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Robust Oscillation Detection Index and Characterization of Oscillating Signals for Valve Stiction Detection

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ABSTRACT: Detection of oscillation is a necessary step for determining valve stiction, which is a common problem in process industries. More specifically, many stiction detection methods assume persistency of the oscillation pattern in the control loop signals, which is a necessary condition to achieve reliable detection results. However, the existing oscillation detection methods do not study the persistency of the oscillation patterns directly. Instead, these methods try to discover the presence of specific periodic characteristics in the signals, their autocorrelation, or power-spectrum. This paper aims to propose an oscillation detection method that directly evaluates the similarity of the shapes of subsequent oscillation periods by means of correlation coefficient. The proposed oscillation detection method is compared against five other methods reported in the literature. Furthermore, the stiction detection methods assuming oscillation in control loops have different robustness to the disturbances corrupting the analyzed signals. In order to prepare a basis for selecting the right stiction detection methods for the available data automatically, the paper introduces two indexes quantifying mean-nonstationarity and presence of noise in oscillating signals.

1. INTRODUCTION

Oscillations in control loops result in high variability of product quality, increased energy consumption, and accelerated equipment aging, which may bring down the plant profit significantly. In particular, the presence of oscillation in control loops caused by valve stiction is a common problem in process industries. The comprehensive fault analysis of the industrial paperboard machine carried out by Jämsä-Jounela et al.¹ showed that valves are the source of nearly 10% of the faults present in the machine yearly operation. Furthermore, the survey by Yang and Clarke² indicated that 30% of all the control loops in the Canadian paper mills were oscillating due to valve problems.

The valve stiction produces specific oscillation patterns, like the triangular, the rectangular, and the "sail" shapes. Many stiction detection methods, including the triangular curve fitting,³ the rectangular fitting,⁴ the histogram,⁶ and the area ratio⁷ methods, classify the oscillation patterns between the listed above ones and the "healthy" sinusoidal shape. From that viewpoint, the reliable classification results can only be achieved when the oscillation periods have the same shape, called oscillation pattern, whereas variations in the oscillation period length and magnitude do not matter much. Therefore, oscillation detection is a preliminary stage of the stiction detection. In the modern large-scale applications, hundreds or even thousands of control loops must be processed, and therefore, it is not possible to inspect manually the results of the oscillation detection algorithms. As a consequence, a stiction detection system requires an oscillation index, which should be robust to all common types of disturbances in the signals, including variations in their mean values, the

general requirement of the stiction detection methods listed above.

The oscillation detection methods presented in the literature analyze the signal itself, the autocorrelation function, or the power spectrum of the original signal. In particular, the method of Forsman and Stattin⁸ evaluates the figures, representing lower and upper oscillation half-periods, which are defined by the zero-crossings of the original signal. In more detail, the approach explores the lengths and the areas of the subsequent upper and lower half-periods. Miao and Seborg⁹ consider the decay ratio of the autocorrelation function of the signal, and Thornhill et al.¹⁰ method is based on the regularity of zero-crossings in the autocorrelation function. Salsbury and Singhal¹¹ compute the damping factor of the second-order ARMA model identified from the autocorrelation function. In addition, the spectral peak method is a simple procedure finding the peak in the power spectrum of the signal. Even though in the most cases the presence of the aforementioned features in a signal correctly indicates an oscillation in the time series, the methods listed above do not evaluate the similarity of the oscillation periods directly. In the result, the indexes sometimes quantify the oscillation persistency inadequately, some examples of which are provided in this article together with a discussion of the disturbances causing such misdiagnosis.

