Faculty of Engineering

DEVELOPMENT OF OE-BASED BROWN-FORSYTHE TEST ALGORITHM FOR CONTROL VALVE STICTION DETECTION

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Bachelor of Engineering with Honours

(Chemical Engineering)

2018

UNIVERSITI MALAYSIA SARAWAK

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DEVELOPMENT OF OE-BASED BROWN-FORSYTHE TEST ALGORITHM FOR CONTROL VALVE STICTION DETECTION

JOLENE DIANDRA JAMES

A dissertation submitted in partial fulfilment
of the requirement for the degree of
Bachelor of Engineering with Honours
(Chemical Engineering)

Faculty of Engineering
Universiti Malaysia Sarawak

2018

Dedicated to my beloved parents and my family, who always bestow me sustainable motivations and encouragements

ACKNOWLEDGEMENT

Upon the completion of this final year project, a lot of guidance and assistance have been received from a lot of parties. Therefore, I would like to extend my deepest appreciation and gratitude targeted to the people who have been assisting in the making of this project since its inception.

First and foremost, a huge appreciation to my supervisor, Ms. Amalina Shairah for her relentless dedication in guiding me throughout this project. I am genuinely grateful for her countless amount of supports and guidance in teaching and providing me all the necessary information to develop an all-rounded report on the research.

Last but not least, I would like to thank my parents, FYP colleague and seniors for their relentless morale support and encouragement when I was facing hardships and obstacles in completing this project.

ABSTRACT

One of the valve nonlinearities is the existence of control valve stiction. Stiction is a condition where the valve stem resists movement and does not give the required response to the output signal from the controller. Control valve stiction has adverse effects to the control loop performance of a process as it introduces variability in the process parameters. This can lead to deterioration in product quality and economic loss. As a result, this project puts an emphasis on the stiction detection methods in the research areas of process control. Therefore, the main objective of the project is to develop an OE-based Brown-Forsythe test algorithm to effectively detect the presence of control valve stiction.

In this study, the proposed OE model is developed using System Identification in MATLAB, where it is used to simulate the process output (PV). Residual distribution is generated from the difference between actual and simulated PV. Brown-Forsythe test statistics, *H(R)* are calculated using Kruskal-Wallis (non-parametric ANOVA) test and hypothesis testing is performed. Stiction is then declared if the values exceed the threshold value, X^2, where the null hypothesis is rejected at 5% significance level.

In order to investigate the effectiveness of the proposed method, two case studies are considered whereby step change and PRBS input signals are introduced for each case study, respectively. Case Study 1 studies three strengths of stiction, which are no stiction (Base Case 1), weak stiction (Case 1.1) and strong stiction (Case 1.2), while Case Study 2 investigates the presence of several sources of process nonlinearities in control loops, which include well-tuned controller (Base Case 2), tight-tuned controller (Case 2.1), presence of external disturbances (Case 2.2) and presence of stiction (Case 2.3).

As a result, the proposed method is able to successfully detect and distinguish presence of stiction for both types of inputs at 95% confidence level. A sensitivity analysis is also conducted for process gain, K and time constant, τ model parameters, whereby the method is considered satisfactorily robust as it is shown to be insensitive to ±10% of changes in the model parameters. The method is also found to be applicable to successfully detect stiction within industrial control loops. Lastly, it is compared with other published stiction detection methods, where it performs as efficient and even better than other methods.

ABSTRAK

Satu bentuk ketidaklinearan dalam injap adalah kewujudan geseran static pada injap kawalan. Sekatan adalah keadaan di mana batang injap menentang pergerakan dan tidak memberi respons kepada isyarat yang dikeluarkan daripada pengawal. Stik injap kawalan mempunyai kesan buruk kepada prestasi kawalan suatu proses kerana ia memperkenalkan kebolehubahan dalam parameter proses. Ini boleh mengakibatkan kemerosotan kualiti produk dan kerugian ekonomi. Akibatnya, projek ini memberikan penekanan kepada kaedah mengesan geseran static pada injap kawalan dalam bidang penyelidikan kawalan proses. Oleh itu, matlamat utama projek ini adalah untuk menghasilkan satu algoritma *OE-based Brown Forsythe test* untuk mengesan geseran static pada injap kawalan dengan berkesan.

