Integrated valve stiction detection system

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ABSTRACT

The performance of a modern industrial plant can be severely affected by the performance of its key devices, such as valves. In particular, valve stiction can cause poor performance in control loops and can consequently lower the efficiency of the plant and the quality of the product. This paper presents an integrated FDD system for valve stiction which employs various FDD methods in a parallel configuration. A reliability index was integrated into each method in order to estimate their degree of influence in the final diagnosis of the system. Each method and the integrated system were tested using industrial data.

1 INTRODUCTION

A process plant aims to deliver a product with specific quality characteristics and to simultaneously maintain efficient process operation. This can be achieved by avoiding faults in the process devices. Valves are one of the most common devices in the process industry. In some specific cases, valve faults can negatively affect the performance of an entire plant. Valve stiction in particular has been found to be a frequent reason for poor performance of control loops. A valve under stiction should be repaired or replaced immediately. However, replacement of the valve would normally interrupt the process completely. Moreover, in most cases, stiction is not discovered due to the high number of devices and control loops present in the plant.

Fault detection in valves is typically based on supervision of the available measured variables. Therefore, most methods can only detect the presence of a specific fault type. Jelali et al. (2010) have reviewed the most common methods for detecting and diagnosing valve stiction discussed in the literature, most of which recognize special characteristics of control-related signals. Particularly, the shape-based methods analyze the characteristic shape of the control-related signals to identify stiction.

Among the shape-based methods, Kano (2004) presented a stiction detection technique based on the difference between the shape produced by sinusoidal oscillations and the shape of oscillations caused by stiction. Singhal et al. (2005) proposed a method based on the symmetry of the oscillation signal produced by a healthy control loop. In this method the area of each half-period of the analyzed signal is calculated in order to construct an index of the symmetry of the signal. Choudhury et al. (2006) introduced a technique for detecting the presence of nonlinearity in a control loop. If nonlinearity is detected, a phase plot is constructed using input-output data. Stiction is identified if the shape of the plot has an elliptical pattern. Scali et al. (2008) introduced a method based on the similarity between the shape of the oscillation caused by stiction and by relay control. In this method a signal generated by a relay model and sinusoidal and triangular functions are matched to the controlled signal. In cases where the triangular function or the relay signal exhibit a closer fit to the controlled variable stiction can be recognized in the control loop. Hägglund (2011) presented a method where rectangular and sinusoidal signals are matched to the control error. A loss function, based on the integral absolute error (IAE), is used to evaluate the matching quality.

The aim of this paper is to present an integrated FDD system for valve stiction using a parallel configuration of common algorithms for stiction detection; in order to improve the reliability of the diagnosis decision on industrial environments. For this purpose, the use of integrated diagnosis index and separate reliability indices for each detection method are proposed. The paper also includes the testing results and a comparison analysis of each stiction algorithm using industrial paperboard machine data. The paper is organized as follows: Section 2 presents the structure of the proposed integrated FDD system, the implemented valve stiction diagnosis methods, and their reliability indices. Section 3 describes the testing procedure and study cases. Section 4 presents the tests results of each stiction diagnosis algorithm and the integrated system. Additionally, the performances of the individual diagnosis algorithms and the integrated system are compared. In the final section, the conclusions of this work are presented and discussed.

2 INTEGRATED FDD SYSTEM FOR VALVE STICTION

The integrated FDD system, developed in this study, employs a parallel configuration, where common valve stiction diagnosis methods were implemented concurrently. A reliability index was integrated into each method defining their degree of influence in the final diagnosis. In this manner, all methods contributed to the final diagnosis decision, improving the reliability of the results and avoiding an ambiguous or contradictory diagnosis. The integrated FDD system for valve stiction consists of the following phases: first data preprocessing during which tasks such as verifying the sampling time and removing outliers, large disturbances, and gaps in the data are performed; second, calculation of the stiction indices; third, calculation of the reliability indices; and the final phase in which the integrated diagnosis decision is achieved. The FDD methods used in the integrated system are the histogram method (Horch, 2006), the curve fitting method (He et al., 2007), the rectangular fitting method (Hägglund, 2011), and the bicoherence method (Choudhury, 2006).

