Control Valve Stiction: Experimentation, Modeling, Model Validation and Detection with Convolution Neural Network

Napoli R. Vazquez, Dan P. Fernandes, and Daniel H. Chen

Abstract—The controller and the control valve are the workhorses of the process industry. The profitability, the reduction in energy consumption and raw material usage along with the increase in product quality are maintained by the process control hardware and software. However, control loops can suffer from poor performance due to ill tuned controllers or mostly due to problems associated with the pneumatic control valves as they are the only moving parts in the control loops. These oscillations will lead to increase energy consumption and increased wear and tear of equipment along with poor product quality.

This paper proposes discrete data-driven models to simulate the stiction and oscillation of a control valve based on first order dynamics. The model is validated through experimental results obtained from a sticky valve test bed. Furthermore, a Convolution Neural Network is utilized successfully to identify the control valve stiction. Libraries for VP (Valve Position) vs. CO (Controller Output) plots were utilized to train the convolution neural network.

Index Terms—Valve stiction, valve positioner, valve oscillation, control valve, control valve model, fault detection, convolution neural network.

I. INTRODUCTION

In today's manufacturing operations in chemical and refining industries; optimal use of energy and raw materials along with safety is needed in a competitive environment where the process economics has to be taken into account. To achieve the above requirements, control loops are essential. A typical process plant will have many loops.

However, control loops also suffer from poor performance which is mainly due to actuator non-linearities or processes. Disturbances and poor tuning of controller can also affect control loops. According to a study conducted by Desborough and Miller in 2002, the performance of two thirds of installed loops was not satisfactory. When a control loop has a performance issue, it is mainly in the form of control loop oscillation. About quarter of the oscillation problems is due to control valve stiction. This impacts both valve longevity and product quality [1].

The pneumatic control valve is typically the final control element of a process control loop [2]. Stiction is a common

fault of a control valve. Degradation in seal, over tightening of the packing nut, depletion of the lubricant, and a high working temperature of the metal are some of the causes of stiction [3]. Due to stiction, the control valve doesn't respond to changes in the controller output; creating oscillations in the controller. High friction on the control valve stem inhibits the control valve movement. Once the friction force is overcome the valve will move. Some of the problems created by faulty valve are poor performance for advanced control schemes, deviation from set point, cost of production and mechanical wear and tear of the control valve [4].

The signature oscillation pattern for a control valve with stiction is the triangular shape on the controller output (CO, also known as output or OP) and square wave shape on the valve position (VP) [5], Fig. 1.



Fig. 2. Valve stiction plot VP vs. CO. adaptation from choudhury *et al.*, (2005).

The valve stiction can be described using the following 3 steps: deadband +stickband, slip jump, and the moving phase, Fig. 2. Firstly, the valve behavior when it is stationary is represented with deadband and stickband even though the valve input is changing. Then, when there is a sudden release in potential energy which is stored in the

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actuator chambers, there is a slip jump which is caused by the high static friction in the form of kinetic energy when the valve starts to move [6].

Two types of models have been used to model the stiction of a control valve: physical and data driven. The physical models are usually difficult to use due to the amount of variables required and higher computational times while data driven models usually are simple to use because they require just a few variables and reduced computational load [5]. Data driven models are the predominant models used. Choudhury *et al.* (2005), and Kano *et al.* (2004), used data driven models to simulate the valve stiction [6], [7].

Various methods have been proposed to detect the stiction of a control valve; like cross correlation function based, limit cycle patterns based, nonlinearity detection based and waveform shape based [5], [8]-[11]. Detection methods based on the shape between CO and the VP have been proposed in the literature [5]. These methods rely on algorithms to detect certain characteristics of the CO vs. VP shape.

Most of the data driven models in the literature are created from data provided by the industry. There is lack of research based on experiments designed to understand the stiction of a control valve along with the real time data obtained from them. Therefore, the first objective of this paper is to create a stiction fault on a control valve and use this information as a platform to build a data driven model. The second objective is to use a detection method based on VP vs. CO plots. The VP vs. CO plots can be used as a tool, by inspecting the shape [8]. However, a chemical plant can have between a hundred to a thousand control loops [5]. Consequently, a neural work will be utilized to recognize the stiction in VP vs OP plots. The use of neural network as a detection tool has been study previously [12]. Kowsalya et al. (2014) utilized a Feed Forward Neural Network to detect control valve faults. However the detection of the stiction fault was not investigated. [13], [14]. Furthermore, Venceslau et al. (2012) used a neural network to detect stiction [15]. PV and CO were used as inputs variables for the model. In this study, a Convolution Neural Network will be evaluated as a detection tool for stiction.