Dalam kajian ini, model OE yang dicadangkan dihasilkan menggunakan *System Identification* dalam MATLAB, di mana ia digunakan untuk mensimulasikan pembolehubah yang dikawal (PV). *Residual distribution* dihasilkan daripada perbezaan antara PV sebenar dan simulasi. Ujian statistik Brown-Forsythe, *H(R)* dihintung menggunakan ujian Kruskal-Wallis (ujian non-parametrik ANOVA) dan ujian hipotesis dilakukan. Geseran statik kemudian diisytiharkan jika nilai melebihi nilai ambang, X^2, di mana hipotesis *null* ditolak pada tahap signifikan 5%.

Untuk mengkaji keberkesanan kaedah, dua kajian kes dijalankan, di mana input perubahan langkah (*step change)* dan PRBS dijalankan untuk setiap kajian kes. Kajian 1es 1 mengkaji tiga kekuatan geseran static seperti, *no stiction* (Kes Asas 1), *weak stiction* (Kes 1.1) dan *strong stiction* (Kes 1.2), manakala Kajian Kes 2 menyiasat kehadiran ketidaklinearan selain daripada geseran static pada process system, iaitu termasuk *well-tuned controller* (Base Case 2), *tightly-tuned controller* (Kes 2.1), *presence of external disturbances* (Kes 2.2) dan *presence of stiction* (Kes 2.3).

Keseluruhannya, kaedah ini dapat mengesan dan membezakan kehadiran geseran statik untuk kedua-dua jenis input. Analisis kepekaan juga dilakukan untuk mendapatkan *process gain*, K dan *time constant*, τ, di mana kaedah dikatakan kurang sensitif kepada ± 10% perubahan dalam parameter model. Kaedah ini juga boleh digunakan untuk mengesan geseran statik dalam gelung kawalan perindustrian. Akhir sekali, kaedah ini juga dibandingkan dengan kaedah lain yang telah diterbitkan, di mana kaedah ini berfungsi dengan cekap dan lebih baik daripada kaedah-kaedah lain.

TABLE OF CONTENTS

		Page
TITLE PAGE		ii
DEDICATION		iii
ACKNOWLEDGEMENT		iv
ABSTRACT		v
ABSTRAK		vi
LIST OF TABLES		ix
LIST OF FIGURES		xi
ABBREVIATION		xiv
LIST OF SYMBOLS		xv
CHAPTER 1	**INTRODUCTION**	1
	1.1 Introduction	1
	1.2 Problem Statement	2
	1.3 Scope and Objectives	3
	1.4 Overview of Thesis	4
	1.5 Summary	5
CHAPTER 2	**LITERATURE REVIEW**	6
	2.1 Introduction	6
	2.2 Process Nonlinearities in Control System	6
	2.3 Control valve stiction: definition, phenomenon & effects	8
	2.4 Valve Stiction Models	10
	2.5 Stiction Detection in Control Loops	11
	2.6 Output-Error model in System Identification	14
	2.7 Brown-Forsythe Test	15
	2.8 Summary	17
CHAPTER 3	**METHODOLOGY**	18
	3.1 Introduction	18
	3.2 Case Study Development	18

3.2.1 Case Study 1 18
3.2.2 Case Study 2 19
3.3 Output-Error (OE) Model in System Identification 21
3.4 OE-based Stiction Detection using Brown-Forsythe Test 21
3.5 Development of OE-based Stiction Detection Algorithm 22
3.6 Sensitivity Analysis 25
3.7 Summary 26

CHAPTER 4 RESULTS AND DISCUSSIONS 27
4.1 Introduction 27
4.2 Case Study 1 27
4.2.1 Step change input signal 29
4.2.2 PRBS input signal 32
4.3 Case Study 2 35
4.3.1 Step change input signal 36
4.3.2 PRBS input signal 40
4.4 Sensitivity Analysis 43
4.4.1 Case Study 1 43
4.4.2 Case Study 2 48
4.5 Application to Industrial Case Study 55
4.6 Comparison of Detection Methods 56
4.6.1 Case Study 1 and 2 56
4.6.2 Industrial Case Study 56
4.7 Summary 57

