A reliability measure for model based stiction detection approaches

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Abstract:

Stiction in control valves is one of the long-standing problems in the process industries that lead to oscillations in closed loop systems. Numerous methods have been developed to detect stiction in linear closed-loop systems. Almost all of these methods utilize the fact that presence of stiction in control valves introduces nonlinearities in the closed loop control system. However, there exist no measure of reliability for the results provided by these techniques. In this work, using frequency domain analysis of closed loop systems, a measure of reliability is developed for model based stiction detection approaches.

Keywords: control valve stiction; control loop performance; oscillation; frequency domain analysis; Hammerstein model approach

1. INTRODUCTION

Plant oscillations are a common cause for variations in product quality and reduction in overall profit (Thornhill and Horch, 2007; Thornhill and Hagglund, 1997). Stiction in control valves is one of the major causes for oscillations in the process industries (Jelali and Huang, 2009; Horch and Isaksson, 1998). Stiction hinders valve movement, and therefore control action is not implemented properly in the control loop. This improper movement causes oscillatory behavior in the control loop by introducing a non-linearity between the outputs of controller and process (Choudhury et al., 2004).

Several methods have been developed for identification of stiction in linear closed-loop systems (Jelali and Huang, 2009). Most existing stiction detection techniques for linear closed-loop systems can be classified into one of the following: (i) shape-based, (Horch and Isaksson, 1998; Rengaswamy et al., 2001) (ii) frequency domain based (Choudhury et al., 2004), and (iii) model based (Stenman et al., 2003; Srinivasan et al., 2005; Ivan and Lakshminarayanan, 2009; Horch and Isaksson, 1998) introduced the first automatic detection method, a pattern classification approach based on the cross-correlation function between the controller output (OP) and the process variable (PV). Rengaswamy et al. (2001) developed a shape-based stiction detection technique in which OP data is fitted in piecewise fashion, to both triangular and sinusoidal waves, using least-squares estimation which is used for valve stiction detection. Alternatively, Choudhury et al. (2004) proposed a frequency domain based method for detecting and quantifying stiction in control valves. Srinivasan et al. (2005) first presented a Hammerstein based model identification approach for the diagnosis and quantification of valve stiction. The idea behind this approach is to fit a Hammerstein model (linear model + nonlinear element) between the OP and PV data sets. The identified nonlinear element is used for detection and quantification of stiction. Later, several variant Hammerstein based methods were proposed for stiction detection in linear closed-loop systems (Jelali, 2008; Lee et al., 2008; Ivan and Lakshminarayanan, 2009; Choudhury et al., 2008; Karra and Karim, 2009). All methods belonging to frameworks (i-iii) above utilize the fact that valve stiction introduces nonlinearities in the closed-loop system (Jelali and Huang, 2009). Though there exist several frameworks to identify stiction in linear closed loop systems, a measure of reliability for the results provided by these approaches has not been reported. In this work, a reliability measure for model based stiction detection approaches is developed using frequency domain analysis of closed loop systems. The use of this reliability measure for Hammerstein based stiction detection approaches is demonstrated using various simulation and industrial case studies. The paper is organized as follows: Section 2 provides a description of the problem addressed in this work. Further, one of the widely used model based stiction approaches, Hammerstein based stiction detection, is also briefly discussed. A frequency domain analysis of the class of closed loop systems of interest is presented in Section 3. This analysis aids in the development of the reliability measure for model based stiction detection approaches as discussed in Section 4. Results from several industrial case studies are presented in Section 5, followed by some concluding remarks in Section 6.

