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Valve Stiction Detection and Quantification Using K-means Clustering Based Moving Window Approach

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ABSTRACT: In this paper, a novel and effective stiction detection method is proposed by combining K-means clustering and moving window approach. As a byproduct, the proposed stiction detection method offers an estimation for stiction band in sticky control valves. The proposed stiction detection method is tested in industrial case studies consisting of benchmark industrial control loops, and control loops from an oil sands industry. In the benchmark industrial control loops, the results of the proposed method are compared with some of the existing stiction detection methods. This comparison shows superior performance of the proposed method. It is noticed through a simulation case study and an industrial case that the proposed method not only provides stiction band estimation but also can detect severe valve stiction or unexpected valve closures.

Keywords: valve stiction, K-means clustering, moving window approach

1. Introduction

A plant in process industries such as petroleum refineries, petrochemical industries, polymer industries, pulp and paper industries, power plants, base metal refineries, pesticides industries, pharmaceuticals etc. has hundreds of control loops maintaining key process variables at their respective desired set points. Desborough[1] conducted an extensive survey over twenty six thousand PID control loops of varied process industries, and reported that only 16% of the loops exhibit excellent performance, among the remaining loops, 38% are categorized into fairly or poorly performing controllers and 32% work in open loop. Poorly performing or oscillating control loops can induce detrimental issues in processing plants, which disrupt normal plant operations, increase variability in product quality, quicken equipment (control valve) wear, and result in excessive energy and raw materials consumption. The reverberations associated with oscillations will eventually lead to reduction in plant profits, and emission of increased amounts of volatile organic compounds, hence, boost environmental footprint. The oscillations in control loops can result from multiple sources such as improper controller tuning, multi-loop interactions, sensor faults, external oscillatory disturbances, and control valve problems. Control valve is responsible for implementing decisions made by controller and plays a crucial role in ensuring safe and efficient plant operation. Control valve problems like stiction, backlash, deadband, deadzone, hysteresis and saturation often ensue from continuous movements of valve stem. Among all causes of loop oscillations, the control valve problems, especially, valve stiction appears to be the main cause of oscillations in 20-30% of all oscillating control loops.[2-5] Stiction is an equipment problem and its origin in valves is static friction. Stiction offers resistance to proper valve movement, and introduces delay between controller output and valve stem position. When a control valve suffers from stiction, its stem may not move even though the controller output keeps changing, hence, the relationship between controller output and valve stem position is nonlinear.[6] The valve stiction is known to exist in process industries for quite a long time, and introduces oscillations in terms of limit cycles in control loops, posing a great impact on control performance and safe operation of process. The early detection of valve stiction facilitates to lessen the negative impact on loop performance in order to operate plants efficiently and safely, increase the life-expectancy of control valves and decrease maintenance cost.

Existing stiction detection methods can be broadly categorized into manual and automatic methods (Figure 1). An industry plant contains hundreds of control valves, and manually inspecting each valve is time consuming and not possible. Moreover, the condition of valves needs to be checked periodically. Therefore, automatic methods receive greater importance. A collection of automatic methods (Kano's shape based methods[7,8] and Yamashita's shape based method,[9] cross-correlation method (CORR),[10] histogram based method (HIST),[11] curve fitting method (CURVE),[12] relay technique (RELAY),[13] area peak method (AREA),[14] Hammerstein system based methods (HAMM1, HAMM2 and HAMM3) (Chapters 10-12 in Jelali and Huang[15]), surrogate analysis based method,[16] bicoherence method (BIC)[17]) reported up to 2009 was provided and discussed in an edited book published by Jelali and Huang.[15] In Chapter 13 of Jelali and Huang,[15] BIC, CORR, HIST, CURVE, RELAY, AREA, HAMM2 and HAMM3 were applied to twenty industrial control loops, in which the actual root causes of oscillations are known, and the comparison made among the results of all methods revealed that BIC and HAMM2 provide less number of false alarms than the remaining methods.

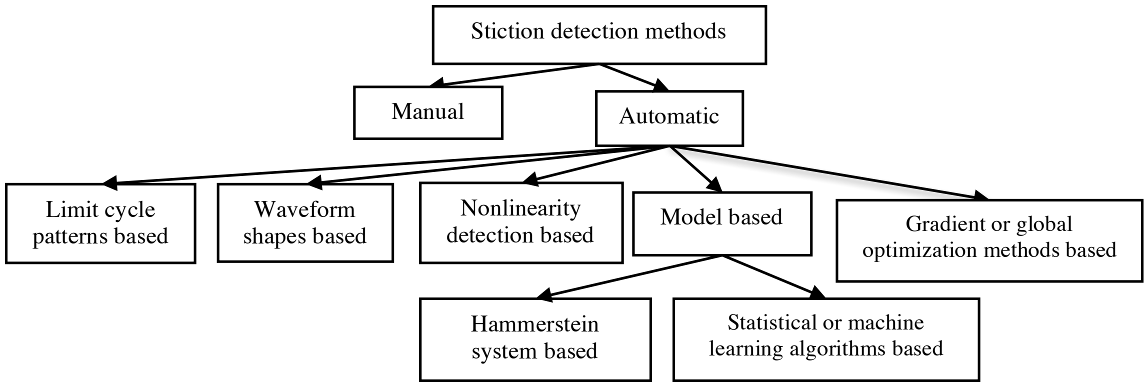

Figure 1. Classification of stiction detection methods.

1.1. Review of methods reported from 2015 to date

Some of the abovementioned methods have limitations restricting their applicability to some types of control loops. Following discussion highlights such limitations, and explains how these were overcome by recently developed methods. In spite of the fact that the methods such as CURVE, AREA, CORR, HIST, Kano's method,[8] Yamashita's method and higher order statistics based method[18] work well for control loops with constant reference (setpoint) signal, they exhibit declining performance when reference signal keeps varying. To identify the cause of oscillations in control loops when reference signal is varying, Dambros et al.[19] proposed two methods based on the slope of signal peaks or valleys (SLOPE), and zone segmentation (ZONE), respectively. Note that both these methods depend on waveform shapes such as triangular and sinusoidal. Brásio et al.[20] pointed out that Yamashita's shape based method performs well in flow control loops only, and fails in level control loops as the method assumes that controlled variable (process output) is directly proportional to real valve position, which is not valid in level control loops. So the authors (Brásio et al.[20]) proposed the use of a transformation function (first order finite difference) to relate PV directly to MV, and then applied the Yamashita's method to the transformed PV, and MV. However, this method requires the measurements of valve position which are not always available in most plants, which is a potential drawback. All shape based methods depend on the identification of triangular, sinusoidal or square shapes in oscillating OP and/or PV. When long sampling time (i.e. slow rate sampling) is used, OP and PV may have obvious oscillations but may not have perfect triangular, square or sinusoidal shapes due to a few data points sampled per cycle. In this case, shape based methods may not be able to detect stiction. Therefore, Dambros et al.[21] conducted a study to investigate the effect of long sampling time on the stiction detection capability of CORR, CURVE, Yamashita's method, SLOPE and ZONE, and provided minimum number of data points required per cycle for each of five methods. In addition to long sampling time, other data features such as mean-nonstionarity, oscillation persistency and noise may weaken the stiction detection ability of data-driven methods, and also shaped based methods may issue uncertain or wrong verdicts when waveform shapes or limit cycle patters are not clearly noticeable in OP and/or PV. Therefore, data quality and features have great impact on the performance of data-driven stiction detection methods. To obtain more reliable results, Garcia et al.[22] developed an integrated stiction detection system which fuses the results of CURVE, CORR, HIST, AREA and exponential fitting method and provides a final decision which more accurately indicates the presence or absence of stiction.

Apart from waveform shape based, and limit cycle patterns based stiction detection methods, there is another class of methods that identify sticky valve by finding the cause of oscillations in OP and PV. Thornhill et al.[23] reported that if oscillations in a control loop are induced by a nonlinear problem such as valve stiction, then OP and PV contain odd harmonics.

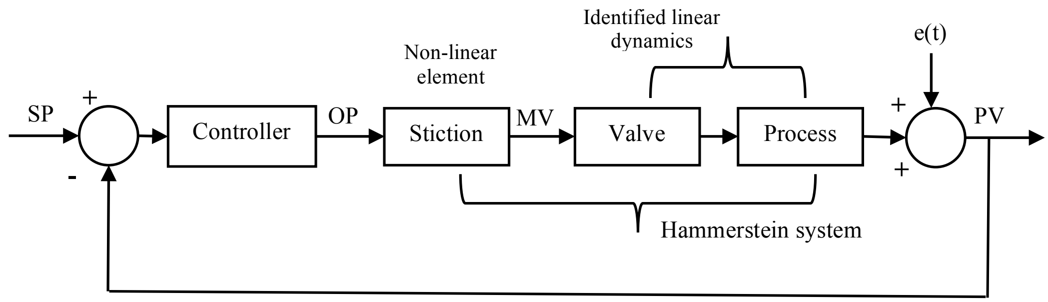

Figure 2. Control loop with stiction.[26] SP-setpoint, OP-controller output, MV-manipulated variable, PV-process output, e(t)-noise.

Centered on this idea, Aftab et al.[24] formulated an adaptive nonlinearity detection algorithm by using Hilbert Huang Transform and intra-wave frequency modulation to detect the presence of harmonics in oscillatory signal (OP or PV) to indicate the presence of valve stiction. However, the adaptive nonlinearity detection method suffers from inherent mode mixing limitation of empirical mode decomposition which may result in false reporting of nonlinearity in the presence of noise and multiple oscillations. This shortcoming was overcome in Aftab et al.[25] by exploiting the dyadic filter bank property of multivariate empirical mode decomposition to reveal the harmonic content of oscillatory signal.