CHAPTER 5 CONCLUSION AND RECOMMENDATION 59
5.1 Conclusion 59
5.2 Recommendation 60

REFERENCES 61
APPENDIX 65

LIST OF TABLES

Table		Page
2.1	Summary of stiction detection methods with their limitations	13
3.1	S and J values for stiction strength in Case Study 1	19
3.2	Condition characteristic for Case Study 2	20
3.3	OE-based Brown-Forsythe test stiction detection algorithm	23
4.1	Brown-Forsythe test statistics, ***H(R)*** for Case Study 1 (step change input signal)	31
4.2	Brown-Forsythe test statistics, ***H(R)*** for Case Study 1 (PRBS input signal)	34
4.3	Brown-Forsythe test statistics, ***H(R)*** for Case Study 2 (step change input signal)	39
4.4	Brown-Forsythe test statistics, ***H(R)*** for Case Study 2 (step change input signal)	42
4.5	Test results for positive changes in process gain, K (step change input)	44
4.6	Test results for negative changes in process gain, K (step change input)	44
4.7	Test results for positive changes in time constant, τ (step change input)	45
4.8	Test results for negative changes in time constant, τ (step change input)	45
4.9	Test results for positive changes in process gain, K (PRBS input)	46
4.10	Test results for negative changes in process gain, K (PRBS input)	47
4.11	Test results for positive changes in time constant, τ (PRBS input)	47
4.12	Test results for negative changes in time constant, τ (PRBS input)	48
4.13	Test results for positive changes in process gain, K (step change input)	49

4.14	Test results for negative changes in process gain, K (step change input)	49
4.15	Test results for positive changes in time constant, τ (step change input)	50
4.16	Test results for negative changes in time constant, τ (step change input)	51
4.17	Test results for positive changes in process gain, K (PRBS input)	52
4.18	Test results for negative changes in process gain, K (PRBS input)	52
4.19	Test results for positive changes in time constant, τ (PRBS input)	53
4.20	Test results for negative changes in time constant, τ (PRBS input)	54
4.21	Result of the proposed method with validation	55
4.22	Comparison on the results of the proposed method with the NLPCA method for stiction detection of two case studies	56
4.23	Comparisons of effectiveness in stiction detection from different techniques	57

LIST OF FIGURES

Figure		Page
2.1	Graphical plot of valve nonlinearities: (a) hysteresis; (b) deadband; (c) hyteresis+deadband; (d) deadzone	7
2.2	Diagram of control valve in a control loop system	8
2.3	Phase plot of input-output behavior of valve stiction	9
2.4	Basic representation of black box modelling	14
2.5	Output-Error model structure	15
3.1	Closed-loop feedback system for Case Study 1	18
3.2	Closed loop feedback system for Case Study 2	19
3.3	Flowchart of OE-based Brown-Forsythe test stiction detection algorithm	24
3.4	Open loop system for change in time constant (Case Study 2)	26
4.1	(a) PV versus OP plot and (b) OP and PV trends for no stiction (Base Case 1) for Case Study 1	28
4.2	(a) PV versus OP plot and (b) OP and PV trends for weak stiction (Case 1.1) for Case Study 1	28
4.3	(a) PV versus OP plot and (b) OP and PV trends for strong stiction (Case 1.2) for Case Study 1	28
4.4	Simulated PV by OE model for Case Study 1 (step change input signal)	29
4.5	(a) Measured and simulated output PV trends and (b) Residual plot for no stiction (Base Case 1) (Step change input signal)	30
4.6	(a) Measured and simulated output PV trends and (b) Residual plot for weak stiction (Case 1.1) (Step change input signal)	30

