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THE DEVELOPMENT AND INVESTIGATION ANALYSIS OF AN ARX-BASED GENERALIZED LIKELIHOOD RATIO (GLR) STICTION DETECTION METHOD

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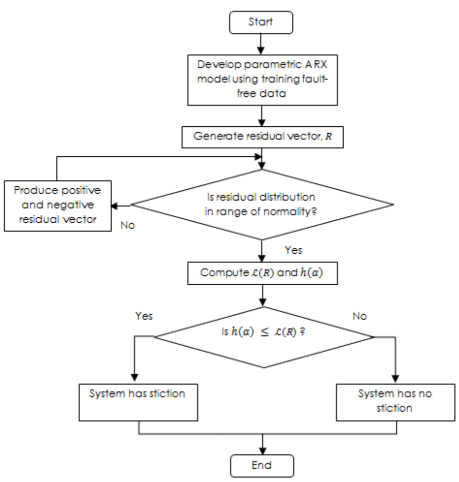
Graphical abstract



Abstract

Control valve stiction is one of the main sources of nonlinearity which can result in many deleterious effects on the control loop performance of a process. The study of stiction detection methods has now becoming one of the essential research areas in process control. In this present work, an ARX-based Generalized Likelihood Ratio (GLR) stiction detection method is proposed and its effectiveness is analyzed. The implementation of the proposed method involves three main stages; 1) ARX model identification, 2) GLR test, and 3) statistical hypothesis testing. The proposed detection method was applied to two benchmark simulated case studies. Results showed that the method effectively detect stiction. The presence of stiction is declared if the GLR test statistics, $\mathcal{L}(R)$ exceeds the decision threshold limit, $h(\alpha) = 3.841$, and the null hypothesis is rejected at 5% significance level. On the other hand, if $\mathcal{L}(R)$ value lies below $h(\alpha) = 3.841$, the null hypothesis is accepted and the absence of stiction is confirmed. In addition, it is also observed that the proposed method is reasonably insensitive and robust to the changes in the process gain, K and time constant, τ as it generally allows up to ±10% changes in the two parameters for both case studies.

Keywords: Control valve, stiction detection, ARX, GLR test, statistical hypothesis testing

Abstrak

Geseran statik injap kawalan adalah salah satu sumber utama tidak linear yang boleh menyebabkan banyak kesan yang merosakkan pada prestasi gelung kawalan suatu proses. Kajian kaedah pengesanan geseran statik telah menjadi salah satu bidang penyelidikan penting dalam kawalan proses. Dalam kerja terkini ini, kaedah pengesanan geseran statik berasaskan ARX yang Nisbah Kemungkinan Umum (GLR) dicadangkan dan keberkesanannya dianalisis. Pelaksanaan kaedah yang dicadangkan melibatkan tiga tahap utama; 1) pengenalan model ARX, 2) ujian GLR, dan 3) pengujian hipotesis statistik. Kaedah pengesanan yang dicadangkan telah digunakan untuk dua kajian kes penanda aras simulasi dan hasil menunjukkan bahawa kaedah ini berkesan dalam mengesan geseran statik. Had stik dinyatakan jika statistik ujian GLR $\mathcal{L}(R)$ melebihi had ambang keputusan, $h(\alpha) = 3.841$, dan hipotesis nol ditolak pada tahap penting 5%. Sebaliknya, jika nilai $\mathcal{L}(R)$ terletak di bawah $h(\alpha) = 3.841$, hipotesis nol diterima dan ketiadaan stik dikonfirmasi. Di samping itu, juga diperhatikan bahawa kaedah yang dicadangkan itu adalah tidak sensitif dan teguh kepada perubahan dalam keuntungan proses, K dan pemalar masa, τ kerana ia secara amnya membenarkan sehingga ± 10% perubahan dalam kedua-dua parameter bagi kedua-dua kajian kes.

Kata kunci: Injap kawalan, pengesanan geseran statik, ARX, ujian GLR, ujian hipotesis statistik

1.0 INTRODUCTION

Modern chemical plants consist of complex process units which involve thousands of control loops. Being one of the important assets to the operation, the performance of control loops needs to be monitored and maintained despite the fact that it is too time-consuming and difficult [1]. However, most process plants have poor control loops performance due to several reasons, which include aggressive controller tuning, presence of external oscillatory disturbances, and control valve malfunction. Among these, control valve malfunction is the main source of control loop performance degradation. It was reported in Desborough and Miller [2] that 32% of the 'fair or poor' controllers has control valve problem. Based on the survey conducted by Yang and Clarke [3], oscillations in 30% of control loops in Canadian paper mills are due to control valve problems. Jämsä-Jounela *et al*.[4] also showed that valve problems contribute to nearly 10% of an industrial paperboard machine faults.

Control valve malfunction includes static friction (or shortly termed as stiction), backlash, hysteresis and deadzone. Valve stiction has long been recognized as the long-standing control valve problem in many process industries. In fact, as reported by Ender [5], 20% of control loops available in paper mills oscillate mainly due to control valve stiction. Stiction introduces nonlinearity to control loops and causes limit cycles, which thus undermines the economic performance of the plant [1]. Due to operational concerns and undesirable consequences, the problem of control valve stiction in process industries has motivated an extensive studies among practitioners and researchers and one of the important fields considered is the stiction detection. There has been a rapid and vast development of stiction detection methods over the past years. The current available stiction detection methods are generally classified as either shape-based or model-based.

The first stiction detection technique was a shape-based approach suggested by Horch [6]. This approach is based on the cross-correlation function (CCF) between controller and process output signals. The obvious advantage of this method is that it does not require detailed process knowledge and process outputs can be easily obtained from the DCS system. However, it is only applicable to non-integrating processes [7]. Horch [7] then proposed another algorithm, which is applicable for both integrating and non-integrating processes. The method utilizes probability density function (histogram) method in detecting stiction. However, it requires the knowledge of the nature of the process [1] and simultaneous filtering and differentiations [8]. Singhal and Salsbury [9] also proposed another method which involves the calculation of the ratio of the areas before and after the peak of an oscillating control error signal. The method requires minimal computational effort but it is only limited for cases without periodic disturbances, which is impractical. When disturbances exist, ambiguous results are produced [10]. It also requires attention on the signal noise and sampling period as they can influence its effectiveness [1; 9]. Choudhury *et al.* [11] on the other hand proposed a higher order statistics-based method that uses non-Gaussianity index (NGI) and the nonlinearity index (NLI) for stiction detection. However, its bicoherence test does not specifically differentiate between valve stiction and other nonlinearities and hence, it subsequently requires the manual inspection of process output-controller output (*pv-op*) relationship [9; 10]. Another approach was developed by Zabiri and Ramasamy [10], which explores the Nonlinear Principal Component Analysis (NLPCA) as a potential tool to diagnose control valve stiction. A regression coefficient, R^2 is first determined to quantify the degree of nonlinearity and is used together with NLPCA curvature index, I_{NC}, to detect the presence of stiction. However, ambiguous results may be observed for integrating processes and significant amount of steady-state data are required [1; 10]. Recently, Daneshwar and Noh [8] proposed stiction detection method which uses a well-developed fuzzy clustering technique. The method observes the dramatic change in the slope of lines connecting the successive cluster centres and is robust against noise. The method however requires two different indexes to be calculated.

