Automatic Detection and Estimation of Amplitudes and Frequencies of Multiple Oscillations in Process Data

M. A. A. Shoukat Choudhury

***Abstract*— This paper presents a novel method for detection and estimation of multiple oscillation frequencies and amplitudes present in a time series. The method is based on the Fourier Series decomposition of the time series utilizing the principle of linear regression technique. First, the frequencies of oscillations are estimated and then their amplitudes are found. Statistical hypothesis tests are performed on the oscillation amplitudes to determine the number of significant frequencies present in a time series. A new oscillation index is defined which is bounded between 0 and 1 and signifies the strength of oscillation. The impact of oscillation on the variable or on the control loop is determined from a new index called, Relative Oscillation Amplitude in Percentage (*ROAP*). The proposed method is evaluated extensively using simulated examples and industrial data.**

I. INTRODUCTION

Large process plants, such as oil refineries, power plants and pulp mills, are complex integrated systems, containing thousands of measurements, hundreds of controllers and tens of recycle streams. The integration of energy and material flow, required for efficiency, results in the spread of fluctuations throughout a plant. The fluctuations force the plant to be operated further from the economic optimum that would otherwise be possible, and thus cause decreased efficiency, lost production and in some cases increased risk. Because of the scale of operation of process plants, a small percentage decrease in productivity has large financial consequences. It can be extremely difficult to pinpoint the cause of these fluctuations. In the most difficult case, the fluctuations are in the form of oscillations. Often times oscillations go unnoticed by the operators because they look at many variables together in the DCS console in a large range ordinate scale. Also, oscillations have no defined beginning and end. Therefore, it is important to detect oscillations, their amplitudes and frequencies as a part of loop performance audit work in an automatic fashion. Once the oscillations are detected and their impacts or strengths are identified, their root cause should be located,isolated and resolved. Finding the cause of oscillations is a tedious and labor-intensive task. Once the cause is understood, removal of the oscillations is usually straightforward. Therefore, it is important to detect oscillations, estimate their periods and quantify their strength. A tool that can automatically detect oscillations and their period and determine the degree of strength of the oscillation from their amplitudes is much desired by the process engineers.

Department of Chemical Engineering, Bangladesh University of Engineering and Technology (BUET), Dhaka - 1000, Bangladesh shoukat@che.buet.ac.bd

Two types of oscillation detection methods appeared in literature. The first kind focuses on the detection of oscillation by a loop by loop analysis [12], [4]. The second category considered the plant-wide nature of oscillations [3], [2], [9], [10], [5]. To detect oscillations in process measurements and identify signals with common oscillatory behavior, use of spectral principal component analysis [11] or autocorrelation functions (acf) [10] is suggested. [13] have also proposed a technique that takes into account the interactions between control loops.[6] used adjaceny matrix to diagnose root cause of plantwide oscillation Power Spectral Density(PSD)and Auto Correlation Function (ACF) based oscillation detection method followed by a model based approach for identifying and quantifying the root-cause of the oscillations is appeared in [7]. The methods appeared in literature can deal with one oscillation at a time. For detection of multiple oscillations, they require filtering of data which involves filter design that may require user's input. This study developed an automatic method for detecting multiple oscillations, their periods and amplitudes in time series data obtained from routine operation of any process.

II. DETECTION OF OSCILLATIONS

A simple oscillation can be represented using the equation of a sinusoid:

$$y(t) = A\sin(\omega t + \phi) \tag{1}$$

As shown in Equation 1, an oscillation can be characterized with three parameters namely its amplitude, frequency and phase. Another important property of oscillation is that it is periodic, which essentially signifies that at least theoretically the half of a period contains full information for characterizing an oscillation. This property holds for any regular periodic signal or time series. Now, a time series containing multiple oscillations is usually also periodic in nature. However, it may or may not be visible depending on the number of sinusoids and noise in the signal. Such a time series can be decomposed into sinusoidal periodic components based on Fourier Series analysis. Any such a signal or time series, $y(t)$, can be decomposed as:

$$y(t) = A_0 + \sum_{i=1}^{\infty} A_i \cos(\omega_i t + \phi_i) \tag{2}$$

where, A_0 is the non-zero or dc component, A_i's are amplitudes of sinusoids having frequencies ω_i's and ϕ_i's are phase. The main idea of this paper is to estimate each component of Equation 2 at a time. Since it is practically impossible to estimate amplitudes, frequencies and phases for infinite number of terms/components of Equation (2), only the first 'm' number of terms are estimated. Therefore, Equation (2) can be rewritten as:

$$y(t) = A_0 + A_1\cos(\omega_1 t + \phi_1) + A_2\cos(\omega_2 t + \phi_2) + \ldots \\ A_m\cos(\omega_m t + \phi_m) + \varepsilon(t) \quad (3)$$

$\varepsilon(t)$ is the error due to omission of terms after the m^{th} term. As the chemical process units acts as a filter for higher order frequencies, from the experience of the author, it would be sufficient to write the equation up to the tenth term, i.e., m=10 [1]. The actual value of m, that is the actual number of sinusoids needs to be estimated and the method for it is discussed in Section V. Iterative Auto-Regressive Moving Average (ARMA) technique with Least Squares Linear Regression has been employed to estimate the frequencies, amplitudes and phases of Equation (3).

III. Estimation of Frequency by an Iterative ARMA Technique

Maximum likelihood and Autoregressive Moving Average (ARMA) techniques are two popular methods for estimating the frequency of a sinusoid that may be present in a time series. Maximum likelihood techniques for estimating frequency are computationally intensive and requires good initial estimates. Good initial estimates are often difficult to obtain. Therefore, a method which works with relatively poor initial estimates are desired. ARMA based method is such a technique whis is robust and works with poor initial estimates. In this study, Quinn & Fernandes [8] technique based on ARMA method has been used. This method is based on the fact that sinusoids are the solutions to the second order difference equations whose auxiliary polynomials have all of their zeros on the unit circle. Thus this method places the outset poles on the unit circle, and iteratively achieves an estimator. So, There is a second order filter which annihilates a discrete-time sinusoid at a given frequency. If any given time series, $y(t)$ satisfies

$$y(t) = A\cos(\lambda\ t + \phi) + \xi(t) \quad (4)$$

where, $\xi(t)$ is a white noise sequence. Then, it can be said that there is a sinusoid with frequency $\lambda/2\pi$ in the time series data.

A second order filter of type $(1 - 2z\cos(\omega') + z^2)^{-1}$ applied to a signal will annihilate a (discrete-time) sinusoid at a given frequency and makes it ring when the frequency ω' is near the true frequency. Thus, if a time trend $y(t)$ satisfies Equation 4, it also satisfies

$$y(t) - 2\cos\omega y(t-1) + y(t-2) = \xi(t) - 2\cos\omega\xi(t-1) + \xi(t-2) \quad (5)$$

Therefore, the time series $y(t)$ satisfies an ARMA(2,2) equation, which does not have a stationary or invertible solution. This representation suggests that ω may be estimated by iterative ARMA-based techniques. Suppose that we wish to estimate α and β in

$$y(t) - \beta y(t-1) + y(t-2) = \xi(t) - \alpha\xi(t-1) + \xi(t-2) \quad (6)$$

while preserving $\alpha = \beta$. If α is known, and the ξ are independent and identically distributed, then β can be estimated by Gaussian maximum likelihood, that is, by minimizing

$$\sum_{t=0}^{N-1}\varepsilon^2_{\alpha,\beta}(t) = \sum_{t=0}^{N-1}\{\xi(t) - \beta\xi(t-1) + \xi(t-2)\}^2 \quad (7)$$

with respect to β, where $\xi(t) = y(t) + \alpha\xi(t-1) - \xi(t-2)$ and $\xi(t) = 0, t < 0$. In other words, $\xi(t)$ is the output signal while by passing $y(t)$ as input signal through a filter as given by $\frac{1}{1-\alpha q^{-1}+q^{-2}}$. As this is quadratic in β, minimizing the value is the regression coefficient of $\xi(t) + \xi(t-2)$ on $\xi(t-1)$,

$$\frac{\sum_{t=0}^{N-1}\{\xi(t)+\xi(t-2)\}\xi(t-1)}{\sum_{t=0}^{N-1}\xi^2(t-1)} = \alpha + \frac{\sum_{t=0}^{N-1}y(t)\xi(t-1)}{\sum_{t=0}^{N-1}\xi^2(t-1)} \\ = \alpha + h_T(\alpha) \quad (8)$$

We then put α equal to this value and re-estimate β using Equation (8) and continue until α and β are sufficiently close. Then, estimate ω from the equation $\alpha = 2\cos\omega$.

