Stiction Quantification based on Time and Frequency Domain Criterions *

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Abstract: Valve stiction is one of the most common causes for poor performance in industrial control loops. Therefore, a non-invasive method which can detect and quantify stiction is urgently needed in the process industry. Most of the current stiction estimation methods use time domain criterion, e.g. Mean Square Error, to jointly identify the stiction and process model parameters. However, stiction induced oscillation is a phenomenon which has some specific characteristics in the frequency domain. Thus, extracting frequency domain information in the routine operation data will provide a more reliable and accurate stiction estimation. In this work, under the framework of Hammerstein model identification and global optimization, a new stiction quantification method based on time and frequency domain criterions is proposed. Several simulation case studies are demonstrated to validate the proposed method.

Keywords: Process monitoring, Valve stiction, Frequency domain analysis, Global optimization

1. INTRODUCTION

Control performance monitoring has attracted considerable research effort due to the increasing tightened environmental regulations and commercial profits. Among various causes of poor performance in industrial control systems, valve stiction is known as the most commonly encountered one and results in about one third of the control loops to oscillate. (Ender (1993), Bialkowski (1993), Paulonis and Cox (2003)) Given that oscillation has a great negative impact on product quality and safety operation, modeling, detection, quantification and compensation of valve stiction is of significant importance in both industrial and academia.

Quantification of stiction is still a highly challenging problem even though many methods have been proposed in the literature. Srinivasan et al. (2005) presented a model-based method which can jointly identify the process model and the stiction parameter under a Hammerstein model framework. This method is then extended to a two parameter model by Choudhury et al. (2008). Choudhury et al. (2006) proposed a non-invasive method by fitting the filtered pv and op signal to an ellipse. By applying global search techniques, Jelali (2008) presented a two-stage procedure for valve stiction quantification. Firstly, genetic algorithms or pattern search method is used to obtain the stiction parameters, then a linear low-order process model is identified by a least square estimator. Farenzena and Trierweiler (2012) improved this method by introducing a single-stage scheme without the dependency of initial guesses of the parameters. Araujo et al. (2012) proposed a describing function analysis based estimation method which requires the knowledge of process and controller models. Most recently, He and Wang (2014) presented a modified valve signature based on a physical and semiphysical valve model. Then a curve fitting method is used to quantify the model parameters on the basis of the proposed signature.

While many researchers have discussed the stiction and process model identification under Hammerstein structure or Wiener-Hammerstein structure, (Srinivasan et al. (2005), Jelali (2008), Farenzena and Trierweiler (2012), Romano and Garcia (2011), Nallasivam et al. (2009)) there is a lack of the identifiability analysis of these models. Romano and Garcia (2011) claimed that in order to improve the process model estimation, a test signal added at the set-point should be considered whenever possible. Bacci di Capaci and Scali (2014) proposed a systematic method to discard the identification data for which the

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estimation is very likely to fail, thus improving the reliability of stiction quantification. In a most recent work of Wang and Zhang (2014), the identifiability of the proposed extended Hammerstein model is analyzed, however, the overall identifiability is guaranteed by the identifiability of the nonlinear part and linear part separately. Hence, this analysis can not be applied directly to the identification framework where the stiction nonlinearity is identified integrally with that of the linear process model.

It is discussed in Srinivasan et al. (2005) that with a one parameter stiction model, the persistence of excitation can be guaranteed by a sufficiently high stiction value since it makes the closed loop system approximately behave as an open loop one. And when there is no stiction and the process is operating around steady state for long periods of time, the identification procedure will fail due to the lack of excitation. However, in the following sections, it is showed that when using Choudhury's two parameter stiction model and the data obtained when the process is operating around steady state, even with a sufficiently high stiction, the identification procedure will still fail to give accurate parameter estimations, especially for the slip jump (J), which is essential to capture the real behavior of a sticky valve but usually difficult to detect since it does not have a clear pattern which can be observed in the input and output data. (Choudhury et al. (2008)) In this work, by exploring the time domain and frequency domain information content of the routine operating data, a method which is capable of giving reliable stiction parameter estimations is proposed.