One of the earliest model-based methods was reported by Stenman *et al*. [12]. It is a segmentation-based approach that relies on change detection and multi-model mode estimation, but it necessitates optimization to obtain the log-likelihood ratio [9; 10]. Srinivasan and Rengaswamy [13] also reported an alternative model-based detection technique that explores the Hammerstein model identification. However, the method considers one parameter stiction model which is not adequate to capture the true stiction behavior [14; 15]. Despite the fact that all techniques proposed are successful and effective in detecting stiction, they vary in complexity and have their own limitation assumptions for general applications. This shows that there is no method that can cover all cases reliably [8].

Though both shaped-based and model-based methods have been extensively studied over the past years, the available methods in the literature still suffer from various problems as highlighted above. In addition, the capability of statistical-based method for stiction detection has not been widely explored. In this present work, a simple hybrid approach is proposed by combining the widely known linear Autoregressive with Exogenous Inputs (ARX) model with statistical analysis, namely the Generalized Likelihood Ratio (GLR) technique, and its efficiency in detecting control valve stiction is investigated. The proposed method can overcome some of the limitations of earlier approaches of stiction detection. The performance of the proposed method is confirmed by benchmark simulation case studies with various stiction parameters.

The subsequent sections of this paper are organized as follows. Section 2 provides brief description of the mechanism and the concept of control valve stiction and Section 3 explains the basic theory of Auto-Regressive with Exogenous input (ARX) model identification. In Section 4, the detailed methodology of the proposed ARX-based GLR detection technique is explained. The results obtained for the two case studies are then presented in Section 5, followed by conclusion and recommendations in Section 6.

2.0 METHODOLOGY

2.1 Control Valve Stiction

The description on the mechanism of stiction in this section is pioneered by Choudhury *et al*. in [16]. Figure 1 illustrates the general cross-sectional view of a typical pneumatic control valve. In general, stiction occurs when there is excessive static friction between the valve stem and the packing that holds the stem back and hinders its motion. As the controller output sufficiently exceeds the frictional force, a sudden slip of the stem occurs. This causes oscillations to the valve output as well as the controlled variable of the process or process output.

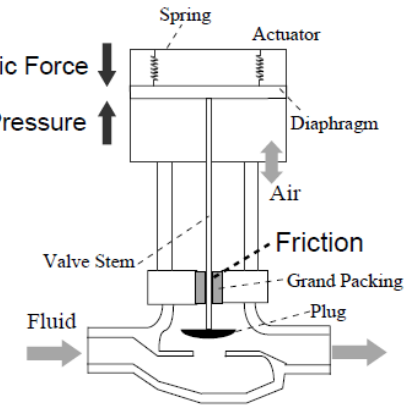


Figure 1 Cross-sectional structure of pneumatic control valve [17]

Static friction (or stiction) consists of a sequence of four distinct components, namely deadband, stickband, slip jump and moving phase. This is shown in Figure 2.

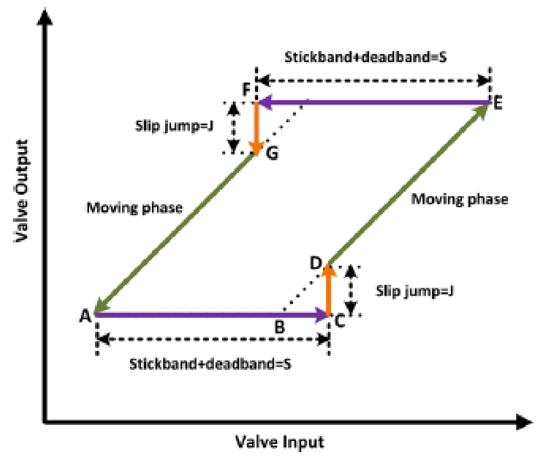


Figure 2 Input-output behavior of control valve stiction [8]

According to Choudhury *et al*. [16], the phenomenon of stiction occurs in several processes. The first phase constitutes of a deadband and stickband, denoted as S. A sticky valve remains at rest from position A to C. Albeit the increase in the amount of controller output (*op*), the valve remains static due to the large maximum static frictional force in the packing area. The valve will start to move at point C only when the controller output (*op*) exceeds the static frictional force. The accumulated potential energy stored in the control valve is converted into kinetic energy; resulting in a slip jump of magnitude J that causes the valve output to move to a new position D.

The valve stem then continues to move linearly with the amount of controller output, from D to E (moving phase), until it encounters another static friction along its motion. It is also possible that valve sticks along this phase. Similar scenario is observed when the controller output (*op*) decreases and the valve moves in the opposite direction (from E to F, F to G and G to A).

2.2 Auto-Regressive With Exogenous Input (ARX) Model Identification

Auto-Regressive with Exogenous Input (ARX) model is one of the simplest type of parametric model structures. The solution to an ARX model estimation is unique such that the global minimum of the loss function is always satisfied. Therefore, ARX model is usually preferred for system identification, especially for high-ordered models. The structure of a linear Single-Input-Single-Output (SISO) ARX model is simply expressed as shown in Equation 1. The structure implies that linear ARX model predicts the current output $y(t)$ based on the weighted sum of its *regressors*; that is, the values of its finite past outputs, $y(t-k)$, and current, $u(t)$, and past inputs, $u(t-k)$.

$$y(t) = \frac{B(q)}{A(q)}u(t-nk) + \frac{1}{A(q)}e(t) \tag{1}$$

where

$A(q) = 1 + a_1q^{-1} + \cdots + a_{na}q^{-na}$;
$B(q) = b_1 + b_2q^{-1} + \cdots + b_{nb}q^{-nb+1}$;
q^{-1} is the backshift operator

2.3 Experimental

This section explains the detailed methods carried out throughout the work. Five subsections are covered including:

1) System Development;
2) ARX Model Identification;
3) ARX-based Stiction Detection using GLR Test,
4) Development of ARX-based Stiction Detection Algorithm; and
5) Sensitivity Analysis.

2.3.1 System Development

The research investigates two benchmark case studies of two different Single-Input-Single-Output (SISO) feedback control systems as used by Zabiri and Ramasamy [10]. The two case studies examine different cases which typically occur in process control loops.

Case Study 1

Three cases of different strengths of stiction are analyzed. They include Base Case 1 (no stiction), Case 1.1 (weak stiction) and Case 1.2 (strong stiction). Figure 3 shows the block diagram of the system.

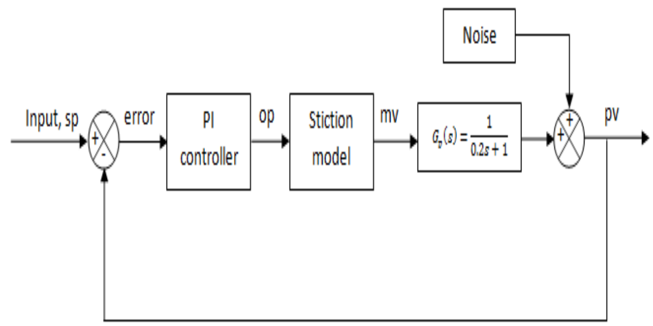


Figure 3 System block diagram for Case Study 1

The system has a continuous process model, $G_p(s) = \frac{1}{0.2s+1}$ with sampling time set at 0.1 min. A PI controller is tuned with controller gain of $K_c = 0.5$ and integral time of $\tau_I = 0.3$min. A positive step change of magnitude 10 is introduced and 6000 sampled data is collected. To consider system without any presence of stiction, the control valve stiction model is removed from the loop. Meanwhile, to analyze the weak and strong stiction cases, the values of stickband plus deadband, S and slipjump, J, as shown in Table 1, are used and specified in the S-function script of the stiction model.