The present paper introduces an oscillation detection method that directly evaluates similarity of the oscillation period shapes. This can be achieved by analyzing signals in the time domain disregarding that the frequency domain approach provides efficient suppression of high-frequency noise. The results of the zero-crossing approach, which is the common

method to determine the oscillation half-periods, are frequently deteriorated by high-frequency noise and mean-nonstationarity of the analyzed signal. Forsman and Stattin⁸ applied a low-pass filter with a pole in 0.8. In some cases, this filter is unable to remove the high-frequency noise completely, which may lead to spurious zero-crossings. Furthermore, because the oscillation period is unknown beforehand, it is unclear how to select an a priori threshold for filtering out low-frequencies that represent the mean-nonstationarity. Thus, a manual tuning of the cutoff thresholds is required to remove the noise efficiently, especially before the oscillation frequency is approximately determined. However, the power spectrum peak is not suitable to estimate the oscillation frequency, because the peak can represent the low-frequency noise rather than the oscillation. Therefore, this paper proposes an alternative algorithm finding the location of the peaks to determine the oscillation half-periods. In order to make the method robust to variations of the period length, the peaks are searched in a sufficiently broad range. The correlation coefficient is utilized to evaluate the similarities between the shapes of the periods, which provides an adequate quantification of the oscillation persistency for all oscillation patterns and disregards variations in the oscillation magnitude and the period length. Furthermore, the lowest 20% of the obtained correlation coefficients are discarded to improve the robustness of the oscillation detection method. In the result, the proposed oscillation index is developed to be robust to the disturbances that commonly present in the control loop signals and to properly quantify the persistency of the oscillation pattern. Thus, the paper contributes to the correct utilization of the stiction detection algorithms that are commonly used in the industry.

Furthermore, the selection of the right stiction detection method often requires much time and effort because of the large number and high diversity of control loops that must be processed. The stiction detection methods, assuming the presence of oscillation in control loops, have different robustness to the disturbances corrupting the analyzed signals. For example, if the available data is heavily corrupted by a high-frequency noise, selecting the cross correlation method,⁵ which is insensitive to this kind of disturbance, could be a better option than using the shape-based methods.^{3,4} The autocorrelation function of a signal can be, in turn, shifted by its mean-nonstationarity. Thus, there is a need to develop a characterization of the available data that would support selecting the right stiction detection methods automatically. Moreover, the aforementioned data characterization can be used to recognize the loops in which none of the methods is applicable and reliable detection decision cannot be obtained automatically. However, applications of data characterization to stiction detection have not yet received much attention in the literature. This article aims to contribute to characterization of oscillating signals by introducing two indexes that quantify the noise level and the mean-nonstationarity of available data. More specifically, the indexes utilize the knowledge of the oscillation half-periods that are defined by the proposed oscillation detection algorithm. The results of this study are employed by work¹² introducing an autonomous stiction detection system based on data characterization.

The article is organized as follows. Section 2 presents the mathematical description of the proposed oscillation detection index and the indexes quantifying the mean-nonstationarity and the noise level in oscillating signals. The robustness study of the oscillation detection index and its comparison to five other

indexes are given in section 3. Section 4 presents the results of performance evaluation of two indexes characterizing oscillating signals. Concluding remarks are provided in section 5.

2. DESCRIPTION OF THE INDEXES

2.1. Description of the Oscillation Detection Index.

The proposed oscillation detection index identifies the periods of oscillation by assuming various upper bounds of the halfperiod length and defining the oscillation peaks accordingly. Namely, given a signal x and a possible integer upper bound for the half-period length d , the proposed method attempts to define the locations of the peaks in each period (the locations of the maximum and the minimum of the i period are denoted as $\hat{m}_i^+$ and $\hat{m}_i^-$), as described by the following formulas:

$$\hat{m}_1^+ = \arg \max_{k=1, \dots, 2d} x(k) \quad (1)$$

$$\hat{m}_i^- = \hat{m}_i^+ - \arg \min_{k=\{d/2\}, \dots, d} x(\hat{m}_i^+ - k) \quad (2)$$

$$\hat{m}_i^+ = \hat{m}_{i-1}^- + \arg \max_{k=\{d/2\}, \dots, d} x(\hat{m}_{i-1}^- + k) \quad (3)$$

where $\{\}$ is the integer part. The intervals between two subsequent maxima are considered as periods, and the period search continues according eqs 2–3, whereas there are at least d samples available after the last maximum or minimum found.

