

DETECTION AND IDENTIFICATION OF STICKTION IN CONTROL VALVES BASED ON FUZZY CLUSTERING METHOD

By

MUHAMMAD AMIN DANESHWAR

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TABLE OF CONTENTS

	Page
ACKNOWLEDGMENTS	ii
TABLE OF CONTENTS	iii
LIST OF TABLES	ix
LIST OF FIGURES	xiv
LIST OF SYMBOLS	xxii
LIST OF ABBREVIATIONS	xxv
ABSTRAK	xxvii
ABSTRACT	xxix
CHAPTER ONE : INTRODUCTION	
1.1 The presence of static friction in control loops	1
1.2 Motivation/Problem Statement	2
1.3 Objectives	3
1.4 The scope of the study	3
1.5 Thesis Outline	4

CHAPTER TWO : LITERATURE REVIEW AND THEORETICAL BACKGROUND

2.1	Literature review	6
2.1.1	Stiction detection and diagnosis	6
2.1.1 (a)	Qualitative shape analysis	6
2.1.1 (b)	Qualitative signal-analysis	13
2.1.1 (c)	Detection of loop non-linearity	22
2.1.2	Stiction quantification	26
2.1.2 (a)	Conventional techniques for stiction quantification	28
2.1.2 (b)	Intelligent techniques for stiction quantification	31
2.2	Theoretical background	35
2.2.1	Type of approaches	35
2.2.2	Fuzzy clustering	38
2.2.3	Fuzzy modelling	40
2.2.4	Radial basis function neural network (RBF)	45
2.3	Summary	47

CHAPTER THREE : METHODOLOGY

3.1	Detection and diagnosis of stiction	49
-----	-------------------------------------	----

3.1.1	Proposed method for loop nonlinearity detection	51
	3.1.1(a) Proposed modification of GK clustering	57
3.1.2	Proposed for nonlinearities diagnosis	68
3.1.3	Investigation of the proposed methods toward noise	82
3.2	Identification of control valves with stiction	84
	3.2.1 Identification with non-smart valves	85
	3.2.1 (a) Configuring of the fuzzy identifier	87
	3.2.1 (b) The Takagi–Sugeno two performance indexes for modelling	90
	3.2.2 Identification with smart valves	91
	3.2.2 (a) Justification of employing RBF	94
3.3	Assessment of the proposed method	96
	3.3.1 Detection and diagnosis	96
	3.3.2 Identification	96
	3.3.3 Comparison	97
3.3	Summary	97

CHAPTER FOUR : RESULTS AND DISSCUSION

4.1	Results of detection and diagnosis of stiction	98
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4.1.1	Performance of simulation case studies	98
4.1.1 (a)	Investigation 1 on model 1	99
4.1.1 (b)	Investigation 2 on model 2	108
4.1.1 (c)	Investigation 3 on model 3	113
4.1.1 (d)	Investigation 4	117
4.1.2	Performance on industrial case study	118
4.1.2 (a)	Industrial investigation 1: Evident absence of stiction in a flow control loop	119
4.1.2 (b)	Industrial investigation 2: The presence of stiction in a flow control loop from a Pulp and Paper plant	120
4.1.2 (c)	Industrial investigation 3: The presence of stiction in a flow control loop in a chemical plant for varying SP	121
4.1.2 (d)	Industrial investigation 5: Presence of external disturbance in a flow control loop with fixed SPs	123
4.1.2 (e)	Industrial investigation 5: Presence of external disturbance in a flow control loop with fixed SPs	125
4.1.2 (f)	Industrial investigation 6: Presence of external disturbance in a flow control loop with changing SPs	126