Table 1 Stiction parameters for Case Study 1

Stiction strength	S	J
No stiction (Base Case 1)	0	0
Weak stiction (Case 1.1)	1	0.3
Strong stiction (Case 1.2)	5	1

Case Study 2

In this study, four general conditions of control loop system are investigated, which include Base Case 2 (well-tuned controller), Case 2.1 (tightly-tuned controller), Case 2.2 (presence of external disturbances) and Case 2.3 (presence of stiction). Figure 4 displays the block diagram of the system for this case study.

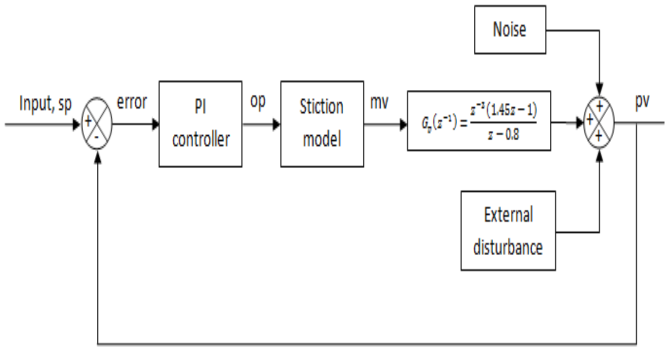


Figure 4 System block diagram for Case Study 2

A discrete process model, $G_p(z^{-1}) = \frac{z^{-3}\times(1.45z-1)}{z-0.8}$ is examined with sampling time of 1s. A random noise is added into the process with mean and variance of 0 and 0.224 respectively. A unit step change is introduced and 6000 samples of *op-pv* data are collected. Table 2 summarizes the settings for the four cases considered for this case study.

Table 2 Settings for four cases of Case Study 2

Case	PI controller tuning	External disturbance	Stiction
Base Case 2 (well-tuned controller)	$K_c = 0.15$; $I = \frac{K_c}{\tau_I} = 0.15\ s^{-1}$	-	-
Case 2.1 (tight-tuned controller)	$K_c = 0.15$; $I = \frac{K_c}{\tau_I} = 0.27\ s^{-1}$	-	-
Case 2.2 (presence of external disturbance)	$K_c = 0.15$; $I = \frac{K_c}{\tau_I} = 0.15\ s^{-1}$	Sinusoidal wave with amplitude of 2 and frequency of 0.02 rad/s	-
Case 2.3 (presence of sticton)	$K_c = 0.15$; $I = \frac{K_c}{\tau_I} = 0.15\ s^{-1}$	-	$S = 3$; $J = 1$

2.3.2 ARX Model Identification

An open loop system is developed to generate the fault-free data or known as the training data. This refers to the vector data of process input (*op*) and output (*pv*) when the system operates under normal operating conditions. The data are then used to build ARX model with orders of four for polynomials A(q) and B(q) and order of one for the time delay term (or deadtime) (Refer to Section 3). The number of parameters for the model development is chosen when the residual distribution for the base cases, where the process has no stiction and operates under normal operating condition, is normally distributed. This means that the developed model has completely captured the dynamics of the system. For practicality, this model identification considers PRBS input signal as the process input, which is set with band of 0 to 0.02 and maximum and minimum levels of -1 and 1 respectively.

2.3.3 ARX-based Stiction Detection using GLR Test

Traditionally, a model-based fault detection problem requires two main steps; 1) the generation of residual and 2) the residual evaluation using statistical test [18-20]. Figure 5 shows the schematic diagram of the proposed ARX-based GLR stiction detection method employed in this research.

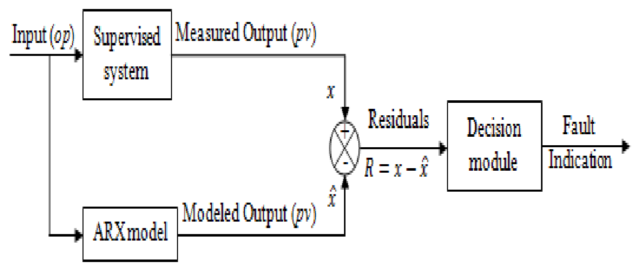


Figure 5 Schematic diagram of the proposed ARX-based GLR stiction detection method

Based on Figure 5, the ARX model, obtained from Section 4.2, is used to simulate the output of the system (*pv*), given the input data (*op*). The modeled output, $\hat{x}$, is then compared to the measured output, x, using Equation (2) to generate the residual vector, R.

$$Residual, R = x - \hat{x} \tag{2}$$

For system without stiction (faultless), the system remains linear and the linear ARX model can perfectly simulate the output (*pv*), generating effectively zero residuals. However, if stiction is present, it introduces nonlinearity within the system, such that the linear ARX model cannot accurately capture the complete dynamics of such system which thus generating non-zero residuals. Before the statistical GLR test and hypothesis testing are performed, the normality of the residual distribution has to be firstly ensured. The residual distribution has to be normal (Gaussian) or approximately normal (within the limits of acceptable normality, -1 and 1). The normality is measured by the skewness of the distribution. If the distribution happens to be not normal (i.e. bimodal), the residual data is firstly pre-treated by performing population data sampling; that is, separating the positive and negative residual data into individual vectors.

Equation (3) computes the generalized likelihood ratio, $\mathcal{L}(R)$ for the GLR test.

$$f_\theta(R) = \frac{1}{\sigma\sqrt{2\pi}} exp^{\frac{-1}{2\sigma^2}(R-\mu)^2}$$

$$\Lambda = \frac{L(R)}{L(R_o)} = \frac{\sup_{\theta \epsilon R^n} f_\theta(R)}{\sup_{\theta \epsilon 0} f_{\theta=0}(R)} = \frac{\|f_\theta(R)\|_2^2}{\|f_{\theta=0}(R)\|_2^2}$$

$$\mathcal{L}(R) = -2\, log(\Lambda) \tag{3}$$

where R is the residual vector, Λ is the likelihood ratio statistics, $L(R)$ is the supremum of the likelihood function for all $\theta \epsilon R^n$, $L(R_o)$ is the supremum of the likelihood function for all $\theta \epsilon\, 0$, $f_\theta(R)$ is the probability density function of R and $\|.\|_2$ refers to the Euclidean norm computation. Based on Equation (3), the GLR test basically uses the ratio of faultless (without stiction) and faulty (with stiction) data distributions to detect the presence of stiction.
The GLR hypothesis test statement is written as Equation (4).

$$\delta(R) = \begin{cases} H_o & if\ \mathcal{L}(R) < h(\alpha) \\ H_a & otherwise \end{cases} \tag{4}$$

where H_o = null hypothesis (no stiction), H_a = alternative hypothesis (stiction exists), $\mathcal{L}(R)$ = GLR test or decision statistics, $h(\alpha)$ = decision threshold value and α = significance level. In this paper, the significance level, α is chosen to be 5%, that is, $\alpha = 0.05$. With one degree of freedom and by referring to the Chi-squared table, the threshold value $h(\alpha)$ is obtained to be 3.841 for both case studies.

2.3.4 Development of ARX-based Stiction Detection Algorithm

An effective algorithm known as the ARX-based GLR stiction detection algorithm is developed as outlined in Table 3. To simplify the algorithm in Table 3, the flow chart in Figure 6 is developed.

2.3.5 Sensitivity Analysis

A sensitivity analysis is carried out to analyze the robustness and effectiveness of the proposed stiction detection system if the process model parameters like process gain, K, and time constant, τ change over the time of operation. The values of the parameters are varied and the effectiveness of the stiction detection method is observed. The tolerable limits to the changes in both of these parameters are also determined.