The fourth class of stiction detection methods relies on Hammerstein system framework, depicted in Figure 2, where the non-linear component is usually modelled by any of the existing data-drive stiction models whereas the linear component is identified by a linear process model.[26] Many stiction detection methods based on the Hammerstein system have been reported. Srinivasan et al.[27] pointed out that Hammerstein model based stiction detection approaches yield ambiguous results, and fail to detect stiction in integrating level control loops. They also claimed that results obtained from Hammerstein model based approaches are sensitive to the choice of search space for the parameters of the linear dynamic model component. So, the authors (Srinivasan et al.[27]) proposed a reliability measure algorithm which validates results (verdicts) acquired from Hammerstein model based approaches, and also determines an optimal search space for linear dynamic process model. In contrast to the most Hammerstein model based methods using time domain criterion (mean squared error), Li et al.[28] argued that more reliable and accurate stiction quantification may be obtained if both time domain criterion and frequency domain criterion (absolute error between real and estimated frequency) are considered in the joint estimation of stiction as well as process model parameters. The authors (Li et al.[28]) formulated a two-stage stiction quantification method based on two domains criterions, and obtained better estimations for S (deadband + stick band) and J (slip jump) than the quantification methods based on time domain criterion only. In di Capaci et al.,[29] a comparative study of five linear models (ARX, ARMAX, state space, extended ARX (EARX), extended ARMAX (EARMAX)) for the controlled process (linear block), and two nonlinear models (Kano's model & He's model) for the sticky valve of the Hammerstein system was carried out to investigate the effect of external unmeasured disturbance and improper controller tuning on the estimation of stiction parameters (S and J), and the linear model identification. The authors (di Capaci et al.[29]) concluded that the non-extended models (ARX, ARMAX and SS) provide a more accurate stiction estimation and better linear model identification when stiction is the only source of control loop oscillations (i.e. the absence of external disturbance), but the extended models are more appropriate to manage the additional presence of external disturbances. The effect of improper controller tuning on stiction estimation and linear model identification was found to be not particularly significant. In addition to the above examination, the authors also addressed a commonly overlooked aspect: Kano's stiction model initialization which can have noteworthy impact on stiction estimation, and provided guidelines to initialize the Kano's model parameters. In di Capaci et al.,[30] a similar comparative study was performed in the presence of nonstationary disturbances. A bootstrap Hammerstein system identification procedure was developed by Yan et al.[31] to derive control limits for stiction parameters. Hutabarat et al.[32] claimed that the cause of control loop oscillations can be found to be either external oscillatory disturbances or poor controller tuning if PV is normally distributed. Authors (Hutabarat et al.[32]) used Hammerstein system based approach to detect and quantify stiction if PV is not normally distributed. In all the Hammerstein model based methods discussed so far, sticky valve was modelled by a data-driven model which was derived based on the input-output behavior shown in Figure 3. Fang and Wang[33] showed that the existing data driven stiction models fail to capture more complex behaviors observed in practice, hence, proposed the use of Preisach model for the nonlinear block of Hammerstein system.

Unsupervised and supervised learning algorithms have also been employed to detect stiction in control loops. Daneshwar and Noh[34] developed a data based stiction detection method using fuzzy c-means clustering to detect stiction in flow control loops. This method detects the cause of oscillation (stiction or external disturbances) in flow control loop in two stages. In the first stage, data (OP and MV or OP and PV) is grouped into four clusters, and a linear equation is fitted to the centers of four clusters. If R^2 statistic of the fit is above 0.9, no oscillations are detected, hence, further investigation is not carried out. Otherwise (R2<0.9), the cause of oscillations such as stiction or disturbances is identified by using a stiction index. A popular multivariate statistical technique, principal component analysis (PCA), finds applications in valve stiction detection. Miskin et al.[35] identified valve faults such as valve wear and stiction in base metals refinery by using principal component analysis (PCA). A nonlinear version of PCA, and autocovariance were employed in Teh et al.[36] to develop stiction detection method (NLPCA-AC) which shows better performance on benchmark industrial control loops than BIC, CORR, HIST, CURVE, RELAY, AREA, HAMM2, HAMM3, SLOPE and ZONE. Dambros et al.[37] formulated waveform shapes-based oscillation detection and diagnosis method using feed forward neural network, in which the shape of PV-OP plot is transformed into an 8×8 pixel image which is used as training data to train the network. Likewise, Mohd Amiruddin et al.[38] adopted deep ANNs to develop stiction detection network (SDN) to determine whether loop oscillations are induced by stiction or non-stiction conditions. Contrary to the most stiction detection methods depending on the elliptical shape of PV-OP phase plot, Kamaruddin et al.[39] derived a butterfly shape from manipulated OP and PV data to detect the presence of stiction and this method is termed butterfly shape detection (BSD) method. The authors (Kamaruddin et al.[39]) also developed stiction quantification method by using butterfly shapes as input to deep convolutional neural network. Aksornsri and Wongsa[40] employed particle swarm optimization technique to estimate the parameters of Kano's stiction model being used in a framework similar to Hammerstein system. An extensive review of stiction models, stiction detection and quantification methods was provided in di Capaci and Scali[41]. Readers can consult di Capaci and Scali[41] for additional information on automatic methods reported up to 2018. A novel cross limit control method was developed by Sun et al.[42] to handle process or mechanic issues such as valve stiction in furnace operation. During valve stiction in furnace control loop, controller output gets changed too much, which exceeds maximum allowed change (OPmax) in OP over an n sampling time period, but change in controlled variable is very small and less than possible minimum change in PV (PVmin), leading to furnace trip. This method prevents furnace trip by choosing OPmax and PVmin in such way that change in PV during stiction is at least greater than PVmin. Hence, this method avoids operational issues by taking necessary action prior to the occurrence of valve stiction.

1.2. Motivation and contributions

It can be understood from the literature reviewed above that majority of methods depend on either waveform shapes (triangular, square or sinusoidal) or limit cycle patterns (elliptical shape). The waveform shapes or elliptical shape may get modified by process noise, multi-loop interactions or simultaneous presence of valve stiction and any one or more of non-stiction conditions etc. In this scenario, the shape based methods may issue wrong verdicts. Even Hammerstein system based methods possess one disadvantage. They depend on data-driven stiction models which sometimes fail to capture complex behavior of sticky valves as reported in Fang and Wang.[33] If stiction model cannot describe the true behavior of sticky valve, then verdict issued by Hammerstein system based method is likely to be wrong. Moreover, the issue of monitoring of valve fault other than stiction has not been addressed yet. In some cases, it is difficult to move the valve due to changes in working environment. For example, a valve is frozen due to cold weather. In such situation, the valve requires a larger-than-normal controller output to make a move. But when the valve moves, it usually leads to an abrupt change in a process input, i.e. a suddenly increased gas flow into a furnace, threatening safe operation of the process. Hence, to prevent unexpected process shut down and performance loss, it is desirable to monitor valve condition and raise necessary alarms when valve abnormalities are detected. The identified research gaps motivated the authors of the present work to develop a new valve stiction detection method. Some features of the proposed method are provided below:

- It completely works in unsupervised way, and does not involve extensive training
- It does not depend on either waveform shapes or limit cycle patterns, and does not require modelling valve stiction and process
- It uses routine operation data (OP and PV) only
- It is applicable to control loops with constant (stationary) or varying reference (non-stationary) signal (or set point)
- It does not issue uncertain verdicts
- As byproducts, in addition to providing an estimation for stiction band (S), it also detects valve abnormality (for e.g. unexpected valve closure)

The remaining part of the manuscript is structured as in the following. The proposed valve stiction detection method is described in Section 2. Estimating stiction band from the results of the proposed stiction detection method is explained in Section 3. In Section 4, the proposed stiction detection and the quantification method are applied to benchmark as well as Syncrude control loops. Conclusions drawn from the present work are provided in Section 5.

2. Stiction detection

Relationship between controller output (OP) and actual valve position (valve output) of a control valve suffering from stiction is shown in Figure 3. If valve stiction does not occur, OP and MV are exactly the same. Under stiction, linear relationship between OP and MV is no longer valid, and valve behaves as depicted in Figure 3. The input-output behavior of sticky valve is composed of deadband, stickband, slip jump (J) and moving phase. When a valve sticks, MV does not change while OP keeps on changing. The valve overcomes stiction when cumulative change in OP equals stiction band (S), and at this point, MV abruptly changes (this is characterized by slip jump). Once the valve stem gets released from stiction, it continuously moves in upward or downward direction (this is termed moving phase). When OP alters its movement direction, the valve sticks again, and the valve stem stops moving. The valve may stick multiple times, and each time, stiction band as well as slip jump may vary. Hence, stiction is perhaps not static but more likely to be dynamic.