2. BACKGROUND

In this section, the problem to be addressed in the remainder of this article is first defined, followed by a brief discussion of the Hammerstein model based approach for stiction detection.
2.1 Problem definition

A typical closed-loop system with stiction phenomenon in the control valve is shown in Figure 1. In Figure 1, for demonstration & clarity, stiction is explicitly shown as a component preceding the valve though it is a nonlinear phenomenon associated with the control valve. Here, \( y_p(t) \) represents the uncorrupted process output (free of disturbance and noise), \( e_c(t) \) represents the error signal to the controller, \( v(t) \) represents the control valve output, \( G_c \) represents the linear controller dynamics, \( d(t) \) represents an output disturbance which follows a linear model, \( e(t) \) represents white noise affecting the process output, while \( u(t) \) and \( y(t) \) represent the controller output (OP) and process output (PV), respectively, which have been sampled at uniform intervals of time. Given this typical closed-loop system, the fundamental problem addressed in this work is to develop a reliability measure for model based stiction detection techniques that identify stiction by building a data-based model between the controller and process outputs.

2.2 Hammerstein model based stiction detection technique

Hammerstein based stiction detection approaches identify a nonlinear stiction element along with a linear dynamical model between the process output \( y(t) \) (PV) and controller output \( u(t) \) (OP). The differences between the measured process outputs and those predicted by model are used to obtain the Root Mean Squared Error (RMSE). Stiction parameters corresponding to minimum RMSE are used for detection and quantification of stiction. Several data driven models have been used for identification of stiction in linear closed loop systems. Some of the data driven models used for the Hammerstein-based approaches have included: (i) a one parameter stiction model (Srinivasan et al., 2005), and a (ii) two parameter stiction model (Choudhury et al., 2008).

The one parameter valve model used by Srinivasan et al is given by:

\[
x(t) = \begin{cases} 
  x(t-1) & \text{if } |u(t) - x(t-1)| \leq d \\
  u(t) & \text{otherwise}
\end{cases}
\]  

(1)

Here \( x(t) \) and \( x(t-1) \) represent the past and the present stem movements, \( u(t) \) is the present controller output, and \( d \) is the valve stiction band. The data driven model for valve stiction proposed by Choudhury et al. (2008) has two parameters namely, (i) \( S \), which provides the information about deadband plus stickband, and (ii) the slip-jump parameter \( J \), which takes into account the offset between valve input and output signals and represents the jump start of the control valve after it overcomes the stiction and deadband.

In the Hammerstein based approach, the best linear model based on Akaike’s Information Criterion (AIC) (Akaike, 1974) is computed for each particular set of stiction parameters. The fitting of a best linear model is repeated at several sets of stiction model parameters. The combination of (i) stiction parameters (e.g. for a one parameter or two parameter model) and (ii) the best linear model determined at those parameters, that provides minimum RMSE is considered to be the best model of the system, and the stiction parameters from this combination are used to obtain information about the presence or absence of stiction in the control loop. In the following, a reliability measure for Hammerstein based stiction detection approaches is developed through frequency domain analysis for the class of closed loop systems shown in Figure 1.

3. FREQUENCY DOMAIN ANALYSIS OF THE CLOSED LOOP SYSTEM

The key frequency domain concepts involved in identification of stiction in linear closed-loop systems are explained through the following two simulation case studies:

3.1 Simulation Example

Let us consider two closed loop systems whose controller and process transfer functions are provided in Table 1. In these closed-loop systems, the controller structures are different from those of regular PI or PID controllers, but these systems will provide a clear illustration of the frequency domain conditions for detection of stiction in linear closed-loop systems. To demonstrate wider applicability of the frequency domain analysis presented herein, industrial case studies are presented in Section 4.

<table>
<thead>
<tr>
<th>Sl.No</th>
<th>Process</th>
<th>Controller</th>
<th>Actual case</th>
<th>Prediction</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>( \frac{3}{100s + 1} )</td>
<td>( \frac{1}{s + 1} )</td>
<td>Stiction</td>
<td>( d = 0 )</td>
</tr>
<tr>
<td>2</td>
<td>( \frac{10}{s + 8} )</td>
<td>( \frac{0.1s + 0.1}{s} )</td>
<td>Stiction</td>
<td>( d = 0.4 )</td>
</tr>
</tbody>
</table>

Table 1. Simulation example details and results from Hammerstein approach

Stiction was introduced in the simulation examples using a physical valve stiction model (Olsson, 1996) which has been used as a benchmark for comparison of a number of data driven parametric valve stiction models (one and two parameter models) (Choudhury et al., 2008; Jelali and Huang, 2009; Srinivasan et al., 2005). The resultant data is shown in Figure 2 (a) and (b). From the figure, it can be clearly seen that the data obtained from the two loops is oscillatory.