Table 3 ARX-based GLR stiction detection algorithm

Step	Action
1.	Given : • SISO closed loop system with different cases of stiction and sampling time, Ts • Significance level for hypothesis testing, α
2.	Build the ARX model using the training fault-free *op-pv* data • Run the open loop system under normal operating condition • Extract the training fault-free *op-pv* data and insert into System Identification (SI) Toolbox in MATLAB • Estimate the linear parametric ARX model with orders of [na:nb:nk] = [4:4:1]
3.	Data preprocessing • Run the closed-loop system and consider conditions (*op-pv* data) at steady state
4.	Generate the residual vector • Input vector data *op* of cases under investigation into the developed ARX model to simulate and estimate its modeled *pv* • Identify the residual vector using Equation (2) • Plot the residual distribution as histogram and check its normality (Gaussian distribution)
5.	Compute GLR test statistic based on the residual vector • For normal or Gaussian distribution (or within the range of normality, -1 to 1), directly calculate the GLR test statistic $\mathcal{L}(R)$, using Equation (3)

Step	Action
	• For bimodal distribution, classify the positive and negative residual data into positive and negative vectors (R_pos and R_neg) i.e. sampling the population. Then, calculate the GLR test statistic $\mathcal{L}(R)$, using Equation (3) for each vector.
6.	Perform hypothesis testing • Compute the decision threshold value, $h(\alpha)$ for the GLR hypothesis test based on the given α value • Perform hypothesis testing according to Equation (4) i. If $\mathcal{L}(R) \geq h(\alpha)$, declare a stiction (fault). ii. If $\mathcal{L}(R) < h(\alpha)$, declare no stiction (fault-free).

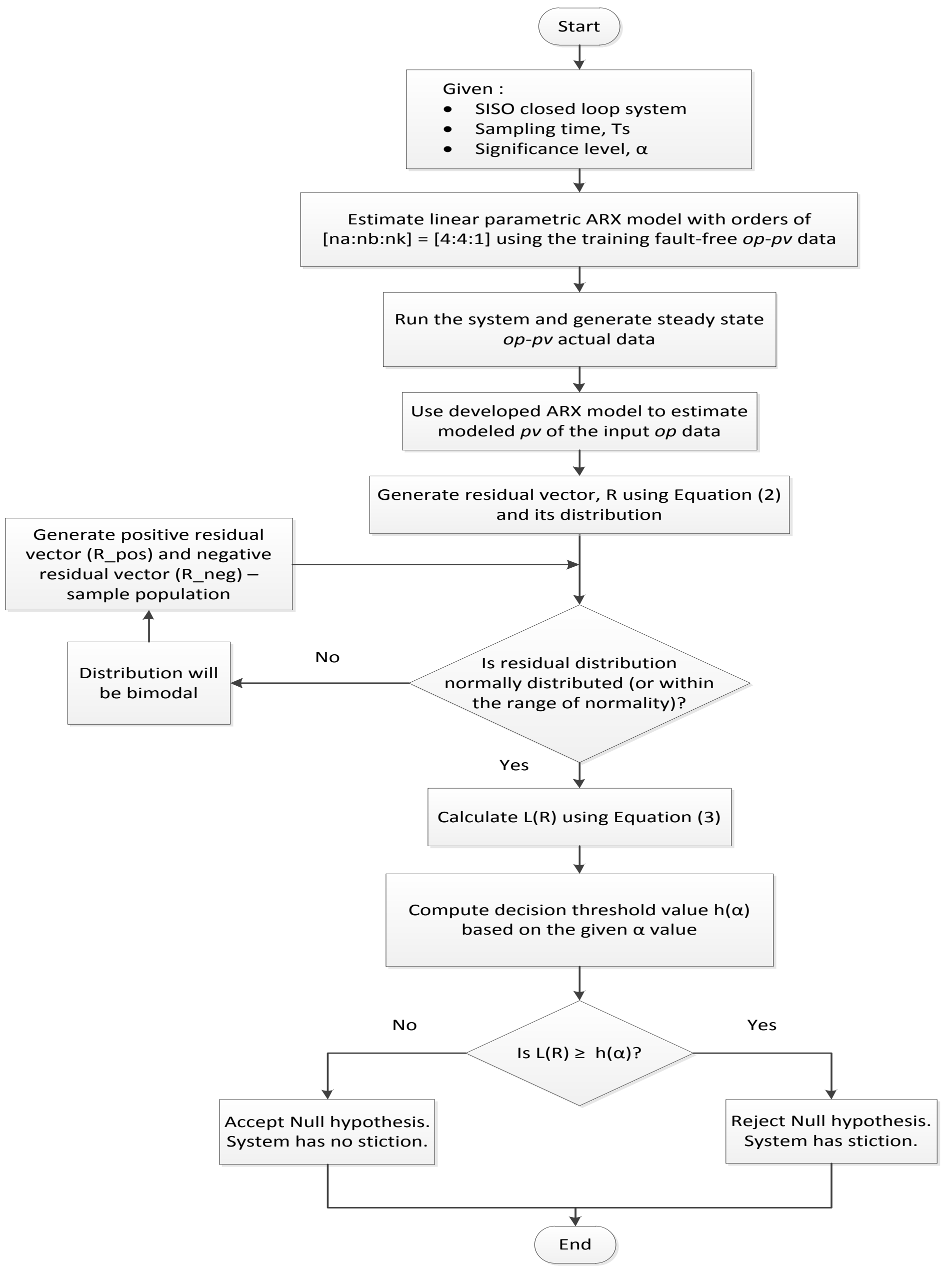


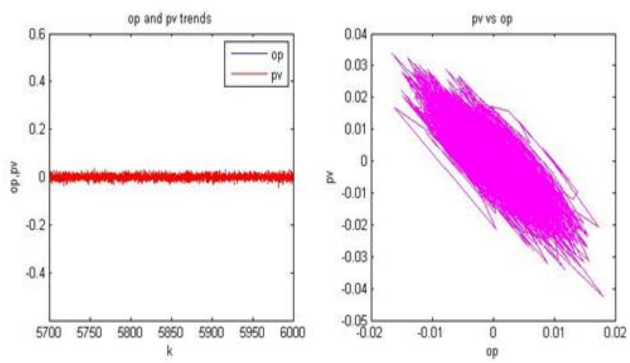
Figure 6 Flowchart of ARX-based GLR stiction detection algorithm

3.0 RESULTS AND DISCUSSION

3.1 Case Study 1

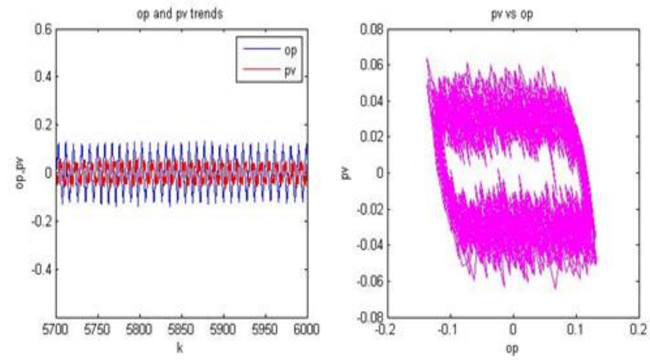
Figures 7-9 show the *pv-op* trends for the three stiction cases whilst Figure 10 shows the residual plots. It is depicted that zero residuals are generated for system without stiction (Base Case 1). However, if stiction exists, the system becomes no longer linear and the nonlinearity creates non-zero residuals as observed in Case 1.1 and Case 1.2.