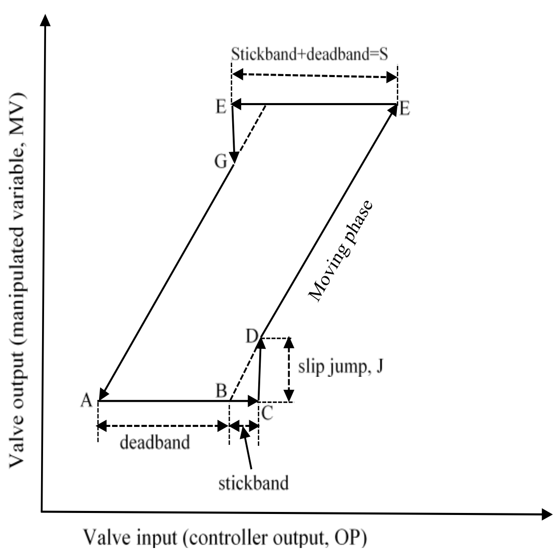

Figure 3. Behavior of sticky control valve.[6]

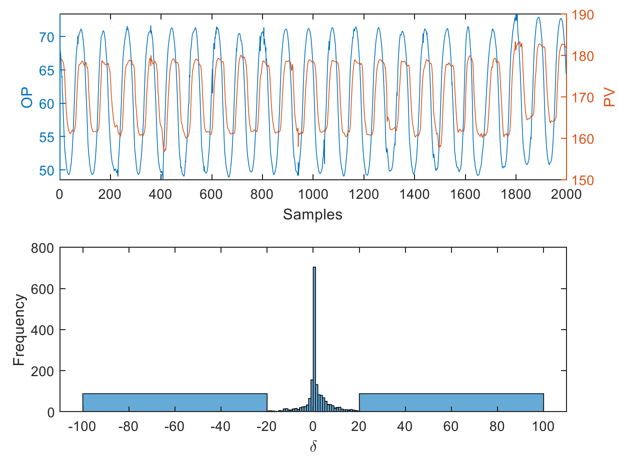

Figure 4. Time trend of OP and PV of flow control loop (top plot), and distribution of corresponding δ (bottom plot).

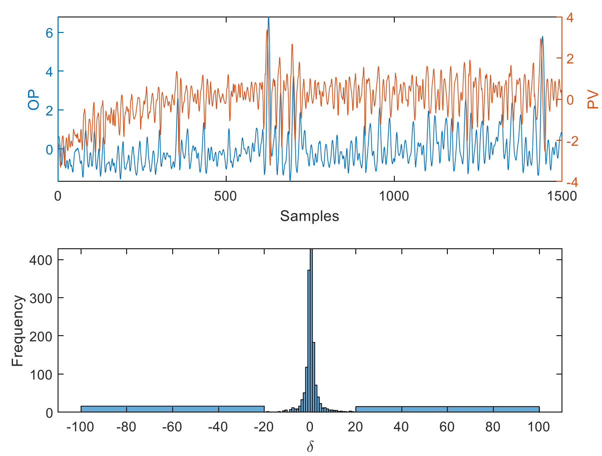

Figure 5. Time trend of OP and PV of pressure control loop (CHEM 16[15]) oscillating due to interactions (top plot), and distribution of corresponding δ (bottom plot).

Brief introduction of the proposed method

The present work proposes a new method for detecting sticky valves in industrial control loops. Following furnishes alluring characteristics of the method to help readers determine the suitability of it to their needs

- Slowly changing behavior of PV, in relation to OP change, during valve stiction is the basis for the proposed method.
- The proposed method needs a simple clustering algorithm; K-means clustering, and relies on PV and OP, which are available in every process industry. Hence, no additional hardware or commercial software is needed to implement it.
- Besides stiction detection, it quantifies stiction, and identify faulty valves such as frozen valves, clogged valves and valves with severe stiction.
- It can work with stationary and non-stationary signals.
- The method can detect stiction in loops exhibiting multiple oscillations.
- Low level of noise in PV or OP does not hamper performance of the method. However, signals with moderate to high level of noise need to be denoised before being tested with the method.
- The method is applicable to flow loop, temperature loop, pressure loop and concentration loop.
- The method does not involve complex training and needs no supervision.
- The method can work with signals with different lengths. As the readers will notice in Subsection 4.2, PV and OP signals of flow loop contain only 60 samples. Yet, the method provided correct diagnosis in this loop.
- The method is applicable to constant and varying reference (setpoint) signal.

From here onwards, theory of the proposed method is discussed.

The top plot of Figure 4 shows oscillatory OP and PV of a flow control loop (CHEM 32) in a refinery.[15] The flow control loop, CHEM 32, is said to be suffering from valve stiction. It can be seen from the figure that PV starts slowly changing when OP changes its movement direction. When a change in OP is sufficiently large to move the valve stem, the valve stem begins to move, and continues to move until OP stops changing or alters its direction. PV more quickly changes during the continuous movements of valve stem than during stiction. Therefore, the ratio of ΔOP to ΔPV is much larger during stiction than during moving phase.

$$\delta_i = \frac{OP_{i+\Delta t} - OP_i}{PV_{i+\Delta t} - PV_i},\ i = 1,2,...,N, \qquad (1)$$

where N is the number of samples of OP or PV and Δt is the step size.

By investigating the distribution of $\delta = \{\delta_i\}_{i=1}^{N}$, it is possible to verify whether control valve is sticky or not. The bottom plot of Figure 4 shows three groups in the distribution of δ. The total number of δ_i in the first and third group is larger than that in the second group for a sticky valve, and the other way around for a healthy valve as shown in Figure 5. Hence, the determination of stiction in a control loop reduces to the identification of three clusters in the distribution of δ.

2.1. Finding clusters and thresholds

Let δ be a set of one-dimensional observations that is to be partitioned into three clusters ($K = 3$) by an unsupervised K-means algorithm. The K-means algorithm assigns the given set of observations into K clusters in such a way that the average measure of dissimilarity (intra-cluster variance) of observations assigned to each of K clusters is minimized. Hence, the K-means algorithm minimizes total cluster variance

$$J(C) = \sum_{j=1}^{K} \sum_{C(i)=j} \left\| \delta_i - \mu_j \right\|_2^2, \qquad (2)$$

where μ_j is the center of cluster j, C is an encoder (many-to-one mapper) which assigns to cluster j all of the observations in δ that are closest to center μ_j, $\|\cdot\|_2^2$ denotes squared Euclidean distance.

The K-means algorithm finds K clusters in δ according to the procedure described in the following steps.

Step 1. The centers of three clusters are randomly initialized, i.e. the encoder C is initially chosen.

Step 2. For the given encoder or cluster centers, the cost function in Equation (2) is minimized

$$\min_{\{\mu_j\}_{j=1}^{K}} \sum_{j=1}^{K} \sum_{C(i)=j} \left\|\delta_i - \mu_j\right\|_2^2, \text{ for a given } C. \quad (3)$$

Step 3. Once the cluster centers are optimized, then the encoder is optimized as follows.

$$C(i) = \arg \min_{1 \le j \le K} \left\|\delta_i - \mu_j\right\|_2^2. \quad (4)$$

The K-means algorithm iterates between Step 2 and 3 until the convergence criterion is met or the cluster assignments do not change. Though the K-means algorithm is simple to implement, its performance is sensitive to the initial choice of cluster centers or encoder. One way to start the algorithm with the best initial values is to select different sets of cluster centers randomly, and evaluate the cost function $J(C)$ using each initial guess. The set of initial cluster centers that provides the least value of $J(C)$ is selected as an optimal initial set.

Once δ is partitioned into 3 three clusters, the next step is to determine thresholds i.e. the minimum and maximum of cluster 2 to identify the members of cluster 1 and 3. Let the identified clusters have centers μ_1, μ_2 and , μ_3, respectively. Center μ_2 is always greater than μ_1, and less than μ_3. The thresholds are determined as

$$\alpha_1 = \min\{\delta_i\}_{i=1}^{N_2},\ \delta_i \in C_2, \quad (5)$$

$$\alpha_2 = \max\{\delta_i\}_{i=1}^{N_2},\ \delta_i \in C_2, \quad (6)$$

where C_2 represents the second cluster and N_2 is the total number of samples in the second cluster.

The rate of stiction is computed in the next equation to determine if the control valve is sticky.

$$\theta = \frac{\sum_{i=1}^{N} \phi_i}{N} \times 100 \tag{7}$$

where

$$\phi_i = \begin{cases} 1, & if\ \delta_i \notin C_2, \\ 0, & \delta_i \in C_2 \end{cases}$$

A large value of θ indicates the likelihood of valve stiction. The procedure described above holds good for any value of step size (Δt), hence, distinct thresholds can be obtained for different values of Δt .

2.2. Moving window based stiction detection

Although a large value of θ highly indicates the presence of valve stiction, it may not be a reliable indicator because ΔPV calculated using the step size of 1 is really small in a slow control loop such as temperature loop or concentration loop. To improve the reliability of stiction detection, a moving window based stiction detection method (MWSD), whose schematic diagram is displayed in Figure 6, is proposed.

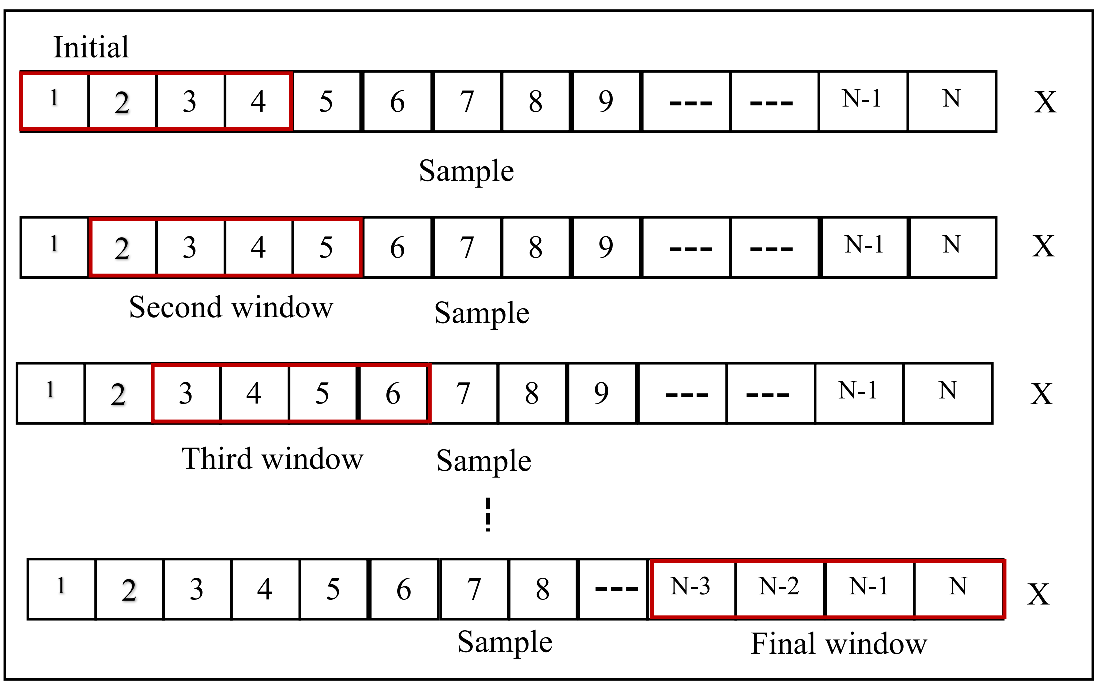

Figure 6. Moving window approach with window size of 4.

