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# Improved oscillation detection via noise-assisted data analysis

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ABSTRACT

Oscillation detection is usually a precursor to more advanced performance monitoring steps such as plant wide oscillation detection and root cause detection. Therefore any false or missed detection can have serious implications. Oscillation detection is a challenging problem due to the presence of noise and multiple modes in the plant data. This paper presents an improved and robust automatic oscillation detection algorithm based on noise-assisted data analysis that can handle multiple oscillatory modes in the presence of both coloured and white noise along with non-stationary effects. The dyadic filter bank property of multivariate empirical mode decomposition has been used to accurately detect the oscillations and to calculate the associated characteristics. This work improves upon the existing auto covariance function based methods. The robustness and reliability of the proposed scheme is demonstrated via simulation and industrial case studies.

## 1. Introduction

Oscillation detection is an important aspect of control loop performance assessment (CLPA) owing to the fact that about 30% of all industrial control loops are reported to be oscillating (Srinivasan, Rengaswamy, & Miller, 2007). Oscillations can be caused by a variety of issues such as process degradation, poor controller tuning, presence of non-linearities, and external disturbances. Oscillations, if allowed to carry on unchecked, can adversely impact productivity, integrity and economics of any industrial process (Chaudhry, Shah, & Thornhill, 2004; Tangirala, Kanodia, & Shah, 2007).

Reliable and accurate detection of oscillation is paramount in identifying control loops requiring further investigation. Such further investigation may involve looking for the cause of oscillation within the loop itself, or looking for causes elsewhere in the plant. Thus detection of any false mode or failure to identify any real oscillation can ruin the whole diagnosis process. Furthermore, accurate estimate of the oscillation characteristics like period of oscillation and amplitude are also helpful in plant wide oscillation detection and fault localization.

Broadly speaking oscillation detection can be subdivided into two groups, namely (a) Oscillation detection in individual loops/variables, and (b) Plant wide oscillation detection where loops/variables oscillating with similar frequencies are grouped together to look for the common cause of performance degradation

The latter group is not an oscillation detection method in a stricter sense, as it only groups different variables without identifying the presence or extent of oscillations within each loop (Li, Wang, Huang, & Lu, 2010). Therefore this work will be focused on the first type, i.e. oscillation detection, and a summary of some oscillation detection methods is presented here. More detailed description can be found in review papers by Thornhill and Horch (2007) and Bacci di Capaci and Scali (2018).

Hägglund (1995) proposed an on-line and a simple yet effective procedure based on monitoring of the control error and computing integral absolute error (IAE) between successive zero crossings, to detect the oscillations. A Modified Empirical Model Decomposition (EMD) method is proposed by Srinivasan et al. (2007) where a non-constant mean from plant data is removed using modified EMD process.

Li et al. (2010) have developed a method where the Discrete Cosine Transform (DCT) is used to isolate the different frequency components in the oscillatory signal followed by checking the regularity of zero crossings in these isolated components to identify the presence or absence of oscillations. The recent list of oscillation detection methods also includes the works by Xie, Lang, Chen, Horch, and Su (2016a) and Xie, Lang, Horch, and Yang (2016b).

Several authors have investigated the use of the Auto Covariance Function (ACF) for detection and characterization of oscillations. The ACF of an oscillating signal oscillates with same period as the original signal and at the same time it is less sensitive to noise as white noise is confined to zero lag only. This idea is being used by Karra, Jelali, Karim, and Horch (2010), Miao and Seborg (1999), Naghoosi and Huang

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(2014), Srinivasan and Rengaswamy (2012), Thornhill, Huang, and Zhang (2003) and Wardana (2015) to detect the oscillations in the control loops data.

Of all the methods listed above the ACF based methods are more robust and reliable in the presence of noise, that is always present in physical measurements and can complicate the analysis to a significant extent. But in spite of all these advantages the presence of multiple oscillations in the presence of white and coloured noise needs special treatment and care even in the ACF based methods. In the work by Thornhill et al. (2003), a filter is used to filter out the different oscillatory modes before the detection procedure. Tuning of filter parameters is an uphill task and needs good understanding of the underlying process dynamics. The EMD based approach given by Srinivasan and Rengaswamy (2012) gets rid of the filter requirement and is reported to be performing better than the DCT based approach given by Li et al. (2010), and can handle non-linear and non-stationary time series, but it suffers from inherent limitations associated with the EMD process itself, i.e. the EMD process is prone to mode mixing, especially in presence of noise and multiple oscillations. Presence of coloured noise complicates the things further. This mode mixing can adversely affect the oscillation detection mechanism and has a tendency to cause erroneous results. Moreover, the accuracy of existing schemes decrease significantly with the increase in the noise variance and with the presence of coloured noise.

### 1.1. Contribution of this paper

In this work, the limitations of the EMD based oscillation detection process are highlighted using simulation studies as well as industrial data, and an improved oscillation detection method based on Noise-Assisted Multivariate EMD (NA-MEMD) is presented. The dyadic filter bank property of MEMD is exploited to improve the accuracy and reliability of the oscillation detection mechanism. The proposed method can handle multiple oscillations in the presence of both white and coloured noise with equal robustness and reliability. Moreover, the proposed method also helps in characterizing the oscillations caused by non-linear effects by highlighting the presence of harmonics.

This paper is organized as follows. Section 2 gives the detailed description of the proposed method with a summary of EMD and the mode mixing issues related with it. It also highlights the basics of MEMD and NA-MEMD procedure. Simulations studies are presented in Section 3 and finally industrial case studies are given in Section 4 followed by conclusions.

## 2. Noise-assisted oscillation detection

In this work, the use of noise-assisted multivariate EMD (NA-MEMD) is proposed to detect the presence and frequency of oscillations in the signal. This method can handle both non-linear and non-stationary time series and is found to be better than existing EMD based method proposed by Srinivasan and Rengaswamy (2012). Here the mode alignment and dyadic filter bank property of MEMD is utilized to formulate a robust and reliable oscillation detection mechanism. The advantages of the proposed method over the standard EMD based method (Srinivasan & Rengaswamy, 2012) are highlighted using Monte-Carlo simulations with varying noise levels and industrial case studies.

