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Diagnosis of root cause for oscillations in closed-loop chemical process systems

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Abstract: Oscillations in process plants degrade the performance of control loops resulting in poor product quality. Therefore, plant-wide oscillation diagnosis is an essential task to maintain the performance of control loops. In recent years, significant research has been performed on plant-wide oscillation diagnosis. It has been reported that the three major causes for oscillations in linear closed-loop Single-Input Single-Output (SISO) systems are: *(i)* aggressively tuned controller, *(ii)* stiction in control valves and, *(iii)* external disturbances. Several offline data-driven methods have been developed to address the diagnosis problem by focusing on only one of the causes for oscillations. In the current study, an offline data driven approach is developed to identify all the three major causes for oscillations. This approach has the following two components: *(i)* parametric Hammerstein model based stiction detection and, *(ii)* non-parametric Hilbert-Huang spectrum analysis for distingusihing between improperly tuned controller and disturbance caused oscillations. Simulation and industrial case studies demonstrate the efficacy of the proposed method for plant-wide oscillation diagnosis.

1. INTRODUCTION

Oscillations are a common type of plant-wide disturbance whose detection and diagnosis have generated considerable interest in recent years (Thornhill et al. [2002], Thornhill and Horch [2007], Choudhury [2004], Jelali and Huang [2009]). Oscillations in control loops increase the variability in product quality, accelerate equipment wear and may cause other issues that could potentially disrupt the regular plant operation Thornhill et al. [2000], Srinivasan et al. [2005b]. Therefore, it is necessary to diagnose the root causes for oscillations in control loops.

The important tasks in plant-wide oscillation diagnosis are: *(i)* detection of oscillations, *(ii)* isolation of oscillatory control loops and, *(iii)* diagnosis of root cause for oscillations. Several methods have been developed for detection of oscillations in control loops. Some of the widely used methods for oscillation detection are detailed in Thornhill and Hagglund [1997] and Thornhill et al. [2003]. Empirical mode decomposition, a key method used in this work has also been used for oscillation detection in control loops Srinivasan et al. [2007]. Numerous multivariate techniques are employed to identify a group of control loops which are likely to contain the sources for oscillations. A couple of well known techniques for isolation of oscillatory loops are described in Xia et al. [2005], Srinivasan and Tangirala [2010], Thornhill et al. [2000], Jiang et al. [2006, 2009].

After identification of oscillatory control loops, the next step is to identify the cause for oscillations among these loops. A survey by Yang and Clarke [1999] indicated that 30% of all control loops in Canadian paper mills were oscillating because of valve problems. Control loop auditing (Torres et al. [2006]) on 700 control loops from 12 different Brazilian companies showed that most of the control loops performed poorly due to valve problems or aggressively tuned controllers.

In short, these surveys indicate that the three major causes for oscillations in linear SISO loops are: *(i)* aggressively tuned controller, *(ii)* oscillatory external disturbances, and *(iii)* control valve nonlinearities such as stiction, backlash and saturation. Most of the existing techniques focus on identification of stiction in control loops. More recently, Karra and Karim [2009] introduced a method that considers all the three root causes. It was assumed that the disturbance corrupting the process was nonstationary. A noise model was developed based on this assumption. However, in reality, it is difficult to model the disturbances corrupting the system, since they are generally not known.

In this article, we propose a method for diagnosis of all the three causes for oscillations in closed loop systems. The proposed approach constitutes of: *(i)* Hammerstein model based stiction identification and *(ii)* amplitude based discrimination analysis using Hilbert Huang (HH) spectrum for distinction between aggressively tuned controller and disturbance caused oscillations. The use of Hammerstein model identification method for stiction detection (Srinivasan et al. [2005b], Lee et al. [2008], Jelali [2008], Ivan and Lakshminarayanan [2009], Karra and Karim [2009]) has been well established in the literature. However, the use of HHT in the area of root cause analysis has not been pursued before. In view of this, before presenting the use of HHT for root cause analysis, we introduce HHT in the context of oscillating signals in the next section.