Suppose that the data is defined as $X = \left[OP, PV\right]$, and the size of initial window (w_s) is considered to be 4. The step size (Δt) accepts integer values in the range $\left[1, w_s - 1\right]$. The first or initial window contains the first four sample of OP and PV:

$$X_1 = \begin{bmatrix} OP_1 & PV_1 \\ OP_2 & PV_2 \\ OP_3 & PV_3 \\ OP_4 & PV_4 \end{bmatrix} \tag{8}$$

For the step size of 1, δ_{11} is calculated.

$$\delta_{11} = \frac{OP_2 - OP_1}{PV_2 - PV_1} \tag{9}$$

Similarly, the following can be computed for the reaming step sizes.

$$\delta_{12} = \frac{OP_3 - OP_1}{PV_3 - PV_1} \tag{10}$$

$$\delta_{13} = \frac{OP_4 - OP_1}{PV_4 - PV_1} \tag{11}$$

The following index is calculated in the first window.

$$\eta_1 = \frac{\sum_{p=1}^{w_s - 1} N_{1p}}{w_s - 1} \tag{12}$$

where

$$N_{1p} = \begin{cases} 1 & \text{if } \delta_{1p} \notin C_2 \\ 0 & if\ \delta_{1p} \in C_2 \end{cases}$$

Note that the thresholds α_{1p} and α_{2p} can be determined using the procedure described in the previous subsection. The window moves forward by taking the next sample (sample 5), and forgetting the oldest sample (sample 1):

$$X_2 = \begin{bmatrix} OP_2 & PV_2 \\ OP_3 & PV_3 \\ OP_4 & PV_4 \\ OP_5 & PV_5 \end{bmatrix} \tag{13}$$

In the second window, the following are determined.

$$\delta_{21} = \frac{OP_3 - OP_2}{PV_3 - PV_2} \tag{14}$$

$$\delta_{22} = \frac{OP_4 - OP_2}{PV_4 - PV_2} \tag{15}$$

$$\delta_{23} = \frac{OP_5 - OP_2}{PV_5 - PV_2} \tag{16}$$

η_2 is calculated in the second window. The window keeps moving forward by forgetting the oldest sample and accepting the next new sample as explained in Figure 6. η is computed in the remaining windows. Once the window reaches the last four samples of OP and PV, and the corresponding η is determined, the following stiction index is computed to determine the presence of stiction in a control loop.

$$\beta = \frac{\sum_{i=1}^{N-(w_s-1)} s_i}{N-(w_s-1)} \times 100 \tag{17}$$

where

$$s_i = \begin{cases} 1 & if\ \eta_i \geq \eta_{th} \\ 0 & if\ \eta_i < \eta_{th} \end{cases}$$

The control valve is considered to be sticky if β is greater than zero.

Main steps involved in the development of the proposed method, which are necessary for implementation, are summarized below. The pictorial description of those steps is provided in Figure S1, which is available in supporting information.

Step 1: PV and OP signals of a control loop are acquired and denoised using noise attenuation techniques.

Step 2: Size of moving window w_s is selected. The step size Δt takes integer values in the range $[0, w_s-1]$. A threshold for η is chosen.

Step 3: For the first value of Δt, a vector of δ is computed. Three clusters in this set are identified using K-means clustering technique. The thresholds (α_1 and α_2) of cluster 2 are determined and stored.

This step is repeated for the remaining values of Δt. Different thresholds of cluster 2 are obtained for different values of Δt.

Step 4: The first w_s number of samples of the data matrix X, where $X = [OP, PV]$, are considered in the first or initial window. The index η_1 is calculated using Eq. (12). The $(w_s+1)^{th}$ sample of X is taken into the window and the oldest sample (i.e. first sample $[OP_1, PV_1]$) in the window is removed. In this second window, η_2 is computed. The window keeps moving forward by forgetting the oldest sample and including the next new sample, and in each window, η is calculated and stored.

Step 5: The stiction index β in Eq. (17) is calculated. If β is greater than zero, then the cause of oscillations in the control loop under consideration is identified as stiction. Otherwise, any of the non-stiction conditions can be the source of oscillations.

3. Moving window based stiction quantification (MWSQ)

Stiction quantification allows to line up sticky valves according to their extent of stiction in order to determine which valves need immediate service. As a byproduct, the proposed stiction detection method provides an estimation of stiction band (S). Figure 7 demonstrates how stiction band is estimated. It can be observed from Fig. 7 that when the valve stops moving, PV starts to change slowly (or stops varying) and the stiction signal (s_i) becomes 1. As long as the valve position does not change, PV either experiences very small changes or remains unchanged, so the stiction signal stays at 1. When the valve overcomes stiction, the stiction signal abruptly drops to zero, and remains at zero until the valve sticks again.

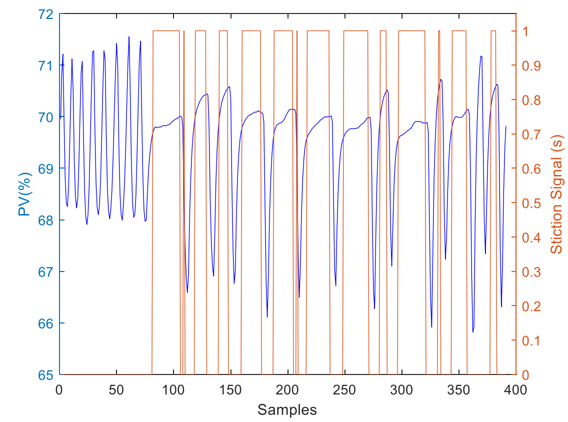

Figure 7. Stiction detection in temperature control loop with sticky valve (PV and OP were provided by Syncrude Canada Limited).

According to the stiction detection results shown in Figure 7, the stiction signal in windows 82 through 105 is 1. The size of moving window is taken to be 4, so the step size accepts integer values like 1, 2 and 3. The threshold η_{th} is taken to be 30%.

Window 82 includes four samples of OP and PV, and the ratios δ_{82-1}, δ_{82-2} and δ_{82-3} are calculated using step size of 1, 2 and 3, respectively, according to Equation (9) through (11).

$$X_{82}=\begin{bmatrix} OP_{82} & PV_{82} \\ OP_{82} & PV_{83} \\ OP_{84} & PV_{84} \\ OP_{85} & PV_{85} \end{bmatrix},\ \Omega_{82}=\left[\delta_{82-1},\delta_{82-2},\delta_{82-3}\right] \tag{18}$$

Similarly, windows 83 through 104 contain the subsequent samples of OP and PV, and δ_i 's are computed.

The following can be obtained in window 105.

$$X_{105}=\begin{bmatrix} OP_{105} & PV_{105} \\ OP_{106} & PV_{106} \\ OP_{107} & PV_{107} \\ OP_{108} & PV_{108} \end{bmatrix},$$
$$\Omega_{105}=\left[\delta_{105-1},\delta_{105-2},\delta_{105-3}\right] \tag{19}$$

Since s_{105} in window 105 is 1, at least one element of Ω_{105} does not obey the corresponding thresholds α_{1p} and α_{2p}. Suppose that δ_{105-3} is not in cluster 2 and both δ_{105-1} and δ_{105-2} may be or may not be in cluster 2. In this case, the samples PV_{82} through PV_{108} change very slowly because of stiction, and the corresponding samples of OP will provide an approximation for the stiction band:

$\Psi_1=\left|OP_{82}-OP_{108}\right|$, if $\delta_{105-3}\notin C_2$, $\left[\delta_{105-1},\delta_{105-2}\right]\notin C_2$ or $\left[\delta_{105-1},\delta_{105-2}\right]\in C_2$ (20)

Similarly different cases can arise and the stiction band can be estimated as explained below.

$\Psi_1=\left|OP_{82}-OP_{107}\right|$, if $\delta_{105-2}\notin C_2$, $\delta_{105-3}\in C_2$, $\delta_{105-1}\notin C_2$ (or $\delta_{105-1}\in C_2$) (21)

$\Psi_1=\left|OP_{82}-OP_{106}\right|$, if $\delta_{105-1}\notin C_2$ and $\left[\delta_{105-2},\delta_{105-3}\right]\in C_2$ (22)

Only one of the three cases explained above can occur in the same time. The stiction signal immediately drops to zero in window 108, and goes to 1 in window 109. In this case, there is only one window in which the stiction signal is 1. Similar to Equation (20) through (22), the stiction band estimated in one of the cases is described below.