4.7	(a) Measured and simulated output PV trends and (b) Residual plot for strong stiction (Case 1.2) (Step change input signal)	30
4.8	Simulated PV by OE model for Case Study 1 (PRBS input signal)	32
4.9	(a) Measured and simulated output PV trends and (b) Residual plot for no stiction (Base Case 1) (PRBS input signal)	33
4.10	(a) Measured and simulated output PV trends and (b) Residual plot for weak stiction (Case 1.1) (PRBS input signal)	33
4.11	(a) Measured and simulated output PV trends and (b) Residual plot for strong stiction (Case 1.2) (PRBS input signal)	33
4.12	(a) PV versus OP plot and (b) OP and PV trends for well-tuned controller (Base Case 2) for Case Study 2	35
4.13	(a) PV versus OP plot and (b) OP and PV trends for tight-tuned controller (Case 2.1) for Case Study 2	35
4.14	(a) PV versus OP plot and (b) OP and PV trends for presence of external disturbances (Case 2.2) for Case Study 2	36
4.15	(a) PV versus OP plot and (b) OP and PV trends for presence of stiction (Case 2.3) for Case Study 2	36
4.16	Simulated PV by OE model for Case Study 2 (step change input signal)	37
4.17	(a) Measured and simulated output PV trends and (b) Residual plot for well-tuned controller (Base Case 2) (Step change input signal)	38
4.18	(a) Measured and simulated output PV trends and (b) Residual plot for tightly-tuned controller (Case 2.1) (Step change input signal)	38
4.19	(a) Measured and simulated output PV trends and (b) Residual plot for presence of external disturbance (Case 2.2) (Step change input signal)	38
4.20	(a) Measured and simulated output PV trends and (b) Residual plot for presence of stiction (Case 2.3) (Step change input signal)	39
4.21	Simulated PV by OE model for Case Study 2 (PRBS input signal)	40

4.22 (a) Measured and simulated output PV trends and (b) Residual plot for well-tuned controller (Base Case 2) (PRBS input signal) 41

4.23 (a) Measured and simulated output PV trends and (b) Residual plot for well-tuned controller (Case 2.1) (PRBS input signal) 41

4.24 (a) Measured and simulated output PV trends and (b) Residual plot for well-tuned controller (Case 2.2) (PRBS input signal) 42

4.25 (a) Measured and simulated output PV trends and (b) Residual plot for well-tuned controller (Case 2.3) (PRBS input signal) 42

ABBREVIATION

OE	Output-Error
PRBS	Pseudo Random Binary Sequence
SI	System Identification
ARX	Auto-Regressive eXogenous
ARMAX	Auto-Regressive Moving Average
BJ	Box-Jenkins
SISO	Single-Input-Single-Output
PI	Proportional Integral Controller
ISA	Instrument Society of Amaerica
ANSI	America National Standards Institue
PV	Process output or controlled variable
OP	Controller output
MV	Valve output
SP	Set point
S	Deadband plus stickband
J	Slipjump
BF	Brown-Forsythe
KW	Kruskal-Wallis
ANOVA	Analysis of Variance
Y	Median
N	Total sample size
ISDB	International Stiction Data Base
NLPCA	Nonlinear Principal Component Analysis
k	Sample size of each group

LIST OF SYMBOLS

H_0	Null Hypothesis
H_a	Alternative Hypothesis
α	Significance level
$H(R)$	Brown-Forsythe test statistics
X^2	Decision threshold value
τ	Process time constant
K	Process gain

CHAPTER 1

INTRODUCTION

1.1 Introduction

Highly integrated processing plants, such as crude oil refineries, power plants, and petrochemical plants have included thousands upon thousands of control loops. Subsequently, integrated operations in manufacturing plants have been increasingly complex and challenging to manage as technology advances rapidly in order to achieve desired product quality while also maintain a safe environment. Therefore, monitoring of control loop and its assessment are imperative in ensuring the high product quality as well as improving the profitability of the plant.

Control valve is a final control element in a control loop that greatly influences the stability of a process control system as compared to other control elements. For the past decade, control valve has been persistently the most common problem in the processing industries (Zakharov & Jämsä-Jounela, Robust oscillation detection index and characterization of oscillating signals for valve stiction detection, 2014). A comprehensive study on the fault analysis of an industrial paperboard machine indicates that valve nonlinearities comprises almost 10% of the faults present in its yearly operation (Jämsä-Jounela, et al., 2013). When automated, especially, the control valve is most likely the first to experience accelerated wear and tear, which could cause variations in the product quality of a plant.