Next, the Hammerstein based stiction detection approach proposed in (Srinivasan et al., 2005) is used for identification of stiction in these systems. As explained earlier in Section 2, the \( d \) value corresponding to this best model is representative of the stiction present in the control valve. Results obtained from the one-parameter Hammerstein based approach are shown in Figure 2 (c) and (d). For the first system \( d \) value is zero indicating that there is no stiction. This determination is incorrect, as stiction was
introduced in the control loop using the physical valve stiction model. For the second system, a \( d \) value of 0.4 was identified, correctly indicating the presence of stiction. The Hammerstein approach is able to detect stiction in the second closed loop system while being unable to detect the presence of stiction in the first loop.

A Hammerstein based approach using a two parameter valve model (discussed in (Choudhury et al., 2008)) is used for stiction detection on the same sets of simulated data. The range of ARMAX model orders explored was the same as that for the one parameter Hammerstein approach. Values of stiction parameters \( S \) and \( J \) in the model providing minimum RMSE are indicative of the stiction present in the control valve. Results obtained on application of the Hammerstein based approach having a two parameter valve model are shown in Figure 2 (e) and (f). It can be clearly seen that for the first system, the approach incorrectly indicates zero stiction, while for the second system, stiction is indicated by the non-zero stiction parameter values of \( S = 0.5, J = 0.5 \). Thus, the conclusions for the Hammerstein based techniques having either one or two stiction parameters are the same; each incorrectly indicates the absence of stiction in the first process and correctly identifies the presence of stiction in the second process.

### 3.2 Analysis of results from simulation studies

Fourier transforms of both controller \( (U(\omega), \omega = [0 2\pi]) \) and process \( (Y(\omega)) \) outputs for the two closed-loop systems are computed. The magnitude of these signals at various frequencies obtained from the Fourier transform is shown in Figure 3 (a) and (b). It can be clearly seen from Figure 3 (a) (along with the inset) that the OP data for System I has appreciable magnitude at all frequencies for which the PV data does. In other words, there exists no extra information at various frequencies in the PV data that is not present in the OP data. Contrastingly, in Figure 3 (b) (along with the inset), it can be seen that the PV data from System 2 does have extra information at various frequencies compared to that of the OP data, extra information being defined as appreciable magnitude in the transform of the PV data at frequencies for which the OP data does not display appreciable magnitude (appreciable magnitude being further defined as magnitude greater than the small amplitude values which are generally considered to be spurious artifacts of the Fourier transform computation). The relation between this extra information at various frequencies and the model based stiction identification approaches is as follows:

1. Model based stiction detection methods build a linear model along with a nonlinear element (such as in the Hammerstein approach) between the controller and process outputs.

2. If there is no extra information contained in the PV data, a linear process and linear disturbance model can be used to fit the data between PV and OP. Therefore, if extra information at various frequencies is not present in the PV data when compared to the OP data, then stiction identification using model based approaches are likely to provide ambiguous results.

3. If there is extra information available at various frequencies in PV data relative to the OP data, a linear process model with nonlinear parameter(s) is needed to fit the data between PV and OP. Therefore, if extra information is present in the PV data at various frequencies compared to OP data, model based stiction detection approaches are likely to provide correct results.

