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Diagnosis of plantwide oscillations: A harmonics analysis approach

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Abstract—Highly complex and integrated modern chemical process plants are susceptible to disturbances propagate throughout the plant from one unit to other interconnected units and create plantwide oscillations. These persisting oscillations are originated due to various faults such as sensor faults, valve faults, process faults, and controller tuning faults. A fundamental frequency and its harmonics can characterize these types of nonlinear faults. This paper demonstrates a novel data-driven off-line time-domain method to identify the root cause of plantwide or unit-wide disturbances to troubleshoot plantwide disturbances using harmonics analysis. The successful application of the proposed method has been demonstrated through simulated data.

I. INTRODUCTION

It is obvious that when an oscillation is generated in a particular part in a highly complex and integrated modern chemical process plants, it then propagates throughout the whole plant or a group of interconnected units. These oscillations are termed as plantwide or unitwide oscillation(s) which ultimately pose a large threat on product quality, running cost and profitability because production and throughput may have to back away from their optimum settings to accommodate process variability [1].

Thus, it is important for process control engineers to detect and diagnose the causes of oscillations or disturbances in a chemical process operation as soon as possible [2], [3]. Over the last few years, some studies were carried out to detect plantwide oscillations [4], [5] and to group the similar oscillations together. For the detection of oscillations in process measurements and identify signals with common oscillatory behavior, the use of spectral principal component analysis (PCA) [6] or autocorrelation function (ACF) [7] is suggested. [8] have proposed a technique that takes into account the interaction between the control loops. [9] introduced a new index called power spectral correlation index (PSCI) which is the correlation between the power spectra of two different measurements.

They proposed the use of PSCMAP (Power spectral

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correlation map) to automatically re-arrange and group variables together, which oscillate at a common frequency. However, after the detection of plantwide oscillation, the next step is the diagnosis of its root-cause. Recently there appeared a few papers that described a few techniques to perform root-cause diagnosis of plant-wide oscillation [9], [10], [11], [12], [13]. [6] Proposed a new procedure based on the spectral envelope method for detection and diagnosis of common oscillation(s). This paper demonstrates a novel data driven off-line time domain method to troubleshoot plantwide disturbances using harmonic analysis.

A. Oscillations and Harmonics

It is observed that nonlinearity induced oscillatory signals generally contain a fundamental frequency and its harmonics. A very common cause for oscillation is the presence of nonlinearity such as a valve stiction which often results in square-like waves in the controlled variable [15]

Figure 1 demonstrates the time series data and corresponding power spectra for a sticky valve. The time trend is almost rectangular and the power spectra give peaks at the normalized frequency of 0.0078, 0.024 and 0.039. Here, 0.0078 is the fundamental frequency and 0.024 and 0.039 are the third and fifth harmonics respectively. According to Fourier series any signal can be represented as a summation of sinusoids. Therefore, any time series y(t), where t Є R can be represented as,

$$y(t) = \sum_{i=0}^{\infty} A_i \cos(\lambda_i t + \phi_i) \quad (1)$$

For a signal containing harmonics, Equation (1) takes the following form:

$$y(t) = \sum_{i=0}^{M} A_i \cos(i * \lambda t + \phi_i) + \varepsilon(t) \quad (2)$$

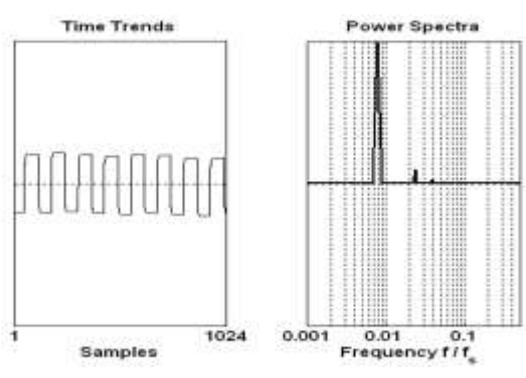

Fig. 1. Time series data and the power spectra for a sticky valve.

