Stiction Identification in Nonlinear Process Control Loops

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Abstract: Nearly 20-30% of all process control loops oscillate due to stiction and lead to loss of productivity. Thus, the detection and quantification of stiction in control valves using just the raw operating data is an important component of any automated controller performance monitoring application. Many techniques have been proposed for the detection and quantification of stiction. Pattern based identification approaches use unique shapes of the PV and OP data to identify stiction. Other approaches that include some measure of nonlinearity index have also been used to identify stiction. A solution technique for stiction detection in nonlinear processes with known process models is also available. In this paper, one possible approach to detect stiction in nonlinear process control loops with unknown process models is discussed.

1. INTRODUCTION

Research on developing automated controller performance monitoring systems has been increasing in the past decade. Control strategies such as Model Predictive Control (MPC) or other supervisory control are crucial for optimization of process operations. Performance gains from such advanced control techniques depend on how effectively the lowest control elements in the control strategy track the desired set points. A spate of surveys on the performance of control loops [Bialkowski, 1993, Ender, 1993, Entech, 2005, Desborough and Miller, 2001] indicate that a majority of control loops in processing industries perform poorly. Performance demographics of 26,000 PID controllers collected across a wide variety of processing industries in a two year time span indicate that the performance of 16% of the loops can be classified as excellent, 16% as acceptable, 22% as fair, 10% as poor, and the remaining 36% are in open loop [Desborough and Miller, 2001]. The impact of this has to be seen from the fact that PID is the dominant control algorithm in the industry accounting for 97% of the regulatory loops [Desborough, 2003]. This has led to increasing interest in automated Controller Performance Assessment (CPA) tools in recent years. The three major reasons for deterioration of control performance are: badly tuned controllers, oscillating load disturbances, or nonlinearities in control valves. 20% to 30% of all control loops oscillate due to valve problems caused by static friction or hysteresis [Bialkowski, 1993, Miller, 2000] resulting in performance deterioration. It was found that over 80% of all valves adjusted by Entech Control Engineering failed dynamic performance standards due to stiction, backlash or oversized design. Thus the task of detecting stiction or other nonlinearities in valves from routine operating data is a challenging task and is an important component in any CPA suite.

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2. PROBLEM DEFINITION

A typical process control loop with stiction in the control valve can best be depicted as shown in the Figure 1. As seen, the stiction precedes the control valve dynamics and the process transfer function also includes the valve dynamics. The fundamental problem that is being solved in this paper is one of identifying the root cause of oscillation in the process variable (PV) as being due to either stiction or external oscillations. In this work, the focus is on a model-based solution approach to this problem. There are solutions for stiction detection based on the analysis of the input-output data such as the shape based analysis proposed by Rengaswamy et al. [2001], Srinivasan et al. [2005a] and higher order statistics based approach proposed by Choudhury et al. [2004]. Most of these approaches rely on the process being linear. For non-linear process Nallasivam and Rengaswamy [2008] proposed a solution strategy that works when the process model is known. However, there is no work on detecting stiction in nonlinear control loops when the process model is not known.

Previous attempts at quantifying stiction were mostly based on measures developed from the data characteristics such as the span of controller output (OP) data, apparent stiction, maximum width of the ellipse fitted by PV-OP plot etc. The first attempt at quantifying stiction through a joint identification procedure was by Srinivasan et al. [2005b]. Srinivasan et al. [2005b] proposed a model-based approach and solved this problem for a linear process. Their approach is based on the identification of a Hammerstein model of the system comprising of the sticky valve and the process (see Figure 1(b)). The identification of the linear dynamics is decoupled from the nonlinear element. The decoupling between the nonlinear and the linear component is achieved by an iterative procedure. The solution proposed in Srinivasan et al. [2005b] is shown in Figure 2. Several stiction quantification attempts based on this approach have started to appear. A similar approach but