The paper is organized as follows: Section 2 introduces some preliminaries and gives an example to demonstrate that with time domain identification criterion, whether different data sets contain enough process information so that they can deliver accurate parameter estimations. The proposed two step stiction quantification method is elaborated in Section 3. Section 4 presents some simulation examples and Section 5 concludes the paper.

2. PRELIMINARIES

2.1 Stiction Model

The valve models can be grouped into two categories: physical model and data-driven model. Physical models can provide detailed and essential descriptions of the stiction phenomenon, nevertheless, these models are difficult to implement in practice since they contain several unknown parameters which cannot be easily observed. Data-driven models, on the other hand, usually have fewer parameters and provide a simplified relationship between the controller output and the valve position. The most commonly used data-driven model by researchers is the two parameter model proposed by Choudhury et al. (2005). The model can be interpreted by Fig.1, where S and J stand for deadband plus stickband and slip jump, respectively.

2.2 Motivation Example

In this section, an example is given to illustrate that whether different identification data sets are informative enough to give accurate parameter estimations. The ex-

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Fig. 1. Typical output-input behaviour of a sticky valve (redrawn from Choudhury et al. (2005))



Fig. 2. Process control loop with valve stiction within an identification framework

ample is taken from Choudhury et al. (2005) as shown in Fig.2. The stiction parameters S=7 and J=5 are used to generate the data for estimation. The linear process is modeled by a first order plus time delay (FOPTD) process, which is shown as:

$$G(s) = \frac{3}{10s+1}e^{-10s} \tag{1}$$

The parameters of the discrete transfer function, which is modeled by a first order ARX process, are: $[a_1 \quad b_1] = [0.9048 \quad 0.2855]$. The controller is a PI controller and its transfer function is given by:

$$G_c = 0.2(1+0.1\frac{1}{s}) \tag{2}$$

The reference signal r(t) is assumed to be 0. The white noise affecting this system is Gaussian distributed with mean 0 and variance 0.01.

To generate a data set which contains more process variations, a step signal is added at time 0. 3000 data points are generated in the Matlab Simulink. Fig.3 shows the time series plot of the PV and OP signal, respectively. Two data sets are chose as identification data set. Data Set 1 contains the first 1000 data points right after the step test, while Data Set 2 contains the last 1000 data points which is the typical closed loop operating data with a clear oscillation pattern. The estimation method used is the two stage stiction quantification method proposed by Jelali (2008). The identification criterion is the Mean Square Error (MSE) between the real output y(t) and the predicted output $\hat{y}(t)$. The results of the estimated stiction parameters and the model parameters are shown in Table.1.



Fig. 3. Time series plot of PV and OP signal

Table 1. Estimation results comparison

	Stiction Parameters	Model Parameters
Data Set 1	S=7.073; J=5.202	$[0.9032 \ 0.2816]$
Data Set 2	S=7.004; J=1.667	$[0.8480 \ 0.6423]$

It is shown from Table 1 that for Data Set 1, the estimated parameters are quite close to the true values, however, for Data Set 2, the estimated stiction parameter 'J' is far from the true value and the same goes for the model parameters. The cross validation plot of the estimated model parameters based on Data Set 2 is shown in Fig.4, it is shown that for Data Set 2, even though the stiction and model parameters are biased from the real values, the predicted output PV_{pre} matches the real output PV very well, which indicates a very small MSE value. It can be concluded that although Data Set 2 represents the most common routine operating data for a oscillated loop, it is not informative enough to give accurate estimations of the stiction and model parameters. On the other hand, Data Set 1 contains more process variations due to the step response, thus it can give a better estimation. However, step responses or test signals added at the set-point would disturb the normal process operation and thus may not be allowed as a technique to improve the identifiability of the model.

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Fig. 4. Cross validation of PV and PV_{pre} for Data Set 2

The reason for this is two fold: firstly, the closed loop oscillating data is not informative enough to discriminate different stiction and model parameters; secondly, the identification procedure, which jointly identify the stiction and model parameters under a Hammerstein model framework, can not yield unique estimates which is equal to the true system with the time domain criterion only.