Where, λ is the fundamental frequency. The general approach is to estimate the amplitudes, frequencies and phases for each term of Equation (2) and then examine the relationships among the frequencies to identify the presence of harmonics in the signal. [4] Suggested that it suffices to write the above expression only up to fifth harmonics for useful application of the analysis of chemical process data.

B. Total Harmonic Content (THC)

A new index called the Total Harmonic Content (THC) can be defined by the following expression of Equation 3,

$$THC = n \times WHM \quad (3)$$

Where, n is the number of harmonics found and WHM is the Weighted Harmonic Mean. WHM is defined as,

$$WHM = \frac{\sum_{i=1}^{M} w_i}{\sum_{i=1}^{M} w_i / A_i} \quad (4)$$

where w_i is weights and is defined as $w_i = i / \sum_{i=1}^{M} i$. Due to the low-pass filtering effect of the chemical processes, the higher harmonics get filtered out gradually as the signal propagates away from the source or the root cause. Hence, more weights are given to the higher harmonics.

For plantwide oscillation(s) detection, the amplitudes, frequencies and phases of first five terms of equation (2) are estimated for time series data of each tag. Tags or variables having the same fundamental frequency and harmonics (if any) are identified. Weighted harmonic mean is calculated using amplitudes whose frequencies are in harmonics and multiplied by number of harmonics present. After calculating the THCs using equation (3), the variables are ranked according to the descending order of THC. The possibility of being the root cause increases with the increase of the value of THC.

II. CASE STUDY

C. Simulation Example

This simulation example involves a large, industrially relevant system of vinyl acetate monomer (VAc) manufacturing process. [14] Developed the Nonlinear Dynamic Model of this VAc process in MatLab which is freely available from the authors' website.

In the VAc process, there are 10 basic unit operations, which include a vaporizer, a catalytic plug flow reactor, a feed-effluent heat exchanger (FEHE), a separator, a gas

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compressor, an absorber, a carbon dioxide (CO_2) removal system, a gas removal system, a tank for the liquid recycle stream and an azeotropic distillation column with a decanter. There are seven chemical components in the VAc process. Ethylene (C_2H_4), pure oxygen (O_2), and acetic acid (HAc) are converted into the vinyl acetate (VAc) product, and water (H_2O) and carbon dioxide (CO_2) are by-products. An inert, ethane (C_2H_6), enters with the fresh C_2H_4 feed stream. For details, refer to [1]. Figure 2 shows a simplified schematic of the Vinyl Acetate Process with the locations of the manipulated variables.

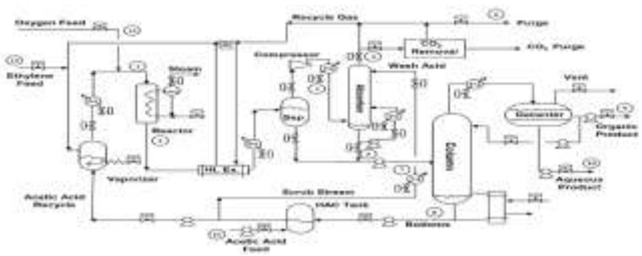

Fig. 2. VAc process flowsheet [1].

In order to create plantwide oscillations disturbance, valve stiction was introduced to control loops 9 and 14, independently. Valve stiction was introduced using Choudhury's stiction model [3]. To create limit cycle oscillations. The oscillation then propagate to the other control loops and eventually to the whole plant or some part of the plant.

In loop 9, the controlled variable is the separator temperature and the manipulated variable is the separator coolant valve corresponding to the cooling water flow rate for the separator jacket. After the process reached steady state, 5% stiction (where S = J) was introduced in the manipulated variable coolant valve. Simulation data set consisted of 2000 minutes of data with a sampling time of 15 seconds; therefore, each variable has 8000 observations. The last 1024 data points were used in this analysis in order to avoid transient behavior due to the sudden introduction of stiction.