$\Psi_2=\left|OP_{109}-OP_{112}\right|$, if $\delta_{109-3}\notin C_2$, $\left[\delta_{109-1},\delta_{109-2}\right]\notin C_2$ or $\left[\delta_{109-1},\delta_{109-2}\right]\in C_2$ (23)

$\Psi_2=\left|OP_{109}-OP_{111}\right|$, if $\delta_{105-2}\notin C_2$, $\delta_{105-3}\in C_2$, $\delta_{105-1}\notin C_2$ (or $\delta_{105-1}\in C_2$) (24)

$\Psi_2=\left|OP_{109}-OP_{110}\right|$, if $\delta_{105-1}\notin C_2$ and $\left[\delta_{105-2},\delta_{105-3}\right]\in C_2$ (25)

In this fashion, the stiction band is estimated every time valve gets stuck. The following equation provides final approximation for the stiction band.

$$\tilde{S} = \max\left\{\Psi_k\right\}_{k=1}^{M} \tag{26}$$

where M is the number of times valve gets stuck.

4. Case studies

The applicability of MWSD to industrial control loops is investigated in this section. The size of moving window (w_s) is selected to be 7 in order to detect sticky valves having varied degrees of stiction. As mentioned above, ΔPV 's calculated with the step size of 1 are sometimes very small not because of stiction but because of slow process dynamics, hence, $\eta_{th} = 30$ is selected to avoid false alarms.

Valve stiction detection and quantification

4.1. Benchmark industrial control loops

Jelali and Huang[15] created an international stiction data base (ISDB) consisting of operation data of control loops taken from chemical industries, pulp and paper industry, power plant, mineral industry, commercial buildings and metal processing industry. The control loops include flow, level, temperature, pressure, concentration, gauge and analyzer control loops. Among 96 control loops available in ISDB, the real root causes of 20 oscillating control loops (given in Table 13.7 in Chapter 13 of Jelali and Huang[15]) are known. These twenty control loops are adopted in this work.

The industrial control loop CHEM 1 is selected to carry out in-depth analysis of the proposed method. It is observed from Figure 8 that this control loop tries to track varying reference signal (non-stationary signal). Both OP and PV were denoised using Symlet wavelet. As discussed in Section 1, parallelogram is not always clearly noticeable in phase plot (PV versus OP plot) of practical data, which is the case here (Figure 9). For various values of step size Δt , δ 's were computed and plotted in Figure S2 (available in supporting information). The distribution within each of the three groups varies with increasing step size. At a first glimpse of these distributions, predictions about the presence of stiction in CHEM 1 can be made before diving deep into other aspects of the proposed method. Irrespective of value of Δt , group 2 holds more samples than groups 1 and 3. Therefore, it may be said that stiction is either absent or negligible.

To confirm forecasts made by visual inspection, K-means clustering was applied to each set of δ values. Analysis of obtained clusters from each set is provided in Table S1 (given in supporting information). The center of clusters 1 and 3 are rapidly changing whereas the center of cluster 2 is slightly oscillating around 0.4. The boundaries of cluster 2 are experiencing slight variations. The moving window approach was applied, and as the window was moving forward, the index η was computed as shown in Figure 10. As mentioned earlier, δ 's calculated using the step size of 1 are always large. If window size of 2 is used, then the method detects stiction in every control loop regardless of the actual cause of oscillations. That is why window size of seven is chosen. This choice allows for fair detection of the presence or absence of stiction. According to the results shown in Figure 11 and Table 1, the proposed method detected the existence of low stiction in CHEM 1. In practice, stiction band less than 0.5 is considered to be less detrimental. This result is close to the prediction made by visual examination.

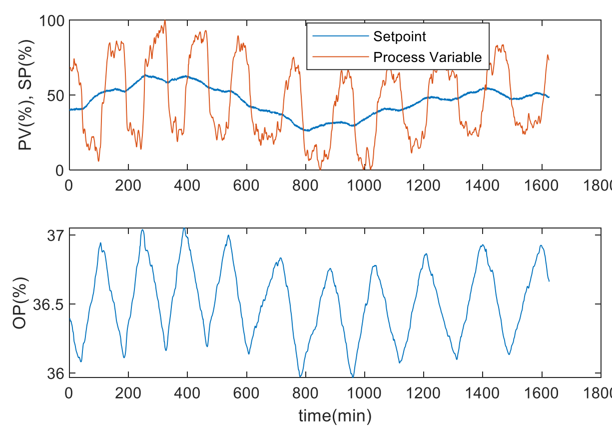

Figure 8. Time trend of OP, PV and SP of CHEM 1.

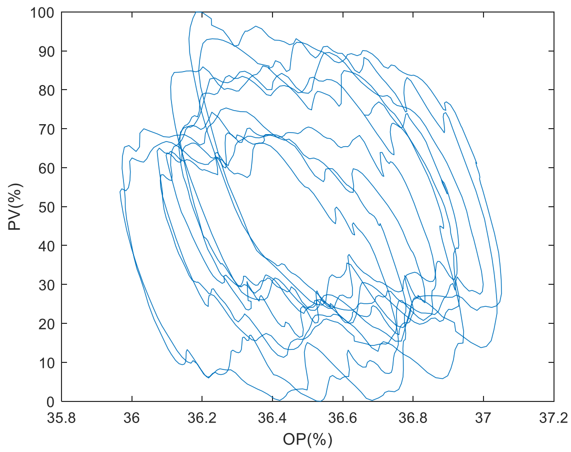

Figure 9. Phase plot of CHEM 1 loop.

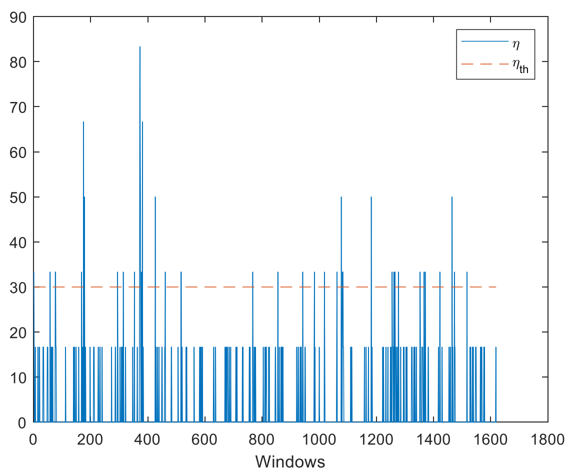

Figure 10. Results of moving window approach.

The stiction index (via MWSD) and the estimated stiction band (via MWSQ) for the remaining control loops are shown in Table 1. Figures 12 to 14 display the stiction signal of control loops representing stiction and non-stiction cases and three types of process industries. For CHEM 23, the results are shown only for few samples but the stiction index as well as the stiction band were

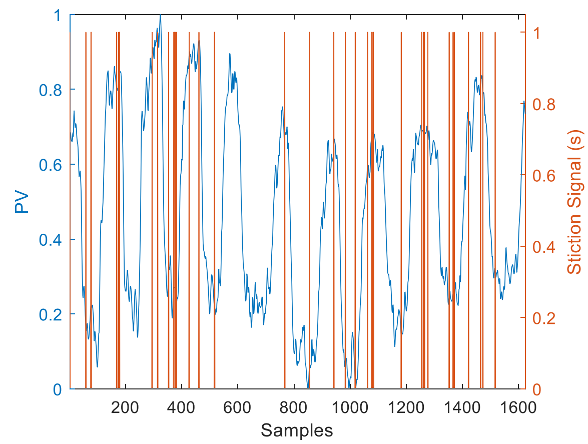

Figure 11. Results for CHEM 1.

calculated using whole datasets. In Table 1, the non-zero value of the stiction index (β) indicates the presence of stiction whereas the absence of stiction is denoted by $\beta = 0$. In Figures 12 through 14, the line in blue color corresponds to PV, and the stiction signal (s) is represented by vertical or horizontal red line.

Table 1. Stiction Detection Results

Loop name	Actual malfunction	Stiction index, β	Correct diagnosis?	Estimated S (%)
CHEM 1	Stiction	0.55	Yes	0.18
CHEM 2	Stiction	4.62	Yes	2.49
CHEM 3	Non-stiction	55.06	No	1.47
CHEM 6	Stiction	27.46	Yes	0.15
CHEM 10	Stiction	1.30	Yes	0.24
CHEM 11	Stiction	0.50	Yes	0.19
CHEM 12	Stiction	1.95	Yes	0.10
CHEM 13	Non-stiction	0	Yes	0
CHEM 14	Non-stiction	1.74	No	2.44
CHEM 16	Non-stiction	0.13	No	0.31
CHEM 23	Stiction	82.12	Yes	26.96
CHEM 24	Stiction	6.42	Yes	20.42
CHEM 29	Stiction	1.40	Yes	7.97
CHEM 32	Stiction	14.65	Yes	12.09
PAP 2	Stiction	1.76	Yes	1.34
PAP 4	Non-stiction	0	Yes	0
PAP 5	Stiction	16.42	Yes	0.21
PAP 7	Non-stiction	1.07	No	0.15
PAP 9	Non-stiction	0	Yes	0
MIN 1	Stiction	4.25	Yes	0.25

The proposed MWSD correctly identified stiction in 13 control loops which are actually having sticky valve. However, the method issued wrong verdict (false positive) for

CHEM 3, CHEM 14, CHEM 16 and PAP 7. The results for CHEM 3 revealed that the proposed MWSD cannot provide correct diagnosis in control loops suffering from quantization issue. For CHEM 6, CHEM 10, CHEM 11, CHEM 12, CHEM 14 and CHEM 16, normalized PV and OP signals are only available in ISDB, hence, the estimated stiction band in those loops is not very accurate. If those signals are in their actual ranges, more accurate estimation for stiction band can be obtained. In Table 2, the performance of the proposed MWSD is compared with that of the stiction detection methods reviewed in Section 1. Excluding BIC and BSD, all the remaining methods produced more false alarms than the proposed method. Both the proposed MWSD and BIC show similar performance whereas BSD yielded incorrect diagnosis in three loops only.