According to Jelali and Huang (2010), nonlinearities in control valve loops are primarily caused by valve stiction. Fluctuations typically caused by valve stiction increase the variability in product quality, accelerate equipment wear, move operating conditions away from optimality, and generally cause excessive or unnecessary energy and raw materials consumption (Bacci di Capaci, Scali, & Pannocchia, 2015). Despite gaining numerous attention in the engineering research field, the diagnosis of nonlinearities for specific fault is still open for more development and improvement.

1.2 Problem Statement

Process disturbances are generally oscillatory fluctuations and inconsistent variations that continuously and intermittently stop and reverse its direction. This causes the control valve to mimic the exact pattern of reversing and stopping. Whenever this situation happens, it accelerates the malfunction of the control valve. Subsequently, nonlinearities in control valve system becomes a problem because the variability of the loop is no longer stable (Jury, 2008), and exhibits a higher tendency to go beyond the allowable upper and lower ranges.

Control valve nonlinearities are usually due to friction, backlash, relay dead zone, hysteresis and fluid turbulence. Among these many types of nonlinearities, valve stiction continues to become one of the major problems in the plant (Jelali & Huang, 2010). The oscillation, often induced by the stiction, is the main cause of poor performance in control system, in which it not only produces limit cycles, but also affects the productivity and economic performance of the plant.

When stiction in control valves go undetected and ignored for an extended period of time, major disruptions within the plant operations could happen which may worsen to a sudden plant shutdown for valve maintenance. This can result in a large loss of profit and production time, as valve maintenance can take about 6 months to 3 years (Subbaraj & Kannapiran, 2014). Therefore, immediate detection of stiction in the early phase is very important to prevent the oscillations from propagating and disturbing other process control loops. Additionally, modelling and detection of valve stiction in control loops are imperative as stiction distinctly contributes to process variability which then adversely causes an impact on the profits of the plant.

In this project, the modelling of open loop system is accomplished using the Output-Error (OE) model in System Identification. OE model is chosen as it gives the highest best-fit estimation with lower orders on a fault-free open loop data compared to ARX, ARMAX and BJ model in System Identification.

Detection of stiction can be performed visually as it displays a distinct oscillatory pattern, but it is infeasible to be implemented in a large process plants with hundreds and thousands of control loops. Consequently, quantitative methods like statistical methods are much more preferable to detect the presence of stiction by analyzing its mathematical characteristics.

There are numerous researches conducted on primarily model-based, shape-based and frequency-domain based stiction detection techniques. However, very few stiction detection methods focus on statistical analysis – particularly statistical hypothesis test. Subsequently, the detection technique of the modelled valve stiction is executed through a developed statistical-based algorithm. Statistical hypothesis testing detection method provides a substantial, quantitative result, which can also be potentially useful for future researches in quantification of stiction. In this paper, a combination of model and statistical-based approach is proposed, whereby the model used is the Output-Error model while Brown-Forsythe test is chosen as the statistical method.

This combined method of model and statistical-based is also useful because it is non-intrusive, which means the whole plant does not need to be shut down in order to detect stiction in control valve. This is done whereby the proposed method analyzes the presence of stiction though previous historical process data and does not affect the operation of the processes.

1.3 Scope and Objectives

The study of valve stiction encompasses four main fields, which are (1) Modelling, (2) Detection, (3) Quantification, and (4) Compensation. This project mainly emphasizes on developing an effective algorithm for the *detection* of control valve stiction in control system loops. The model proposed for the identification of valve stiction is the polynomial Output-Error (OE) model.

This project emphasizes on analyzing two case studies surrounding the Single-Input-Single-Output (SISO) feedback control systems. These case studies are adapted from a research journal by Zabiri and Ramasamy (2009). The case studies focus on the different situations that typically occur in a process control system. The case studies are stated as follows.

Case Study 1: Examines an ideal condition (no process nonlinearities exists, except for valve stiction) where only stiction of differing strengths exist in the system.

Objective: To detect the presence of stiction despite differing strengths.

1.1) No stiction (Base Case 1)

1.2) Weak stiction (Case 1.1)

1.3) Strong stiction (Case 1.2)

Case Study 2: Examines a general condition where other process nonlinearities including stiction exist in the system.