II. EXPERIMENTAL SETUP AND METHODOLOGY

This section discusses the experimental setup used in this study; the methodology for the conduction of the experiment is with the valve in normal condition and with the valve in stiction. The data obtained from this experiment is recorded and analyzed by the ABB data manager pro. Software.

A. Experiment Setup

The experiment setup consists of a control valve with a valve positioner, differential flow meter, controller, recorder, pump and tank is shown in Fig. 3. The water flow is controlled with a feedback control loop. The control valve position is regulated by the positioner, where the controller output serves as a set point. The following variables are recorded: flow (PV), flow set point (SP), valve position (VP) and controller output (CO). The recorded data is transferred to Excel spreadsheets. The PI gain (K_c) and integral (Ti) were calculated by the auto tune feature of the ABB CM30

controller. The values for K_c and Ti are shown on Table I.



Fig. 3. Experiment setup.

B. Experiment Methodology and Results

Two experiments were conducted: operation of the control valve at normal condition and with stiction.

At normal condition, the water flow was controlled at the set point of 20%, Fig. 4. There was not a significant difference between the CO and the VP, therefore the positioner controlled the valve position. Consequently, the control valve didn't show signs of stiction.



To create the fault on the control valve, additional packing was utilized, and the packing nut was tightened. The water flow set point was set at 24%, Fig. 5. The PV fluctuated from 24% to 22.5 % and a significant difference between the CO and the VP was observed, therefore the positioner didn't control the valve position. The shape of CO signal is triangular and the shape of the VP is square. Therefore, the fault can be classified as stiction. This is the case of stiction with overshoot [5].



Although this is a stiction case, it is not a common pattern. The valve is stuck at 8.5% for 12s and at 6.5% for 3s. In a typical pattern, there is not a significant change between the VP position times. Also, the slope of the CO triangular shape is not constant. The reason is that on side of the PV oscillation occurs at the setpoint, where the error between the setpoint and the PV is close to 0. At this point the CO reaches steady state and the dCO/dt is approximately 0. However, the difference between the CO and VP is at the highest. The positioner increases the pressure to reach the set point, the CO. Then the stiction friction force is overcome and moves the control valve position in the opposite direction, where it get stuck again.

Furthermore, the VP and the PV variables behave like first order systems. Therefore, the PV and VP can be simulated with first order equations [16], [17].

III. CONTROL VALVE MODELING AND VALIDATION

This section discusses the development of the stiction and oscillation models. It presents a summary of the equations used in each model. Finally, the validation of the stiction model with experimental data is described.

A. Valve Stiction Modeling

The VP is simulated with a first order equation. The input for the VP equation is a square wave, Fig. 6, where D1 and D2 represent the positions where the valve is stuck.



The flow variable is simulated with a first order equation. A PID controller equation is used to simulate the CO. The following equations in the discrete form ([18], [19]) were used in Excel to model the stiction fault with $\Delta t=1$ and $t=n\Delta t$.

$$VP_{(n)} = e^{\frac{-1}{\tau_{valve}}} \times VP_{(n-1)} + K_{valve} \left(1 - e^{\frac{-1}{\tau_{valve}}}\right) \times Input_{FF}$$
(1)

$$PV_{flow(n)} = e^{\frac{-1}{\tau_{flow}}} \times PV_{flow(n-1)} + K_{flow} \left(1 - e^{\frac{-1}{\tau_{flow}}}\right) \times VP_{(n-1)}$$
(2)

$$error = Set Point - PV_{flow}$$
(3)

$$CO_{(n)} = K_c \times (error)_n + \frac{\kappa_c}{\tau_l} \sum_{k=0}^n (error)_k + Cs$$
(4)

where τ_{valve} is the valve process time constant in seconds, K_{valve} is the valve gain in %VP/%Input_{FF}, Input_{FF} is the square wave input in %, τ_{flow} is the flow process time constant in seconds, K_{flow} is the flow gain in %MV_{flow}/%VP, K_c is the controller gain in %CO/%MV_{flow}, τ_I is the controller integral time in seconds and Cs is the controller bias in %. Fig. 7 shows the output graph of the valve stiction simulation as described above.