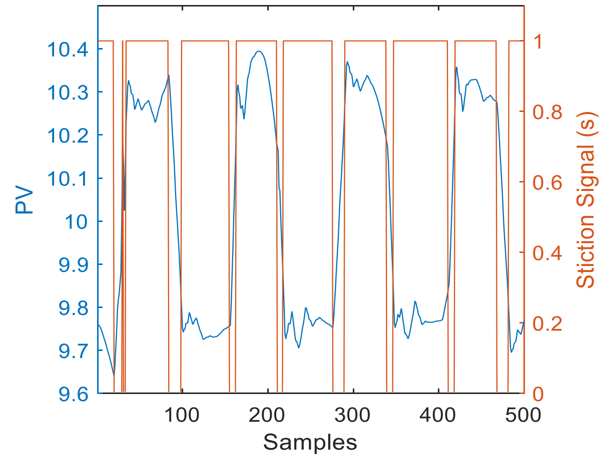

Figure 12. Result for CHEM 23.

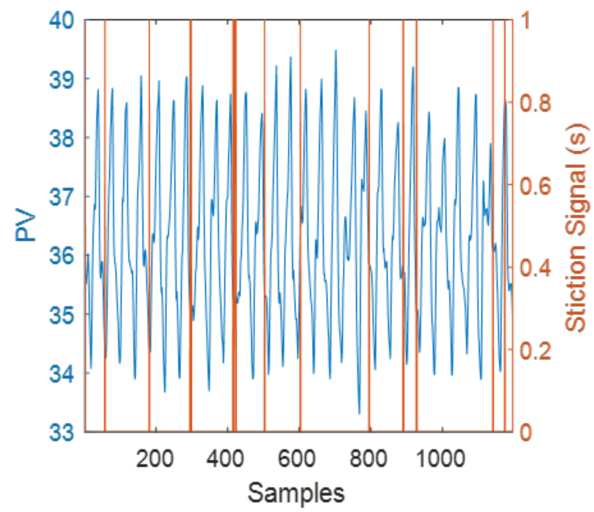

Figure 13. Result for PAP 2.

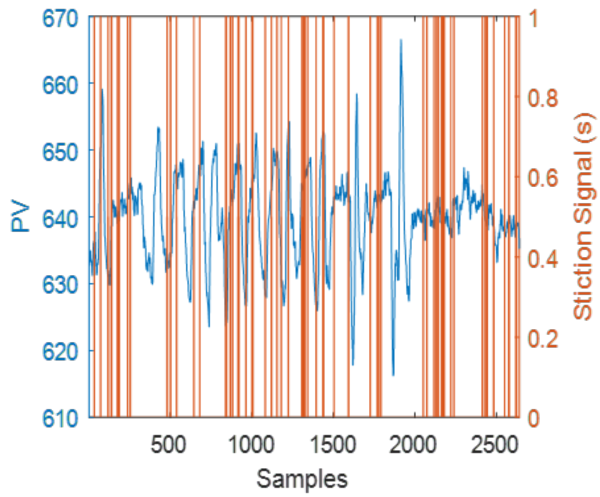

Figure 14. Result for MIN 1.

4.2. Oil sands industry control loops

Aside from the benchmark industrial datasets, the routine operation data of control loops from an oil sands industry were also considered to further examine the stiction detection ability of MWSD. Figure 15 through 20 show the time trend of OP and PV of flow, temperature and pressure control loop, respectively, exhibiting oscillations. Due to proprietary reasons, PV signals were rescaled to the range [0, 100%] from their real ranges. The sampling time of 1 minute was used in three loops to collected data. Results are provided in Table 3 and Figure 21 through 23.

Stiction in three control loops was successfully detected and estimated by MWSD and MWSQ, respectively.

Table 2. Comparison Analysis

Stiction detection Method	Number of correct diagnosis
BSD	17
proposed method	16
BIC	16
SDN	15
HAMM2	15
HAMM3	14
CORR	13
HIST	13
RELAY	13
ZONE	13
CURVE	12
SLOPE	12
NLPCA-AC	11
AREA	10

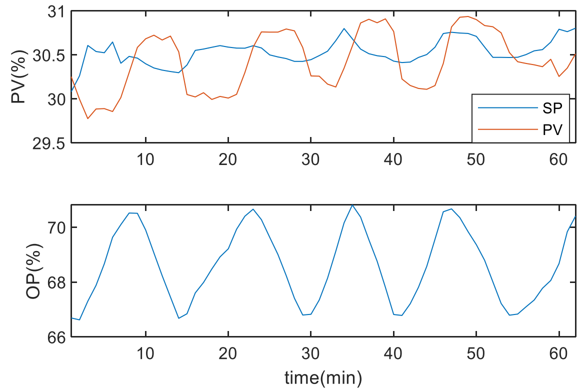

Figure 15. PV and OP of flow control loop.

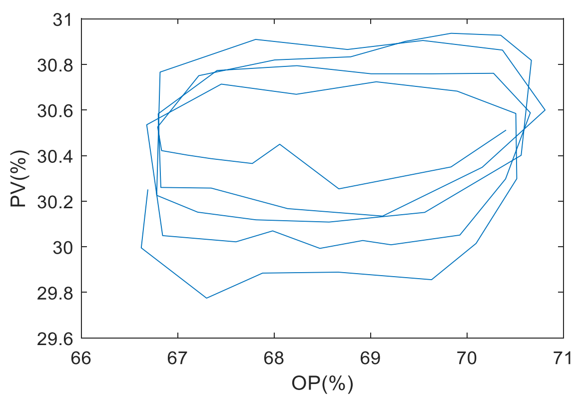

Figure 16. PV-OP phase plot.

Table 3. Results for Syncrude Control Loops Data

Type of loop	β	Verdict issued	S
Flow control	35.71	Stiction	3.82
Temp. control	44.15	Stiction	21.31
Pressure control	20.38	Stiction	1.17

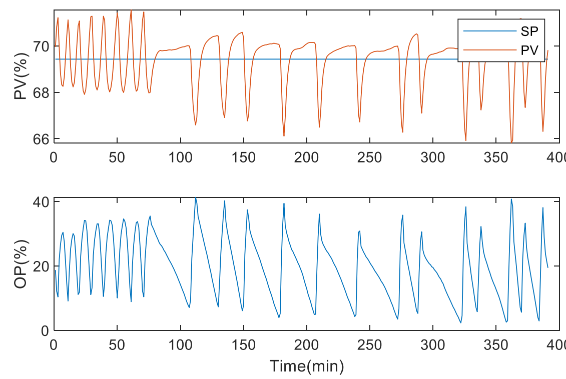

Figure 17. PV and OP of temperature control loop.

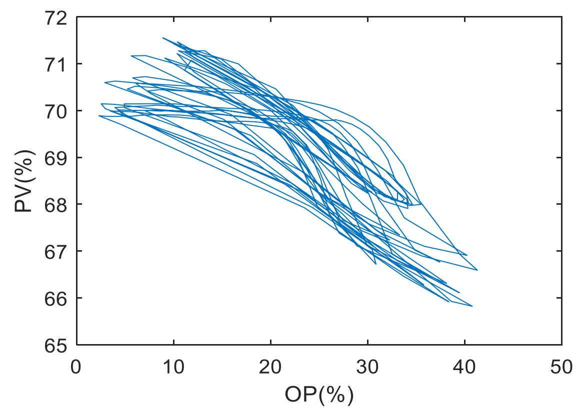

Figure 18. PV-OP phase plot.

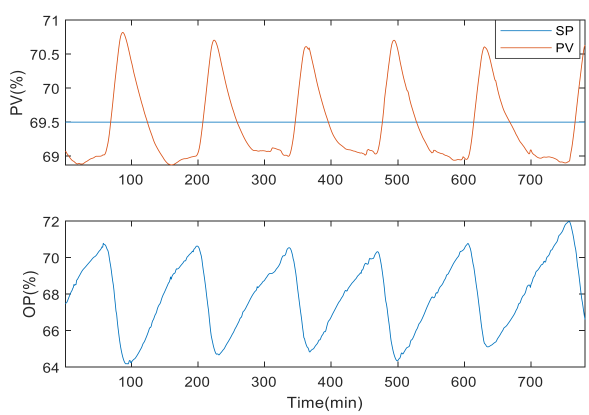

Figure 19. PV and OP of pressure control loop.

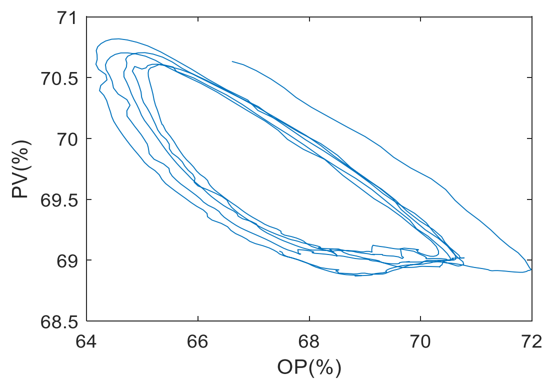

Figure 20. PV-OP phase plot.

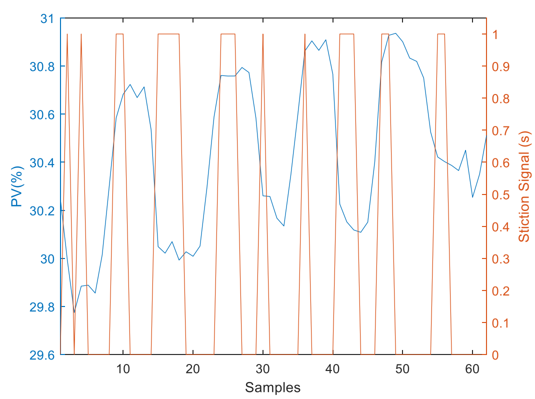

Figure 21. Stiction detection results for Syncrude flow control loop.

