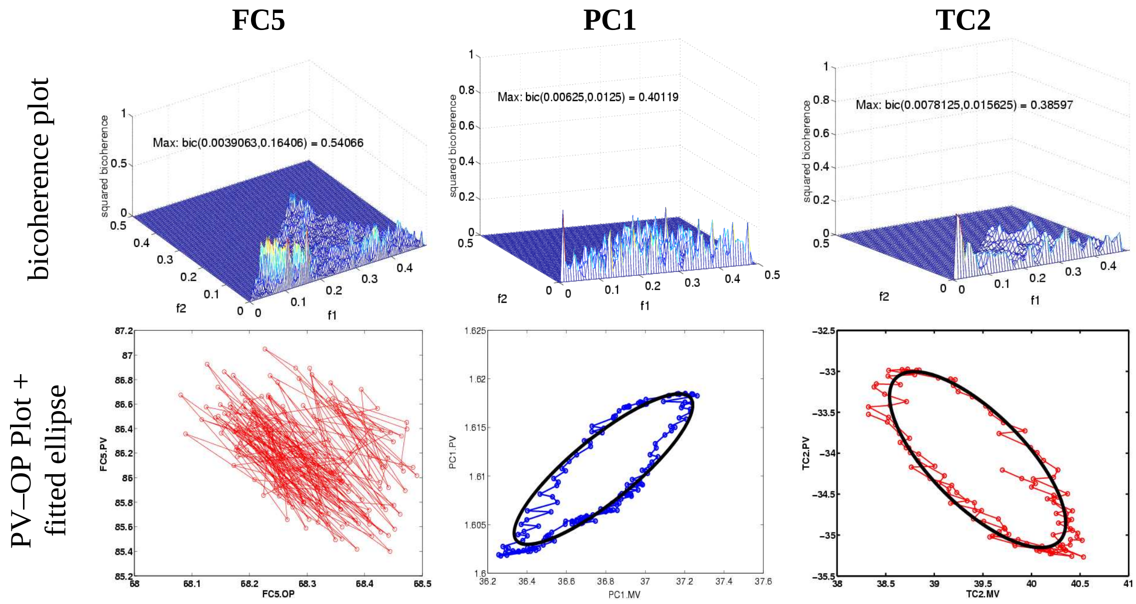

Figure 2. Results of condenser level oscillation diagnosis

then the *pv-op* plot is used to isolate its cause. It is well known [5, 6, 11, 10] that the presence of stiction in control valve in a control loop produces limit cycles in the controlled variable (*pv*) and the controller output (*op*). For such a case, the *pv-op* plot shows cyclic or elliptic patterns, which are taken as a signature of valve stiction. If no such patterns are observed, it is concluded that there are valve problems but these are not due to the stiction.

3.3. Quantifying Stiction

It is important to be able to quantify stiction so that a list of sticky valves in order of their maintenance priority can be prepared. A segment of the data that has regular oscillations is used for the construction of the *pv-op* plot. An ellipse in the least square sense can be fitted to the *pv-op* plot and can be used for quantifying stiction. Since apparent stiction is defined as the maximum width of the ellipse along the *op* axis, the distance between two points lying on the intersections of the ellipse and a line parallel to the *op* axis and passing through the center of the ellipse will be the amount of stiction present in the loop. If m and n are the length of the major and minor axes of the fitted ellipse respectively, and α is the angle of rotation of the ellipse from positive x-axis, then the amount of stiction can be obtained using the following expression [2]

$$\text{stiction}(\%) = \frac{2mn}{\sqrt{(m^2\ sin^2\alpha + n^2\ cos^2\alpha)}} \quad (8)$$

Remark 5 *The quantified stiction is termed as* apparent stiction *because the actual amount of stiction to be obtained from the mv-op plot may differ from the estimated quantity because of the role of the controller in attempting to regulate the process variable.*

3.4. Results

The higher order statistics based NGI and NLI indices were calculated for the variables of control loops that oscillate with same time period as condenser level and the results are shown in Table 2. It is clear from Table 2 that only three loops, namely FC5, PC1, and TC2 show nonlinear behavior. Figure 2 shows the bicoherence plots for these loops. A large peak in the bicoherence plot represents significant nonlinear interactions between those two frequencies of the signal. It is clear from the Figure 2 that in each of the loop there are significant nonlinear interactions.