Figure 11 demonstrates the histograms of the residuals for all the cases. By visual inspection, it can be viewed that the distributions are all normal. The skewness for Base Case 1, Case 1.1 and Case 1.2 are obtained as -0.008, 0.0008 and -0.0015 respectively, indicating that they are all within the range of normality. By performing the GLR test, the values of $\mathcal{L}(R)$ test statistics are obtained as in Table 4. The results lead to a decision whereby Base Case 1 declares an absence of stiction as its $\mathcal{L}(R)$ is less than the decision threshold value, $h(\alpha) = 3.841$ and its null hypothesis is accepted at 5% significance level. On the other hand, Case 1.1 and Case 1.2 report the presence of stiction as their $\mathcal{L}(R)$ values are greater than $h(\alpha)$. Their null hypothesis are both rejected at 5% significance level. The larger $\mathcal{L}(R)$ value in Case 1.2 signifies greater strength of stiction. These results conform to the known status of presence of stiction for all the cases considered.



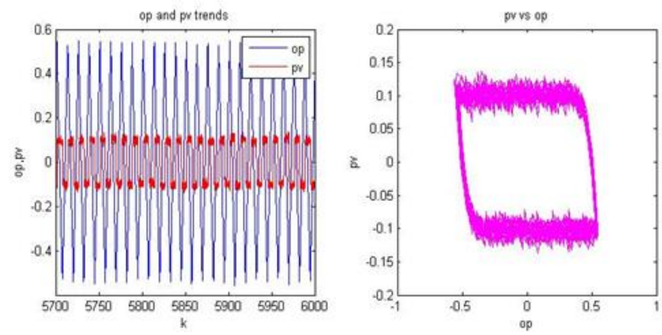
(a) (b)

Figure 7 (a) OP and PV trends and (b) PV versus OP plot for Base Case 1 (no stiction)



(a) (b)

Figure 8 OP and PV trends and (b) PV versus OP plot for Case 1.1 (weak stiction)

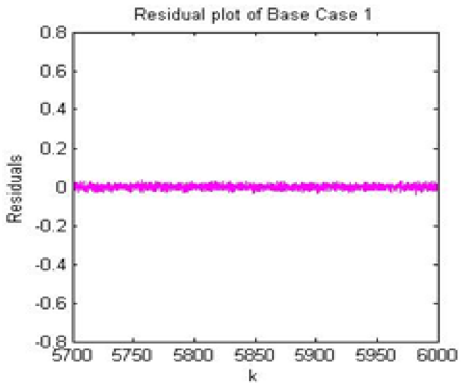


(a) (b)

Figure 9 OP and PV trends and (b) PV versus OP plot for Case 1.2 (strong stiction)

3.2 Case Study 2

In this section, four sources of nonlinearity in control loops are examined. The *pv-op* trends for the four situations are plotted in Figures 12-15 and residual plots for each of the situation are as shown in Figure 16. Figure 17 illustrates the normality of the residual distribution. Based on Figure 17, Base Case 2 and Case 2.1 have normal (or approximately normal) residual distributions whilst Case 2.2 has a bit skewed distribution. Despite this, the normality of the distribution is still within the limits of -1 and 1, and hence, the GLR test is still applicable. However, bimodal distribution is observed for Case 2.3 which disallows the GLR analysis. Therefore, the residual data is firstly pre-treated such that the positive and negative values are separated into two individual residual vectors, R_pos and R_neg (population sampling). The distributions for these vectors are plotted in Figure 18.



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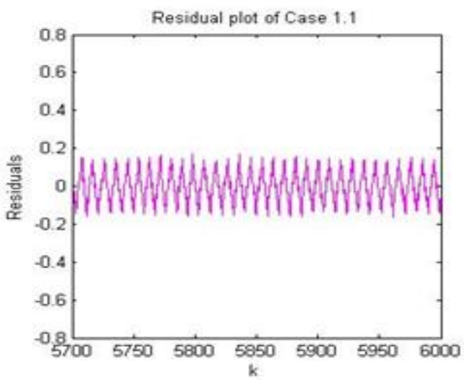

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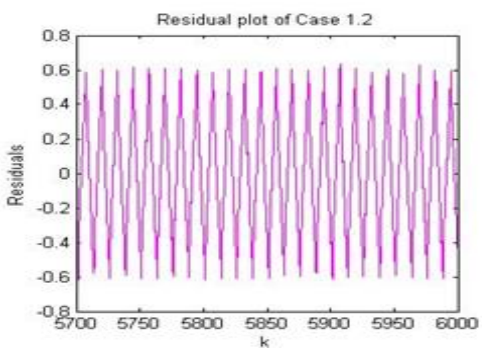
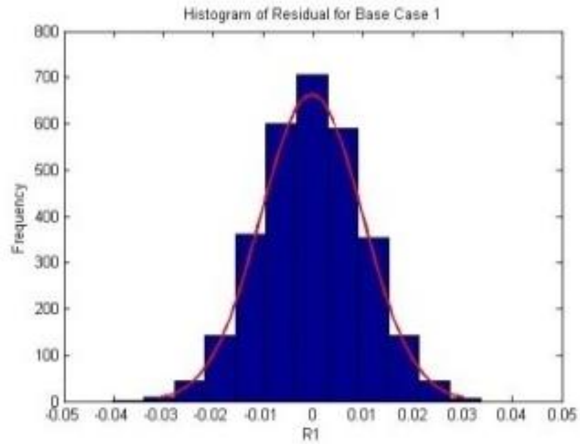
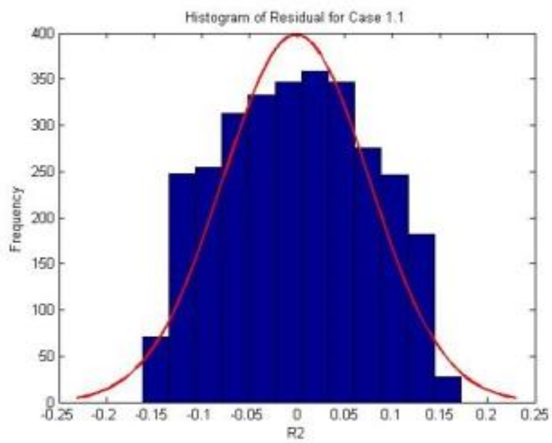


(c)

Figure 10 Residual plots for (a) Base Case 1, (b) Case 1.1 and (c) Case 1.2



(a)



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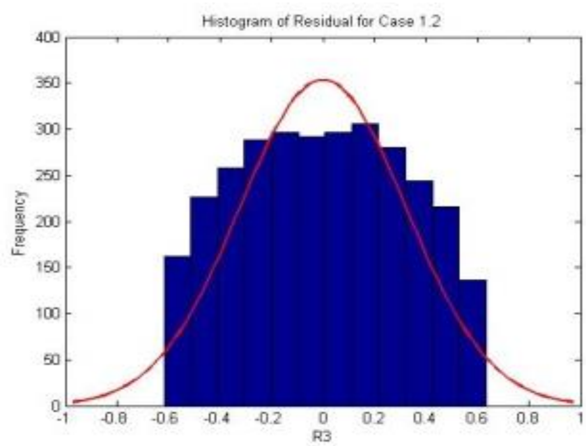