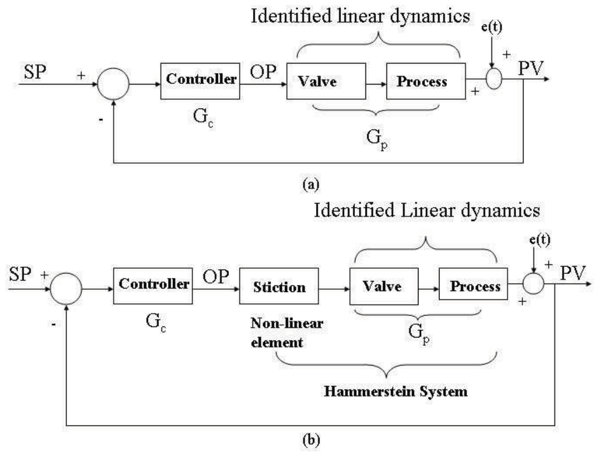

Fig. 1. (a) General process control loop, (b) Process control loop with stiction element

with a two parameter model to quantify stiction is discussed in Choudhury et al. [2008]. Another work using a Hammerstein ID approach with a two parameter model can be found in Jelali [2008]. The difference between Choudhury et al. [2008] and Jelali [2008] seem to be that while a gird search, similar to Srinivasan et al. [2005b], is used in Choudhury et al. [2008], genetic algorithms (GAs) are used to identify the stiction parameters in Jelali [2008]. However, all these methods assume that the process is linear. Nallasivam and Rengaswamy [2008] have shown that these approaches fail if the underlying process is nonlinear and solved this problem for the nonlinear case when the process model is known. The present work is on detecting stiction in nonlinear control loops when the process model is unknown.

Figure 3 depicts the control loop that is being addressed in this work. From this figure,

$$
\begin{aligned}
y &= y_p + y_d \\
y &= N(u) + y_d \\
y &= N(V(v)) + y_d
\end{aligned}
\tag{1}
$$

where y is the measured process variable pv, which includes the process component y_p and the disturbance component y_d, which are additive. N is the non linear process transfer function and u is the valve output, which might not be a measured variable. The valve output u is a function (V) of the op (v) dictated by the stiction phenomenon. In this paper, the detection, quantification and isolation of stiction from external disturbances for the system given in equation 1 is addressed.

$$
x(t) = \{ \begin{matrix} x(t-1) & if\ |u(t) - x(t-1)| \leq d, \\ u(t) & otherwise \end{matrix}
\tag{2}
$$

3. SOLUTION APPROACH

A single parameter stiction model is given by equation 2. In this model, the value of the parameter d goes to zero when stiction is absent in the valve. Thus a non-zero value for this parameter d indicates the presence of stiction and also quantifies the stiction level. The estimation of this parameter is achieved by decoupling the stiction parameter estimation from the estimation of the process dynamics. This is achieved by