These nonlinear loops were further investigated using the *pv-op* plot. For the loop FC5, the *pv-op* plot does not show any pattern (see the left plot of the second row in Figure 2). As is confirmed by using CLPA [3], this loop contains a hardware fault. Loop PC1 shows that the valve has approximately 0.5% stiction. The right plot in the second row of Figure 2 shows the presence of 1.25% stiction in the valve for loop TC2.

Based on this analysis, we conclude that one or both of the loops PC1 and TC2 is most likely to be the root cause of the oscillations. These results have been com-

Tag	NGI	NLI	Apparent Stiction (%)	Remarks
AC1	–	–	–	No control valve
AC2	–	–	–	No control valve
FC5	0.01	0.235	no stiction	nonlinear
FC6	0	–	–	linear
FC7	0	–	–	linear
FC8	0	–	–	linear
PC1	0.01	0.12	0.5	nonlinear
PC2	–	–	–	No control valve
PC3	–	–	–	No control valve
PC4	–	–	–	No control valve
PC5	–	–	–	No control valve
LC2	0	–	–	linear
LC3	0	–	–	linear
LC4	0.021	0	–	linear
LC5	0	–	–	linear
LC7	–	–	–	cascaded (FC5)
LC8	–	–	–	cascaded (FC6)
TC2	0.080	0.227	1.25	nonlinear

Table 2. Valve Stiction Diagnosis

municated to the plant personnel and the confirmation through bump tests or by taking these loops off-line is currently awaited.

4. Directions for future work

In the earlier sections, we demonstrated the utility of some powerful methods for detection and diagnosis of plant wide oscillations. Though useful, these methods show some limitations, which are discussed here. In addition, we also discuss some important issues for root cause diagnosis, which have received limited attention, as observed during this application study.

For dealing with large scale systems, it is important that the detection algorithm be implemented in a fully automated form. Additional benefits can be reaped when this algorithm is used as a stand alone unit, that can infrequently collect data from historian and analyze it independently. Such methods have been available for some time for loop by loop analysis (see *e.g.* [5]), but these methods do not take the plant wide nature of oscillations into account. The acf based detection algorithm [15] is a promising technique that addresses this issue, but is prone to premature termination (see Remark 2) and false detections (see Remark 3) and further improvement is required.

The higher order statistics based methods are useful for identifying nonlinear loops with the help of detection of nonlinearity in process measurements. But the method described in [1] currently works on single loop basis. The method needs to be extended to take into account the multivariate nature of the chemical processes. Further, in its present form, the method assumes that the only source of nonlinearity in the control loop is the valve. The nonlinearities present in the external disturbances may also show elliptic patterns in the $pv - op$ plots and isolating the source of nonlinearity can be difficult.

As pointed out by Thornhill *et.al.*(2003) [14] that it is necessary to find a feasible mechanism that explains the oscillation propagation to different measurements. For this purpose, use of process understanding can be very challenging for systems with severe mass, energy and information integration, such as the present case study. Huang *et.al.*(2002) [7] have suggested using correlation based signed digraphs for path analysis of plant wide disturbances. This method requires that a clear distinction be made between the variables that are affected and variables causing the effect. In many industrial processes, particulary under multivariate control, such a distinction is difficult, which limits the application of this method.

During the past few years, use of model based predictive controllers has increased rapidly in process industries. The success of these applications depends heavily on the model accuracy and severe model mismatch can also give rise to oscillations [4]. Assessing the feasibility of oscillations due to model mismatch is a difficult issue, primarily due to fact that the true model is never known. To this end, Loquasto and Seborg (2003) [8] have proposed a method, where the closed loop response of the model based controller is simulated using different scenarios of disturbances and plant changes to diagnose the fault. However, in practical scenarios, it may be difficult to find the appropriate model mismatch to simulate the oscillatory behavior of the measurements.

5. Conclusions

Despite its significant economic incentives, detection and diagnosis of plant wide oscillations have received limited attention from academia. This paper demonstrated the utility of some emerging techniques useful for root cause analysis of oscillations through an industrial case study. It is pointed out however that many issues need to be resolved before a systematic method requiring minimal human interaction becomes available for problems arising in this technically challenging area having significant practical applicability.

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