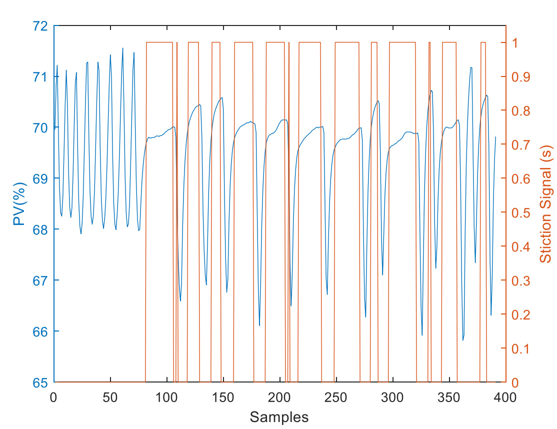

Figure 22. Stiction detection results for Syncrude temperature control loop.

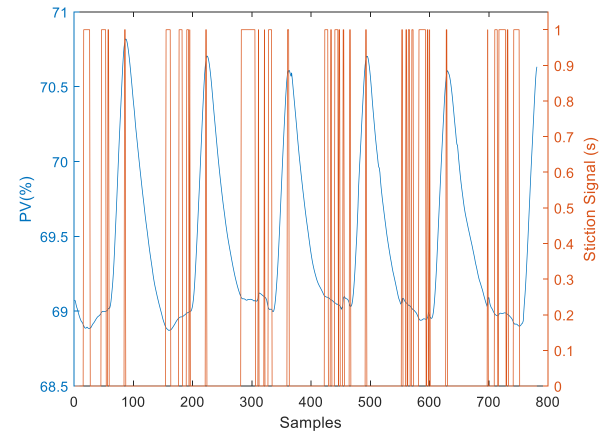

Figure 23. Stiction detection results for Syncrude pressure control loop.

Valve fault detection

4.3. Simulation case study

A healthy control valve, which often works properly during normal weather condition, may get frozen due to severe cold weather. As a result, stiction sets in, therefore, valve position does not change in response to changing controller output. In this situation, the valve may not be able to overcome stiction. Valve fault, such as severe stiction as explained above, may severely disrupt normal plant operations. So it is extremely important to monitor control valves to detect such fault. By virtue of the proposed method, it is possible to detect the valve fault. To simulate the behavior of a frozen valve, a concentration control loop was adopted from Choudhury et al.[5] Figure 24 shows the closed loop block diagram of concentration control loop.

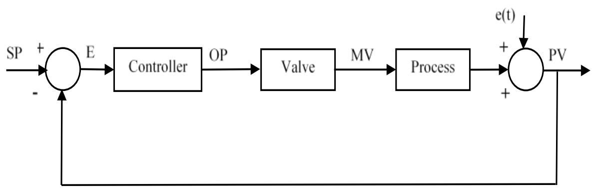

Figure 24. Concentration control loop.

Valve stiction model proposed by Choudhury et al.[5] was considered to create valve fault. A PI controller was used to control the process. The process model as well as the controller transfer function is given in the following equations.

$$G_P = \frac{3e^{-10s}}{10s+1}, \quad (27)$$

$$G_C = 0.2\left(\frac{10s+1}{10s}\right). \quad (28)$$

Simulation was carried out for 1000 seconds with sampling time of 1 second. During the simulation, the valve was forcefully closed after 700 seconds, and the valve position remained at zero for the rest of the simulation. Simulation results are shown in Figures 25 and 26. The control loop performance is satisfactory as long as the control valve behaves well. When unexpected valve closure occurs, PV starts declining, and the control error (E) slowly increases. PV and E gradually reaches zero and one, respectively, and remains at these values for the rest of the operation. As PV is away from SP, the controller tries to increase its output to bring PV back to one (set point). The results of the proposed method are shown in Figure 27. When the valve closure takes place, the ratio δ_i becomes very large, hence, the second cluster contains all samples measured after the valve closure. This is why the proposed method is able to detect valve abnormality. The stiction index and stiction band were computed as provided in Table 4.

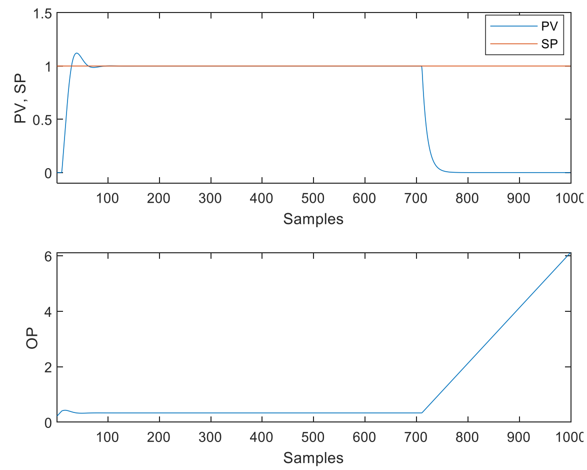

Figure 25. Concentration control loop signals.

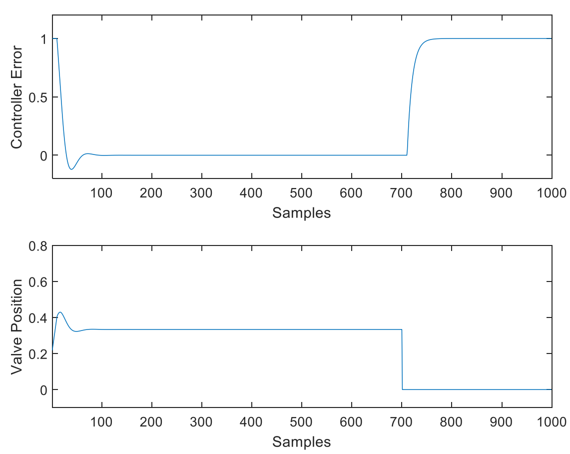

Figure 26. Concentration control loop signals.

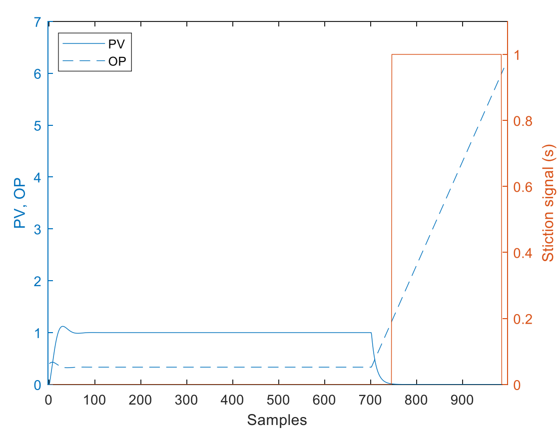

Figure 27. Stiction detection results for simulation case study 4.3.

Table 4. Results for Case Studies 4.3 and 4.4

Type of loop	β	Verdict issued	Estimated stiction band
Conc. control	24.28	Stiction	4.88
Flow control	6.56	Stiction	17.14

4.4.Industrial case study

Consider a steam flow control loop taken from the same oil sands industry adopted in Subsection 4.2. The PV and OP signals of the steam flow control loop are displayed in Figure 28, and Figure 29 displays the respective phase plot. The steam combines with treated feed gas, which is the bottom product of a packed bed reactor, in mixed tee to form a mixed stream. It is important to maintain steam to carbon ratio in the mixed stream at a desired value. From Figure 28, it is noticed that PV follows SP until 63rd sample, and then both PV and SP change in opposite direction for some time due to process disturbances. At around the 64th sample, the steam controller starts closing steam control valve slowly, as a result, OP keeps decreasing, but PV didn't follow the OP change due to severe valve stiction. When OP dropped large enough, it caused the steam valve suddenly moving, and thus steam flow reduced below to its trip setpoint, which resulted in plant trip. When such valve closures came about, the proposed method (MWSD) detected it as shown in Figure 30 and Table 4. Therefore, the proposed method can successfully detect severe valve stiction and be leveraged to prevent potential plant trips.

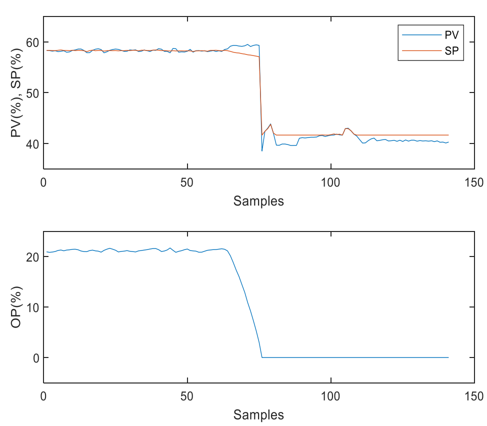

Figure 28. Steam flow control loop (industrial case study 4.4).

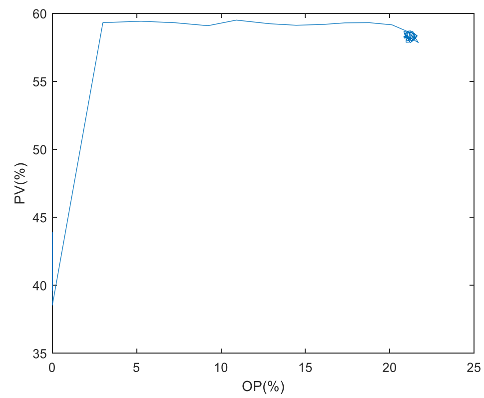

Figure 29. Steam flow control loop (industrial case study 4.4).