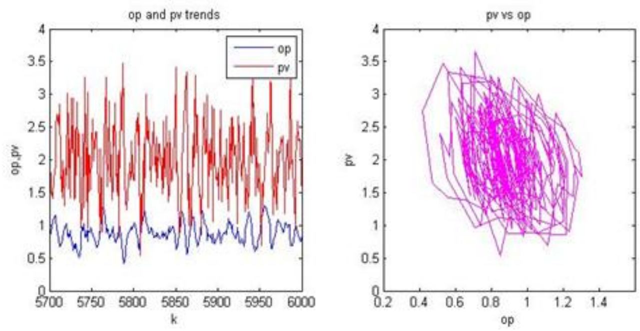
(c)

Figure 11 Histogram of Residuals for (a) Base Case 1, (b) Case 1.1, and (c) Case 1.2

Table 4 GLR test statistics, $\mathcal{L}(\boldsymbol{R})$for Case Study 1

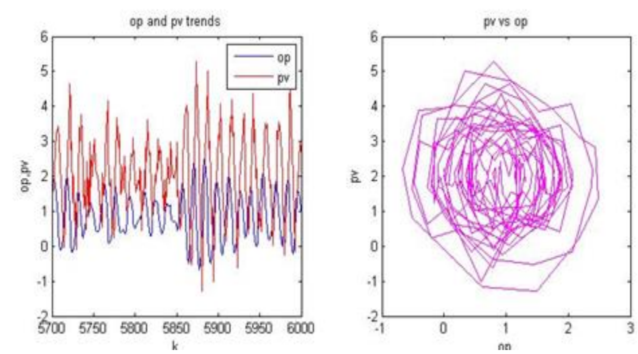
Case	$\mathcal{L}(\boldsymbol{R})$
Base Case 1 (no stiction)	0
Case 1.1 (weak stiction)	4.1337
Case 1.2 (strong stiction)	7.0241

The skewness for Base Case 2, Case 2.1, Case 2.2 and Case 2.3 (positive and negative residuals) are obtained as 0.1047, 0.1022, -0.3733 and -0.4586 and 0.4525 respectively, which thus indicate that they are all within the range of normality.



(a) (b)

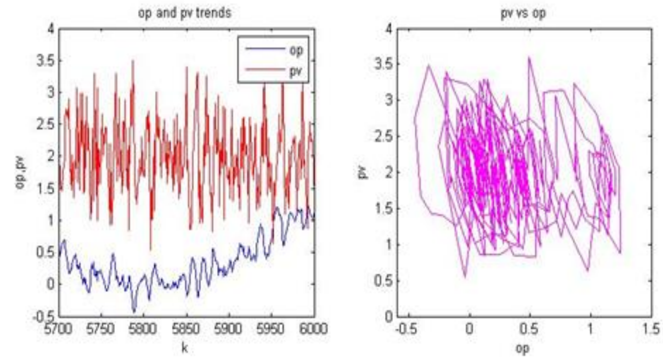
Figure 12 (a) OP and PV trends and (b) PV versus OP plot for Base Case 2 (well-tuned controller)



(a) (b)

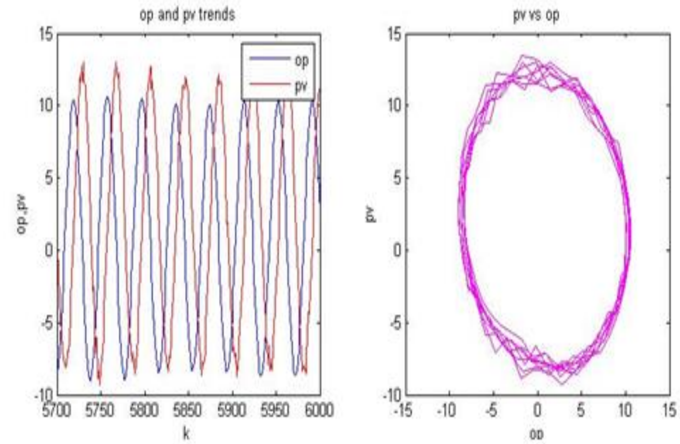
(a)

Figure 13 (a) OP and PV trends and (b) PV versus OP plot for Case 2.1 (tight-tuned controller)



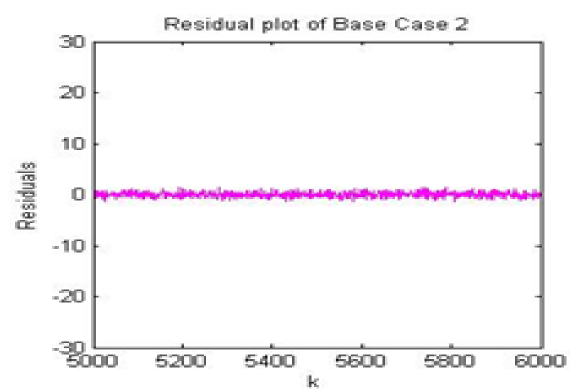
(a) (b)

Figure 14 (a) OP and PV trends and (b) PV versus OP plot for Case 2.2 (external disturbance)



(a) (b)

Figure 15 (a) OP and PV trends and (b) PV versus OP plot for Case 2.3 (stiction)



(a)