The introduction of a reliability index for the stiction diagnosis algorithms aims to define the degree of certainty of the diagnosis decision. However before defining the reliability index it is necessary to consider two issues. First, a method is able to provide trustworthy results only if the assumptions behind the method hold. In particular, the usual requirements of the stiction diagnosis methods are the presence of clear oscillations and the stationarity of the process data. In addition, some methods are applicable only if the process under consideration contains or does not contain integration. These listed assumptions should be tested for each stiction detection method and summarized in its applicability index a_i. Secondly, even if all the assumptions of a method are fulfilled, the decision of the method may be uncertain because of process noise, disturbances propagating from other loops and the presence of a small-magnitude stiction. This second part of the reliability index (the resolution index) must represent the degree of matching of the process data to one of the patterns related to healthy or stiction valve cases. In other words, the resolution index has a high value if the method can clearly classify the valve as healthy or under stiction, and the resolution index is low in the opposite case when the process data cannot be described satisfactorily. Assuming a normal distribution of the fitting errors, the resolution index (degree of certainty) of the decision can be represented in terms of the following likelihood ratios:

$$L_i = \log p_i(1)/p_i(0) = (d_i(0)\text{-}d_i(1))/2\sigma^2,$$

if $D_i = 1$ and $L_i = \log p_i(0)/p_i(1) = (d_i(1) - d_i(0))/2\sigma^2,$ (1)

if $D_i = -1$, where $d(1)$ and $d_i(1)$ are the fitting errors for the faulty and healthy pattern respectively, $p_i(0)$ and $p_i(1)$ are the probability densities of the process data in the case of a healthy and a faulty valve respectively, and D_i is the decision of the method. Equation (1) can then be aggregated to form the combined reliability index of the group of methods as shown in equation 2.

$$L = \log\frac{\prod_i p_i(1)}{\prod_i p_i(0)} = \sum_i D_i L_i. \tag{2}$$

The drawback of the proposed index (2) is that it can produce high values even when the process data can be fitted to neither a faulty nor a healthy pattern and when both $d(0)$ and $d(1)$ are high. Therefore, in order to obtain a reliable diagnosis the following alternative resolution index is proposed and used in this paper (eq. 3).

$$r_i = 1 - 2\frac{\min(d_i(0), d_i(1))}{d_i(0) + d_i(1)} \tag{3}$$

Summarizing the applicability and resolution sub-indexes, the diagnosis index can be then calculated in the following way:

$$R = \sum_i D_i \min(r_i, a_i) \tag{4}$$

and the final decision is determined by the sign of the sum in the equation $D_i = 1$ (stiction) if $\sum_i D_i \min(r_i, a_i) > 0$, and $D_i = 0$ (there is no stiction) if $\sum_i D_i \min(r_i, a_i) < 0$ (5)

In Equations (4) and (5), the impact of every method is limited by its applicability index, which represents the fact that the results of the method cannot be trusted if the assumptions of the method fail, even if the process data can be fitted to one of the patterns very accurately.

The resolution index for the histogram method can be constructed using the Gaussian and camel fitting errors, so the reliability index is calculated as follows:

$$r_{ih} = 1 - \frac{\min(d_g^2, d_c^2)}{(d_g^2 + d_c^2)}$$

where d_g^2 is the squared 2-norm of the error fitting of the Gaussian distribution and d_c^2 is the squared 2-norm of the error fitting of the Camel distribution. r_{ih} is a resolution index with values from 0 to 1; the closer the value is to 1, the more reliable the stiction index can be considered.