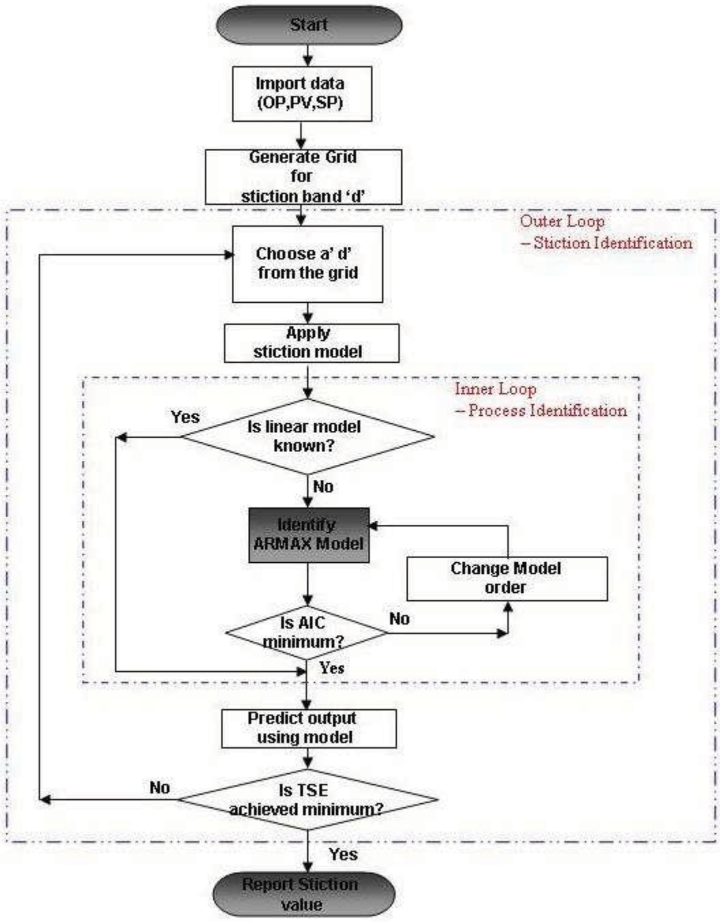

Fig. 2. Solution algorithm proposed by Srinivasan et al. [2005b]

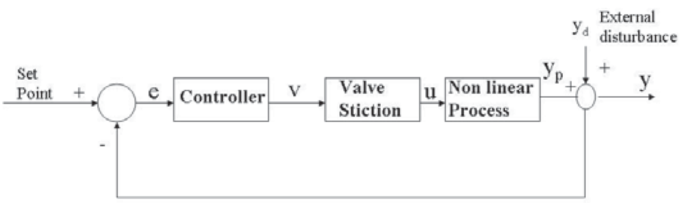

Fig. 3. Nonlinear control loop in presence of stiction

an iterative process in which a value for d is assumed in an outer loop and the best fit model for the remaining dynamics in the inner loop is identified. From Figure 3, since the controller parameters θ_c are known, v (op) can be calculated from y. Using the equation 2 for a given selected value of d, u can be calculated. Thus the identification problem becomes,

$$
\begin{aligned}
y &= y_p + y_d \\
y &= N(u) + y_d
\end{aligned}
$$

Since the process model is not known, by considering y_d as a moving average process, we can write

$$A(q)y(t) = B(u,q) + C(q)e(t) \tag{3}$$

where

$$A(q) = [1 + a_1 q^{-1} + ... + a_{n_a} q^{-n_a}]$$
$$C(q) = [1 + c_1 q^{-1} + ... + c_{n_c} q^{-n_c}]$$

$B(u,q)$ represents a general nonlinear process. As before u is known based on the actual output, the controller parameters and the assumed d value. A predictor form can be obtained for the system given by equation 3. In the linear model case, this will lead to a pseudolinear regression problem. One approach to retain the pseudolinear regression framework in the nonlinear case would be to parameterize the nonlinear function using a N^{th} order discrete Volterra series approximation as below

$$B(u,q) = \sum_{n=1}^{N} \sum_{i_1=1}^{M_1} ... \sum_{i_n=1}^{M_n} h_n(i_1,...,i_n) \\ q^{-i_1}u(k)...q^{-i_n}u(k)$$

With this expression, equation 3 now represents a Volterra MA model. By considering only the first and second order terms in the above Volterra series,

$$B(u,q) = \sum_{i=1}^{n_b} h_1(i)q^{-i}u(k) + \sum_{i=1}^{n_b}\sum_{j=1}^{n_b} h_2(i,j)q^{-i}u(k)q^{-j}u(k)$$

Now the predictor for equation 3 can be derived as

$$y(k/k-1) = B(u,q) + [1 - A(q)]y(k) + [C(q) - 1]e(k)$$

which is

$$y(k/k-1) = \sum_{i=1}^{n_b} h_1(i)q^{-i}u(k) + \sum_{i=1}^{n_b}\sum_{j=1}^{n_b} h_2(i,j)q^{-i}u(k)q^{-j}u(k) \\ -a_1 y(k-1) - a_2 y(k-2) - ... - a_{n_a} y(k-n_a) \\ +c_1 e(k-1) + c_2 e(k-2) + ... + c_{n_c} y(k-n_c)$$

When this predictor is applied to n samples, one would get n equations which results in the following equation in the matrix form

$Y = XH$

This equation can be solved iteratively till the solution converges for a given given selected model order of n_a, n_b and n_c using the following relationship.

$H = [X^T X]^{-1} X^T Y$

Based on this second order approximation of the Volterra series, an approach similar to the one that was used by Nallasivam and Rengaswamy [2008] for the known model case can be followed. However, now the model parameters and the MA process parameters have to be jointly estimated and evaluated through the AIC criteria. The overall best fit could then be chosen based on the d parameter that results in the minimum TSE. This approach is shown in Figure 4.