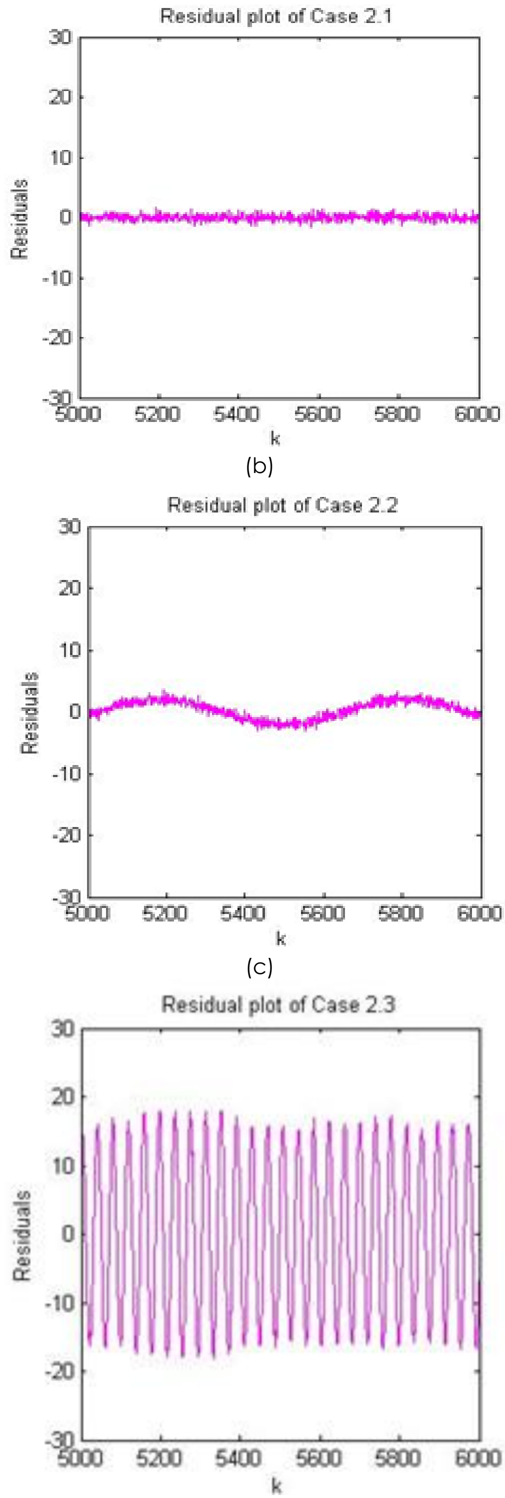
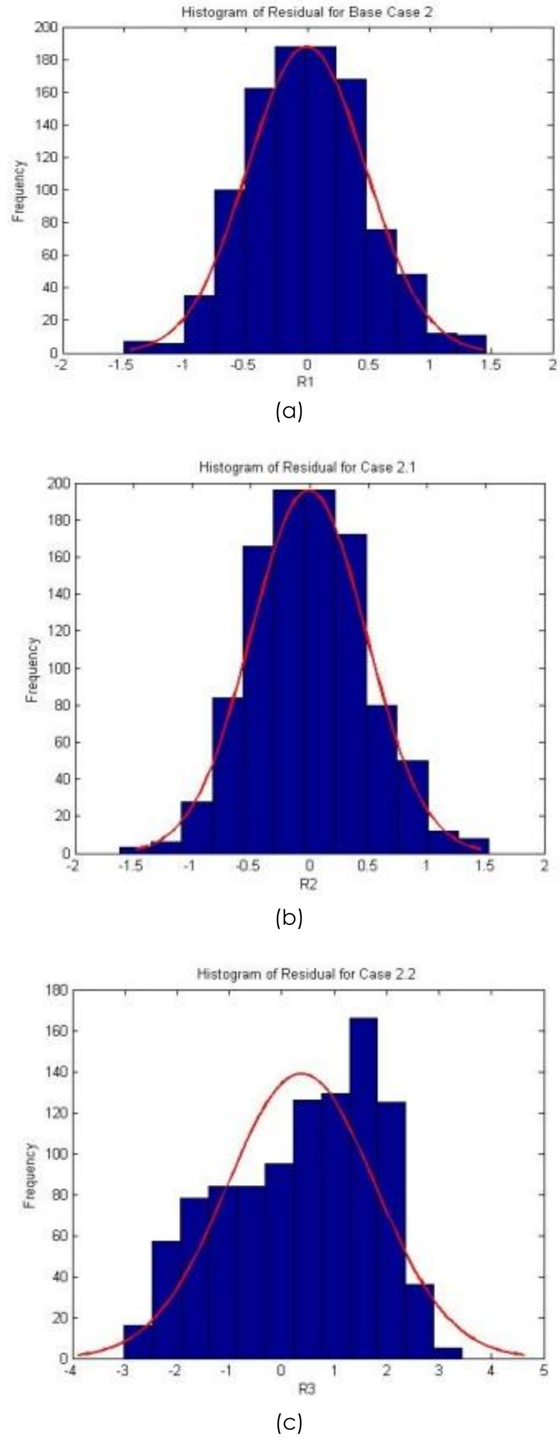
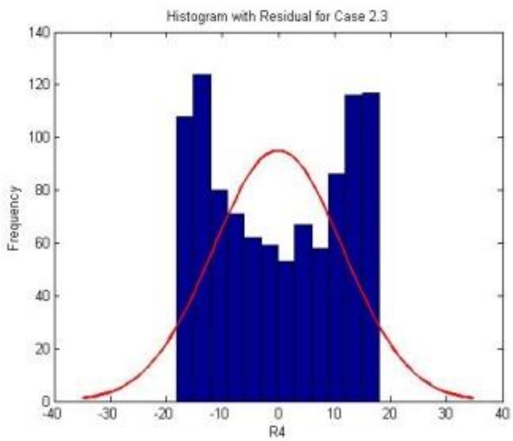


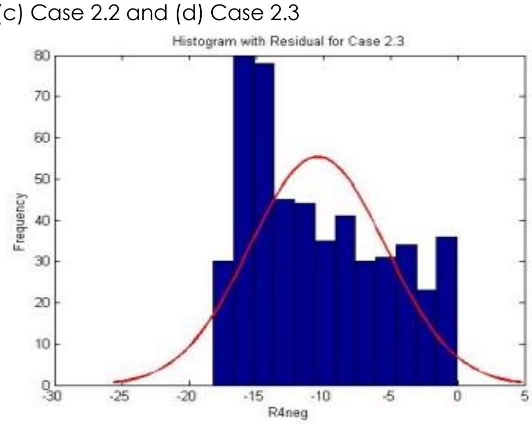
Figure 16 Residual plots for (a) Base Case 2, (b) Case 2.1, (c) Case 2.2 and (d) Case 2.3



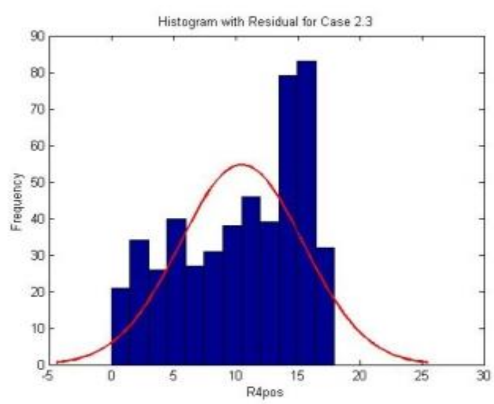


(d)

Figure 17 Histogram of Residuals for (a) Base Case 2, (b) Case 2.1, (c) Case 2.2 and (d) Case 2.3



(a)



(b)

Figure 18 Histogram of (a) R_neg and (b) R_pos for Case 2.3

Table 5 provides the values of GLR test statistics computed for each case. It is depicted that the null hypothesis for Base Case 2, Case 2.1 and Case 2.2 are to be accepted at 5% significance level as their $\mathcal{L}(R)$ values lie below the decision threshold value, $h(\alpha) = 3.841$. These three cases are hence, reported to be stiction-free. On the other hand, the $\mathcal{L}(R)$ values for Case 2.3 both exceed the threshold limit. Consequently, the null hypothesis is rejected at 5% significance level and presence of stiction is declared.

Table 5 GLR test statistics, $\boldsymbol{\mathcal{L}(R)}$ for Case Study 2

Case	$\boldsymbol{\mathcal{L}(R)}$
Base Case 2 (well-tuned controller)	0
Case 2.1 (tight-tuned controller)	0.0363
Case 2.2 (external disturbance)	2.2536
Case 2.3 (stiction of $S = 3$ and $J = 1$) – positive residuals	5.5005
Case 2.3 (stiction of $S = 3$ and $J = 1$) – negative residuals	5.5144

3.3 Sensitivity Analysis

In this section, a sensitivity analysis is carried out to analyze the effectiveness and robustness of the proposed ARX-based GLR stiction detection method when the process is subjected to changes in its model parameters. If the detection system can tolerate at least ±10% changes in the parameters, it is sufficient enough to declare that the scheme is reasonably insensitive to the modeling errors. Both case studies examine the changes in process gain, K and time constant, τ.

3.3.1 Case Study 1

Based on the results on sensitivity analysis in Tables 6-7, it can be observed that the proposed GLR stiction detection method is effective for a wide range of K up to +60% and -27%, respectively. This indicates that the method is reasonably robust to the changes in K. As for the variations in τ, the allowable range of τ is even bigger such that the method can tolerate any positive and negative changes of τ, up to >50% as depicted in Tables 8-9. The results indicate that the detection scheme is robust and insensitive to the τ changes.