In the curve fitting method, the stiction index may provide inaccurate results when the MSE of both sinusoidal and triangular signals is unable to match the original signal. Thus, the resolution index is constructed using the fitting residual of both signals. According to (5), it can be calculated in the following manner:

$$r_{ic} = 1 - 2\frac{\min(d_{sin}, d_{tri})}{d_{sin} + d_{tri}}$$

where d_{sin} and d_{tri} are the fitting errors of the sinusoidal and triangular signal respectively and r_{ic} is the resolution index for the curve-fitting method. r_{ic} can have values from *0* to *1*; the closer the index value is to *1*, the more reliable the stiction index result can be considered.

The resolution index of the rectangular fitting method employs the values of the sine and square loss functions (Hägglund, 201), since functionally they are similar to the fitting errors used in the histogram and curve fitting methods. The resolution index can be calculated as follows:

$$r_{ir} = 1 - \left(\frac{\min(V_{sine}, V_{square})}{V_{sine} + V_{square}}\right)$$

where r_{ir} is the resolution index for the rectangular fitting method with a range of values from *0* to *1*. r_{ir} values above *0.5* are considered reliable, so therefore values below *0.5* are considered unreliable.

In terms of reliability, the most important feature of the data for the bicoherence based nonlinearity indices is the stationarity of the data. To estimate the skewness of the data distribution, the mean and the standard deviation of the data must remain constant over the calculation period. This requirement is however seldom achieved when using real industrial data, even after it has been pre-processed. To this end, a reliability index was defined for the NGI and NLI computation. Standard statistical tests, Student's t-test and χ^2 -test are used to calculate the mean and the standard deviation, respectively. To compute of the reliability index, the data is divided into *l* segments for which the mean $\bar{x}_i$ and standard deviation σ_i are calculated and tested against the null hypothesis $\bar{x}_i = 0$ and $\sigma_i = 1$. The reliability index R_{BIC} is defined as follows:

$$R_{BIC} = r_{\bar{x}} \cdot r_{\sigma}, \quad \text{where} \quad r_{\bar{x}} = 1 - \frac{\#\{\bar{x}_i \mid |T_i| > T_{lim}\}}{l} \quad \text{and} \quad r_{\sigma} = 1 - \frac{\#\{\sigma_i \mid \chi_i^2 < \chi_{lim,l}^2 \text{ or } \chi_i^2 > \chi_{lim,u}^2\}}{l}.$$

In the above, $T_i = \frac{\bar{x}_i}{s/\sqrt{n}}$ is the t-statistic for testing the mean of the data segment *i*, $T_{\lim}$ is the limit for the confidence level of 0.05. The variable $\chi_i^2 = \frac{(n-1)\sigma_i^2}{\sigma^2}$ denotes the test statistic for testing the standard deviation for the data segment *i*, while $\chi_{lim,l}^2$ and $\chi_{lim,u}^2$ are the lower and upper limits for the confidence level of 0.05. The operator #{ } takes the number of elements in the set.

3 DESCRIPTION OF THE CASE STUDIES

A comprehensive fault analysis of the board machine was performed based on the operational and maintenance data of the year 2010. The aim of the study was to determine the fault types in the machine and the devices most affected by them. One of the most important findings of the study was the discovery that valves were one of the most critical devices in the process Moreover, the maintenance reports showed stiction to be the main cause for the valve malfunctioning as reported by Jämsä-Jounela et al. (2012).

The integrated FDD system was tested employing data from four critical control loops of an industrial paperboard machine: The pressure control loop in the second drying group, a flow control loop in the birch dosing, the pressure difference loop in the steam group 8 and a stock mixing flow loop. The loops are located in the drying and the stock preparation sections of the machine. The operation data was gathered from months of

January to June of 2011. The first case was a pressure control loop in the second drying group described by the maintenance reports as “sticky”. The second case was a flow control valve in the birch dosing which was reported as having a malfunction. The third case was a pressure control loop in the drying section. The valve was reported as being stuck at the start of movement. The last case was a flow control valve in the stock mixing which was reported as malfunctioning due to not being able to open properly.

