

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

**By**

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**Thesis submitted in fulfillment of the requirements for  
the degree of**

**Doctor of Philosophy**

**August 2016**

## ACKNOWLEDGMENTS

I would like to express my sincere appreciation to Dr. Norlaili Mohd Noh, my supervisor for her help, for believing in me, for her invaluable guidance and supervision in making sure that I am always on the right track and making this research possible for me.

I am most grateful to my mother, Nazdar, my brothers, my sisters, my father in-law, and my mother in-law for their support.

I don't, forget help and useful comments of my dear friend Sadegh Aminifar.

Last, but definitely not least, I am really grateful to my lovely wife, Shiva, my son, Raman, my daughter, Avan. Without their endless support and belief in me, this thesis would never have been accomplished.

I would like to thank Alexander Horch (ABB, Germany), Claudio Scali (University of Pisa, Italy), Sirish Shah and Bau Huang (University of Alberta, Canada), Shoukat Choudhury (Bangladesh University of Engineering and Technology), Jin Wang (Peking University, China), Cludio Scali (University of Pizza, Italy), Nina F. Thornhill (Imperial College London, UK), and Peter He (Tuskegee University, USA) for their permission to using their experimental and industrial data to check the performance of proposed methods of detection, diagnosis and identification.

This thesis was supported by Universiti Sains Malaysia with RU-PRGS grant number 1001/PELECT/8046015.

I would like to dedicate this thesis to my late father Muhammad Ali (who passed away three years ago). He encouraged me all the way from preschool to my postgraduate studies; I wish he was here to see his dream come true.

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## 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
$\tau_l$	Zero-crossing for negative lags of CCF
$\tau_r$	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
$\alpha$	Valve design parameter
$\Delta P_v$	Pressure drop across the valve
$\theta_{th}$	Threshold
$\Omega_i$	The degree of activation of the $i$ -th rule