4.1.3	Robustness of the proposed method against noise	127
4.1.3 (a)	Performance of proposed method in the presence of white noise	127
4.1.3 (b)	Performance of the proposed method in the presence of coloring noise	129
4.1.4	Comparison of the proposed method of with earlier works on industrial flow control loops with known causes of oscillation	131
4.2	Results of identification	138
4.2.1	Identification of the process with a sticky valve using the fuzzy identifier (for non-smart valves)	138
4.2.1.2	Performance of industrial case study	145
4.2.1.2 (a)	Industrial investigation 1: Flow control with fixed set point	145
4.2.1.2 (b)	Industrial investigation 2: Flow control with changing set point	146
4.2.1.2 (c)	Industrial investigation 3: Concentration control	147
4.2.1.2 (d)	Industrial investigation 4: Level control	148
4.2.1.2 (e)	Industrial investigation 5: Pressure control	149

4.2.1.3	The sensitivity of the model	151
4.2.1.4	Comparison of the identification with earlier works on industrial control loops	155
4.2.2	Identification with smart valves	156
4.2.2(a)	Identification based on proposed fuzzy identifier	156
4.2.2(b)	Identification based on radial basis function (RBF) neural network	156
4.2.2(c)	Performance comparison between RBF and the fuzzy identifier for sticky valves	158
4.3	Summary	160

CHAPTER FIVE : CONCLUSIONS AND RECOMMENDATION

5.1	Conclusions	162
5.2	Recommendations for future research	163
5.2.1	Detection and diagnosis	163
5.2.2	Identification	164
	REFERENCES	166
	LIST OF PUBLICATIONS	173

LIST OF TABLES

		Page
Table 2.1	Symbolic representation of behavior of a time series in OP-MV plots	12
Table 2.2	Different methods for stiction detection and diagnosis with their limitations	25
Table 2.3	Different methods for stiction quantification (estimation of stiction parameters) with their limitations	34
Table 2.4	Summary of earlier stiction detection, diagnosis and quantification method	34
Table 2.5	Parameters adjusted by different training methods	46
Table 3.1	Calculation of goodness-of-fit (R^2) for different flow control loops with different amount of stiction obtained from simulation and different industrial control loops	67
Table 4.1	Characteristics of simulated control loops for generating of data (investigation 1)	99
Table 4.2	Some samples of the generated data for all cases of	105

	stiction for investigation 1	
Table 4.3	Obtained indexes from applying proposed method of stiction detection and diagnosis	107
Table 4.4	Characteristics of simulated control loops for generating of data (Investigation 2)	108
Table 4.5	Some samples of the generated data for investigation 2	111
Table 4.6	Obtained indexes from applying proposed method of stiction detection and diagnosis (investigation 2)	113
Table 4.7	Obtained indexes from applying proposed method of stiction detection and diagnosis (investigation 3)	116
Table 4.8	Obtained indexes from applying the proposed method to the data obtained from experimental set up (Wang, 2013) for investigation 4.	118
Table 4.9	Obtained indexes from applying proposed method to data collected from an industrial flow control loop (Thornhill, 2007) for industrial investigation 1	119
Table 4.10	Obtained indexes from applying proposed method to the industrial data (Horch, 2006) for industrial investigation 2	121
Table 4.11	Obtained indexes from applying proposed method to the industrial data (Scali and Ghelardoni, 2008)	122

for industrial investigation 3

Table 4.12	Obtained indexes from applying proposed method to the industrial control loop with short period of data (He et al., 2007) for industrial investigation 4	124
Table 4.13	Obtained indexes from applying proposed method to the industrial control loop which has been affected by external disturbance (Scali and Ghelardoni, 2008) for industrial investigation 5	125
Table 4.14	Obtained indexes from applying proposed method to the industrial control loop which has been affected by external disturbance with changing set point (Scali and Ghelardoni, 2008) for industrial investigation 6	127
Table 4.15	Performance of the proposed method of stiction detection and diagnosis in the presence of white noise with different SNRs on all cases of stiction	129
Table 4.16	Performance of proposed method of stiction detection and diagnosis in the presence of coloring noise with different alpha	130
Table 4.17	Characteristics of industrial flow control loops used in comparison techniques	132
Table 4.18	Obtained indexes from applying proposed method	133