Table 6 GLR test results for positive changes in process gain, K (Case Study 1)

Increase process gain, K by 50%		
	$\mathcal{L}(R)$	Remark
no stiction	0	No stiction
weak stiction	4.6508	Stiction present
strong stiction	7.4745	Stiction present
Increase process gain, K by 60%		
	$\mathcal{L}(R)$	Remark
no stiction	0	No stiction
weak stiction	4.7494	Stiction present
strong stiction	7.5694	Stiction present

Table 7 GLR test results for negative changes in process gain, K (Case Study 1)

Decrease process gain, K by 25%		
	$\mathcal{L}(R)$	Remark
no stiction	0	No stiction
weak stiction	3.8545	Stiction present
strong stiction	6.8092	Stiction present

Decrease process gain, K by 27%		
	$\mathcal{L}(R)$	Remark
no stiction	0	No stiction
weak stiction	3.8598	Stiction present
strong stiction	6.7969	Stiction present

Decrease process gain, K by 28%		
	$\mathcal{L}(R)$	Remark
no stiction	0	No stiction
weak stiction	3.8092	No stiction
strong stiction	6.7861	Stiction present

Table 8 GLR test results for positive changes in time constant, τ (Case Study 1)

Increase time constant, τ by 50%		
	$\mathcal{L}(R)$	Remark
no stiction	0	No stiction
weak stiction	4.2223	Stiction present
strong stiction	7.1061	Stiction present

Table 9 GLR test results for negative changes in time constant, τ (Case Study 1)

Decrease time constant, τ by 90%		
	$\mathcal{L}(R)$	Remark
no stiction	0	No stiction
weak stiction	3.8824	Stiction present
strong stiction	6.8391	Stiction present

Decrease time constant, τ by 99%		
	$\mathcal{L}(R)$	Remark
no stiction	0	No stiction
weak stiction	3.9023	No stiction
strong stiction	6.8557	Stiction present

3.3.2 Case Study 2

The sensitivity analysis for this case study shows that K can only be varied up to +11% and -22% respectively, whilst τ can be varied between -16% and +43%. If K and τ are varied beyond these limits, the proposed ARX-based GLR system will be ineffective in detecting stiction. Since the method allows at least ±10% changes in K and τ, the method is declared acceptably robust and reasonably insensitive to these changes. The results on this analysis are provided in Tables 10-13.

Table 10 GLR test results for positive changes in process gain, K (Case Study 2)

Increase process gain, K by 10%		
	$\mathcal{L}(R)$	Remark
well tuned controller	0	no stiction
tight tuned controller	0.2502	no stiction
presence of external disturbances	2.0798	no stiction
presence of stiction (-)	6.7082	Stiction is present
presence of stiction (+)	6.7219	Stiction is present

Increase process gain, K by 11%		
	$\mathcal{L}(R)$	Remark
well tuned controller	0	no stiction
tight tuned controller	1.9906	no stiction
presence of external disturbances	2.0633	no stiction
presence of stiction (-)	6.7444	Stiction is present
presence of stiction (+)	6.7592	Stiction is present

Increase process gain, K by 12%		
	$\mathcal{L}(R)$	Remark
well tuned controller	0	no stiction
tight tuned controller	14.2624	Stiction is present
presence of external disturbances	2.0470	no stiction
presence of stiction (-)	6.7886	Stiction is present
presence of stiction (+)	6.7874	Stiction is present

Table 11 GLR test results for negative changes in process gain, K (Case Study 2)

Decrease process gain, K by 20%		
	$\mathcal{L}(R)$	Remark
well tuned controller	0	no stiction
tight tuned controller	0.0475	no stiction
presence of external disturbances	2.6616	no stiction
presence of stiction (-)	2.0221	no stiction
presence of stiction (+)	7.3552	Stiction is present

Decrease process gain, K by 22%		
	$\mathcal{L}(R)$	Remark
well tuned controller	0	no stiction
tight tuned controller	0.0490	no stiction
presence of external disturbances	2.7080	no stiction
presence of stiction (-)	1.9335	no stiction
presence of stiction (+)	7.2626	Stiction is present
Decrease process gain, K by 23%		
	$\mathcal{L}(R)$	Remark
well tuned controller	0	no stiction
tight tuned controller	0.0497	no stiction
presence of external disturbances	2.7317	no stiction
presence of stiction	2.3837	no stiction

Table 12 GLR test results for positive changes in time constant, τ (Case Study 2)

Increase time constant, τ by 42%		
	$\mathcal{L}(R)$	Remark
well tuned controller	0	no stiction
tight tuned controller	1.7135	no stiction
presence of external disturbances	2.0644	no stiction
presence of stiction (-)	6.7723	Stiction is present
presence of stiction (+)	6.7524	Stiction is present
Increase time constant, τ by 44%		
	$\mathcal{L}(R)$	Remark
well tuned controller	0	no stiction
tight tuned controller	4.4675	Stiction is present
presence of external disturbances	2.0566	no stiction
presence of stiction (-)	6.7638	Stiction is present
presence of stiction (+)	6.7676	Stiction is present

Table 13 GLR test results for negative changes in time constant, τ (Case Study 2)

Decrease time constant, τ by 15%		
	$\mathcal{L}(R)$	Remark
well tuned controller	0	no stiction
tight tuned controller	0.0477	no stiction
presence of external disturbances	2.6703	no stiction
presence of stiction (-)	2.0294	no stiction
presence of stiction (+)	5.2730	Stiction is present
Decrease time constant, τ by 16%		
	$\mathcal{L}(R)$	Remark
well tuned controller	0	no stiction
tight tuned controller	0.0487	no stiction
presence of external disturbances	2.6996	no stiction
presence of stiction (-)	1.9897	no stiction
presence of stiction (+)	5.2715	Stiction is present
Decrease time constant, τ by 17%		
	$\mathcal{L}(R)$	Remark
well tuned controller	0	no stiction
tight tuned controller	0.0496	no stiction
presence of external disturbances	2.7292	no stiction
presence of stiction	2.2610	no stiction

The effectiveness between a published method, known as the Nonlinear Principal Component Analysis (NLPCA), by Zabiri and Ramasamy [10] and the proposed ARX-based GLR method for stiction detection is compared in Table 14. It is shown that the proposed method is as effective as the published technique, without the need for substantial data for the stiction detection analysis.

Table 14 Comparison on the effectiveness of the proposed method with Nonlinear Principal Component Analysis (NLPCA) method for stiction detection in two simulated case studies

Case	NLPCA method [10]	Proposed method
Case Study 1 :		
Base Case 1	No	No
Case 1.1	Stiction	Stiction
Case 1.2	Stiction	Stiction
Case Study 2 :		
Base Case 2	No	No
Case 2.1	No	No
Case 2.2	No	No
Case 2.3	Stiction	Stiction

4.0 CONCLUSIONS

In conclusion, the ARX-based GLR method has been found to be able to effectively diagnose the presence of valve stiction in the control loop for both benchmark case studies. The presence of stiction is declared if the GLR test statistics, $\mathcal{L}(R)$ exceeds the decision threshold limit, $h(\alpha)$ and the null hypothesis is rejected at 5% significance level. On the other hand, if $\mathcal{L}(R)$ value lies below $h(\alpha)$, the null hypothesis is accepted and the absence of stiction is confirmed. In addition, it has also been shown that the proposed method is reasonably insensitive and robust to the changes in the process gain, K and time constant, τ as it generally allows up to at least ±10% changes in the two parameters for both case studies. The proposed method also overcomes some of the limitations of other published methods in terms of the relatively smaller number of data needed and removing the need for the calculation of new indices.

4.1 Recommendation

As this method simply employs visual inspection and the measurements of skewness to ensure the normality of the residual distributions, a more appropriate normality test is recommended for accurate evaluation of normality in the future analysis, i.e. the Kolmogorov-Smirnov (K-S) test. Finally, as there is very limited study conducted on statistical methods for stiction detection, it is also recommended that this area of research should be explored further.

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