The peak locations defined by eqs 1–3, however, can be shifted by high-frequency noise. A more robust estimation of the maximum location in period i is obtained in the following way:

$$I_i^+ = [\max(\hat{m}_i^+ - \{d/3\}, \hat{m}_{i-1}^- + \{d/3\}), \min(\hat{m}_i^+ + \{d/3\}, \hat{m}_i^- - \{d/3\})] \quad i = 2, 3, \dots \quad (4)$$

$$\hat{m}_i^+ = \text{median}\{k | x(k) > 0.8 * \max_{i \in I_i^+} x(i) + 0.2 * \min(x(\hat{m}_{i-1}^-), x(\hat{m}_i^-)), k \in I_i^+\} \quad i = 2, 3, \dots \quad (5)$$

In other words, eq 4 defines an interval containing the preliminary maximum location $\hat{m}_i^+$, and the robust estimation of the maximum location is obtained according to eq 5 as the median of the set of the points at which the signal value is close to its maximum. The procedure is repeated for each oscillation period and the minimum locations are treated similarly.

At the next stage, similarity of two subsequent periods is evaluated using the correlation coefficient. Because the lengths of the identified periods are usually different due to deviations of the oscillation periods from the pattern and noise, a resampling is required to obtain two data sets of the same length. Namely, if the length d_1 of the first period $[m_i^+, m_{i+1}^+]$ is higher than the length d_2 of the second period $[m_{i+1}^+, m_{i+2}^+]$, the signal is interpolated at the points

$$m_i^+ + k \frac{d_1}{d_2} \quad k = 0, \dots, d_2 \quad (6)$$

according to the equations

$$f = (1 - \alpha)x(m^+ + l) + \alpha x(m^+ + l + 1) \quad k = 0, \dots, d$$

Figure 1. Scheme of the oscillation detection algorithm.

where

$$l = \left\{ k \frac{d_1}{d_2} \right\} \quad (8)$$

$$\alpha = k \frac{d_1}{d_2} - l \quad (9)$$

Conversely, if the length of the second period d_2 exceeds the length of the first one, the signal is resampled in the second period. As the result, two data sets, representing two full periods, are obtained having the same length.

The correlation coefficient between these two data sets $C(i)$, $i = 1, 2, \dots$ are computed to characterize the similarity of the subsequent periods i and $i + 1$. The presence of oscillations in the signal is recognized if most of the coefficients $C(i)$ are close to the unity, and thus, it can be measured with 80% quantile of the aforementioned coefficients

$$I_{osc}(d) = \max\{\theta: \theta \leq C(i) \quad \text{for } 80\% \text{ of } i\} \quad (10)$$

Finally, all possible lengths of the oscillation period are considered, and the oscillation index is defined as the maximum value of the quantile (10) reached

$$I_{osc} = \max_d I_{osc}(d) \quad (11)$$

In brief, the algorithm is summarized in the scheme presented in Figure 1.

The oscillation in a signal is very steadfast when the oscillation index is above 0.85. When the index is between 0.70 and 0.85, the signal is usually noisy and the oscillation periods frequently differ from the pattern. If the index is below 0.7, it is typically impossible to recognize any oscillations on the signal plot, and it can be concluded that the signal is nonoscillating.

2.2. Description of the Mean-Nonstationarity Index. Many stiction detection algorithms, including the triangular

curve fitting,³ the rectangular fitting,⁴ and the area ratio⁷ methods, analyze oscillation half-periods defined by two subsequent zero-crossings. As it is mentioned earlier in the paper, the zero-crossing approach sometimes provides improper results. In particular, because of the mean-nonstationarity of the available signals, the periods may be split to very unequal parts or several consequent periods can be even considered as a single half-period. Hence, the mean-nonstationarity index is suggested in this work that is suitable to check the applicability of the zero-crossing method to available signals. Moreover, the proposed algorithm introduces the “middle-level” of each oscillation period, which can replace the “zero level” while defining the half-periods if the zero-crossing method is inapplicable.

The “middle level” of the signal in an oscillation period is defined as the point at which the respective areas of the upper and lower half-periods are equal, as is shown in Figure 2. More specifically, the proposed method requires the determination of the oscillation periods, which is achieved by computing the

Figure 2. The “middle level” of an oscillation period of the control error of Loop 17.