The input signal is decomposed into constituent IMFs using NA-MEMD. The IMFs so obtained are converted to the corresponding ACFs and the zero crossings are used to detect the presence or absence of oscillations. In this section the limitations of the standard EMD process, especially with regards to mode mixing problems, are highlighted.

Next, a brief overview of the multivariate EMD is given, followed by the steps involved in proposed oscillation detection algorithm.

### 2.1. Empirical mode decomposition: Basics and inherent limitations

#### 2.1.1. Empirical mode decomposition

Empirical mode decomposition adaptively decomposes the signal into sub-components called Intrinsic Mode Functions or IMFs. Each IMF is a function that has zero mean and the number of extrema and zero crossings in the whole data set must either be equal or at most differ by one. The advantage lies in the fact that the procedure does not need any *a priori* assumption or knowledge about the underlying process dynamics (Huang et al., 1998). The EMD process basically sifts out fast oscillations from the input time series ($x(t)$) by iteratively removing slow frequencies. These slow oscillations or modes are in fact local means $m(t)$ of the envelope defined by spline fitting of the extrema.

$$d(t) = x(t) - m(t) \tag{1}$$

where $d(t)$ represents the local fast mode (Rilling, Patrick, & Paulo, 2003). The sifting process is iterated on $d$ until it is an IMF (named $c_1(t)$). Once the IMF is extracted it is subtracted from the original signal and the sifting procedure is started again on the residue. This continues until there are no more IMFs to be extracted. If $c_i(t)$ is the $i$th IMF and $r(t)$ is the residue, the sifting procedure gives

$$x(t) = \sum_{i=1}^{N} c_i(t) + r(t) \tag{2}$$

where $N$ is the total number of IMFs. The details of the procedure can be seen in Huang et al. (1998) and Rilling et al. (2003).

#### 2.1.2. Limitations of EMD

Although the EMD process is finding its way into a number of application areas yet it is not free from problems or shortcomings. The foremost of them all, that is well known and documented, is the mode mixing problem (Gao, Ge, Sheng, & Sang, 2008). Mode mixing is defined as when one oscillatory mode (here *mode* refers to an oscillation frequency) is present in more than one IMF or one IMF contains several contrasting modes (ur Rehman, Park, Huang, & Mandic, 2013; Wu & Huang, 2009). This mode mixing can lead to erroneous results when it comes to the detection of oscillations in a signal having multiple oscillatory modes, noise and non-stationary effects. The simulation case study (Section 3) highlights the effect of this mode mixing on the oscillation detection problem.

### 2.2. Multivariate EMD (MEMD)

Multivariate EMD (MEMD) as the name suggests is an extension of the standard univariate EMD algorithm, to multivariate or $n$-dimensional signals. The term *univariate signal* here refers to a time series consisting of single variable.[1] Similarly time series having more than one variables are termed multivariate or multidimensional.[2] For instance a multivariate signal $\mathbf{X}$ consisting of $n$ variables $x_1 \dots x_n$ with each variable having $l$ samples is given by

$$\mathbf{X} = \begin{Bmatrix} x_1(1) & x_2(1) & \dots & x_n(1) \\ x_1(2) & x_2(2) & \dots & x_n(2) \\ \vdots & \vdots & \dots & \vdots \\ x_1(l) & x_2(l) & \dots & x_n(l) \end{Bmatrix} \tag{3}$$

The critical issue is how to get the envelope and its local mean in a higher dimensional space. Rehman and Mandic (Rehman & Mandic, 2010) proposed to get the signal projection in multiple directions in $n$-dimensional space. Multiple directions are represented via direction vectors from the centre of a unit sphere to uniformly spaced points on its surface. The details can be seen in Rehman and Mandic (2010) and Aftab, Hovd, and Sivalingam (2017).

[1] The same definition applies to a *single channel* signal.

[2] Thus, a *n-dimensional* signal means a time series consisting of $n$ variables.

#### 2.2.1. Multivariate EMD (MEMD):: Algorithm

The MEMD of a multivariate signal $X$ (given in Eq. (3)) is carried out using the following steps.

- Step I Set up $K$ direction vectors $\mathbf{u}^\mathbf{k}$ ($k = 1 \dots K$) via uniform sampling on the $n$-dimensional sphere.
- Step II Find the projections $p^k(t)$ of the input signal along the direction vectors using:

$$p^k(t) = \mathbf{X}u^k \quad \forall \quad k = 1 \dots K \tag{4}$$

- Step III Identify the extrema of the projections $p^k(t)$ and the corresponding time instants $t^k$.
- Step IV Generate an $n$-dimensional envelope curve $\mathbf{e}^k(t)$ by interpolating $[t^k, \mathbf{X}(t^k)]$ using cubic splines.
- Step V The multidimensional mean envelope curve $\mathbf{m}(t)$ is then given by

$$\mathbf{m}(t) = \frac{1}{K}\sum_{k=1}^{K}\mathbf{e}^k(t) \tag{5}$$

- Step VI Extract the $n$-dimensional detail $\mathbf{d}(t)$ (fast component) using $\mathbf{d}(t) = \mathbf{X}(t) - \mathbf{m}(t)$.
- Step VII Repeat the steps I–VI using $\mathbf{d}(t)$ as input till it fulfils the criteria for an IMF.
- Step VIII Calculate the residue $\mathbf{r}(t) = \mathbf{X}(t) - \mathbf{d}(t)$ and iterate the procedure on $\mathbf{r}(t)$ till there are no more IMFs left to be extracted.