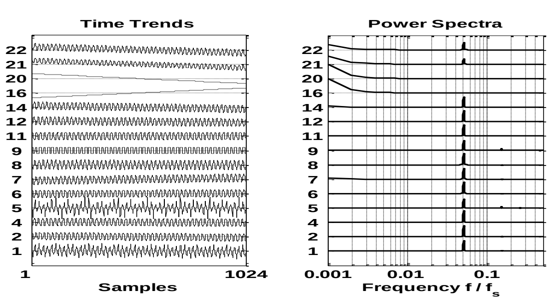

Fig. 3. Time trends and power spectra for the VAc process variables, applied stiction in loop 9 is 5%.

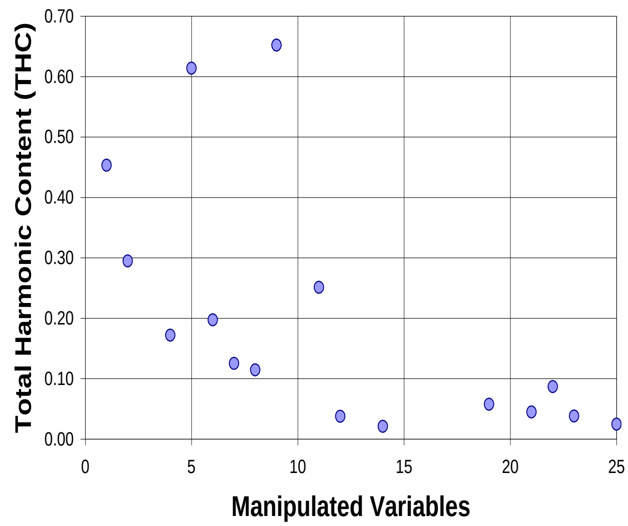

Fig. 4. THC values for the VAc process variables for 5% stiction applied in loop 9.

Figure 3 shows the time trends and power spectra which indicates that the variables 1, 2, 4, 5, 6, 7, 8, 9, 11, 12, 14, 21 and 22 are oscillating together. The high density plot reveals that they are oscillating at a normalized frequency of 0.0505.

Table 1 shows the harmonic analysis of the simulated data. The algorithm correctly identifies the presence of sinusoids in the signal. Five sinusoids are estimated for each signal. Total Harmonic Content (THC) was calculated for these variables. The maximum THC corresponds to tag 9 indicating the source or root-cause of the propagated oscillation because stiction was introduced in this variable during simulation. Figure 4 shows the calculated THC values against the variable or tag number.

D. An Industrial Example-Application to a Refinery Data Set

The proposed method was applied to a benchmark industrial data set for plantwide oscillations study appeared in the literature such as [9]-[10].

The data set, courtesy of a SE Asian Refinery, consists of 512 samples of 37 measurements sampled at 1 min interval. It comprises measurements of temperature, flow, pressure and level loop along with some composition measurements. Figure 5 depicts the time trends of the controller errors and the corresponding power spectra.

The calculated THC values are plotted against the tag number in Figure 6. The highest THC value corresponds to the tag no. 34, which is the first candidate for the possible

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root-cause of this plantwide oscillation.

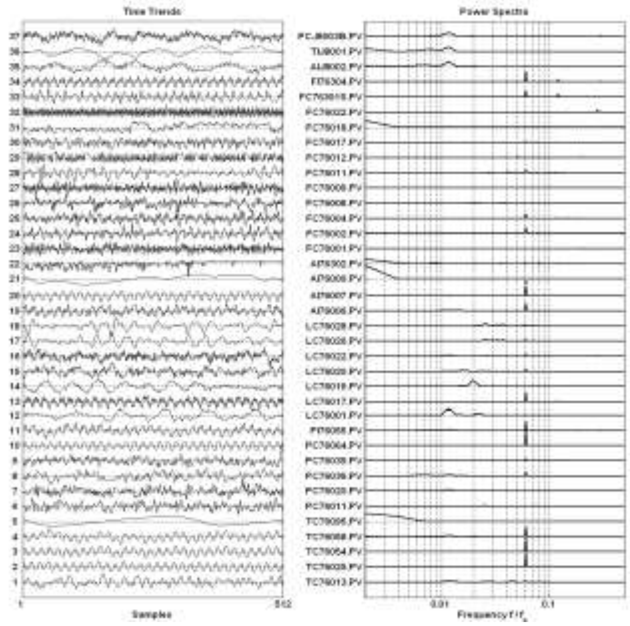

Fig. 5. Time trends and power spectra for the South-East Asia refinery data set.