to all industrial flow control loops

Table 4.19	Comparison of performance of proposed method of stiction detection and diagnosis with other methods on industrial data set	135
Table 4.20	Percent of success of previous works along with proposed work	136
Table 4.21	Amount of VAF and RMS corresponding to different number of clusters and different amount of stiction obtained from simulation	139
Table 4.22	Obtained consequents parameters of each rule in all three cases of stiction	141
Table 4.23	Obtained performance indexes i.e. VAF and RMS and Elapsed time from different industrial control loops	149
Table 4.24	Obtained performance indexes i.e. VAF and RMS on undershoot case of stiction with $S=5$ and $J=1$ vs. different variances of noise	153
Table 4.25	Comparison of performance of proposed method with earlier works in term of elapsed time and number of stiction parameters	155
Table 4.26	Performance of RBF with different numbers of hidden neurons	157

Table 4.27 Performance of RBF with assigned goal (i.e., MSE=0.0152) 159

LIST OF FIGURES

	Page
Figure 2.1 Set of primitives in QSA algorithm (Rengaswamy et al., 2001)	7
Figure 2.2 Relations between the controller output and the valve position under valve stiction (Kano et al., 2004)	9
Figure 2.3 Symbolic representations of time series: Increasing (I), Steady (S) and Decreasing (D)	10
Figure 2.4 Qualitative shapes found in typical sticky valves (Yamashita, 2006)	11
Figure 2.5 A shape found in sticky valves in industrial plants (Scali and Ghelardoni, 2008), but can not detected by Yamashita's approach (Yamashita, 2006)	12
Figure 2.6 The dead zone (the interval between the light and the dark grey bars) is appeared in method developed by Horch (1999)	14
Figure 2.7 The stiction model assumed by Stenman et al. (2003)	16
Figure 2.8 Control error signal shapes for valve stiction and aggressive control (Salsbury and Singhal, 2010)	17

Figure 2.9	Conventional procedure for dealing with stiction problem	26
Figure 2.10	Conventional methods of stiction compensation	26
Figure 2.11	Hammerstein model (Sliwinski, 2012)	27
Figure 2.12	Modelling a process with control valve stiction using Hammerstein approach (Capaci and Scali, 2013)	28
Figure 2.13	One stage identification approach of (Farenzena and Trierweiler, 2012)	31
Figure 2.14	Two stages identification used by Jelali (2008)	32
Figure 2.15	Type of approaches and models used in the study (dark grey)	38
Figure 2.16	Structure of a single input-single output (SISO) radial basis function (RBF) neural network	46
Figure 3.1	Block diagram of the whole process of the proposed methodology for detection and diagnosis	50
Figure 3.2	Calculation of error of fitting in the presence of stiction	63
Figure 3.3	A schematic diagram for a flow control loop with pneumatic control valve	69
Figure 3.4	Typical sticky valve with relevant cluster centers	70
Figure 3.5	The slopes of the lines obtained from all four successive cluster centers in the presence of stiction	72
Figure 3.6	Typical sticky valve with relevant cluster centers (The	74

moving phase is considerable in comparison with the dead band plus stick band; scenario 2)

Figure 3.7	Flowchart of proposed method of stiction detection and diagnosis	81
Figure 3.8	An application of proposed method of identification in compensation stage of stiction	85
Figure 3.9	Proposed procedure for stiction problem	85
Figure 3.10	Block diagram of valve positioner for smart valve	92
Figure 3.11	Applications of RBF in identification for smart valves	93
Figure 4.1	Block diagram of a control loop with a sticky valve	98
Figure 4.2	Flowchart of Kano's stiction model (Kano et al., 2004) used in the control loop for stiction block with nonlinear behavior for generating simulated data	100
Figure 4.3	a) Typical nonlinear characteristics of a sticky valve, b) The corresponding nonlinear trend of valve position with time. Desired performance or linear characteristics (dashed line)	102
Figure 4.4	Simulink of Kano's stiction model implemented in MATLAB for generating simulated data	104
Figure 4.5	SP, OP, MV and PV trend of generated data for strong stiction (S=5, J=1) from simulated control loop based on Kano's model: a) SP and PV; b) OP and MV; c) OP-PV; d)	105

OP-MV.