#### 2.2.2. Dyadic filter bank property of multivariate EMD

An important aspect of EMD is its dyadic filter bank property in the presence of noise. By virtue of this property the EMD process essentially behaves like a sequence of band pass filters. Flandrin, Gonçalves, and Rilling (2014), Flandrin, Rilling, and Goncalves (2004) and Wu and Huang (2004) have empirically demonstrated the dyadic filter bank characteristics of the EMD by applying it to a white noise sequence. The same dyadic filter bank structure of standard EMD is preserved in higher order variants i.e. MEMD (Rehman & Mandic, 2011).

The dyadic filter bank property is further elaborated here by processing a three channel[3] white noise sequence using MEMD. The power spectrum of the resulting IMFs show two important properties of the MEMD: (a) The IMF power spectrum can be seen as the output of a series of band pass filters, with band frequencies decreasing with IMF index, and (b) the mode alignment characteristics, *i.e.*, the same indexed IMFs have similar frequency content.

These effects are quite clear in Fig. 1, where the average power spectrum of a three-channel noise sequence for 1000 white noise realizations is plotted.

### 2.3. Noise-assisted MEMD (NA-MEMD)

The dyadic filter bank and mode alignment property of MEMD, as discussed in the previous section, is exploited to eliminate the mode mixing problem in the standard EMD procedure. The idea is to add two channels of white noise sequences to the signal under study to make a 3-channel sequence This three channel signal is processed using MEMD and the IMFs corresponding to the original signal are retained whereas IMFs of the noise sequences are discarded (ur Rehman et al., 2013). This procedure is called Noise-Assisted MEMD (NA-MEMD) and the detailed algorithm is given in Table 1.

As the noise channels span a broad frequency range, the MEMD arranges their IMFs according to the dyadic filter bank structure. The IMFs of the original signal also follow the same pattern, thereby reducing the mode mixing to a considerable extent.

[3] The term *channel signal* here refers to a time series consisting of single variable.

### 2.4. Discarding spurious and noisy IMFs

#### 2.4.1. Discarding spurious IMFs

The NA-MEMD method used in this work, like the standard EMD process, may also generate spurious IMFs, due to spline fitting issues, as highlighted in Peng, Peter, and Chu (2005), Aftab, Hovd, Huang, and Sivalingam (2016), Srinivasan and Rengaswamy (2012). These pseudo-components will be poorly correlated with the original signal as both EMD and MEMD yields near orthogonal IMFs. The correlation coefficient therefore can be used to identify significant IMFs as reported in Peng et al. (2005), Srinivasan and Rengaswamy (2012) and Aftab et al. (2016). The correlation coefficient $\rho_i$ of the $i$th IMF $c_i$ with the input signal $x(t)$ is calculated from

$$\rho_i = \frac{Cov(c_i, x)}{\sigma_x \sigma_{c_i}}, \quad i = 1, 2, 3 \dots N \tag{6}$$

where $Cov$ denotes the covariance; $\sigma_x$ and $\sigma_{c_i}$ are the standard deviations of the signal and the IMF, respectively, and $N$ is total number of IMFs. Next the correlation coefficient $\rho_i$ is normalized using (7). IMFs with normalized coefficient $\lambda$ greater than a certain threshold $\eta$ are retained, while the others are eliminated and added to the residue. The threshold $\eta = 0.5$ is used in this work to remain consistent with the standard EMD based method of Srinivasan and Rengaswamy (2012), so that results can be compared in an unbiased manner.

$$\lambda_i = \frac{\rho_i}{\max(\rho_i)}, \quad i = 1, 2, 3 \dots N \tag{7}$$

#### 2.4.2. Discarding noisy IMFs

NA-MEMD, like the standard EMD may produce noisy IMFs that are correlated with the original signal (especially when noise amplitude is higher). In order to eliminate these IMFs, the method proposed by Hoyer (2004) and used by Srinivasan and Rengaswamy (2012) is adopted. The sparseness index of signal $X$ (here $X$ denotes the magnitude of power spectrum of the signal $x$), given by (8), will be approximately zero for a white noise signal and will be nearly one for a periodically oscillatory signal.

$$Sparseness(x) = \frac{\sqrt{I} - \left(\sum_{i=1}^{I}|X_i| / \sqrt{\sum_{i=1}^{I}|X_i|^2}\right)}{\sqrt{I} - 1} \tag{8}$$

where $I$ gives the number of frequency bins in power spectrum, while the index $i$ identifies a particular frequency bin. IMFs with sparseness greater than certain threshold are retained. The threshold used in this work is 0.5 to be consistent with the standard EMD based procedure, so that the comparison of proposed method is not influenced by the choice of this threshold.

### 2.5. Auto Covariance Function (ACF) of IMFs

The Auto Covariance Function (ACF) of a signal is a popular choice to analyse oscillations owing to the fact that white noise is confined to zero lag of the ACF. The zero crossings of the ACF of the oscillatory IMFs, that have qualified the correlation and sparseness test, is used to compute the average period of oscillation $\bar{T}_p$ and regularity index $r$ of oscillations. If $\Delta t$ is the time interval between two successive zero crossings, then the average period of oscillation $\bar{T}_p$ for $H$ such intervals will then be given by Srinivasan and Rengaswamy (2012) and Thornhill et al. (2003)

$$\bar{T}_p = \frac{2}{H}\sum_{i=1}^{H}(\Delta t_i) \tag{9}$$

and the corresponding $r$ statistic, that shows the regularity of oscillations is then