The square wave forcing function can be linked to CO, where the $Input_{\rm ff}$, can be expressed as

$$Input_{ff} = K_1 * \frac{dCO}{dt} + K_2 = K_1 * (CO_{(n-1)} - CO_{(n-2)} + K_2)$$
(5)

where K_1 is the square wave magnitude constant in s and K_2 is the square wave position constant in %. Note in Fig. 1, the triangular shaped controller output CO changes slope periodically. As a result, the derivative of CO forms a pulse function, i.e., a square wave.

Valve Stiction



B. Valve Oscillation Modeling

The input of this model is the process set point. The flow and valve position variables are simulated with first order equations, Fig. 8. The oscillation fault was created by decreasing the integral time in the PID controller. This fault can be described as disturbance in the process created by quick changes of the CO where the process eventually reaches the set point. The following equations in the discrete form were used in Excel to model the oscillation fault.

$$VP_{(n)} = e^{\frac{-1}{\tau_{valve}}} \times VP_{(n-1)} + K_{valve} \left(1 - e^{\frac{-1}{\tau_{valve}}}\right) \times CO_{(n-1)}$$
(6)
$$PV_{flow(n)} = e^{\frac{-1}{\tau_{flow}}} \times PV_{flow_{(n-1)}} + K_{flow} \left(1 - e^{\frac{-1}{\tau_{flow}}}\right) \times VP_{(n-1)}$$
(7)



C. Validation of the Stiction Model

The model was validated with the experiment data. The VP from the experiment was used as the input variable to generate the CO and PV variables. Table I summarizes the parameters used in the model and the experiment.

TABLE I: EXPERIMENT VS. MODEL PARAMETERS		
Parameters	Exp.	Model
	Values	Values
K _{flow}	3	2.85
τ_{flow}	5 s	1s
sp	23.3 %	23.3%
Ċs	N/A	7.3%
K _c	.13	.13
Ti	9 s	9s

The model can replicate the CO variable, but it can also reproduce the patterns of the PV even though there are some discrepancies, Fig. 9.



IV. FAULT DETECTION USING CONVOLUTION NEURAL NETWORK (CNN)

This section describes the method used to identify the control valve faults and the results.

A. Detection

A CNN was selected over other neural networks as a detection tool due to the superior accuracy on image classification on big datasets [20].

A VP vs CO (i.e., OP) library of normalized plots with different cases of stiction and oscillation was created. The VP vs. CO plots were created with simulated data. This library was utilized to train an existing Convolution Neural Network (CNN). Once the CNN was trained, it was used to identify the faults of the control valve.

The CNN used in this study is GoogLeNet [21], [22]. This is one of the 13 pretrained CNN options that MATLAB offers. The CNN was tested with VP vs CO plots from simulated and experiment data. The CNN identified the oscillation and stiction faults. The predicted probability ranges from 96.8 to 68.3%, Fig. 10 to Fig .14.







Fig. 11. Simulated fault for oscillation.



Fig. 12. Stiction fault from experiment, example 1.



Fig. 13. Stiction fault from experiment, example 2.



Fig. 14. Stiction fault from experiment, example 3.

V. CONCLUSIONS

The control valve stiction experiment shows that the valve position and the PV behave like first order systems as evidenced by the simulations with first order equations. Furthermore, the stiction fault validation results show that the PV variable serves as a link between the CO and VP modeling. To detect the control valve faults including stiction and oscillation, a CNN was utilized. The CNN was trained with simulated VP v. CO plots. The CNN was tested with simulated and experimental data and successfully identified the control valve faults.

Future research should be devoted to the development of VP vs. CO plots for control valve faults as stiction, dead band, hysteresis and oscillations that create a difference between VP and CO. These libraries can be created initially from a simulation model but experimental data needs to be added to enhance them. The information provide by this type of research will help better train a CNN and therefore build a robust detection tool.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Napoli Rosario conducted the research and wrote the paper. Napoli Rosario and Dan Fernandes built the experimental setup. Dan contributed to the abstract and the introduction. Daniel Chen supervised the research. All authors had approved the final version.