2. PRELIMINARIES - HILBERT HUANG TRANSFORM OF PROCESS SIGNALS

Recently, Huang et al. [1996] developed the Hilbert-Huang transformation (HHT) to analyze the time-frequency characteristics of time-dependent signals. HHT comprises of two distinct parts: *(i)* Empirical Model Decomposition (EMD) of the signal to identify the so called Intrinsic Mode Functions (IMFs) and *(ii)* Hilbert transform of the IMFs to obtain instantaneous frequency. EMD is an adaptive technique which is derived from the assumption that any signal consists of characteristic oscillations (IMFs) that are separated on a time-scale. A rigorous description of the EMD method can be found in the seminal paper by Huang et al. [1996]. In the second step, Hilbert transform of all the IMFs are computed, which yields the amplitude spectra along with the instantaneous frequencies. The amplitude and instantaneous frequencies from all IMFs are plotted as a function of time, either as a 3-D plot(z axis surface is amplitude) or as 2-D plot (color scale represents amplitude). This plot of superposition of all instantaneous frequencies obtained from all IMFs in the time-frequency plane along with their amplitudes is called as the Hilbert-Huang spectrum.

We will now present a layman description of why HHT is important for oscillation characterization and how it is different from Fourier Transform (FT). The key difference between HHT and FT is the notion of instantaneous frequency at every time instant that HHT uses to describe signals. This use of instantaneous frequency results in nonlinear distortions to frequency components being handled in a completely different manner in HHT when compared to FT. When a single sine wave is nonlinearly transformed, FT of the transformed time signal will show several frequency components that are integer multiples of the original frequency component. This is usually referred to as harmonic distortion. This spreads the single frequency into multiple frequencies as shown in Figure 1. When the same output time signal is analyzed using HHT, the HH spectrum of the nonlinear time series is represented as modulation around the fundamental frequency of the input signal as seen in Figure 1. We exploit this behavior in our root cause analysis work.

The importance of this representation can be clearly seen when we look at a nonlinear transformation of a sum of two sinusoidal input signals as shown in Figure 2. FT spreads the two frequencies in the frequency scale due to harmonic distortions and hence from a FT plot it becomes difficult to infer that the input signal had two frequency components. However, the HH spectrum shown in Figure 2 shows two waves around the fundamental frequencies that are clearly separated and easy to identify. As a result, when oscillations are generated at different parts of a control loop (controller, disturbance) and passed through a nonlinear element such as stiction, separating the different components becomes straight-forward.

3. SOLUTION APPROACH

Our solution approach for root cause diagnosis of oscillating loops is depicted in Figure 3. In this work, we

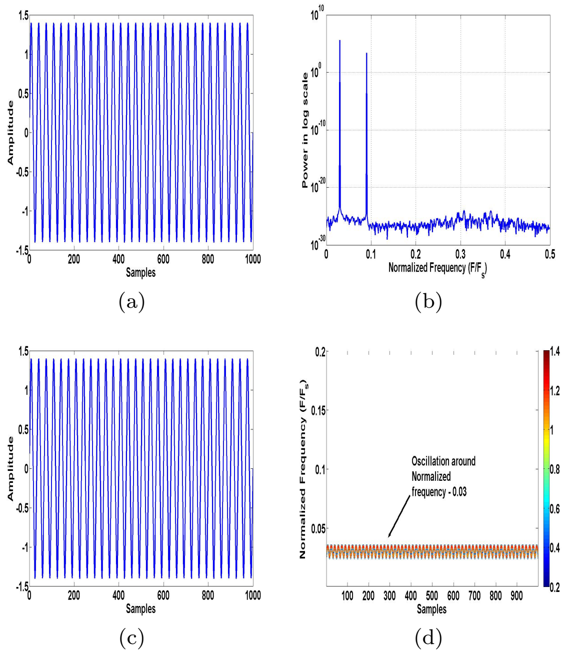


Fig. 1. (a) Nonlinear signal (Sinusoidal signal of frequency 0.03 is passed through a cubic function) (b) Power spectrum obtained from Fourier Transform (c) One individual IMF obtained from EMD (d) HH spectrum of the signal