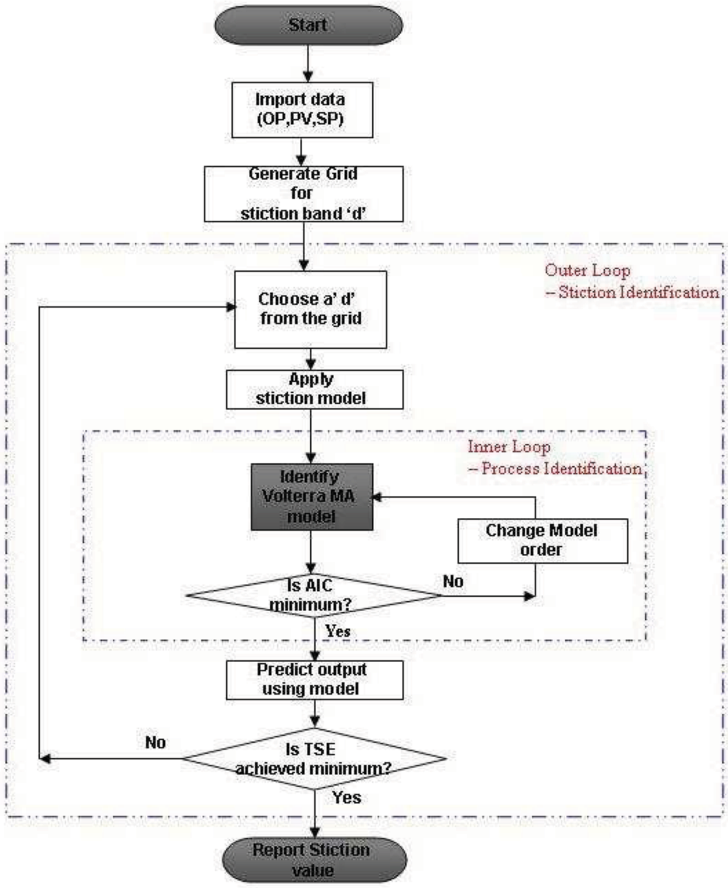

Fig. 4. Proposed approach

4. CASE STUDY

In this case study, a nonlinear polymerization reactor process from Doyle et al. [1995] is used. In this nonlinear process a polymerization reaction takes place in a jacketed CSTR where the controlled variable is the number-average molecular weight and the manipulated variable is the volumetric flowrate of the initiator. A second-order Volterra model in the frequency domain as given below describes this non-linear process.

$$P_1 = c_1^T(sI - A_{11})^{-1}b_1$$
$$P_2 = c^T[(s_1+s_2)I - A]^{-1}N(s_1 - A)^{-1}b \tag{4}$$

Details on the matrices c, A, N, b can be found in Doyle et al. [1995].

4.1 Data for testing of the solution approach

This case study is used to demonstrate the effectiveness of the proposed solution approach in three different scenarios for stiction detection. These are:

(a) No stiction case
(b) Stiction alone case
(c) Stiction and external oscillation case

Three datasets were generated by using equation 4 as the nonlinear process in Figure 3 to address all the above three scenarios. A PI controller with $K_p = 0.3$, $T_i = 1.0$ was used. Data were

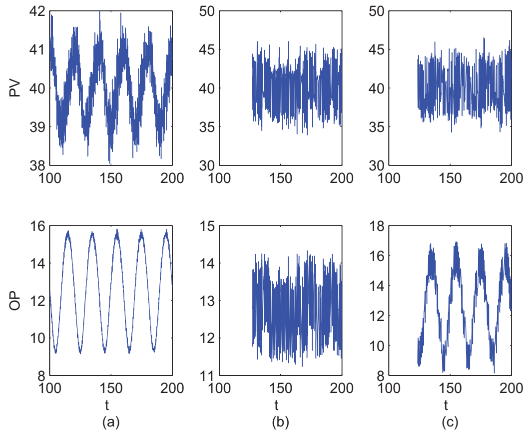

Fig. 5. Data for (a) No stiction (b) Stiction alone (c) Stiction and external oscillation