4 TEST RESULTS

The diagnosis of the curve fitting method showed high consistency and was able to determine the presence of stiction in most of the case studies tested. However, for some time periods, the method was unable to provide any diagnosis decision. This was related to sudden changes in the shape of the analyzed signal affecting the MSE ratio calculation of the stiction index. Figure 1 (left side) shows the measurement signal for the first case study tested (top), the histogram of the stiction index (bottom left), the fitting errors for the triangular and sinusoidal functions (bottom right). The distribution of values of the index is clearly skewed towards values indicating stiction. However, the stiction index values are low, ranging from 0.5 to 0.6. The reliability index, for this case, shows a low value of 0.13, and thus the diagnosis decision cannot be fully trusted. This phenomenon can be seen in the figure (bottom right), where the blue lines indicate the stiction zone, where the fitting error for the triangular signal was significantly lower; the purple lines indicate the no stiction zone where the sinusoidal fitting error is lower; the black lines indicate the zone where no decision could be made since the fitting errors are similar for both functions. The figure shows a number of fitting points in the stiction zone. However, there were also a significant number of fitting points in the no decision zone. The similar fittings were perhaps caused by small disturbances which affected the shape of the signal.

The results obtained from the histogram method show that the algorithm performed better when implemented for long periods of time. This is logical due its use of a data histogram to analyze the behavior of the process. However, in certain cases, due to the binary values given by the diagnosis index, its diagnosis behavior can be considered contradictory. The diagnosis results of this method change abruptly for consecutive periods of time. This behavior can be explained by studying the characteristics of the data histogram constructed by the method. Figure 2 (right side), shows the data histogram and the fitted Gaussian and camel distributions. In this example, the data fits better to the Gaussian distribution better and therefore stiction was diagnosed. However, both fittings were similar, and thus the reliability index was low, with a value barely above 0.55. Under these conditions the diagnosis was still considered reliable but not definitive. This phenomenon can occur due to slight alterations in the shape of the data histogram, which are caused by disturbances and noise.

The stiction index of the rectangular fitting method showed inconsistent behavior jumping between high and low values. This phenomenon was a consequence of the presence of small disturbances or variations in the data, such as sudden changes in the period or amplitude of the oscillation. Nevertheless, in this method, the index values did not reflect the strength or weakness of the stiction, the diagnosis was given by the sign of the index. Thus, the diagnosis of this algorithm can be trusted as long as the index sign remains consistent for consecutive periods. The main source of ambiguity in the diagnosis can come from sudden changes in the sign, which are caused by sporadic disturbances in the signal and the use of the mean value to calculate the stiction index for large periods of time. Figure 2 shows the stiction index distribution (top) and the rectangular and sinusoidal loss functions values for each half period (bottom). In this example, the overall stiction index had the value of -0.10 and the reliability index had the value of 0.57. The low value obtained by the reliability index was related to the high variance shown in the sinusoidal loss function and the triangular loss function.

The bicoherence-based indices also exhibited high consistency in the results. However, it must be noted that the process in question was not linear and a certain degree of nonlinearity was constantly present. The variations in the results can be explained by variations in the data, such as small disturbances that distort the data distribution. Since NGI and NLI both measure high-order statistics, they are significantly affected by abnormal values, for example. This is illustrated in Figure 2 (left side), which displays three data segments in the February data set. The signals are assumed to represent similar stiction behavior, but the corresponding NGI and NLI values are very different. The corresponding reliability indices for the NGI and NLI values in the three data segments are 1, 0.81 and 0.4, respectively, from top bottom in Figure 10, which indicates that the skewness of the data distribution is clearly affected by the changes in the mean and variance of the data.