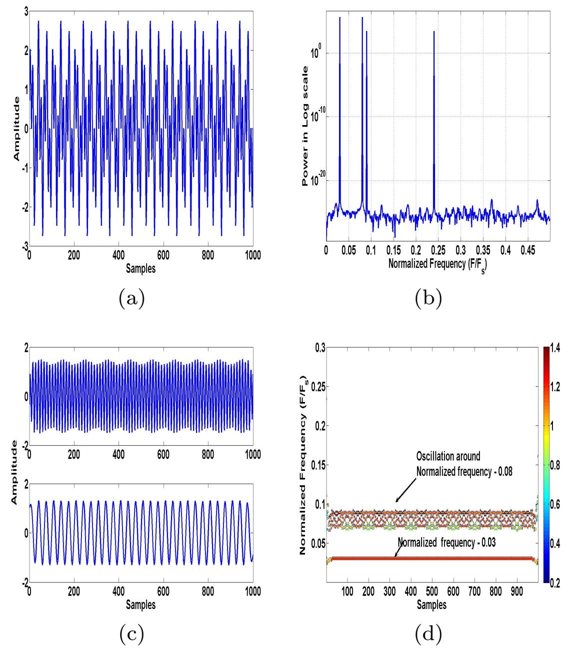


Fig. 2. (a) Nonlinear signal (Sum of sinusoidal signals of frequencies 0.03 and 0.08 is passed through a cubic function) (b) Power spectrum obtained from Fourier Transform (c) One individual IMF obtained from EMD (d) HH spectrum of the signal

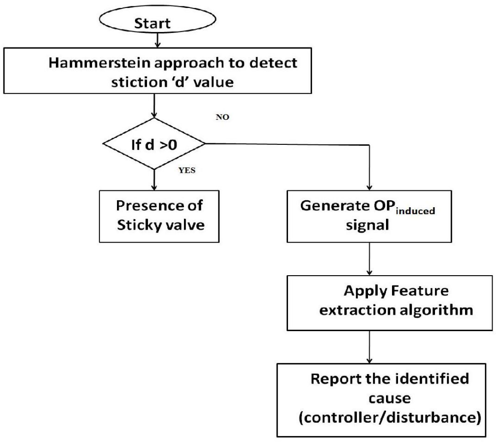


Fig. 3. Flow chart of RCA algorithm

assume that only one root cause is present at a time. While multiple causes at the same time are definitely possible, comprehensive solutions do not exist even for a single failure scenario at this time. It has been shown in our prior work (Srinivasan et al. [2005b]) that stiction detection can be decoupled effectively from controller tuning and disturbance related problems. In view of this, the first step of the approach determines presence/absence of stiction. The algorithm terminates if stiction is detected due to the assumption of single root cause. If stiction is not detected then further analysis is needed. Before this analysis is discussed, a brief description of the well established stiction detection idea is summarized.

3.1 Stiction detection in linear closed loop systems

In this work, Hammerstein based joint identification algorithm proposed by Srinivasan et al. [2005b] is used for detection of stiction in control valves. This algorithm is based on the following one parameter model given by

$$x(t) = \begin{cases} x(t-1) & \text{if } \quad |u(t) - x(t-1)| \leq d \\ u(t) & \text{otherwise} \end{cases} \tag{1}$$

Here $x(t)$ and $x(t-1)$ are past and present stem movements, $u(t)$ is the present controller output and 'd' is the valve stiction band. The value of $'d'$ is expressed in terms of the percentage or fraction of valve movement corresponding to the amount of stiction present in the valve. Hammerstein based method uses a linear model along with nonlinear stiction parameter to fit the data between controller output (OP) and process output (PV). The squared errors between the model predicted and process outputs are summed over a period of time to obtain the Total Squared Error (TSE). The value of stiction parameter 'd' corresponding to the model with minimum TSE is used for stiction detection. A non-zero value of 'd' indicates stiction while a zero value implies the absence of stiction in the control valve. If stiction is detected, then the root cause analysis algorithm is terminated. If stiction is not present in the control loop, the next step is to distinguish between aggressively tuned controller and disturbance caused oscillations. This is discussed next.

3.2 Amplitude based discrimination analysis using HH spectrum

It is difficult to identify the oscillations caused due to aggressively tuned controller and external disturbances. This is mainly due to the following reasons: *(i)* according to linear systems theory, it has been shown that under noise-free conditions, sinusoidal disturbances and aggressively tuned controller lead to identical PV and OP signals in control loops (Horch [2000]) and, *(ii)* regular operating data from industries with constant set-points restrict us from development of closed-loop models for oscillation diagnosis. Some of the ways to address this problem are: *(i)* using process transfer function, *(ii)* applying frequency domain based minimum variance index approach discussed in Horch [2000] and, *(iii)* use of the fact that control loop operating at marginally stable conditions exhibit higher oscillation amplitude compared to external disturbance (Horch [2000], Ordys et al. [2007]). HH spectrum based approach falls under the third category.