Figure 4.6	Obtained cluster centers for strong stiction of simulated flow control loop (investigation 1)	107
Figure 4.7	He's stiction flowchart for representing of nonlinearity caused by stiction block	109
Figure 4.8	Simulink of He's stiction model implemented in MATLAB for generating the simulated data	110
Figure 4.9	Generated data for undershoot case of stiction (with $fs=2$, $fd=1$) by using He's model for simulated control loop based: a) SP and PV; b) OP and MV; c) OP-PV; d) OP-MV.	111
Figure 4.10	Obtained cluster centers for strong stiction of simulated flow control loop (investigation 2)	112
Figure 4.11	Choudhury's stiction model for representing of nonlinearity caused by stiction block	115
Figure 4.12	Obtained cluster centers for: (a) no stiction; (b) undershoot with $S=3$, $J=1$; (c) no offset, with $S=J=3$; (d) overshoot with $S=3$ and $J=5$ in the case of stiction using Choudhury's model	116
Figure 4.13	SP, OP and PV trends and the obtained cluster centers from OP-PV in the presence of stiction for the experimental data obtained from Wang (2013) : a) SP and PV trend; b) MV trend; c) OP trend; d) OP-PV.	117
Figure 4.14	Figure 1.1: a) SP and PV trend; b) OP-PV ; c) OP trend and	120

d) the obtained cluster centers from OP-PV in the presence of stiction with the varying set point obtained from a chemical plant (Industrial investigation 3).

Figure 4.15 Figure 1.2: a) SP and PV trend; b) OP-PV ; c) OP trend and d) the obtained cluster centers from OP-PV in the presence of stiction with the varying set point obtained from a chemical plant (Industrial investigation 3). 122

Figure 4.16 Figure 1.3: a) SP and PV trend; b) OP-PV ; c) OP trend and d) the obtained cluster centers from OP-PV in the presence of stiction for the industrial data obtained from a chemical plant (Industrial investigation 4). 124

Figure 4.17 Figure 1.17 : a) SP and PV trend; b) OP-PV ; c) OP trend and d) the obtained cluster centers from OP-PV in the presence of an external disturbance with fixed set points obtained from a chemical plant (Industrial investigation 5). 126

Figure 4.18 Figure 1.4 : a) SP and PV trend; b) OP-PV ; c) OP trend and d) the obtained cluster centers from OP-PV in the presence of an external disturbance for data obtained from a chemical plant (Industrial investigation 6). 127

Figure 4.19 Figure 1.5 Generated colored noise with different α for evaluation performance of proposed method: a) $\alpha=0$; b) $\alpha=0.5$; c) $\alpha=1$ and d) $\alpha=2$. 130

Figure 4.20 Performance of VAF and RMS with different amount of 140

fuzziness in undershoot case of stiction

- Figure 4.21 Performance of VAF and RMS with different amount of fuzziness in overshoot case of stiction : a)VAF; b) RMS 140
- Figure 4.22 Performance of VAF and RMS with different amount of fuzziness in no offset case of stiction: a)VAF; b) RMS 141
- Figure 4.23 Performance of the fuzzy model on strong stiction (undershoot): a) the set point and the control signal (OP) trends; b) the valve output (MV) trend; c) the apparent stiction in the OP-MV part of the plant; d) the control output and the process out (OP-PV); e) the process output (blue dashed) and the fuzzy model (red dotted) with VAF =98.3835 and RMS=0.0751 142
- Figure 4.24 Performance of the fuzzy model on strong stiction (undershoot):a) set point and control signal (OP) trend, b) Valve output (MV) trend, c) apparent stiction in OP-MV part of the plant, d) control output and process output (OP-PV), e)the process output((blue dashed) and the fuzzy model (red dotted) with VAF =94.2387 and RMS=0.1016 143
- Figure 4.25 Performance of the fuzzy model on strong stiction (no offset):a) set point and control signal (OP) trend, b) Valve output (MV) trend, c) apparent stiction in OP-MV part of the plant, d) control output and process output (OP-PV), e)the process output (blue dashed) and the fuzzy model (red 144