**Remark 3.1.** The linear disturbance model can be used to model the extra information available at various frequencies in PV data, since the input to the model is a white noise which has equal amplitude at all frequencies. However, if stiction is present between the OP and PV, the extra information in the PV data occurs at harmonic frequencies (since stiction is a nonlinear phenomenon), and can be modeled by one/two nonlinear stiction parameters, compared with adding many parameters to a linear disturbance model. Most of the model based approaches such as the Hammerstein based approaches use AIC (Akaike Information Criterion) or BIC (Bayesian Information Criterion) to select the model order. These criteria select the model parameters in such a way that penalizes for both error as well as the use of higher numbers of parameters. Therefore, if stiction is present between the
OP and PV, and if its behavior is approximated using one/two parameter stiction model, then it is highly likely that a linear process and disturbance model along with nonlinear stiction parameters will be identified between the PV & OP data. However, if no extra information is available at various frequencies in the PV data, though stiction is present, it is likely that only a linear process and disturbance model will be identified between the PV & OP. This is because the use of nonlinear stiction parameters would introduce amplitude at harmonic frequencies not present in the original PV data.

Remark 3.2. In this work, we show through several industrial case studies that the extra information at various frequencies in PV data compared to OP data is critical for proper identification of stiction using Hammerstein model based approaches. However, the theoretical conditions for success/failure of model based approaches in linear closed-loop systems are not presented here. This important question is addressed in (Srinivasan et al., 2012).

4. DEVELOPMENT FOR RELIABILITY MEASURE

In the previous section, visual inspection of the Fourier transform of controller and process outputs is performed in order to understand the importance of extra information being available at various frequencies in the PV data compared to the OP data. Here, we develop a methodology relying upon the Fourier transforms of the PV and OP data to quantify the extra information available, for use as a measure of reliability for results obtained from Hammerstein based stiction detection approaches.

The steps involved in the algorithm for identifying the extra information in the process output at various frequencies beyond the critical frequency \( \omega_1 = 2\pi f_1 \) (beyond this critical frequency the controller output has ideally zero magnitude) using a threshold value for the amplitude (required to account for the presence of small noises and computational effects of the Fourier transform) are provided below:

- Compute the Fourier transform of process output \((Y(\omega))\) and controller output \((U(\omega))\).
- Compute the maximum possible amplitude of oscillation in the controller output given by \(u_{\text{max}} = \max(u) - \min(u)\).
- Generate a signum function given by
  \[
  s(t) = \begin{cases} 
  -A & \text{if } u(t) < 0 \\
  0 & \text{if } u(t) = 0 \\
  A & \text{if } u(t) > 0 
  \end{cases}
  \]

The value of \(A\) used in the simulation and industrial case studies is 2.5% of \(u_{\text{max}}\). The Fourier transform of signal \(s(t)\) given by \(S(\omega) = \int_{0}^{\infty} s(t)e^{-j\omega t}dt\) is used as a frequency domain threshold value for the magnitudes of the process \((Y(\omega))\) and controller \((U(\omega))\) outputs. The reasons for coming up with this particular kind of threshold are: (i) the physical valve model equation (Olsson, 1996) involves a signum function to describe the valve nonlinearity and (ii) in practice, any oscillation in the controller signal due to valve stiction with amplitude below 10% of \(u_{\text{max}}\) is considered negligible.

- Now compute a new frequency domain signal \(Y_{\text{sig}}(\omega)\) which is given by,
  \[
  |Y_{\text{sig}}(\omega)| = \begin{cases} 
  Y(\omega) & \text{if } |U(\omega)| < |S(\omega)| \text{ and } |Y(\omega)| < |S(\omega)| \\
  0 & \text{otherwise} 
  \end{cases}
  \]

The condition \(|U(\omega)| < |S(\omega)|\) in Equation 3 helps to identify the critical frequency \(\omega_{\text{sig}}\) beyond which the magnitude of the controller output decays below the threshold, while the condition \(|Y(\omega)| > |S(\omega)|\) ensures that \(Y_{\text{sig}}(\omega)\) is greater than the threshold value (since detection below this stiction band is negligible). Now \(Y_{\text{sig}}(\omega)\) represents the magnitude of the process output at frequencies beyond the critical frequency of the controller output and provides an idea about the extra information in \(Y(\omega)\) as compared to \(U(\omega)\).