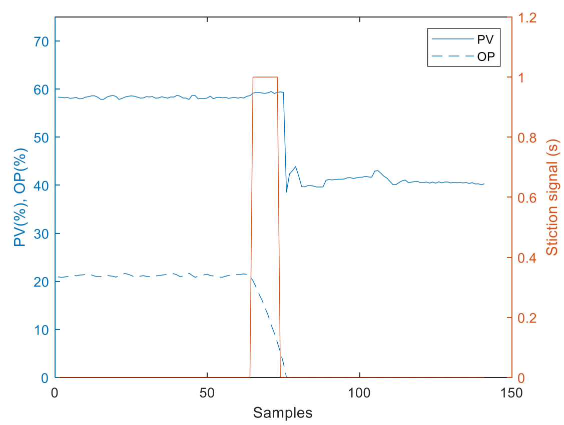

Figure 30. Stiction detection results for industrial case study 4.4.

4.5.Comparison between MWSD and existing methods

Stiction detection

In this subsection, the advantages of the proposed method (MWSD) are discussed with respect to the existing methods.

a) As reported in Dambros et al.,[19] methods like CURVE, AREA, CORR, HIST, Kano's method,[8] Yamashita's method and BIC may not perform well when setpoint keeps changing i.e. these methods may issue wrong verdicts in control loops with non-stationary PV and OP signal. As observed from Figure 12 and Figure 21, the proposed method is applicable to stationary and non-stationary signals, which is a significant advantage over those methods, particularly, BIC.

b) The lower performance of CORR, CURVE, SLOPE and ZONE can be attributed to their dependency on the waveform shapes, which is a major drawback of these methods. The proposed method does not possess this limitation.

c) In Fang and Wang,[33] it was shown that the existing data-driven stiction models cannot approximate more complex relationship between the input and output of a sticky valve than that was shown in Figure 3. If stiction model cannot describe the true behavior of the sticky valve, then verdict issued by a Hammerstein system based method (HAMM) may not be valid. Also, HAMMs need analytical or numerical optimization methods to estimate the parameters of stiction model and process model. Compared to HAMM2 and HAMM3, the proposed method is relatively simple to interpret, develop and implement, and does not depend on the stiction models.

d) Unlike NLPCA-AC and SDN, the proposed method does not require training algorithms, and produces results in a single pass.

e) In Mohd Amiruddin et al.,[38] the authors claimed that if a control loop exhibits oscillations due to valve stiction, then a butterfly shape appears in Y ($Y = |OP(k) - PV(k-1)|$) versus $PV(k)$ phase plot. However, as observed from Figures 31 and 32, the shape is sometimes not clearly noticeable in the phase plot even if the valve is sticky. The performance of shape dependent methods is likely to be hampered by noise in PV or OP signals, multi-loop interactions, the effect of simultaneous occurrence of stiction and one or more of non-stiction conditions, etc.

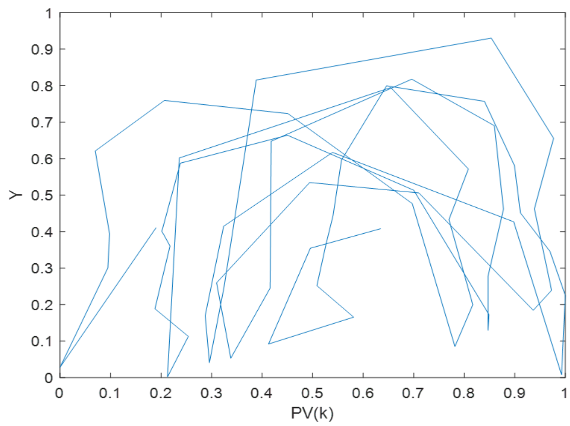

Figure 31. BSD plot for flow control loop in Subsection 4.2 (oil sands industry control loops).

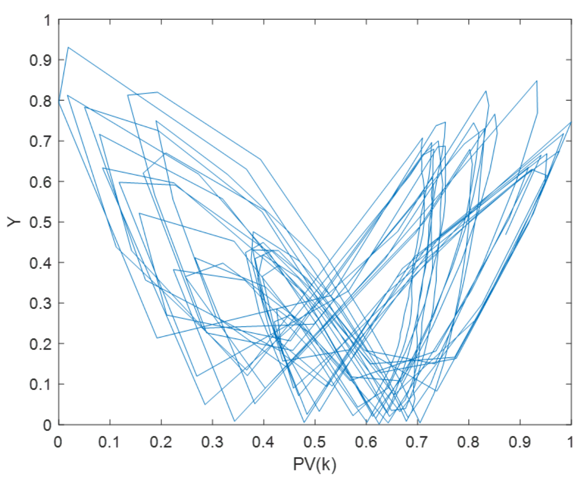

Figure 32. BSD plot for temperature control loop (right subplot) in Subsection 4.2 (oil sands industry control loops).

Valve fault detection

In view of detecting valve fault (severe stiction) discussed in Subsection 4.3, the following observations are worthy to be taken into consideration.

a) It is noticed in Figure 28 that when the valve fault occurs, the waveform shapes do not appear in either PV or OP, hence, the waveform shapes based methods, like SLOPE, ZONE, CORR, CURVE and Yamashita's method, cannot be applied to detect the fault.

b) When the valve fault takes place, the behaviour of the sticky valve, shown in Figures 33 and 34, is different from the one illustrated in Figure 3 i.e. complete parallelogram does not exist in MV versus OP plot. The data-driven stiction model based methods like HAMMs may not be able to detect the valve fault.

c) In addition to stiction and non-stiction examples, SDN also needs to be trained with several PV and OP signals corresponding to control loop with faulty valve in order to detect the fault, which necessitates SDN to have more hidden layers or hidden neurons, thus, increasing training time.

d) Even BSD method fails to identify the valve fault because $|OP(k) - PV(k-1)|$ versus $PV(k)$ phase plot (Figure 35) of simulation case study 4.3 does not have butterfly shape.

e) The results reported in Tables 1 through 4 and Figures 11 through 35, and the discussion held in this subsection emphasize that the proposed method is competitive with the existing methods.

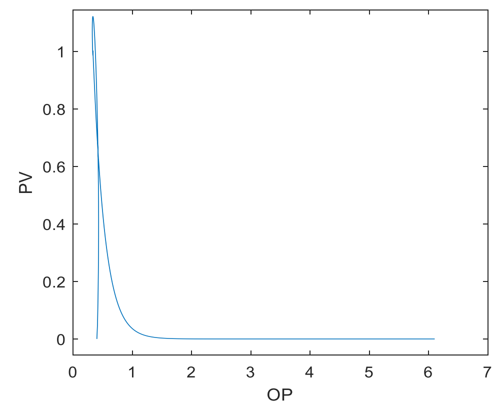

Figure 33. Phase plots for simulation case study 4.3.

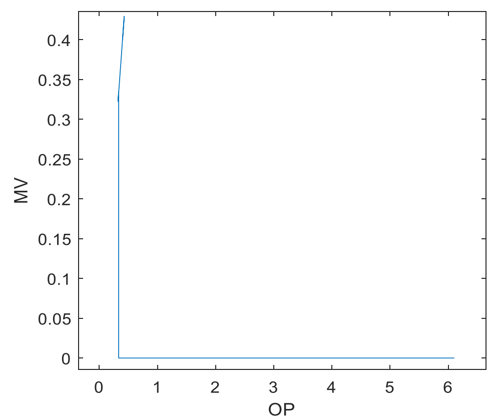

Figure 34. Phase plots for simulation case study 4.3.

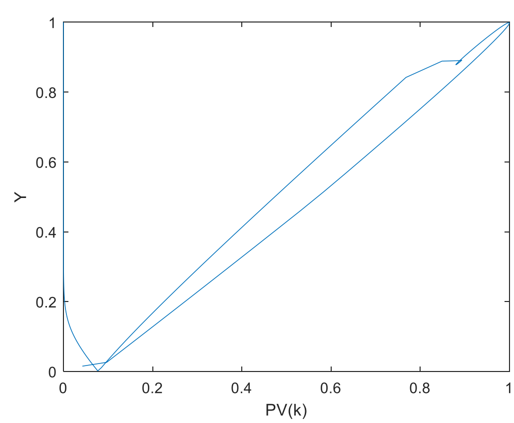

Figure 35. BSD plot for simulation case study 4.3.

5. Conclusions

Process industries often experience production loss and reduced profits, and produces inferior-quality products because of stiction in control valves. Stiction is more likely to be cause of oscillations in industrial control loops. The present work addresses this industrial problem from a different perspective. Slow dynamics of PV during valve stiction is the basis of proposed stiction detection method (MWSD). MWSD paved way for the estimation of stiction band (S) in sticky control valves. In the loops studied, MWSD achieved success rate of 80% in benchmark industrial loops, and 100% in Syncrude control loops. MWSD outperformed waveform shape based methods, limit cycle patterns (elliptical shape) based methods, model based methods, and even supervised learning based method such as SDN. MWSD and MWSQ, respectively and can detect and quantify low, moderate and high stiction. MWSD allows to monitor control valves in a real time manner for the detection of valve abnormality, an issue not addressed by any of the stiction detection methods reviewed in Section 1.

The discussion of recent publications in stiction detection and quantification, which was carried out in Section 1, reveals that research in the first four categories of automatic methods (classification is sown in Figure 1) is gradually declining. All the methods reported from 2018 to till date are based on either PCA or ANNs, indicating that the future research efforts in stiction detection will be oriented toward chemometric techniques or machine learning (ML) algorithms. Many ML algorithms and chemometric techniques are yet to be explored, and efforts in this direction will hopefully yield fruitful results.

Supporting Information

This information is available free of charge via the Internet at http://pubs.acs.org/.

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