Figure 3. Location of the peaks in the control error of four loops (loops 4, 26, 22, and 23).

oscillation index according to the technique presented in section 2.1. In particular, the peak locations m_i^+ and m_i^- , with $i = 1, 2, \dots$, respectively corresponding to the maxima and the minimums of the signal over each period are used. Given an initial approximation of the middle level L_i of the signal in the i th period, the lower and the upper half-periods are, respectively, defined as the subsets of the intervals between two subsequent maxima and minimums, according to the following formulas:

$$P_i^-(L_i) = [m_i^+, m_{i+1}^+] \cap \{k | x(k) < L_i\} \quad (12)$$

$$P_i^+(L_i) = [m_i^-, m_{i+1}^-] \cap \{k | x(k) > L_i\} \quad (13)$$

An iterative procedure, like bisection, is then employed to determine the middle level as that particular value of L_i such that

$$\sum_{i \in P_i^-(L_i)} (L_i - x(i)) = \sum_{i \in P_i^+(L_i)} (x(i) - L_i) \quad (14)$$

is satisfied. The mean nonstationarity index is finally computed as the ratio of the estimations of the standard deviation of the middle levels and the mean magnitude in the oscillation periods

$$I_{NS} = \frac{\sqrt{\sum_{i=1, \dots, n} (L_i - \bar{L})^2 / n}}{(\sum_{i=1, \dots, n} (x(m_i^+) - x(m_i^-)) / n)} \quad (15)$$

where

$$\bar{L} = \sum_{i=1, \dots, n} L_i / n$$

is the mean value of the middle level.

For stationary signals, the index value is below 0.1. The index value exceeding 0.25 indicates significant mean-value variations. In particular, for signals with very strong nonstationary behavior, the index value is above 0.7.

2.3. Description of the Noise Index. Even though high-frequency noise deteriorates the results of most valve stiction

detection methods, no indexes quantifying the presence of noise in the control loop signals are used in the literature. A clear bound between the frequencies relating to the oscillation pattern and the frequencies representing the noise cannot be sometimes determined. Therefore, automatic removing the high-frequencies from the signals may shift the oscillation pattern. Second, an automatic evaluation of the noise level based on frequency domain data may provide inadequate results. The index proposed in this work relies on the fact that the parts of the oscillation patterns located between two peaks are typically monotonous. However, in signals with high-frequency noise, the behavior of the signal over the half-periods is no longer monotonous. Thus, the index introduced in the paper quantifies the high-frequency noise level automatically, which cannot be achieved by analyzing the frequency domain data.

In more details, the level of noise is evaluated according to the following reasoning. The total variation of a signal in the interval $[m_1^+, m_n^+]$ is defined by

$$V(x, m_1^+, m_n^+) = \sum_{i=m_1^+}^{m_n^+-1} |x(i+1) - x(i)| \quad (16)$$

where the set of values m_i^+ , with $i = 1, \dots, n$, are determined according to the technique presented in section 2.1. The noise index is defined as the increase of the total variation of the signal caused by high-frequency noise

$$I_{NO} = \frac{\left(\frac{V(x, m_1^+, m_n^+)}{\sum_{i=1}^{n-1} (|x(m_i^-) - x(m_i^+)| + |x(m_{i+1}^+) - x(m_i^-)|)} - 1 \right)}{\sqrt{d}} \quad (17)$$

where d is the average number of samples in the oscillation half-periods. It is worth noting that, in the case of a noiseless signal, the total variation of the signal in the interval $[m_1^+, m_n^+]$ is given by

Figure 4. Control error, autocorrelation function, and power spectrum of three oscillating control loops (loops 5, 14, and 20).

$$V(x, m_1^+, m_n^+) = \sum_{i=1}^{n-1} (|x(m_i^-) - x(m_i^+)| + |x(m_{i+1}^+) - x(m_i^-)|) \quad (18)$$

Hence, $I_{NO} = 0$, according to 17. In fact, scaling is introduced to eq 17 to correctly reflect the ability of noise to corrupt the signal shape, depending on the number of samples in the half-periods. Namely, availability of only few samples in a half-period frequently makes an oscillation pattern impossible to recognize even in an almost noiseless signal. Instead, availability of many samples in a half-period makes the oscillation pattern easy to identify also in noisy signals.

For almost noiseless signals, the value of the noise index is below 0.1. For higher values of the noise index, it is difficult to precisely distinguish the oscillation pattern, particularly when the noise index becomes greater than 0.25.