In general, assumptions regarding the characteristics of the noises and external disturbances have to be made in the development of root cause analysis algorithm. The assumptions made in the proposed root cause analysis algorithm are: *(i)* the measurement noise corrutping the process output is white and, *(ii)* the amplitude of oscillations caused due to aggressively tuned controller is much higher compared to oscillations caused due to external disturbance. The latter assumption is infact true for systems operating at marginally stable conditions. We will now introduce our key idea for root cause diagnosis through a simple simulation example.

Let us consider a second order plus dead time system whose transfer function is given by $\dfrac{2e^{-3s}}{30s^2+13s+1}$. Stable PID controller transfer function is given by $1.1(1+\dfrac{1}{11s}+0.182s)$ with controller gain $K_c = 1.1$, integral time constant $\tau_i = 11$ and differential time constant $\tau_d = 0.182$. The output of the system is corrupted with white noise of signal to noise ratio (SNR) 10. Data for badly tuned controller and disturbance caused oscillations are generated using this model. For the aggressively tuned controller case, the stable closed-loop system is rendered marginally stable (producing sustained oscillation) by changing the controller gain to $K_c = 2.5$. The disturbance corrupted process output was generated using a sinusoidal signal of frequency $\omega = 2\pi 0.1$.

The task now is to distinguish between the controller and disturbance caused oscillations with just from this PV and OP data with no further information. The first step is to see if any discriminatory information is available in Fourier or HH spectrums of the PV and OP signals. HH spectrum of PV signals for controller and disturbance caused oscillations are shown in Figure 4. From this Figure, it is hard to identify any significant information that can be used to distinguish between controller and disturbance caused oscillations. Again, same results are obtained with the Fourier spectrum of PV and OP signals. We now present a novel transformation and analysis using HHT that is used to uncover diagnostic information from just the PV-OP data. We transform the OP data into what we term as the OP_{ind} (*ind* for induced) data by passing the OP data through a stiction nonlinearity. One could view this transformation as a device for feature extraction (Venkatasubramanian et al. [2003]). The value of the stiction value 'd' is fixed as 30% of the maximum value of oscillatory component in the OP signal. Fourier and HH spectrums of the OP_{ind} signal for controller and disturbance caused oscillations are shown in Figure 5. Remarkably, notice that the HH spectrum of OP_{ind} signal for disturbance caused oscillation shows two distinct frequency bands. However, the HH spectrum of OP_{ind} signal for controller caused oscillation does not contain such distinct frequency bands. This diagnostic feature of the transfomed input can be used to distinguish between the disturbance and controller caused oscillations. Notice that such obvious distinguishing features are missing in the Fourier spectrum of the transformed variable.

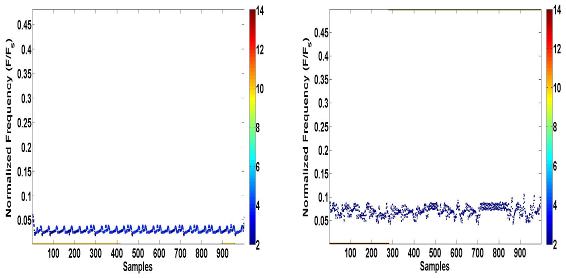
A rigorous analysis of the reasons for obtaining distinct information in OP_{ind} data is discussed in the manuscript which is under preparation. In this work, we focus on the development of the algorithm for root cause analysis and its application to various industrial control loops. The feature extraction algorithm developed for distincition between controller and disturbance caused oscillations is discussed next.

3.3 Feature extraction algorithm for distinguishing controller and disturbance caused oscillations

(1) Compute the HH spectrum of the OP_{ind} signal.
(2) Divide the total normalized frequency range (F/F_s) of $0 - 0.5$ into various frequency bands with a band interval of 0.02 with F_s being the sampling frequency. Let the starting and ending frequencies be 0.02 and 0.46 respectively. In other words, the frequency bands are in the range $\omega_i = 0.02 : 0.02 : 0.46$. The band interval of 0.02 is just 6% in the total frequency scale of 0.5 and therefore does not pose any problems in the identification of root cause for oscillations.
(3) Compute the normalized power from HH spectrum at various frequency bands for OP_{ind} signal using the following equation:

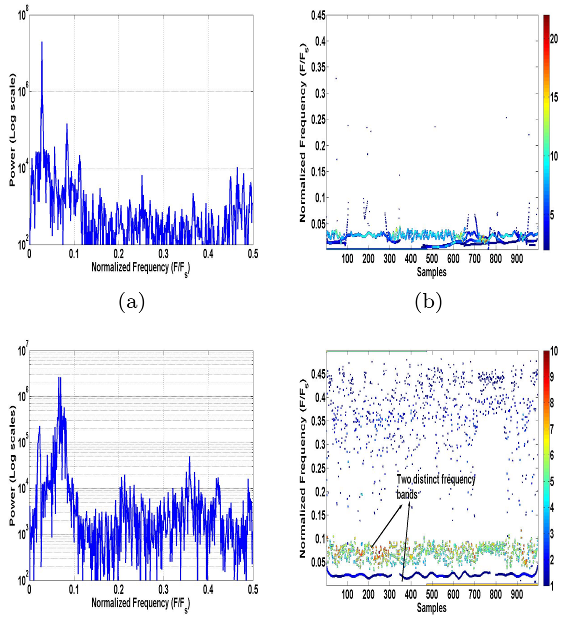
$$P_{hht}(\omega(i)) = \sqrt{\frac{\sum_{\omega=\omega(i-1)}^{\omega(i)} P_{hht}^2(\omega)}{N}} \qquad (2)$$

Similarly, compute the value $P_{hht}(\omega(i))$ at various frequency bands for PV signal.
(4) To distinguish between controller and disturbance caused oscillations, P_{hht} of OP_{ind} and PV signals are compared at low frequencies using a threshold. If there is no separation then the diagnosis is controller tuning induced oscillations and if there is a separation then the diagnosis is that the cause for oscillations is external to the loop.
(5) In practice, for comparison of P_{hht} of OP_{ind} and PV signals, a threshold value is required. This is to neglect small power values at various frequencies due to the presence of noise. In this work, the threshold value is chosen to be 5% of the maximum value of P_{hht} computed from PV. This normalizes the threshold based on the data directly. Only the power values above this threshold are considered to be significant. This threshold can be raised or lowered, if *a priori* knowledge on noise corrupting the process is known.



(a) (b)

Fig. 4. **SOPTD** (a) Fourier Spectrum of process output (PV) - Controller caused oscillation (b) HH spectrum of process output (PV) - Controller caused oscillation



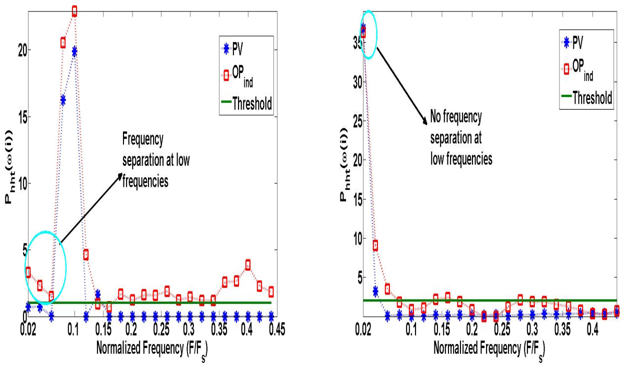
(a) (b)

(c) (d)

Fig. 5. **SOPTD** (a) Fourier Spectrum of OP_{ind} data - Controller caused oscillation (b) HH spectrum of OP_{ind} data - Controller caused oscillation (c) Fourier Spectrum of OP_{ind} data - disturbance caused oscillation (d) HH spectrum of OP_{ind} data - disturbance caused oscillation

The above feature extraction algorithm is implemented on the SOPTD system discussed previously. In case of disturbance caused oscillations, P_{hht} computed for OP_{ind} data contain significant values at lower frequencies compared to the P_{hht} of OP_{ind} data obtained for oscillations caused due aggressively tuned controller. This can be clearly observed from Figures 6 (a) and (b).

Several simulation studies were performed using the proposed root cause analysis algorithm depicted in Figure 3. However, due to space constraints, we present only the results obtained from industrial control loops.