The plot of \(Y_{\text{sig}}(\omega)\) in the plot, frequency \(f = \omega/2\pi\) is used for the two closed-loop systems discussed in Section 3 is shown in Figure 4 (a) and (b). It can clearly be seen that in the case of System I, the process output \(y(t)\) does not contain information (appreciable magnitude) at frequency values beyond the critical frequency, \(\omega_{\text{sig}}\), of the controller output while the second system has significant information at frequencies beyond the critical frequency of the controller. In fact the ratio \(Y_{\text{per}} = \frac{\sum_{\omega_{\text{sig}}} |Y_{\text{sig}}(\omega)|}{\sum_{\omega} |Y(\omega)|}\)

where \(\omega\) varies from \([0, 2\pi]\), is a clear indication of the significant percentage of power present in \(Y_{\text{sig}}(\omega)\). For the first system, the ratio is zero while for the second closed-loop system it is \(Y_{\text{per}} = 8\%\). \(Y_{\text{per}}\) indicates the presence of extra information available in the PV relative to the OP data. This example also illustrates that \(Y_{\text{per}}\) is a factor that influences Hammerstein based approaches for stiction detection. Thus, \(Y_{\text{per}}\) acts as a reliability measure for stiction detection using Hammerstein based approaches in linear systems. If the value of \(Y_{\text{per}}\) is high and Hammerstein based approach detects non-zero stiction, then the result from Hammerstein approach is more reliable. However, if the value of \(Y_{\text{per}}\) is low and Hammerstein approach still gives a non-zero stiction, then the results from Hammerstein approach are not reliable. Table 4 provides information on the use of \(Y_{\text{per}}\) as a reliability measure for Hammerstein based stiction detection approaches. In the next section, simulation and industrial case studies are presented to show the utility of the proposed reliability measure algorithm.

Remark 4.1. If knowledge of the process model is available, then one can use this knowledge to set the threshold value at various frequencies. Nevertheless, through several
Fig. 4. Stiction - Simulated using physical valve stiction model (a) Plot of $|Y_{sig}(\omega)|$ for System 1 (b) Plot of $|Y_{sig}(\omega)|$ for System 2

Table 2. Use of $Y_{per}$ as reliability measure

<table>
<thead>
<tr>
<th>$Y_{per}$</th>
<th>Prediction</th>
<th>Reliability</th>
</tr>
</thead>
<tbody>
<tr>
<td>High ($\geq 0$)</td>
<td>No Stiction</td>
<td>Not Reliable</td>
</tr>
<tr>
<td>Low ($\leq 0$)</td>
<td>Stiction</td>
<td>Not Reliable</td>
</tr>
<tr>
<td>Low ($\leq 0$)</td>
<td>No stiction</td>
<td>Reliable</td>
</tr>
</tbody>
</table>

industrial case studies we show that the algorithm with the current threshold value is able to provide a good reliability measure for Hammerstein based stiction detection algorithms. 

Remark 4.2. In this work, $Y_{per}$ values greater than 1% are treated as high, while a value below this threshold is considered low. The authors have arrived at this value from various simulation and industrial case studies. Our future work is directed towards obtaining this threshold value using rigorous statistical analysis.

5. INDUSTRIAL CASE STUDIES

In this section, the validity of the proposed conditions for stiction detection are analyzed using industrial control loop data sets provided by Horch (2006). Three industrial datasets are studied and the results obtained from Hammerstein approaches using both one and two parameter stiction models are analyzed based on the reliability measure developed in the earlier section.

5.1 Flow Loop - I

The controller (OP) and process (PV) outputs obtained from a flow control loop (tag name: FC525) having stiction in the control valve is shown in Figure 5 (a). The Hammerstein based approaches with one and two parameter nonlinearities for stiction identification were applied to this loop. A stiction band value of $d = 2.16$ for the one parameter model and parameter values of $S = 2.0$, $J = 0.5$ for the two parameter method indicate that both methods detect stiction. The plot of $|Y_{sig}(\omega)|$ against $\omega$ is shown in Figure 5 (b) which clearly indicates the presence of extra information in $Y(\omega)$ beyond the critical frequency $\omega_y$ of the controller output. The ratio $Y_{per} = \frac{\sum |Y_{sig}(\omega)|}{\sum |Y(\omega)|}$ for this loop is 3.78%. This high value indicates that, as per arguments provided in Section 3, stiction can be detected unambiguously in this loop. The result from the Hammerstein approach ($d = 2.16$) is also in agreement with the proposed theoretical arguments ($Y_{per} = 3.78$).