3. RESULTS OF THE OSCILLATION INDEX EVALUATION

The robustness of the proposed oscillation detection index was first evaluated on the benchmark set of 76 industrial control loops taken from ref 13. Next, the same data was used to compare the proposed method to five other oscillation detection methods found in the literature.

3.1. Results of the Robustness Evaluation of the Proposed Index. The benchmark set, which contains control loops disturbed in various ways, provides a good ground for testing the oscillation detection algorithms. Figure 3 shows the control error of four loops containing the aforementioned disturbances. The rectangle and triangle marks indicate the discovered maxima and the minimums of the oscillation periods. Being applied to the control error of loop 4, the proposed algorithm precisely located the peaks of oscillation periods despite the signal being mean nonstationary. The oscillation index value is 0.96, and therefore, a highly persistent oscillation was correctly recognized. For the control error of loop 26, the index value is 0.90, which provides adequate

quantification of the similarity level of the oscillation period shapes. In fact, both the high-frequency noise and the variations of the oscillation magnitude have a minor effect on the index value in this example. It is possible to recognize oscillation of the control error of loop 22 on the plot. However, the oscillation pattern cannot be determined accurately because the periods have different shapes. This was confirmed by the oscillation index value of 0.74, indicating very weak oscillation persistence.

Even though there are no peaks in the periods of the control error of loop 23 because of its rectangular shape, the method was able to recognize the presence of oscillations in the signal. The index value is only 0.83, whereas the rectangular oscillation pattern is clearly seen on the plot. In this case study, the index value was slightly corrupted by the rectangular shape of the signal hindering proper determination of the location of the periods. Alternatively, the modification of the oscillation index utilizing the middle-level crossings to locate the periods was implemented and tested. The value of that index slightly increases for the rectangular signals (for loop 23, the index value rises to 0.90), and it provides very close results in almost all other cases. The only exception is the signals deteriorated by noise around the middle-level, such as loop 14 shown in Figure 4, for which the alternative index is slightly worse (for loop 14, the index value drops from 0.81 to 0.73). Furthermore, the index based on middle-level crossings requires computing the middle levels for each candidate half-period length d , which noticeably increases its computational load and implementation complexity.

Summarizing the testing results, the proposed algorithm was able to define the peak location correctly in all cases except when it was applied to signals with the rectangular oscillation pattern. However, even in this case, the persistency of the oscillations was defined reasonably well. The examples considered in this section demonstrate the robustness of the method to the common disturbances in the signals, including variations in their mean values and magnitude, presence of high-frequency noise, and arbitrary oscillation pattern.

Figure 5. Control error, autocorrelation function, and power spectrum of three nonoscillating control loops (loops 27, 57, and 66).

Table 1. Results of the Comparison of the Developed Oscillation Detection Method against Five Other Methods^a

	proposed method	Forsman And Stattin (1999)	Miao And Seborg (1999)	Thornhill (2003)	Salsbury And Singhal (2005)	power spectrum peak
conditions for oscillation	>0.7	>0.4	>0.8	>20	<0.1	>0.5
loop 5	0.85	0.89	0.80	15.07	0.14	0.22
loop 14	0.81	0.10	0.65	2.40	0.16	0.16
loop 20	0.93	0.28	0.73	2.27	0.35	0.26
loop 27	0.62	0.19	0.66	13.94	0.03	0.52
loop 57	0.44	0.07	0.05	48.38	0.17	0.58
loop 66	0.59	0.10	0.82	20.29	0.11	0.57

^aThe values resulting in misdiagnosis are given in bold.

3.2. Results of the Comparison of the Proposed Oscillation Detection Index to Five Other Methods. In this section, the developed oscillation detection index is compared against four other methods reported in the literature,^{8–11} and the spectral peak method finding the peak in the power spectrum of the signal. Three oscillating and three nonoscillating loops are selected to demonstrate the effects of the aforementioned disturbances (variations in the oscillation period length, magnitude, mean-nonstationarity, high-frequency noise, various oscillation patterns) on the results of the methods. The section is organized as follows. First, the analysis of the results of the proposed algorithm and the method presented in ref 8, which both explore the signal itself, are given. Next, the results of the methods found in refs 9–11 are reported, which consider the autocorrelation of the original signal. Finally, the performance of the approach is discussed that finds peaks in the power spectrum of the signal.