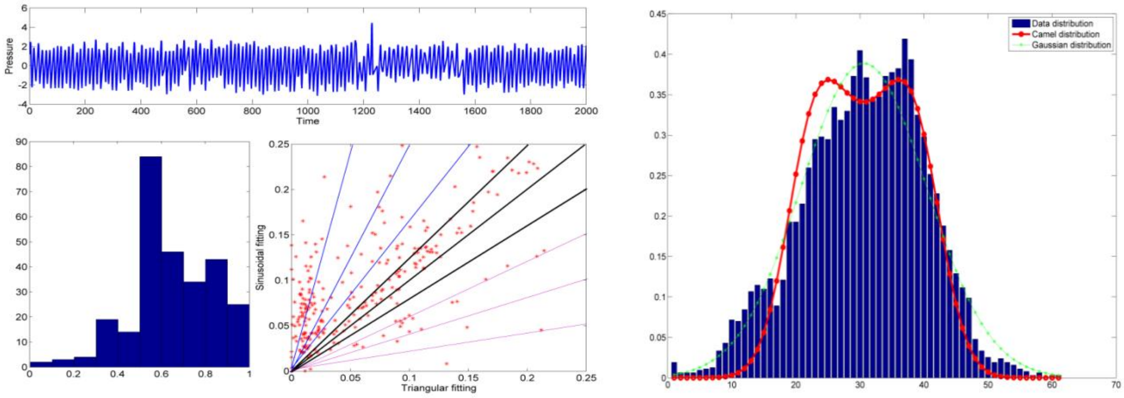

Figure 1. : Pressure measurement (top), Index histogram (bottom left), triangular and sinusoidal fitting errors (bottom right) (right) Data histogram, Camel and Sinusoidal signal (left).

The integrated FDD system was tested with the case studies reported in Section 4. The results obtained by using the integrated diagnosis index showed that the use of the reliability indices proposed in Section 2 was effective in combining and weighting the diagnosis decisions of the previously tested algorithms, providing a more robust and stable diagnosis than the ones provided by any of the individual stiction FDD algorithms. The behavior of the integrated system was constant without any sudden changes in its diagnosis and in accordance with the fault information found in the maintenance reports.

The diagnosis indices of the individual methods showed all the methods provided similar diagnoses in the cases in which the oscillation was strong. However, there were some periods of time where the methods did not agree on the diagnosis. Table 1 summarizes the diagnosis indices produced by means of each individual method and the integrated FDD system for all the testing cases. However, the results shown in Table 1 are unable to capture the dynamic behavior of the methods. If their trends are observed is possible to observe small and large variations in the stiction indices caused by each algorithm's false diagnoses or performance issues. By comparing the behavior of any of the individual diagnoses indices and the integrated FDD system, shows that the dynamic behavior of the integrated system is more stable without sudden or contradictory changes.

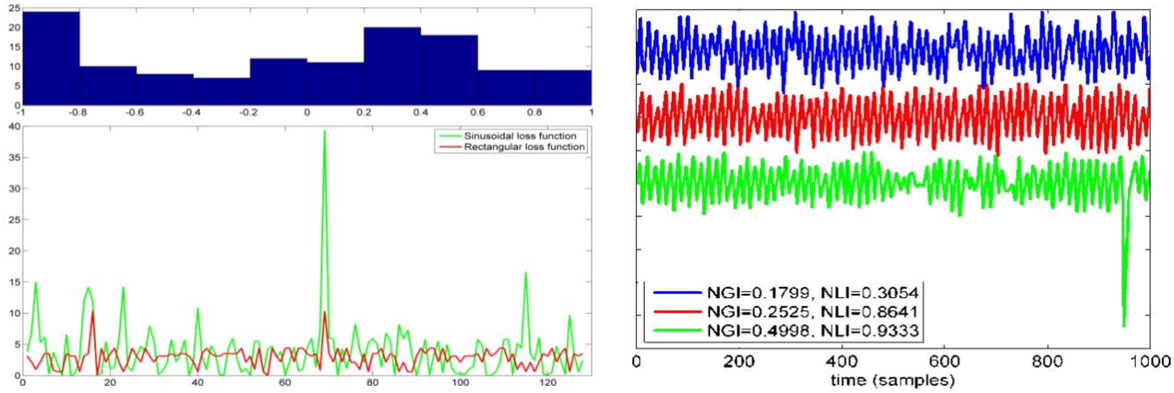

Figure 2. Index histogram (top), rectangular loss function (bottom, red) and sinusoidal loss function (bottom, green) (left). Analysis of bicoherence based nonlinearity indices and their variations (rigth)

5 CONCLUSIONS

In this work, an integrated FDD system for valve stiction was developed in which different algorithms were implemented to be run in a parallel configuration. Reliability indices for each method were proposed to facilitate the combination of the individual diagnoses. The integrated FDD system was tested with industrial data from a board machine and its performance was compared to the performances of the individual methods. The results show that an integrated valve stiction FDD system was able to overcome the drawbacks of the individual methods and to form a combined stiction index with more robust and consistent decisions in an industrial environment.