3. QUANTIFICATION OF STICTION USING TIME AND FREQUENCY DOMAIN CRITERION

While the selection of identification methods is of great importance in system identification, the choice of different identification criterion will also affect the properties of resulting estimates (Ljung (1987)). Most of the current works in stiction estimation consider the Mean Square Error between the predicted output and the real output as an objective function and by minimizing the MSE, different optimization methods are applied to find the optimal stiction parameters and model parameters. It is known that MSE or the norm of prediction errors is the most commonly used time domain criterion in identification. However, frequency domain criterions should be considered in stiction estimation since the stiction leads to an oscillating loop which has specific characteristics in the frequency domain.

The frequency of the stiction induced oscillation in a closed loop can be approximately determined by Describing Function (DF) Analysis, providing that the linear part can be considered as a low-pass filter (Slotine et al. (1991), Vander Velde (1968)). Compared with the current works which apply time domain criterion only, the proposed method considers both time domain and frequency domain criterions which will yield more accurate and more reliable stiction parameter and model parameter estimates. The two step identification criterion is given by:

$$Step_{-1}: J_T(\hat{\theta}, \hat{S}, \hat{J}) = \frac{1}{N} \sum_{k=1}^N \varepsilon_{\hat{\theta}, \hat{S}, \hat{J}}^2(k)$$
(3)

$$Step_2: J_F(\hat{\theta}, \hat{S}, \hat{J}) = |\varepsilon_{\hat{\omega}, \hat{S}, \hat{J}}|$$
(4)

where $\varepsilon_{\hat{\theta},\hat{S},\hat{J}}$ is the prediction error between the real output y and the estimated output \hat{y} , $\varepsilon_{\hat{\omega},\hat{S},\hat{J}} = \omega - \hat{\omega}$ is the error between the real frequency ω and the estimated

frequency $\hat{\omega}$. The real frequency can be determined directly from the output data pattern or can be calculated by the methods proposed by Thornhill and Hägglund (1997), etc. The estimated frequency $\hat{\omega}$ is calculated by solving Eq.5, which is the existence condition of oscillations in a feedback control loop as shown in Fig.2.

$$G(j\hat{\omega}) = -\frac{1}{N(A)} \tag{5}$$

where $G(j\hat{\omega})$ is the transfer function of the controller and linear process, N(A) is the describing function of a sticky valve derived based on Choudhury's data-driven model and is given by Choudhury et al. (2005):

$$\phi = \sin^{-1}(\frac{A-S}{A})$$

$$P_{im} = -\frac{3A}{2} + \frac{A}{2}\cos(2\phi) + 2A\sin(\phi) - 2(S-J)\sin(\phi)$$

$$P_{re} = \frac{A}{2}\sin(2\phi) - 2A\cos(\phi) - A(\frac{\pi}{2} + \phi) + 2(S-J)\cos(\phi)$$

$$N = -\frac{1}{\pi A}(P_{re} - jP_{im})$$
(6)

where A is the magnitude of the harmonic input, and S and J are stiction parameters introduced in the datadriven model.

It can be seen from Eq.5 and Eq.6 that the estimated frequency $\hat{\omega}$ is directly related to the stiction parameters S and J in the frequency domain. Thus integrating the frequency criterion into the identification objective function can improve the estimation results since it provides the frequency domain information which is critical to the stiction induced loop oscillation and is also a useful supplement to the time domain criterion. The procedure of the proposed estimation method is described in Fig.5. The process model is identified in the time domain step for different settings of the stiction parameters S and J, then the optimal model parameters and stiction parameters are determined by minimizing both the time domain and frequency domain identification criterions.

Remark 1

One of the basic assumptions of describing function analysis is that the oscillation at the input is sinusoidal, thus, the accuracy of the describing function analysis mostly depends on how well the oscillation can be described by a sinusoidal wave. This assumption can be fulfilled if the linear part has a nice low-pass filtering quality.

Remark 2

It is difficult to get an analytical solution of estimated frequency $\hat{\omega}$ from Eq.5 since the describing function of stiction is very complicated as shown in Eq.6. Therefore, the value of $\hat{\omega}$ is determined numerically. In this work, the estimated frequency is determined by the intersection between the describing function and process transfer function trajectories.