The oscillation in the control error of loop 5, shown in Figure 4, is persistent. Both the proposed index and the method of Forsman and Stattin⁸ provided adequate diagnosis, despite the oscillation pattern being asymmetric (the upper half-periods are much shorter than the lower ones), the period length slightly varying from one period to another and the signal being corrupted by a small-magnitude noise.

The control error of loop 14 is corrupted by a strong high-frequency noise. As a result, the method reported in ref 8 defined numerous spurious zero-crossings and produced the index value that corresponds to a white noise signal. The proposed index classified the oscillation as weakly persistent, which is confirmed by the signal plot.

The control error of loop 20 is a strongly mean-nonstationary oscillating signal. Consequently, most of the half-periods determined by the zero crossing points are much larger or much smaller than the actual oscillation half-periods are, and the Forsman and Stattin⁸ index is slightly below the oscillation detection threshold. In contrast, the persistent oscillation in the signal was successfully recognized by the proposed index.

The control errors of three loops presented in Figure 5 do not contain any repeated signal pattern, and therefore, the signals are classified as nonoscillating. It can be seen from Table 1 that both algorithms performed well in all three cases.

To conclude, the reliability of the method of Forsman and Stattin⁸ degrades if the signals are corrupted by a high frequency noise or a mean-nonstationarity. Prefiltering could improve the diagnosis results in many cases, however, automatic determination of a suitable cutoff frequency is difficult, especially without knowing the oscillation period length. During the comparison studies, the proposed index did not generate inadequate results.

The autocorrelation function of the control error of loop 5 contains three oscillation periods, after which it stays nearly zero because of variations in the period length of the control error signal. The method of Miao and Seborg,⁹ which only considers first one and a half oscillation periods, achieved the correct diagnosis. In contrast to that, the method presented in ref 10, which requires at least 10 oscillation periods in the autocorrelation function to present, was not able to recognize oscillations. The algorithm of Salsbury and Singhal¹¹ obtained a model, describing fairly well the first period of the autocorrelation function. However, the magnitude of the later oscillation periods decrease slower than it is predicted by the model, as it is shown in Figure 6. Consequently, the method overestimated the decay coefficient of the autocorrelation function and provided a misdiagnosis.

Figure 6. Autocorrelation of loop 5 and its approximation by the second-order model of Salsbury and Singhal.¹¹

The nonsinusoidal oscillation pattern of the control error of loop 14 produces an irregular shape of its autocorrelation function. As a result, the magnitude of the first period located between samples 1 and 22 is significantly higher than the magnitude of the period located between samples 9 and 31, and therefore, the decay index introduced in ref 9 is below the detection threshold. Similarly to the previous case, the method

of Thornhill et al.¹⁰ was not able to find 10 oscillation periods, thereby failing to provide the correct detection result. Because the first local minimum of the autocorrelation function is only slightly below the zero, the method of Salsbury and Singhal¹¹ obtained the value of the damping factor exceeding the detection threshold.

The autocorrelation function of the control error of loop 20 is a superposition of two sinusoidal oscillations. Namely, the higher frequency harmonic is produced by the oscillations in the control error, and the harmonic with the lower frequency represents the mean-nonstationarity of the original signal. Since the methods reported by Miao and Seborg⁹ and Thornhill et al.¹⁰ do not assume the presence of a second harmonics, both were not able to provide the correct diagnosis for this loop. Moreover, the method introduced in ref 11 was not able to identify an accurate second-order model, and a misleading damping factor estimation was obtained.

Conversely, the autocorrelation functions of the control error of loops 27, 57, and 66 are similar to sinusoidal signals with decay, which is exactly the assumption when the original time series oscillates persistently. Therefore, all three methods^{9–11} generated false diagnosis results in some cases.