The obtained results were also in line with the maintenance reports from the paperboard machine studied, which indicates that the proposed system was able to successfully diagnose the presence of stiction. The reliability indices were shown to successfully measure the diagnosis uncertainty of the individual stiction detection algorithms in the presence of small disturbances. These indices were then used to determine the importance of the corresponding methods in the final diagnosis by weighting the individual results. As a result, the diagnosis decision of the integrated FDD system was able to take into account the diagnosis indices of the methods, providing a robust and unified diagnosis.

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Table 1. Resulting stiction indices

Test cases	**Month**	**CF index**	**Histogram index**	**RF index**	**Bicoherence NGI**	**NLI**	**Integrated index**
Case 1:	January	0.59	0	-0.04	0,21	0.46	0,54
	February	0.71	1	0.17	0,21	0.87	0,65
Sticky valve	March	0.67	1	0.21	0,20	0.67	0,64
Case 2 :	January	0.56	0.5	0.49	0,22	0.45	0,64
	February	0.6	1	0.44	0,22	0.41	0,44
Malfunction	March	0.55	1	0.43	0,21	0.50	0,58
Case 3:	May	0.66	1	0.44		0.66	0.68
	July	0.33	0	-0.18		0.64	0.18
Case 4:	January	0.50	1	0.13	0,29	0.22	0,61
	February	0.57	1	0.43	0,21	0.41	0,55
Malfunction	March	0.54	1	0.40	0,27	0.43	0,84

References:

1. Bendat P., Piersol AG. (1971), *Random data: Analysis and measurement procedure*s. Wiley, New York.
2. Choudhury, M.A.A.S., Shook D. S., and Shah S.L., (2006), Linear or Nonlinear? A bicoherence based metric of Nonlinearity measure, Proceedings of IFAC-Safeprocess 2006 Symposium, Beijing, Zhang Zhang pp. 617–622
3. Hägglund, T. (2011), A shape-analysis approach for diagnosis of stiction in control valves, *Control Engineering Practice 19*, pp.782-789.
4. Horch. A. (2006), Method and a system for evaluation of static friction, *US patent 7047152*, http://www.freepatentsonline.com/7047152.html
5. He P., Wang J., Pottmann M., Qin J. (2007), A curve fitting method for detecting valve stiction in oscillating control loops. *Industrial and Engineering Chemistry Research. 46*, pp.4549-4560
6. Jelali, M., & Huang,B. (2010), Detection and diagnosis of stiction in control loops—state of the art and advanced method. Springer-Verlag London, pp. 103-265
7. Jämsä-Jounela, S.L., Tikkala, V.M., Laavi, H., Myller, T., Kulomaa, T., Hämäläinen V., (2012), Outline of a fault diagnosis system for a large-scale board machine, *International Journal of Advanced Manufacturing Technology (in print).*
8. Kano, M., Maruta, M., Shimizu, K., & Kugemoto, H. (2004), Practical model and detection algorithm for valve stiction. *Seventh international conference on dynamics and control of process systems* (*DYCOPS7*). Cambridge
9. Singhal, A., Salsbury T.I., (2005). A simple method for detecting valve stiction in oscillating control loops, *Journal of Process Control 15*, pp.371-382.
10. Scali C., Ghelardoni C., (2008), "An Improved Qualitative Shape Analysis Technique for Automatic Detection of Valve Stiction in Flow Control loops", *Control Engineering Practice, 16*; pp. 1501-1508.