This algorithm can be summarized as below:

1) Put $\alpha_1 = 2\cos\hat{\omega}_1$, where $\hat{\omega}_1$ is an initial estimator of the true value ω_0. This can be estimated from power spectrum.
2) For $j > 1$, put $\xi(t) = y(t) + \alpha_j\xi(t-1) - \xi(t-2)$, $t = 0, \ldots, N-1$ where $\xi(t) = 0, t < 0$.
3) Put $\beta_j = \alpha_j + 2\frac{\sum_{t=0}^{N-1}y(t)\xi(t-1)}{\sum_{t=0}^{N-1}\xi^2(t-1)}$
4) If $|\beta_j - \alpha_j|$ is suitably small, estimate $\hat{\omega} = \cos^{-1}(\beta_j/2)$. Otherwise, let $\alpha_{j+1} = \beta_j$ and go to step 2.

The factor 2 in step 3 is introduced for rapid convergence. Once the frequency is estimated, the amplitudes and phases can be estimated using least-square regression method.

IV. Least Squares Linear Regression Method for Estimating Amplitudes and Phases

Data are available as time series sampled at a fixed interval of time. Least-square regression technique is used to estimate each component of any time series data $y(t)$, shown in Equation (9).

$$y(t) = \sum_{t=0}^{m} A_i\cos(\omega_i t + \phi_i) + \varepsilon(t) \quad (9)$$

For example, if y is the time series data, $y_1 = A_1\cos(\omega_1 t + \phi_1)$ will be first estimated. Therefore, let us write,

$$\begin{aligned} y &= A_0 + A_1\cos(\omega_1 t + \phi_1) + e_1 \\ &= A_0 + \alpha\cos(\omega_1 t) + \beta\sin(\omega_1 t) + e_1 \end{aligned} \quad (10)$$

where, $\alpha = A_1\cos(\phi_1)$ and $\beta = -A_1\sin(\phi_1)$. Equation (10) contains four unknowns namely A_0, α, ω_1 and β. The frequency ω_1 will be estimated first by using the technique discussed in the last section. If ω_1 is known, parameters of Equation (10) can be calculated using simple linear regression techniques. Predictions of y can be made from the regression model,

$$\hat{y} = \hat{A_0} + \hat{\alpha}\cos(\omega t) + \hat{\beta}\cos(\omega t) \tag{11}$$

where $\hat{A_0}, \hat{\alpha}$ and $\hat{\beta}$ denote the esimated values of A_0, α and β, $\hat{y}$ denotes the predicted value of y. Each observation or sample of y will satisfy

$$y_i = A_0 + \alpha\cos(\omega_1 t_i) + \beta\sin(\omega_1 t_i) + e_i$$

The least square method calculates values of A_0, α and β, that minimizes the sum of the squares of the errors SSE for an arbitrary number of data points, N:

$$SSE = \sum_{i=1}^{N} e_i^2$$

Using least-squares regression technique, it can be shown that the least-squares estimates of A_0, α and β is as follows:

$$\begin{bmatrix} \widehat{A}_0 \\ \widehat{\alpha} \\ \widehat{\beta} \end{bmatrix} = D^{-1}(\omega_1)E(\omega_1)$$

where

$$D(\omega_1) = \begin{bmatrix} N & \sum_{t=0}^{N-1}\cos(\omega_1 t) & \sum_{t=0}^{N-1}\sin(\omega_1 t) \\ \sum_{t=0}^{N-1}\cos(\omega_1 t) & \sum_{t=0}^{N-1}\cos^2(\omega_1 t) & \sum_{t=0}^{N-1}\sin(\omega_1 t)\cos(\omega_1 t) \\ \sum_{t=0}^{N-1}\sin(\omega_1 t) & \sum_{t=0}^{N-1}\sin(\omega_1 t)\cos(\omega_1 t) & \sum_{t=0}^{N-1}\sin^2(\omega_1 t) \end{bmatrix} \tag{12}$$

$$E(\omega_1) = \begin{bmatrix} N \\ \sum_{t=0}^{N-1} y(t)\cos(\omega_1 t) \\ \sum_{t=0}^{N-1} y(t)\sin(\omega_1 t) \end{bmatrix} \tag{13}$$