To conclude, the autocorrelation function of an oscillating signal can be affected by many types of disturbances, such as variations in the period length (loop 5), nonsinusoidal oscillation pattern (loop 14), and mean nonstationarity in the original signal (loop 20). Consequently, the methods analyzing the autocorrelation function sometimes fail to recognize oscillations, which are very obvious in the original signal. Despite the above criticisms, the oscillation detection methods exploring the autocorrelation function are robust to high-frequency noise, and thus, these algorithms are able to recognize oscillations in most of the cases. Conversely, the provided examples clearly demonstrate that some nonoscillating signals produce the autocorrelation function which is very similar to what is typically generated by the persistently

Figure 7. Control error of the control loops (loops 1, 14, 13, and 4) used for the mean-nonstationarity index testing.

Figure 8. Control error of the control loops (loops 25, 32, 1, 67, 26, and 23) used for the noise index testing.

oscillating time series. In this case, oscillation presence is frequently falsely detected.

The examples provided in Figures 4 and 5 demonstrate that many types of disturbances can produce a relatively wide peak in the power spectrum of oscillating signals. On the other hand, the peak in the power spectrum of nonoscillating signals is sometimes sharp. Therefore, the power spectrum analysis was unable to provide the correct result in many cases.

4. RESULTS OF EVALUATION OF THE MEAN-NONSTATIONARITY INDEX AND THE NOISE INDEX

4.1. Results of Evaluation of the Mean-Nonstationarity Index. The mean-nonstationarity index was tested on the oscillating loops from the benchmark data set and some examples are presented in Figure 7 also showing the middle levels of the periods. For the control error of loops 1 and 14, the index values, which are 0.03 and 0.02 respectively, indicate that both signals are mean-stationary. Both loops were classified correctly despite the deterioration of the signals by the disturbances: in the first signal, the period length varies as well as the share of the lower and upper half-period lengths in the total period duration. The second signal is toughly corrupted by a high-frequency noise and its oscillation persistency is very poor (the oscillation index is only 0.70).

Furthermore, loop 13 provides an example of a signal with strong variations of the oscillation magnitude. According to the index value of 0.10, the signal was classified as weakly nonstationary which is confirmed by the signal plot. It is possible to see from Figure 7 that the zero-crossing method still determines adequately most of the half-periods in this time series. According to the mean-nonstationarity index value of the control error of loop 4, which is 0.20, the signal is clearly mean-nonstationary and the zero-crossing method is not able to perform well. This conclusion is confirmed by Figure 7 showing that the zero crossing points split very unequally many periods into lower and upper half-periods.

The presented examples demonstrate that the zero-crossing method performs well only when the mean-nonstationarity index stays below 0.1. On the other hand, the results proved that the middle-level is suitable to properly define oscillation half-periods even in mean-nonstationary signals. Thus, the modification of the shape-based stiction detection algorithms based on the middle-level is applicable to moderately mean-nonstationary signals, if no other disturbances occur deteriorating the performance of the methods.

4.2. Results of Evaluation of the Noise Index. The index was tested on the benchmark set, and some of the results are presented in Figure 8. The control error of loops 25 and 32 are nearly noiseless signals, and therefore, the noise index for these two loops has very low values of 0.016 and 0.044. The

magnitude of the high frequency noise in the control error of loops 1 and 67 is moderate, and the index values are 0.118 and 0.155. The control errors of loops 26 and 23 are significantly corrupted by the noise, which was indicated by the high values of the noise index (0.467 and 0.477, respectively). In fact, loop 23 shows an interesting example of a signal the rectangular pattern of which can be recognized despite the high magnitude noise. In most cases, however, the patterns cannot be defined precisely if the noise index is above 0.25. To conclude, the noise level was quantified adequately in all cases despite the considered signals contain many disturbances, including mean-nonstationarity, variations in oscillation period, weak oscillation persistency and nonsinusoidal oscillation patterns.

5. CONCLUSION

This paper contributes to the correct utilization of the valve stiction detection algorithms that are commonly used in the chemical industry. To this end, an oscillation detection method is proposed that directly evaluates similarity of the oscillation periods by means of correlation coefficient. The proposed approach is based on determining the signal peaks which, in turn, define oscillation half-periods. Results are presented demonstrating robustness of the proposed method to common disturbances in the signals, such as variations in their mean values, the oscillation period length and magnitude variations, presence of high-frequency noise, and occurrence of nonsinusoidal oscillation patterns. Results of comparison studies to five other oscillation detection methods are also provided and the detection decisions are analyzed. In particular, the benefits of the proposed method compared the oscillation detection algorithms based on frequency domain data are demonstrated.