Objective: To distinguish the presence of stiction from other sources of process nonlinearities.

2.1) Well-tuned controller (Base Case 2)

2.2) Tight-tuned controller (Case 2.1)

2.3) External disturbances (Case 2.2)

2.4) Presence of valve stiction (Case 2.3)

The models used in the case studies are continuous process model (**Eq. 1.1**) for Case Study 1 and discrete process model (**Eq 1.2**) for Case Study 2. The models used in the abovementioned case studies are as shown in **Eq 1.1** and **Eq 1.2** respectively.

Case Study 1: $$G_p(s) = \frac{1}{0.2s + 1} \tag{1.1}$$

Case Study 2: $$G_p(z^{-1}) = \frac{z^{-2} \times (1.45z - 1)}{z - 0.8} \tag{1.2}$$

The objectives of the project are as follows:

1) To develop OE models for stiction detection analysis.
2) To develop an effective OE-based Brown-Forsythe test algorithm in detecting and assessing the presence of control valve stiction in a closed-loop system.
3) To assess the effectiveness of the algorithm proposed towards changes in model parameters through sensitivity analysis.
4) To validate the effectiveness of the statistical algorithm developed in actual industrial data.

1.4 Overview of Thesis

This thesis is organized according to the following chapters:

Chapter 2: Literature Review

This chapter includes the types of nonlinearities in control system, definition, phenomenon, and effects of control valve stiction and modelling of control valve stiction. The chapter also discusses about past researches on stiction detection methods in control loops, as well as the theories of Output-Error model for System Identification, Brown-Forsythe test and Kruskal-Wallis tests.

Chapter 3: Methodology

This chapter covers the detailed steps applied to accomplish the objectives of this research. The important steps are Case Study Development, Output Error Model developed through System Identification, OE-based Stiction Detection Algorithm and Sensitivity Analysis.

Chapter 4: Results and Discussions

This chapter presents the results from the two case studies, whereby the algorithm runs for both step change and PRBS input signals separately. The results include visual plot of controller output (OP) and controller variable (PV), the residual distribution plots, the histogram of the residual distribution vectors, the Brown-Forsythe test statistics computation (*H(R)*), and lastly the results of the hypothesis testing. Moreover, the results of the sensitivity analysis of the algorithm are also discussed. Lastly, to validate the effectiveness of the algorithm, testing results of 5 loops from verified industrial data are presented and analyzed further.

Chapter 5: Conclusion and Recommendations

This chapter summarizes all the findings mainly from the previous chapter and concludes the overall effectiveness of the proposed OE-based Brown-Forsythe method in detecting control valve stiction in SISO control loops. The chapter also includes some constructive recommendation that could help future researches on this field.

1.5 Summary

This chapter introduces briefly on the problems in process control system of complex process plants. It also describes the significance of developing an effective technique or algorithm to detect and assess control valve stiction within a process to avoid loss of profit and product quality. In this project, an OE-based Brown-Forsythe test algorithm is proposed to diagnose the presence of control valve stiction.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter provides a brief understanding of process nonlinearities in control system, explanations related to control valve stiction, its effect and phenomenon, as well as the recurring models and stiction detection methods. It also includes the theory of Output-Error (OE) model for System Identification, Brown-Forsythe and Kruskal-Wallis tests.

2.2 Process Nonlinearities in Control System

A control loop generally consists of a sensor, transmitter, controller and final control element (actuator) that compares the process variable received from the transmitter to the desired process condition (set point). The controller then sends signals to the control valve (final control element) to take corrective actions. The responses or actions taken by the control valve strongly affects the performance stability of many process control loops. For throttling control, the key performance factors are the ability of the control valve to respond consistently to small input changes and the installed loop gain resulting from the match of the valve to the other loop components (Jelali & Huang, 2010). The behavior of the valve will vary depending on its position, direction and magnitude when a command (manipulated variable) is given to a control valve for a new flow rate or position.

The following definitions of terms related to nonlinearities in control loop are briefly explained and reviewed by American National Standards Institute (1979). The valve nonlinearities are displayed in **Figure 2.1**.

Backlash: *"In process instrumentation, it is a relative movement between interacting mechanical parts due to looseness when the motion is reversed."*