Thus, $\hat{A_1}, \omega_1$ and ϕ_1 of first term of Fourier series expansion are estimated. Now, the residuals can be found from $y(t) - \hat{y(t)}$. From the residuals, the second sinusoidal components can be estimated. Similarly, all m terms of equation 3 can be estimated.

V. Determination of Significant Number of Oscillation Components or Sinusoids, 'm'

In practice, all signals contain noise. Therefore, the power spectrum used for an initial estimate of frequencies will have peaks that can be mistakenly identified as a sinusoid. To test whether there is a sinusoid or not, consider the subset of sinusoidal models

$$y(t) = \mu + A\cos(\lambda_j t + \phi) + x(t), \quad t = 0,\ 1,\ \ldots,N-1 \tag{14}$$

where $\lambda_j = 2\pi j/N$ but j is unknown and $x(t)$ is Gaussian and an independent sequence, and therefore 'white'. It is not practically possible to estimate all sinusoidal components in the Equation 14. Null hypothesis test was employed to see whether an error signal may contain sinusoid or not in the Equation 14. Hence, We wish to test

$$H_0 : A_i = 0 \tag{15}$$

against

$$H_1 : A_i > 0 \tag{16}$$

A test which has usually good asymptotic properties and simple to derive is the likelihood ratio test, which rejects the null hypothesis on large values of the ratio of the maximum likelihood under H_1 to the maximized likelihood under H_0. The former is just

$$-\tfrac{N}{2}\log(2\pi\hat{\sigma}_A^2) - \tfrac{N}{2}$$

while the latter is

$$-\tfrac{N}{2}\log(2\pi\hat{\sigma}_0^2) - \tfrac{N}{2}$$

where

$$\hat{\sigma}_0^2 = \tfrac{1}{N}\textstyle\sum_{t=0}^{N-1}\{y(t) - \bar{y}\}^2$$

$$\hat{\sigma}_A^2 = \tfrac{1}{N}[\textstyle\sum_{t=0}^{N-1}\{y(t) - \bar{y}\}^2 - \max_{1\le j\le n} I_y(\lambda_j)]$$

and $n = \lfloor (N-1)/2 \rfloor$. We thus rejects H_0 if $\hat{\sigma}_A^2/\hat{\sigma}_0^2$ is too large, or, equivalently if Fisher's g factor is too small. Fisher's g factor as defined by

$$g = \frac{max_{1\le j\le n} I_y(\omega_j)}{\sum_{t=0}^{N-1}\{y(t) - \bar{y}\}^2} \tag{17}$$

was used in the test. We thus rejects H_0 if g is too small.

VI. Simulation Example

The purpose of this section is to evaluate the proposed oscillation detection technique in a controlled simulated environment where everything is known. An analytical signal is generated using the following formulation

$$x_1(k) = \sin(2*\pi*f_1*k) + \ sin(2*\pi*f_2*k\ +\phi) \\ +\ sin(2*pi*f_3*k+\phi_3)\ +\ d(k) \tag{18}$$

where, $f_1 = 0.01$, $f_2 = 0.12$, $f_3 = 0.30$, $\phi_2 = \pi/3$, $\phi_3 = 2*\pi/3$, and $d(k)$ is a random noise whose variance can be adjusted to increase or decrease the signal to noise ratio (SNR). The SNR is defined as:

$$SNR = \frac{variance\ of\ noise\ free\ signal}{variance\ \ of\ noise} \tag{19}$$

Ten time series data for varying signal to noise ratios have been generated and are shown in Figure 1. The time series in the topmost panel has the SNR of 22.18 and the bottom-most signal has a SNR of 0.23. This means the noise in the bottom-most panel is 5 times more than the actual signal.