$$r = \frac{1}{3}\frac{\bar{T}_p}{\sigma_{T_p}} \tag{10}$$

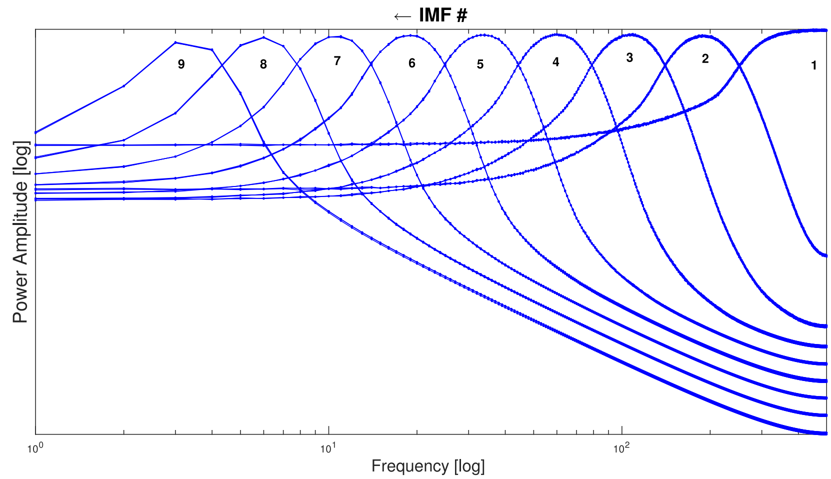


**Fig. 1.** Dyadic filter bank property of MEMD (Aftab et al., 2017).

**Table 1**
Noise-Assisted Multivariate EMD algorithm.

| | |
|---|---|
| Step I | Generate two uncorrelated white Gaussian noise sequences with the same length as that of the original signal. |
| Step II | Add the two noise sequences (from step I) to the original signal to make a multivariate signal of three variables/channels. |
| Step III | Process the signal using MEMD. The resulting IMFs will have three channels or variables. |
| Step IV | Retain the IMFs in the channel corresponding to the original signal, and discard the IMFs corresponding to the noise channels. |

where $\sigma_{T_p}$ is the standard deviation of the time intervals between zero crossings.

As discussed by Thornhill et al. (2003), oscillations are reported only if the regularity index $r$ for that particular signal is greater than 1. Furthermore, as recommended by Thornhill et al. (2003), the first 11 zero crossings of the ACF are used in this work for calculating the average period of oscillation and regularity index.

### 2.6. Proposed algorithm

The proposed oscillation detection algorithm based on Noise-assisted MEMD is given below.

- Step I Process the signal using NA-MEMD according to the steps in Table 1.
- Step II Discard the IMFs that are noisy or uncorrelated with the original signal according to criteria given in Sections 2.4.2 and 2.4.1.
- Step III Calculate the ACF of each retained IMF.
- Step IV Calculate the regularity index of oscillation $r$, mean period of oscillation $\bar{T}p$ and standard deviation $\sigma_{T_p}$.
- Step V Report the presence of oscillation if the regularity index $r > 1$, along with estimates of $\bar{T}p$ and $\sigma_{T_p}$.

## 3. Simulation studies

The simulation studies are aimed at highlighting the advantages of the proposed scheme in presence of non-stationary effects and both white and coloured noise. The simulations studies are carried out using examples from Srinivasan and Rengaswamy (2012) and Li et al. (2010) with varying white noise levels and also with coloured noise. The results for 10000 such simulation runs for each case are compared with the existing standard EMD based approach to ascertain the robustness and reliability of the proposed scheme. The standard EMD based scheme, as already discussed, is prone to report inaccurate results due to the mode mixing problem and this inaccuracy increases with increase in the noise level.

**Table 2**
No of successful iterations as %age of 10000 noise realizations.

| | Noise type | Success rate(%) | |
|---|---|---|---|
| | | EMD based method | Proposed method |
| Example 1 | White $\sigma_v^2 = 1.30$ | 76% | 97% |
| | White $\sigma_v^2 = 3.0$ | 50% | 96% |
| | White $\sigma_v^2 = 4.0$ | 39% | 94% |
| Example 2 | Coloured | 66% | 80% |

### 3.1. Example 1: Oscillation detection with varying white noise levels

Consider a signal containing two modes or frequencies and a non-stationarity corrupted with white noise (same as Example 3 from Srinivasan and Rengaswamy 2012 and Li et al. 2010).

$$x(k) = 0.05k^2 + \sin(2\pi f_1 k) + \sin(2\pi f_2 k) + v(k) \tag{11}$$

with $f_1 = 0.2$ Hz, $f_2 = 1.0$ Hz, sampling rate 0.1 s and white Gaussian noise $v$ with variance $\sigma_v^2$. Note that the parabolic term introduces non-stationarity in the data. Simulations with 10000 different realizations of white noise are carried out to compare the performance of proposed and existing methods for different noise variances; $\sigma_v^2 = 1.3$, $\sigma_v^2 = 3$ and $\sigma_v^2 = 4$ that gives the signal to noise ratio (SNR)[4] of 2.5, 1.7 and 1.4 respectively. The results in terms of success rate % are summarized in Table 2.

The oscillation detection is defined as successful if two oscillation frequencies are reported for a simulation. Any other number of oscillations mean that the detection has failed.

[4] SNR as defined in Li et al. (2010).

**Table 3**
Oscillation characteristics case study-I.

| Tag | Method | IMF | r value | $T_p$ [min] | $\sigma_{T_p}$ [min] | Oscillation |
|---|---|---|---|---|---|---|
| Tag 6 | Std. EMD | 1 | 1.20 | 21.6 | 6.0 | Yes |
| | Proposed | 1 | 2.51 | 17.6 | 2.3 | Yes |
| | | 2 | 5.1 | 39.8 | 2.6 | Yes |
| Tag 11 | Std. EMD | 1 | 5.5 | 16.7 | 1.0 | Yes |
| | Proposed | 1 | 5.9 | 16.5 | 0.93 | Yes |
| | | 2 | 2.13 | 83.2 | 13.00 | Yes |
| Tag 14 | Std. EMD | 1 | 3.2 | 48.2 | 4.9 | Yes |
| | proposed method | 1 | 7.9 | 49.8 | 2.1 | Yes |
| Tag 19 | Std. EMD | 1 | 3.46 | 16.4 | 1.577 | Yes |
| | | 2 | 2.73 | 70.6 | 8.59 | Yes |
| | proposed method | 1 | 6.48 | 16.4 | 0.84 | Yes |
| | | 2 | 5.74 | 82.20 | 4.70 | Yes |
| Tag 33 | Std. EMD | 1 | 5.90 | 16.54 | 0.93 | Yes |
| | proposed method | 1 | 1.95 | 5.45 | 0.934 | Yes (3rd harmonic) |
| | | 2 | 4.52 | 8.18 | 0.60 | Yes (2nd harmonic) |
| | | 3 | 5.90 | 16.54 | 0.93 | Yes |