Furthermore, the selection of the right stiction detection methods often requires human expertise because of high diversity of control loops. To this end, there is a need to develop a characterization of available data which would support selecting the suitable stiction detection methods automatically. This paper contributes to characterization of oscillating signals by introducing two indexes that quantify the mean-nonstationarity and the noise level of available data. More specifically, the mean-nonstationarity is suitable to check the applicability of the zero-crossing method, which is used by the shape-based stiction detection algorithms to determine oscillation half-periods, to available signals. Moreover, the proposed index is based on the "middle-level" of each oscillation period, which can replace the "zero level" while defining lower and upper half-periods location. Second, the noise index proposed in this work relies on the fact that the parts of the oscillation patterns located between two peaks are typically monotonous. However, in signals with high-frequency noise, the behavior of the signal over the half-periods is no longer monotonous. Thus, the index introduced in the paper quantifies the high-frequency noise level automatically without assuming a bound between the frequencies relating to the oscillation pattern and the noise. Both indexes characterizing oscillating signals utilize the knowledge of the oscillation halfperiods that are defined by the proposed oscillation detection algorithm. The results of evaluation of these two indexes are provided confirming their robustness.

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Notes

The authors declare no competing financial interest.

■ REFERENCES

- (1) Jamsä-Jounela, S.-L.; Tikkala, V.; Zakharov, A.; Pozo Garcia, O.; Laavi, H.; Myller, T.; Kulomaa, T.; Hämäläinen, V. Outline of a fault diagnosis system for a large-scale board machine. *Int. J. Adv. Manuf. Technol.* **2013**, *65*, 1741–1755.
- (2) Yang, J. C.; Clarke, J. C. The self-validating actuator. *Control Eng. Pract.* **1999**, *7*, 249–260.
- (3) He, Q. P.; Wang, J.; Pottman, M.; Qin, S. J. A curve fitting method for detecting valve stiction in oscillating control loops. *Ind. Eng. Chem. Res.* **2007**, *46*, 4549–4560.
- (4) Hägglund, T. A shape-analysis approach for diagnosis of stiction in control valves. *Control Eng. Pract.* **2011**, *19*, 782–789.
- (5) Horch, A. A simple method for detection of stiction in control valves. *Control Eng. Pract.* **1999**, *7*, 1221–1231.
- (6) Horch, A. Benchmarking control loops with oscillation and stiction. In *Process Control Performance Assessment*; Ordys, A. W., Udeh, D., Johnson, M. A., Eds.; Springer: London, 2006.
- (7) Singhal, A.; Salisbury, T. I. A simple method for detecting valve stiction in oscillating control loops. *J. Process Control* **2005**, *15*, 371–382.
- (8) Forsman, K.; Stattin, A. A new criterion for detecting oscillations in control loops. *Proc. Eur. Control Conf.*, Karlsruhe, Germany, 31 Aug – 3 Sep, **1999**.
- (9) Miao, T.; Seborg, D. E. Automatic detection of excessively oscillatory feedback control loops. *Proc. IEEE Int. Conf. Control Appl.* **1999**, 359–364.
- (10) Thornhill, N. F.; Huang, B.; Zhang, B. Detection of multiple oscillations in control loops. *J. Process Control* **2003**, *13*, 91–100.
- (11) Salisbury, T. I.; Singhal, A. A new approach for ARMA pole estimation using higher order crossings. *Proc. Am. Control Conf.* **2005**, 4458–4463.
- (12) Zakharov, A.; Zattoni, E.; Xie, L.; Pozo Garcia, O.; Jamsä-Jounela, S.-L. An autonomous valve stiction detection system based on data characterization. *Control Eng. Pract.* **2013**, *21*, 1507–1518.
- (13) Jelali, M.; Scali, C. Comparative study of valve-stiction-detectoin methods. In *Detection and Diagnosis of Stiction in Control Loops: State of the Art and Advanced Methods*; Jelali, M., Huang, M., Eds.; Springer-Verlag: London, 2010.