Since in practice, the number of sinusoids are not known a priori, here five sinusoids were estimated. The estimated amplitudes, frequencies and phases are shown in Table I. As shown in this Figure, the frequencies f_1 f_2 and f_3 are the 3 frequencies that were used to construct the signal. Other two frequencies f_4 and f_5 are also estimated but their amplitudes are much smaller compared to the amplitudes of the other three frequencies. As the noise increases, the magnitudes of these spurious frequencies also increase and this makes sense. In order to decide whether the estimated frequencies are significant, statistical hypothesis tests were carried out. The test described in Section V was applied to each time series and Fisher's discriminant factor,g, was calculated. These calculated g values are plotted in Figure 2. As shown in Figure 2, the threshold or critical value of g can safely be chosen as 10 below which the estimated sinusoids

Fig. 1. Time Trends of Analytical Signals

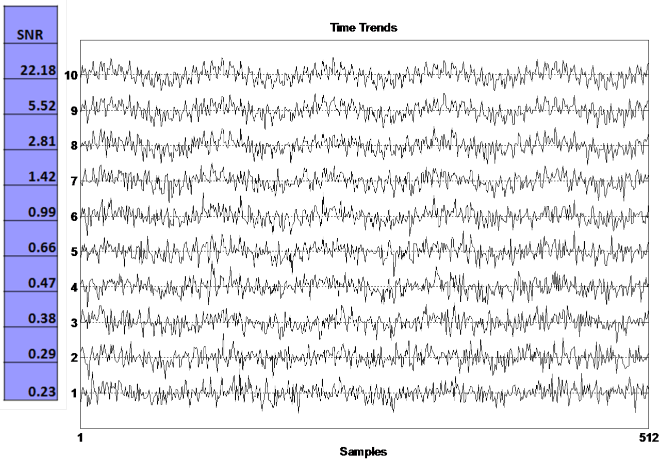
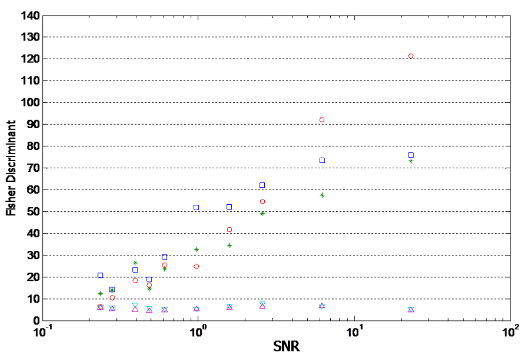


TABLE I
ESTIMATED FREQUENCIES, AMPLITUDES AND PHASES OF FIVE SINUSOIDS

SNR	f1	f2	f3	f4	f5	A1	A2	A3	A4	A5	ph1	ph2	ph3	ph4	ph5	SSE
22.18	0.010	0.300	0.120	0.074	0.422	0.99	1.00	1.03	0.07	0.06	-1.42	-1.56	1.57	1.54	-0.97	33
5.52	0.010	0.300	0.120	0.232	0.151	1.02	1.04	1.02	0.11	0.10	-1.50	1.46	1.51	-1.17	0.35	131
2.81	0.010	0.300	0.120	0.102	0.053	1.00	1.10	0.99	0.16	0.15	-1.53	-1.46	1.56	-0.48	-1.16	257
1.42	0.010	0.120	0.300	0.070	0.199	1.05	1.01	0.88	0.27	0.21	-1.52	1.34	-1.48	0.55	0.56	500
0.99	0.010	0.300	0.120	0.357	0.185	1.01	0.93	0.97	0.27	0.28	1.48	1.33	-1.40	-0.65	0.75	716
0.66	0.010	0.300	0.120	0.227	0.356	0.97	1.03	1.20	0.41	0.37	-1.42	-1.47	1.32	-0.75	1.27	1073
0.47	0.010	0.120	0.300	0.408	0.055	1.11	1.01	0.84	0.43	0.37	1.24	-1.38	-1.39	-0.80	0.45	1503
0.38	0.010	0.120	0.300	0.016	0.252	1.06	0.99	1.06	0.39	0.37	1.46	1.16	-1.30	-0.20	0.74	1901
0.29	0.300	0.010	0.120	0.024	0.352	1.13	0.84	1.21	0.52	0.54	0.96	-1.53	1.14	0.18	0.01	2470
0.23	0.010	0.300	0.120	0.293	0.410	1.03	1.12	1.00	0.51	0.50	-1.52	-1.03	-1.52	0.17	0.88	3167