**Table 4**
Oscillation characteristics case study-II.

| Tag | Method | IMF | r value | $T_p$ [min] | $\sigma_{T_p}$ [min] | Oscillation |
|---|---|---|---|---|---|---|
| Tag-8 | Std. EMD | 1 | r < 1 | | | No |
| | Proposed | 1 | 13.3 | 517.3 | 12.94 | Yes |
| Tag-9 | Std. EMD | 1 | 5.29 | 514.33 | 32.4 | Yes |
| | Proposed | 1 | 76.98 | 253 | 1.09 | Yes (harmonic) |
| | | 2 | 45.71 | 510.6 | 3.72 | Yes |
| Tag-11 | Std. EMD | 1 | 3.0 | 23.27 | 2.5 | Yes |
| | | 2 | 8.2 | 51.0 | 2.07 | Yes |
| | Proposed | 1 | 4.08 | 22.9 | 1.86 | Yes |
| | | 2 | 16.9 | 51.27 | 1.0 | Yes |
| Tag-12 | Std. EMD | 1 | 4.0 | 572.3 | 46.7 | Yes |
| | Proposed | 1 | 23.2 | 501.2 | 7.24 | Yes |

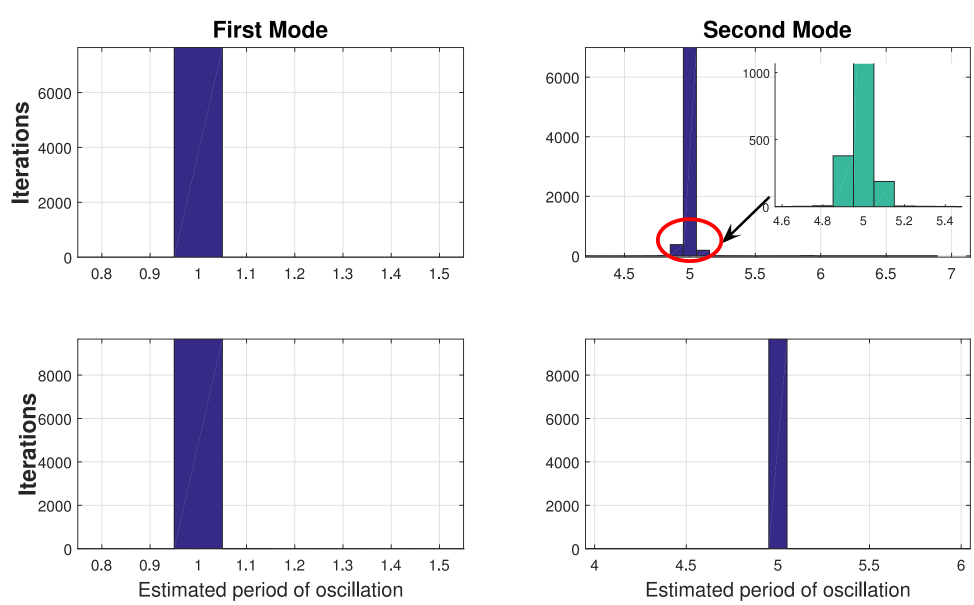


**Fig. 2.** Histograms for estimates of period of oscillation, example 1 (white noise $\sigma^2 = 1.3$). First row (EMD based method), second row (proposed method).

It can be seen that the proposed methods performed much better than the EMD based method whose detection capability is greatly compromised with increasing noise levels. For barely 39% of the simulations it could detect the two frequencies successfully when noise variance was 4 (SNR=1.4) as compared to 94% for the proposed method. The histograms of estimated mean periods of oscillation (with bin size 0.1) for the successful iterations are plotted in Figs. 2–4. The vertical axis of the figures show the number of iterations for a particular estimate of the period of oscillation, whereas the horizontal axis shows the spread of estimated period of oscillations. The proposed method gives quite

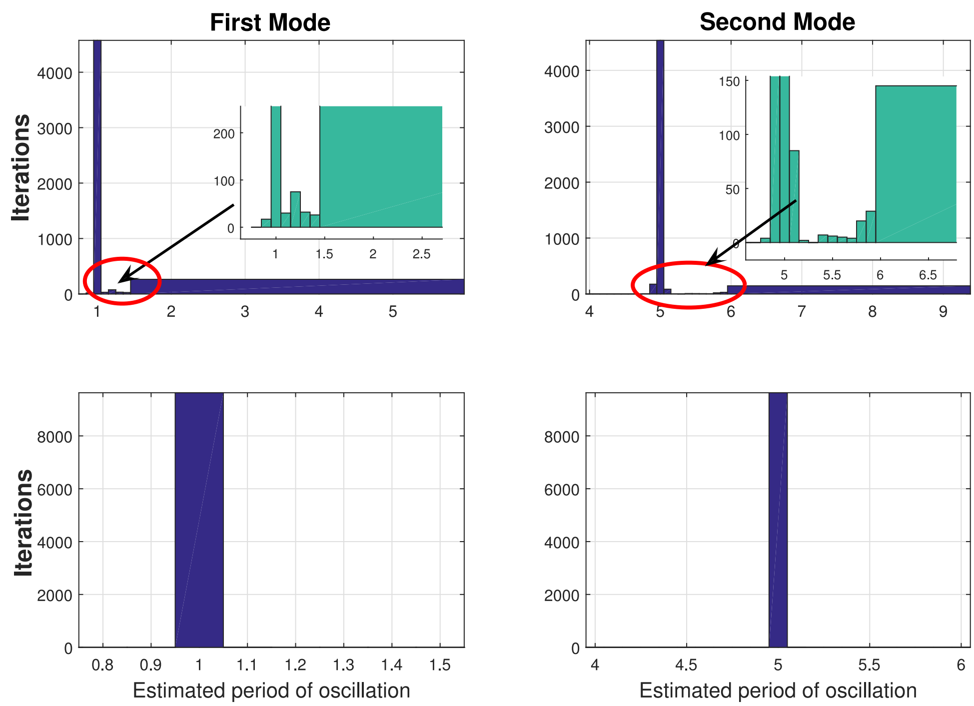


**Fig. 3.** Histograms for estimates of period of oscillation, example 1 (white noise $\sigma^2 = 3$). First row (EMD based method), second row (proposed method).