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REFERENCES

- B. M. S. Arifin, C. J. Munaro, M. A. A. Choudhury, and S. L. Shah, "A model free approach for online stiction compensation," in *Proc. the International Federation of Automatic Control*, 2014, pp. 5957-5962.
- [2] C. A. Smith and A. B. Corripio, *Principles and Practice of Automatic Process Control*, 2nd ed. United States: John Wiley & Sons, Inc, 1997, ch. 1.
- [3] T. Hagglund, "Control loop performance monitor," *Control Engineering Practice*, vol. 3, pp. 1543-1551, November 1995, 1995.
- [4] W. P. Swan, "Selected topics in process diagnostics and advisories," Eng. D. dissertation, Dept. Chemical Engineering, Lamar University, Beaumont, TX, 2006.
- [5] M. Jelali and B. Huang, Detection and Diagnosis of Stiction in Control Loops: State of the Art and Advance Methods, Springer-Verlag London, 2010, ch 1-2, ch 5-12.
- [6] M. A. A Choudhury, N. F. Thornhill, and S. L. Shah, "Modelling valve stiction," *Control Engineering Practice*, vol. 13, pp. 641-658, May 2005.
- [7] M. Kano, H. Maruta, H. Kugemoto, and K. Shimizu, "Practical model and detection algorithm for valve stiction," in *Proc. the International Federation of Automatic Control*, 2004, pp. 859-864.
- [8] M. A. A. Choudhury, S. L. Shan, and N. F. Thornhill, *Diagnosis of Process Nonlinearities and Valve Stiction: Data Driven Approches*, 1st ed. Springer-Verlag Berlin Heidelberg, 2008.
- [9] M. Ahammad and M. A. A. Choudhury, "A simple harmonics based stiction detection method," presented at the Dynamics of Process Systems Symposium, Leuven, Belgium, July 5-7, 2010.
- [10] A. Zakharov, E. Zattoni, L. Xie, O. Pozo, and S. L. J. Jounela, "An autonomous valve stiction detection system based on data characterization," *Control Engineering Practice*, vol. 21, pp. 1507-1518, November 2013.
- [11] M. A. A. Choudhury, S. L. Shan, and N. F. Thornhill, "Automatic detection and quantification of control valve stiction," *Control Engineering Practice*, vol. 12, pp. 1395-1412, December 2006.
- [12] A. A. A. M Amiruddin, H. Zabiri, and S. A. A. Taqvi, "Neural network applications in fault and detection: An overview of implementations in engineering-related systems," *Neural Computing* and Applications, pp. 1-26, December 2018.
- [13] A. Kowsalya and B. Kannapiran, "Principal component analysis based approach for fault diagnosis in pneumatic valve using DAMADICS benchmark simulator," *International Journal of Research in Engineering and Technology*, vol. 3, pp. 702-707, May 2014.
- [14] R. B. Capaci and C. Scali, "Review and comparison techniques of analysis of valve stiction: From to smart diagnosis," *Chemical Engineering Research and Design*, vol. 130, pp. 230-265, February 2018.

- [15] A. R. S. Venceslau, L. A. Guedes, and D. R. C. Silva, "Artificial neural network approach for detection and diagnosis of valve stiction," presented at the ETFA Conference, 2012.
- [16] D. Karthiga and S. Kalaivani, "A new stiction compensation method in pneumatic control valves," *International Journal of Electronics* and Computer Science, vol. 1, pp. 2604-2612, 2012.
- [17] H. Zhang, X. Wang, and Z. Wang, "A valve stiction and time delay control method based on fuzzy Smith internal model principle," *Chemical Engineering Transactions*, vol. 61, pp. 577-582, 2017.
- [18] G. Stephanopoulos, Chemical Process Control: An Introduction to Theory and Practice, New Jersey: PTR Prentice Hall, 1984, ch. 27.
- [19] T. E. Marlin, Process Control: Designing Processes and Control Systems for Dynamic Performance, Mc Graw Hill, 2000, appx. F.
- [20] A. Bhandare, M. Bhide, P. Gokhale, and R. Chandavarkar, "Applications of convolutional neural networks," *International Journal of Computer Science and Information Technologies*, vol. 7, pp. 2206-2215, 2016.
- [21] Training deep learning network to classify new images. (April 4, 2018). Math Works. [Online]. Available: https://www.mathworks.com/help/deeplearning/examples/train-deeplearning-network-to-classify-new-images.html
- [22] Classify image using GoogLeNet. (April 4, 2018). Math Works. [Online]. Available: https://www.mathworks.com/help/deeplearning/examples/classifyimage-using-googlenet.html

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