can be treated as spurious. In practice or for real life data, it is often fruitless task to analyze data for which the *SNR* is below 1. Therefore, for analysis of real industrial data, the threshold value of g can be chosen as 25 as suggested by the close examination of Figure 2.

Fig. 2. Fisher's Discriminant Factor, g



VII. QUANTIFYING IMPACT OF OSCILLATION

Oscillations can be regular or irregular. It can have sinusoidal component with a single frequency or multiple frequencies. If plotted, the oscillatory signal or time series with a single or multiple frequencies are easily visible by naked eye. However, for process industries where thousands of variables are logged every minute, it is not practical to plot each variable and detect oscillations visually. This necessitates an automatic method for quantifying the regularity of oscillation and its strength.

A. Oscillation Index

A new oscillation index is defined based on the Fisher's discriminant factor, g described in Section V. The new oscillation index is defined as

$$OI = 1 - \frac{g_{critical}}{\sum g_{significant}} \tag{20}$$

where, OI is the oscillation index, $g_{critical}$ is the threshold value of g below which there is no oscillation and $g_{significant}$ are the values of g for which the null hypothesis in Equation 15 is rejected, i.e., g values for significant oscillatory components. By definition, the OI is bounded between 0 and 1. An OI value close to zero means there is no oscillation, while a value close to 1 means a very strong oscillation. If there is no significant oscillation, the OI value is set to 0.

B. Strength of Oscillation

In industrial practice, many variables may be somewhat oscillatory. The oscillation index value may be high but the oscillation itself may not deserve attention because of its small amplitude compared to the mean value of the signal. Therefore, the determination of relative amplitude of oscillation as compared to its mean value is important. This can be calculated using the following equation.

$$ROAP = \frac{Amplitude\ of\ fundamental frequency}{Mean\ of\ the\ variable} * 100\% \tag{21}$$

where *ROAP* is the Relative Oscillation Amplitude in Percentage. The definition of *ROAP* may appear fragile as it implies that an oscillation of same amplitude for a particular variable with a mean of 400 unit is less severe than that with a mean of 40 unit. This observation stands valid in industrial practice. In reality, the process engineers look at the oscillation amplitude and compare it with the nominal value. The threshold value for *ROAP* will depend on the type or critical nature of the loop. From the author's experience with industrial data analysis, an oscillation with a *ROAP* value of above 0.1 should not be neglected and deserves attention by the maintenance people.