Similar analysis is performed for a level loop which is discussed next.

5.2 Level process

Let us consider the level loop (tag name: LC011). This control loop actually has stiction in the valve as previously reported (Horch, 2006). This loop is interesting, because it has been reported in (Horch, 2006) that the model based segmentation approach for stiction detection by Stenman et al (Stenman et al., 2003) indicated that there is no stiction in this loop. The controller and process outputs ($u(t), y(t)$) of this loop are shown in Figure 6 (a). Hammerstein based approaches for stiction identification having both one and two parameter nonlinearities are applied to this loop. The method with the one parameter model provided a stiction band value of $d = 0$ indicating that there is no stiction. Further, the Hammerstein based approach with two parameter model obtained minimum RMSE at the values $S = 0$ and $J = 0.5$, indicating that there is no stiction in this control loop. The reliability measure algorithm proposed in Section 4 is used to find $Y_{sig}(\omega)$ and $Y_{per}$. Figure 6 (b) shows the plot of $|Y_{sig}(\omega)|$ for all $\omega$. From the figure it can be clearly seen that there is no extra information in Fourier transform of process output $Y(\omega)$ as compared to that of the controller output $U(\omega)$. Here, it is found that $Y_{per} = 0.04\%$. This low value indicates that there is almost zero amplitude at frequencies beyond the critical frequency $\omega_y$ of the controller, and therefore, as per the arguments in Section 3, stiction cannot be detected unambiguously for this integrating loop using Hammerstein based approaches. This is the reason for the failure of both the Hammerstein based approach and the model based approach of Stenman et al (Stenman et al., 2003) for this particular level loop.

In integrating processes (simulation Example 1 and the level loop), though stiction is present, the Hammerstein based approach fails to identify the same. The proposed reliability algorithm indicates that there will be no extra information available in integrating processes even if stiction is present. Therefore, Hammerstein based approaches are not suitable for identifying stiction unambiguously in integrating processes. This is an important observation obtained from development of reliability measure for Hammerstein based stiction detection approaches.
Further, results obtained from the various other industrial control loops are tabulated in Table 3.

Table 3. Results - Industrial case studies using Hammerstein approach

<table>
<thead>
<tr>
<th>Tag name</th>
<th>Actual</th>
<th>Prediction</th>
<th>Y_{perc} in %</th>
</tr>
</thead>
<tbody>
<tr>
<td>FC525</td>
<td>Stiction</td>
<td>Stiction</td>
<td>0.306</td>
</tr>
<tr>
<td>FC145</td>
<td>Stiction</td>
<td>Stiction</td>
<td>15.2</td>
</tr>
<tr>
<td>Pulp &amp; paper data</td>
<td>No stiction</td>
<td>No stiction</td>
<td>0.001</td>
</tr>
<tr>
<td>LC011</td>
<td>Stiction</td>
<td>No Stiction</td>
<td>0.2</td>
</tr>
</tbody>
</table>

6. CONCLUSIONS AND SCOPE FOR FUTURE WORK

A reliability measure algorithm is developed (using the frequency domain analysis of closed loop systems) to provide confidence on the results obtained from Hammerstein (model) based stiction detection approaches. This reliability measure acts independently to validate the results provided by Hammerstein based stiction detection approaches for linear systems. Several industrial case studies are presented to demonstrate the applicability of the proposed reliability measure on Hammerstein based techniques using one and two parameter valve models. A few guidelines on the use of the reliability measure are also provided. Our current work is directed towards development of reliability measure for stiction identification approaches in nonlinear processes.

REFERENCES