4. SIMULATION EXAMPLE

The FOPTD process and PI controller described in the motivation example are investigated in this section.

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Fig. 5. Flowchart of the proposed method

Choudhury's stiction model is used and simulation results of different values of S and J are given. The overshoot and offset scenarios where $J \geq S$ are not considered since they are not typical in practice. The sampling time is 1 second. Genetic Algorithm (GA) is chose as the global optimization method. The lower and upper bounds of the parameters are set as $1 \leq S \leq 8, 1 \leq J \leq 8$. The comparison of the estimation results are shown in Table 2 and Table 3.

It can be shown from Table 2 that when using the time domain criterion only, the estimation of the slip jump J is far from the real value. In case 2 and case 3, the estimation of J hit its lower bound, indicating that the time domain estimation method can not extract enough information from the identification data set and give accurate results. In Table 3, the estimated model parameters using time domain criterion only and time and frequency domain criterion are compared. It is clearly shown in Table 3 that the proposed method can give more accurate model parameter estimations than the method using time domain criterion only.

Fig.6 and 9 show the time series plots of OP and PV used for identification in case 1 and case 3, respectively. The corresponding frequency response and describing function trajectories of case 1 and case 3 are shown in Fig.8 and Fig.11, while the OP vs PV plot are shown in Fig.7 and

Sconario	Estimated Stiction Par	Actual Stiction Parameters	
Scenario -	Time and Frequency Domain Criterion	Time Domain Criterion	Actual Stiction Farameters
1	$\hat{S} = 7.005; \hat{J} = 4.705$	$\hat{S} = 7.001; \hat{J} = 1.664$	S = 7; J = 5
2	$\hat{S} = 6.000; \hat{J} = 4.213$	$\hat{S} = 6.048; \hat{J} = 1.000$	S = 6; J = 4
3	$\hat{S} = 5.029; \hat{J} = 3.756$	$\hat{S} = 5.161; \hat{J} = 1.000$	S = 5; J = 3

Table 2. Estimation	results	comparison
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Scenario	Estimated Model Para	Actual Model Parameters		
Scenario -	Time and Frequency Domain Criterion	Time Domain Criterion	Actual Model I arameters	
1	[0.8902 0.3285]	[0.8480 0.6723]		
2	[0.8918 0.3033]	[0.8310 0.7930]	[0.9048 0.2855]	
3	[0.8813 0.2935]	[0.8082 0.8608]		



Fig. 6. Time series plot for case 1(S=7;J=5)



Fig. 7. OP&PV plot for case 1(S=7;J=5)

10, respectively. In case 1, the estimated frequency by the describing function analysis is 0.0558 rad/s as shown in Fig.8, while the real frequency estimated from the PV data in Fig.6 is 0.0554 rad/s. The estimated frequency and the real frequency estimation from process data in case 3 are 0.0479 rad/s and 0.0510 rad/s, respectively. It indicates that the DF method indeed provides a reliable estimation of the oscillation frequency and the requency domain information is extracted and then utilized through

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Fig. 8. Describing function and frequency response for case $1(\mathrm{S}{=}7;\mathrm{J}{=}5)$



Fig. 9. Time series plot for case 3(S=5;J=3)the proposed time and frequency domain criterion method.

5. CONCLUSION

In this work, a two step stiction quantification method is proposed. Both time and frequency domain information carried by the routine operation data is extracted by



Fig. 10. OP&PV plot for case 3(S=5;J=3)



Fig. 11. Describing function and frequency response for case 3(S=5;J=3)

utilizing the two domains criterions. The proposed method needs the parameters of the controller and the process time delay. The stiction parameters estimation, especially for the slip jump J, is improved significantly compared to the traditional methods. The proposed analysis is validated by some simulation examples.

However, the method assumes that the stiction induced oscillation has one dominated frequency for which the process output signal has a clear sinusoidal shape. Future research should focus on the situations where multiple oscillations are present in a system and the scheme to explore the frequency domain information carried by the process data when describing function method can not be directly applied under such situations.

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