VIII. INDUSTRIAL EXAMPLE

This section evaluates the proposed oscillation detection methodology using an industrial data set from an ammonia plant. The method has been successfully applied in a few chemical plants. For the sake of brevity, result for 11 tags are presented here. Figure 3 shows the time trends and power spectra of these 11 variables. Data were collected at 4 s time interval. The results of oscillation detection algorithm are shown in Table II. Tag 1, U1FIC104BPV, does have some oscillations but not very strong. The power spectrum of this tag shows a peak at frequency 0.1. The *OI* obtained for this loop is 0.51 indicating a mild oscillation while the *ROAP* value is 0.11 indicating an insignificant variation in amplitude due to this oscillation. The time trend of Tag 2 indicates some sensor problem likely. The trends show some rectangular nature for some time and for some time it remains constant. There is no defined oscillation in this loop. The oscillation index is 0.07 only. Tag 3, variable U1FIC132, shows a complex oscillation. From the time trend and power spectra, it is visible that there are at least two oscillation - one with large oscillation period and another with high frequency or small oscillation period. The oscillation diagnosis metric in Table II shows that the dominant oscillation period is 70 samples or 280 s. The oscillation amplitude is 14.04 which is only 0.11 percent of the mean value of 13129. Therefore, the *ROAP* value is 0.11 indicating this oscillation may not be very significant because of its low amplitude though the presence of multiple oscillation in this loop indicates the poor condition of this loop. The time trend and power spectra of Tag 4 shows that this tag does not have any oscillation. The oscillation detection algorithm correctly calculates a 0 value of *OI* for this loop as shown in Table II. The time trend and power spectra of Tag 5, U1FIC201, shows a strong oscillation. The *OI* index for this loop is 0.71. The *ROAP* value for this loop is 0.81 indicating a significant impact of this oscillation on this loop and it deserves attention of maintenance people for possible maintenance. Tags 6, 9 and 10 (U1FIC305PV, U1LIC311PV,U1LIC316PV) contain a low frequency oscillation. The *OI* values for these variables are 0.81, 0.77 and 0.86, respectively indicating the presence of a dominant oscillation with oscillation period of 159, 157 and 188 samples, respectively. The *ROAP* values for these variables are 0.31, 0.22 and 0.39, respectively. The high *ROAP* values indicate the impact of oscillation on the performance of these loops cannot be neglected and should be diagnosed for further actions. Tags 7 and 11 have a very low frequency oscillation with a period of 515 and 641 samples, respectively. Since only 512 samples were used to run the oscillation detection algorithm, these results may have less reliability. Currently, for such cases the algorithm or program issues a warning message, 'Data length is shorter than oscillation period. Longer data length should be used or downsample the data'. For tag 8, the oscillation period is 509 samples and *OI* value is 0.88 indicating a strong oscillation. The data window used in the analysis barely contains one oscillation period. The algorithm is good enough to correctly detect this oscillation from this one oscillation period long data. This was possible because of the periodic nature of oscillation. As stated earlier, the half of a oscillation period data theoretically contains all information for characterizing an oscillation.

Fig. 3. Time Trends of an Industrial Dataset

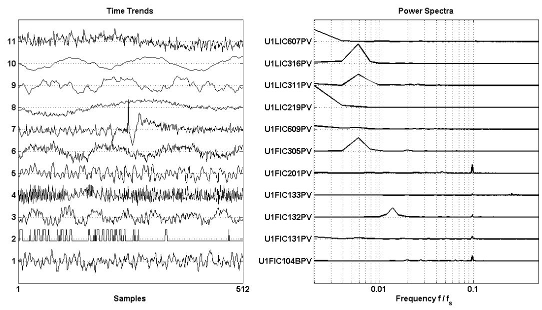


TABLE II

RESULTS OF OSCILLATION DETECTION ALGORITHM FOR INDUSTRIAL DATA SET

Loop No.	PV mean	PV std	Osc Ampltd	ROAP	Osc Period	OSC. Index
U1FIC104	38003	54.18	38.33	0.10	10	0.51
U1FIC131	4	0	0	0.00	10	0.07
U1FIC132	13129	14.51	14.04	0.11	70	0.72
U1FIC133	900	1.89	0	0.00	0	0
U1FIC201	259	2.41	2.09	0.81	10	0.71
U1FIC305	1333	3.59	4.09	0.31	159	0.81
U1FIC609	2712	19.43	9.97	0.37	515	0.36
U1LIC219	50	0.09	0.11	0.22	509	0.88
U1LIC311	55	0.11	0.12	0.22	157	0.77
U1LIC316	71	0.22	0.28	0.39	188	0.86
U1LIC607	29	0.08	0.07	0.24	641	0.78

IX. CONCLUSIONS

This paper presents a novel method for detection of a single or multiple oscillations in time series data or in process data in one step. There is no need of use intervention or filtering the data for detecting multiple oscillations. The method is based on the Fourier decomposition of time series data utilizing the principles of linear regression techniques. The proposed method can estimate amplitudes, frequencies and phases of sinusoidal components present in a time series. The time series does not need to be sinusoidal. The method is robust enough to detect oscillation even from a very noisy time series data. Two indices namely Oscillation Index (*OI*) and Relative Oscillation Amplitude in Percent (*ROAP*) are defined. The *OI* shows the regularity of oscillation and *ROAP* signifies the impact of oscillation in the particular variable. The method was successfully evaluated using simulated and industrial data sets.

X. ACKNOWLEDGMENT

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