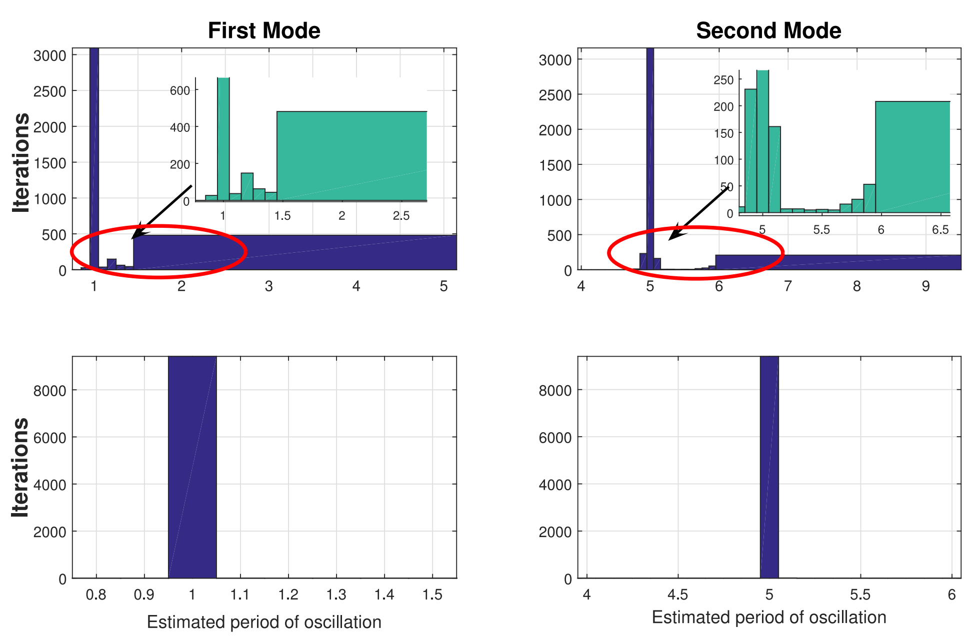


**Fig. 4.** Histograms for the estimates of period of oscillation, example 1 (white noise $\sigma^2 = 4$). First row (EMD based method), second row (proposed method).

accurate estimate, with almost all estimates confined to one bin. In comparison the period estimates from the EMD based method show quite significant spread specially for higher noise levels.

*3.2. Example 2:: Effect of coloured noise*

The presence of coloured noise in the oscillating signal makes the detection more difficult as discussed in Karra et al. (2010) and Li et al. (2010). The coloured noise ACF is not confined to zero lag, and oscillation detection in the presence of coloured noise therefore needs extra care. In this example the accuracy of the existing and proposed methods is analysed using the signal containing two frequencies (as in example 1) in the presence of a non-stationary trend and coloured noise. Coloured noise is generated by passing a white noise of unit variance through a low pass filter $1/(1 - 0.7z^{-1})$.

The signal composition remains the same as in example 1 except that the white noise has been replaced by coloured noise. The simulations for 10000 different realizations of coloured noise are carried out and results are summarized in last row of Table 2. The results confirm the fact that the introduction of coloured noise has reduced the success rate. In this case again the proposed method performs better with success rate of 80% as compared to 66% of EMD based method in determining the two oscillation frequencies correctly. The proposed method also gives better estimates of the period of oscillation (Histogram Fig. 5).

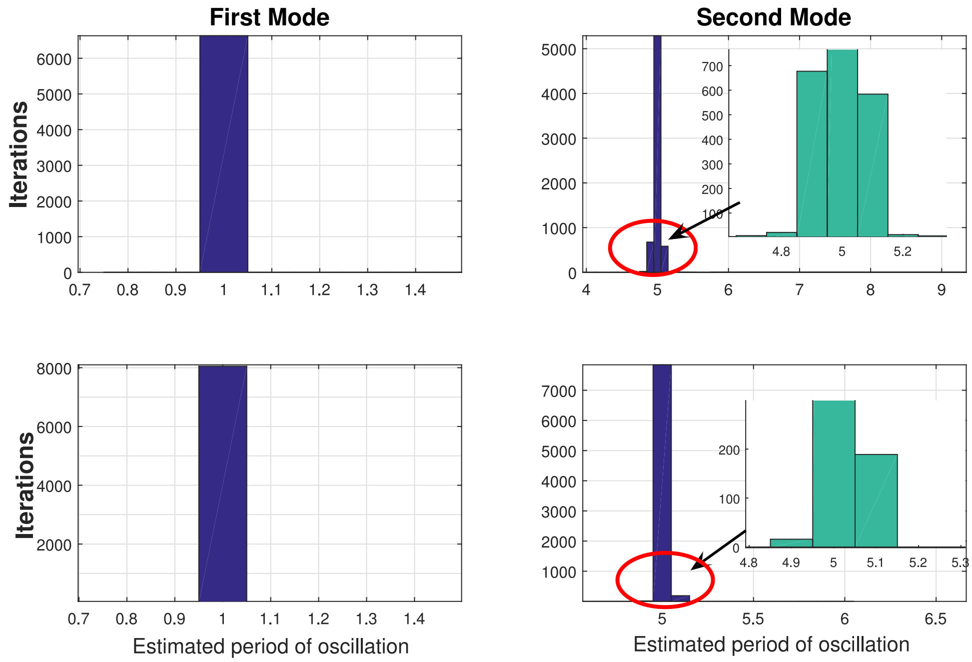


**Fig. 5.** Histograms for the estimates of period of oscillation, example 2 (coloured noise). First row (EMD based method), second row (proposed method).