From these figures, it can be found that the tags 2, 3, 4, 8, 9, 10, 11, 13, 15, 16, 17, 19, 20, 24, 25, 28, 33 and 34 are oscillating together with a common frequency of 0.0605 or 17 samples/cycle approximately. All data corresponding to the variables with the common frequency were first normalized so that they had zero mean and unit variance. Then the amplitudes, frequencies and phases for first five sinusoids were estimated and THCs were calculated for these variables.

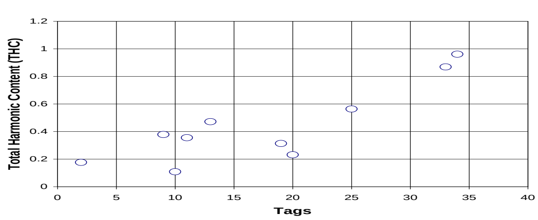

Fig. 6. Total harmonic contents (THC) results for SEA refinery data set.

In real plant investigation if this tag is not found to be the root cause, then the tag corresponding to next highest value of THC should be investigated. For this case, earlier studies [9], [10] and [11] found tag 34 as the root-cause. Therefore, the proposed THC index correctly detected the root-cause of this plantwide oscillation.

III. CONCLUSION AND FUTURE WORK

In this paper a new index called THC (Total Harmonic Content) is introduced to troubleshoot plantwide oscillation(s). Through simulation and industrial data analysis case studies, it has been shown that THC is an effective tool for isolating the root cause of plantwide oscillation(s). The method can be automated to facilitate troubleshooting of plantwide oscillation.