(a) (b)

Fig. 6. **SOPTD** (a) Comparison of power from HH spectrum of process output (PV) and OP_{ind} data - Disturbance caused oscillation (b) Comparison of power from HH spectrum of process output (PV) and OP_{ind} data - Controller caused oscillation

4. INDUSTRIAL CASE STUDIES

In this section, industrial data sets provided in Horch [2000] are used for validating the proposed RCA methodology. Four control loops are analyzed using the RCA algorithm and the results obtained on these four loops are tabulated in Table 1. However, a detailed analysis for the results obtained from two loops are provided here.

4.1 Level Loop

Results obtained using the RCA algorithm on a level control loop (LC 621) is discussed. According to the algorithm detailed in Figure 3, Hammerstein algorithm is applied on the PV and OP data. The Hammerstein based stiction algorithm indicated a stiction value of $d = 0$. Then, according to the algorithm, 30% of stiction is introduced in the OP data to obtain the OP_{ind} signal. The HH spectrum of the resulting OP_{ind} is computed and P_{hht} of both OP_{ind} and PV data are compared. This power value comparison indicated that the cause for the oscillations is aggressively tuned controller. Horch [1999] also showed that aggressively tuned controller is the cause for oscillations in this loop.

4.2 Flow loop

Data obtained from the flow control loop (FC525) is used to test the proposed algorithm. Hammerstein algorithm applied to this PV and OP data set provided a stiction value of $d = 2.16$ indicating the presence of stiction. The data obtained from the process along with the results from stiction detection technique are shown in Figure 7. According to the proposed algorithm, the cause for oscillations in this loop is due to a sticky valve which is also confirmed by Horch [1999].

4.3 Industrial Case study - II

The data sets used for analysis in this section are obtained from another industry. In this section, results obtained on three industrial loops using the RCA algorithm are provided in Table 2. Analysis of these loops using the

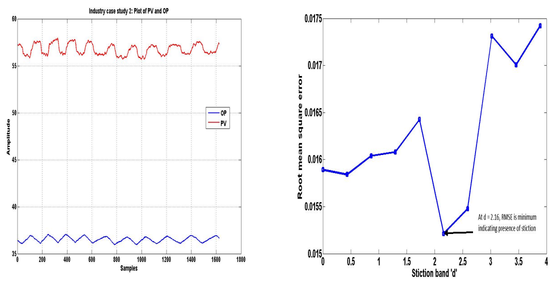


Fig. 7. **Flow loop process - FC525** (a) Plot of process output PV and controller output OP (u) (b) Plot of results from one parameter model based Hammerstein approach

Loop	*Loopname*	Actual case	d	predicted case
Flow	FC525	Stiction	2.16	Stiction
Flow	FC392	Stiction	2.6	Stiction
Level	LC621	Controller	0	Controller
Flow	FC145	Stiction	0.33	Stiction

Table 1. Results obtained from industrial control loops provided by Horch

RCA algorithm indicated that two out of three loops contained stiction. The Hammerstein algorithm indicated a value of stiction in these two loops (d values are 0.17 and 0.36). The industry also reported that these loops contain sticky valves. Interestingly, the RCA algorithm indicated presence of no stiction in the third loop. Further, no conclusion could be made from the RCA algorithm on this particular loop. Industrial analysis reported that there was no stiction in the valve. However, the root cause for the oscillation in this loop was not reported by the industry.

Loop	Actual case	d	predicted case
Chemical	Stiction	0.17	Stiction
Chemical	Stiction	0.36	Stiction
Pressure	No stiction	0	Disturbance

Table 2. Results obtained from industrial case study II

5. CONCLUSIONS

A novel and robust method for diagnosis of cause of oscillation in closed-loop systems is developed. The proposed method combines both the parametric and non-parametric techniques for root cause analysis of oscillatory systems. The advantages of the proposed method are: *(i)* a unique signature for distinguishing between controller and external disturbance is developed, *(ii)* non-stationary nature of the disturbance can be naturally handled since HHT is a time-frequency analysis tool and, *(iii)* no assumptions on noise structure is necessary.

There are only two tuning parameters namely, *(i)* introduction of 30% stiction in OP data and *(ii)* threshold value (5% of maximum power value in PV). These two values are maintained as the same for all the validation results that include simulation and industrial data. The results obtained from simulation and industrial data sets shows the power of the proposed method for root cause analysis. Future work will focus on the enhancement of the current algorithm to identify causes for oscillations in nonlinear closed-loop systems.

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