dotted) with VAF =93.8982 and RMS=0.0826

- Figure 4.26 Data from the flow control loop (industrial investigation 1): 146
a) SP and OP trends; b) PV–OP plot c) the process output
(blue dashed) and the fuzzy model (Red dotted)
- Figure 4.27 Data from the flow control loop in a refinery (industrial 147
investigation 2): a) SP; b) the PV–OP plot; c) the process
output (blue dashed) and the fuzzy model (red dotted)
- Figure 4.28 Data from the Concentration Control loop from the Pulp and 148
Papers plant(industrial investigation 3): a) OP; b) PV–OP
plot; c) the process output (blue dashed) and the fuzzy model
(red dotted)
- Figure 4.29 Data from the Level Control loop (Industrial investigation 4) 149
from the Pulp and Papers plant a) OP; b) PV–OP plot; c) the
process output (blue dashed) and the fuzzy model (red
dotted)
- Figure 4.30 Data from the pressure control loop from the chemical 150
plant(industrial investigation 5); a) control signal and setting
point ; b) PV–OP plot; c) the process output (blue dashed)
and the fuzzy model (red dotted)
- Figure 4.31 Impact of too much noise with variance=0.17 on the 153
identification With VAF=78.8153, RMS=0.9578
- Figure 4.32 Impact of too much noise with variance=0.19 on the 154

identification with VAF=67.6740, RMS=1.8090

Figure 4.33 Impact of too much noise with variance=0.21 on the 154
identification With VAF=48.4027, RMS=2.3916

Figure 4.34 Figure 1.6 Performance of RBF neural network based 175
identification on sets of testing data: a) output vs. target, b)
regression. c) Enlargement part of a, d) error histogram.

LIST OF SYMBOLS

A_i	The antecedent fuzzy set
C	Number of clusters
C_v	Valve coefficient
D_{ik}^2	Squared inner-product distance norm
e	Error
F	Volumetric flow rate
F_a	Applied force
F_f	Applied external force
F_i	Fuzzy covariance matrix
f_d	Dynamic friction
F_r	Spring force
f_s	Static friction
F_v	Viscous friction
I_{stic}	Stiction performance index
J	Slip Jump
J_m	Cost function for clustering

K	Process gain
K_c	Controller gain
m	Amount of fuzziness
MSE_{\sin}	Mean-squared error for sinusoidal fitting
MSE_{tri}	Mean-squared error for triangular fitting
N	Length of data (Number of samples)
OP_{hg}	Upper bond of control signal
OP_{lw}	Lower bond of control signal
R^2	Goodness-of-fit
r_{xy}	Correlation coefficient
S	Stick band plus dead band
sg	Specific gravity of the fluid
stp	Moving state of the valve
T_d	Time delay
T_{fin}	Time window
T_s	Sampling time
τ_l	Zero-crossing for negative lags of CCF
τ_r	Zero-crossing for positive lags of CCF

r_0	CCF at lag zero
U	Fuzzy partition matrix
u_s	Control signal at resting state of the valve
V	Vector of cluster prototypes (centers)
x_{ss}	The value of the input signal when the valve gets stuck
z_k	Data of the k -th sample
α	Valve design parameter
ΔP_v	Pressure drop across the valve
θ_{th}	Threshold
Ω_i	The degree of activation of the i -th rule