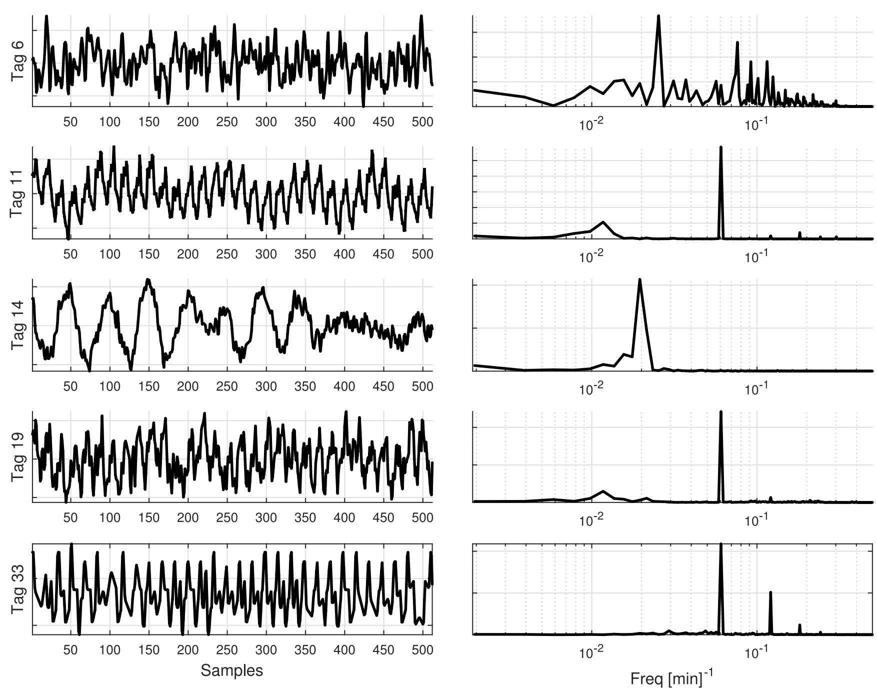


**Fig. 6.** Time trends and spectra for case study-I.

## 4. Industrial case studies

In this section the robustness and advantages of the proposed scheme are highlighted using the three industrial case studies. The measurements have multiple oscillatory modes or frequencies and also contain non-linearity induced oscillations. Therefore, the case studies can effectively test the ability of the proposed scheme to detect multiple oscillations in a real plant data.

### 4.1. Case study-I

The data from a hydrogen reformer, also analysed in Thornhill, Shah, Huang, and Vishnubhotla (2002), Aftab et al. (2017), Karra et al. (2010) and Tangirala, Shah, and Thornhill (2005), is used in this case study. Five different tags 6, 11, 14, 19 and 33 (Fig. 6) show presence of multiple oscillations that are hard to identify manually. The trends are processed by the existing and proposed oscillation detection methods. The results given in Table 3 show that the proposed method is more effective and accurate in detecting the presence of multiple oscillations and related characteristics. Moreover the proposed method also highlights