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Appendix

MV	λ_1	λ_2	λ_3	λ_4	λ_5	A_1	A_2	A_3	A_4	A_5	ϕ_1	ϕ_2	ϕ_3	ϕ_4	ϕ_5	λ_1/λ_1	λ_2/λ_1	λ_3/λ_1	λ_4/λ_1	λ_5/λ_1	RESS	THC
1	**0.317**	0.951	1.585	2.219	2.853	1.339	0.309	0.169	0.114	0.083	-0.69	2.812	0.856	-0.91	-2.63	1.000	3.000	5.000	7.000	9.000	30.8	0.450
2	**0.317**	0.951	1.585	2.219	2.853	1.383	0.266	0.101	0.051	0.029	-2.44	1.366	-0.50	-2.24	2.397	1.000	3.000	5.000	7.000	9.000	1.8	0.293
3	0.006	0.317	0.012	0.018	0.043	1.004	0.968	0.237	0.073	0.033	-0.17	2.731	0.479	0.874	1.374	1.000	50.00	1.891	2.846	6.711	2.7	
4	**0.317**	0.951	1.585	2.219	0.323	1.401	0.161	0.058	0.029	0.024	0.123	-2.13	2.376	0.692	-1.61	1.000	3.000	5.000	7.000	1.019	1.2	0.136
5	**0.317**	0.951	1.585	2.219	2.853	1.218	0.389	0.235	0.168	0.130	-1.00	2.952	1.142	-0.46	-2.01	1.000	3.000	5.000	7.000	9.000	135.4	0.603
6	**0.317**	0.951	1.585	2.219	0.323	1.399	0.184	0.067	0.033	0.025	-2.60	1.229	-0.66	-2.43	1.934	1.000	3.000	5.000	7.000	1.019	1.2	0.151
7	**0.317**	0.951	1.585	2.219	0.323	1.401	0.181	0.057	0.025	0.026	-2.37	0.709	-1.38	2.947	2.175	1.000	3.000	5.000	7.000	1.019	0.9	0.140
8	**0.317**	0.951	1.585	2.219	0.323	1.402	0.150	0.052	0.025	0.026	-0.76	-2.44	2.196	0.567	-2.50	1.000	3.000	5.000	7.000	1.019	0.9	0.129
9	**0.317**	0.951	1.585	2.220	2.854	1.272	0.423	0.252	0.178	0.137	-2.33	2.400	0.848	-0.69	-2.22	1.000	3.000	5.000	7.000	9.000	45.0	**0.649**
10	0.004	0.012	0.021	0.029	0.038	1.316	0.445	0.264	0.177	0.137	-3.08	0.600	-2.44	0.951	-1.99	1.000	2.854	4.858	6.838	8.735	36.0	
11	**0.317**	0.951	1.585	2.219	0.323	1.387	0.245	0.085	0.037	0.024	-3.01	0.791	-1.28	3.055	1.558	1.000	3.000	5.000	7.000	1.019	1.2	0.177
12	**0.317**	0.951	0.323	0.311	1.585	1.412	0.067	0.026	0.025	0.009	0.613	-2.90	-1.14	-0.98	1.160	1.000	3.000	1.019	0.982	5.000	0.3	0.033
13	0.004	0.030	0.009	0.063	0.093	1.254	0.231	0.242	0.101	0.071	2.791	2.051	-3.04	-1.73	1.769	1.000	7.966	2.402	16.54	24.55	10.5	
14	**0.317**	0.323	0.311	0.951	0.029	1.411	0.025	0.025	0.018	0.015	0.059	-1.68	-1.61	-2.98	-0.75	1.000	1.020	0.982	3.000	0.090	0.5	0.024
15	0.004	0.025	0.009	0.078	0.052	1.241	0.236	0.238	0.086	0.127	2.823	2.336	-2.96	2.133	-1.10	1.000	6.474	2.399	20.46	13.55	14.8	
16	0.006	0.012	0.017	0.029	0.023	1.404	0.346	0.134	0.091	0.093	3.104	-3.09	-3.03	2.895	3.065	1.000	1.902	2.719	4.547	3.630	3.0	
17	0.007	0.014	0.024	0.030	0.042	1.245	0.516	0.299	0.203	0.140	2.886	0.549	2.713	1.675	-3.12	1.000	1.971	3.407	4.190	5.909	31.6	
18	0.007	0.011	0.004	0.020	0.025	0.927	0.382	0.798	0.181	0.082	-2.71	2.195	-2.50	-2.48	2.587	1.000	1.581	0.611	2.840	3.556	10.7	
19	**0.317**	0.951	0.323	0.311	1.585	1.409	0.085	0.026	0.024	0.022	2.335	-1.29	0.610	0.687	2.766	1.000	3.000	1.019	0.982	5.000	0.4	0.064
20	0.006	0.157	0.314	0.471	0.012	0.944	0.807	0.407	0.272	0.168	-0.14	1.508	1.434	1.323	0.049	1.000	24.41	48.82	73.25	1.926	102.4	
21	**0.317**	0.006	0.951	0.157	0.323	1.411	0.052	0.043	0.039	0.028	-1.55	-0.02	-1.33	-0.14	3.088	1.000	0.020	3.000	0.496	1.018	0.5	
22	**0.317**	0.951	0.006	1.585	0.323	1.408	0.099	0.037	0.028	0.026	-1.15	-2.27	0.144	2.112	-2.80	1.000	3.000	0.020	5.000	1.019	1.0	
23	**0.317**	0.157	0.951	0.323	0.311	1.411	0.069	0.033	0.028	0.017	-2.63	-2.19	2.428	2.162	2.553	1.000	0.495	3.000	1.018	0.980	0.3	
24	0.006	0.317	0.012	0.018	0.024	1.110	0.853	0.241	0.091	0.046	-0.14	-2.75	0.449	0.587	0.446	1.000	50.19	1.870	2.831	3.842	2.1	
25	**0.317**	0.006	0.012	0.323	0.311	1.395	0.214	0.046	0.027	0.024	1.083	2.980	-2.69	-0.70	-0.34	1.000	0.020	0.038	1.019	0.982	0.7	
26	0.004	0.012	0.021	0.029	0.038	1.316	0.445	0.264	0.177	0.137	0.060	-2.54	0.701	-2.19	1.148	1.000	2.854	4.858	6.838	8.735	36.0	