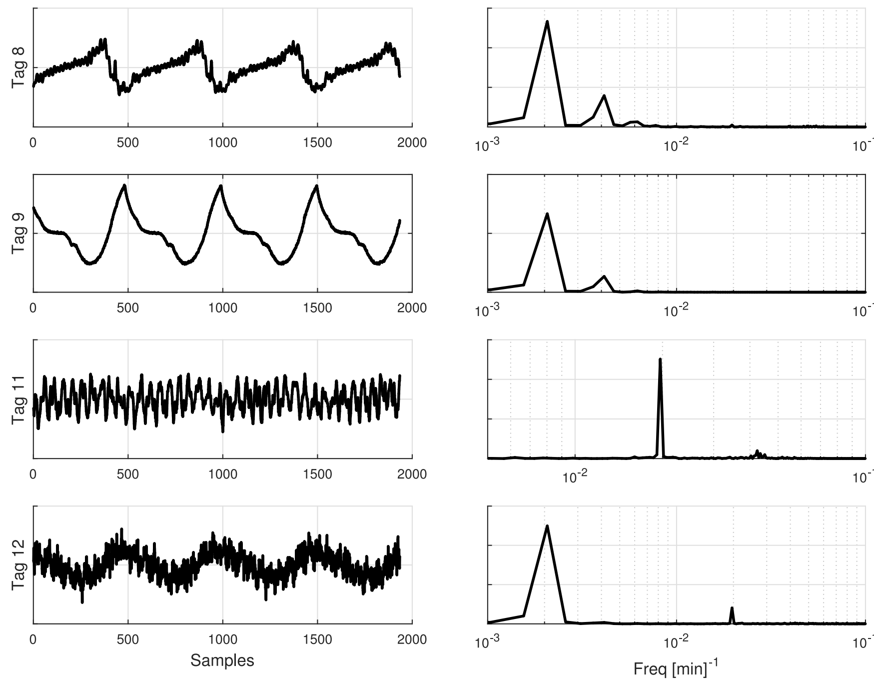


**Fig. 7.** Time trends and spectra for case study-II.

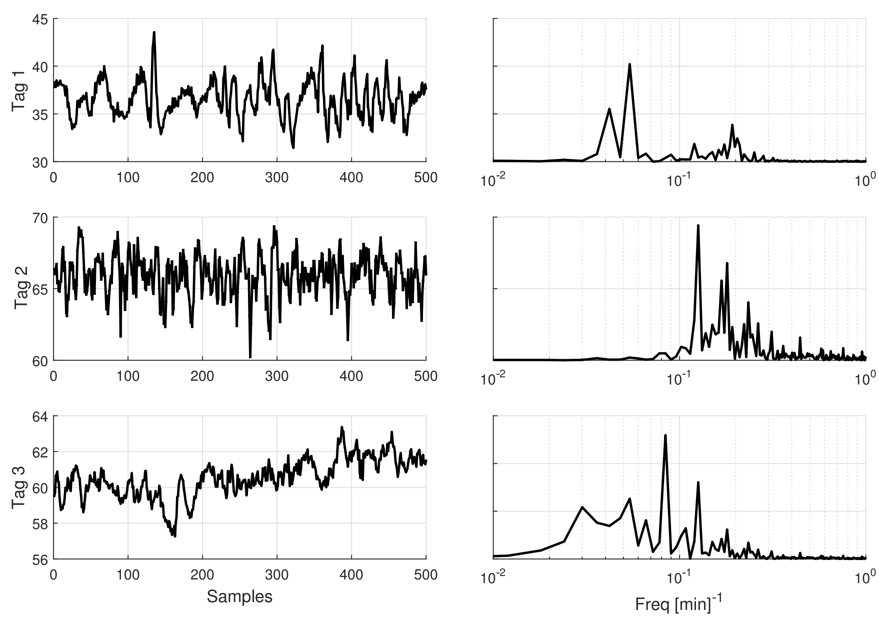


**Fig. 8.** Time trends and spectra for case study-III.

the presence of harmonics in case of oscillations generated due to non-linearity.

The proposed method is able to identify multiple oscillations in tag 6, whereas the existing EMD based method could only identify one oscillatory frequency. Similar results are reported for tag 11 where standard EMD based method fail to identify the slow frequency oscillation.

For tags 14 and 19, the proposed method gives more reliable and accurate estimates of oscillations characteristics. As far as tag 33 is concerned the proposed method has correctly highlighted the presence of harmonics, a characteristic of oscillations due to non-linearity. It has been reported in a number of studies that the said oscillations are generated due to valve non-linearity, thus the proposed oscillation detection method has also confirmed this fact. The detailed method for automatic detection of harmonics can be seen in our previous work Aftab et al., 2017.

*4.1.1. Comparison with other methods*

This case study has been mostly used for the plant-wide oscillation detection and root cause analysis. Karra et al. (2010) has used the same data set for the oscillation detection problem. The results reported in Karra et al. (2010) did not identify the multiple oscillations in different tags. Moreover, the results reported for the one oscillation frequency are also less accurate as compared to the method proposed in this paper. The work by Karra et al. (2010) requires additional filtering to isolate multiple oscillations and noise effects and that requires the frequency to be known in advance.

**Table 5**
Oscillation characteristics case study-III.

| Tag | Method | IMF | r value | $T_p$ [min] | $\sigma_{T_p}$ [min] | Oscillation |
|---|---|---|---|---|---|---|
| Tag 1 | Std. EMD | 1 | 3.98 | 5.15 | 0.43 | Yes |
| | | 2 | 1.6 | 19.7 | 4.0 | Yes |
| | Proposed | 1 | 4.8 | 5.03 | 0.34 | Yes |
| | | 2 | 1.87 | 8.24 | 1.47 | Yes |
| | | 3 | 3.37 | 18.85 | 1.86 | Yes |
| Tag 2 | Std. EMD | 1 | 1.0 | 6.72 | 2.24 | Yes |
| | Proposed | 1 | 1.38 | 3.51 | 0.84 | Yes |
| | | 2 | 2.0 | 6.67 | 1.07 | Yes |
| | | 3 | 3.28 | 8.85 | 0.90 | Yes |
| Tag 3 | Std. EMD | < 1 | – | – | – | No |
| | Proposed | 1 | 4.27 | 11.78 | 0.91 | Yes |

### 4.2. Case study-II

The data from four control loops, represented by tags 8, 9, 11 and 12 (time trends and spectra given in Fig. 7), from the challenge problem (Thornhill et al., 2002) are also analysed. The results for both the schemes, the proposed and existing one, are given in Table 4.

The time trend and spectrum of tag 8 shows a slow oscillation with period around 500 mins. The existing EMD based method cannot capture this oscillation ($r < 1$). In contrast the proposed method is able to detect this oscillation in the signal. Moreover, the proposed method has correctly pointed out the presence of harmonics in tag 9, thereby confirming the non-linearity as the source of oscillation. EMD based method only identified the fundamental harmonic. The oscillation statistics reported by proposed method are also more accurate than the standard EMD based method.

Similarly for the multiple oscillations in tag 11, the $r$ statistic and $\sigma_{T_p}$ show that the proposed method gives more accurate estimates of related characteristics as compared to the existing method. Same is the case with the slow oscillation in tag 12.

### 4.3. Case study-III

The data for three control loops, namely tag 1, 2 and 3 from an industrial paper plant has been analysed for the presence of oscillations. The time trends and the spectra are shown in Fig. 8. The results presented in Table 5 clearly indicate the advantages of the proposed method.

The proposed method identifies three oscillation frequencies in tag 1 but the standard EMD approach can only identify two of them. Similarly for tag 2 the standard EMD can identify only one oscillation whereas the proposed method indicates the presence of multiple (three) oscillations. Moreover, the noise-assisted technique has correctly identified the presence of single oscillation in Tag 3 that the standard EMD method could not detect.

## 5. Conclusions

An improved and more robust oscillation detection method based on Noise-Assisted Multivariate EMD (NA-MEMD) is presented. It is shown with the help of both simulations and industrial case studies that the proposed method is less prone to the mode mixing problem, and is more reliable and accurate in determining the presence of multiple oscillations and related oscillation characteristics as compared to the standard EMD based approach. The proposed method can handle the non-stationary effects and can highlight the presence of harmonics in non-linearity induced oscillations as well.

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