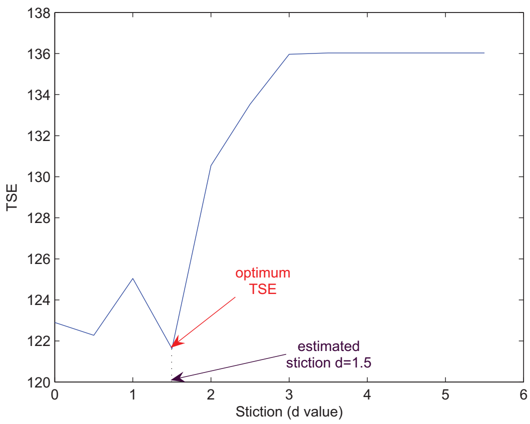

Fig. 6. Result for the approach of Srinivasan et al. [2005b]

simulated for scenario (a) using an external sine oscillation disturbance of amplitude 20 at a frequency of $0.3142 rad/sec$ as y_d. For scenario (b), a stiction value of $d = 1.5$ was used. For scenario (c), both the sine oscillation of scenario (i) and a stiction value of $d = 1.5$ were used. The data that are generated are shown in Figure 5.

4.2 Discussion on the existing approaches

The existing techniques based nonlinearity detection as in Choudhury et al. [2004] and qualitative pattern matching approaches as the one proposed in Rengaswamy et al. [2001] will not work for this dataset. As shown in Nallasivam and Rengaswamy [2008], the model-based approach proposed by Srinivasan et al. [2005b] is also not likely to work for this dataset. To verify this, the data shown in Figure 5(a) for the no stiction case is tested using the approach suggested in Srinivasan et al. [2005b] (approach shown in Figure 2). The resulting d vs TSE plot is shown in Figure 6. As expected, the value of d is incorrectly identified. In other words, stiction is detected where it is not actually present.

5. RESULTS

The dataset (Figure 5(a)), where the approach of Srinivasan et al. [2005b] failed is used to test the performance of the proposed approach shown in Figure 4. Figure 7 shows the result and as seen, it is clear that the scenario is correctly diagnosed as being a no stiction case. The minimum TSE is achieved at $d = 0$.

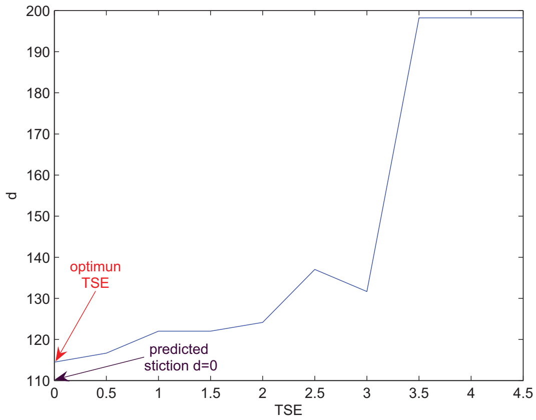

Fig. 7. Result for the no stiction case

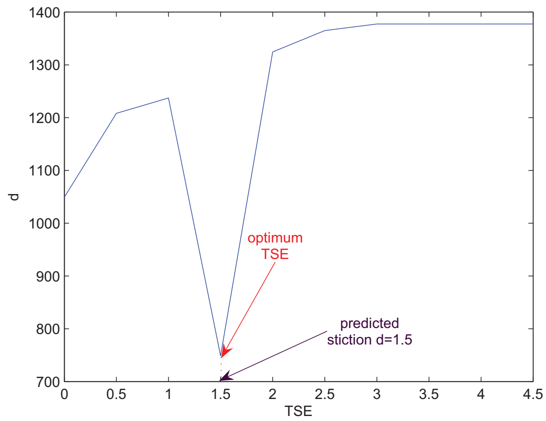

Fig. 8. Result for the stiction alone case

The dataset for the other two scenarios (Figures 5(b) and 5(c)) are also tested using this proposed approach. The results are shown in Figures 8-9. It can be seen from Figure 8, the case of stiction is also correctly identified with an accurate estimation of the stiction level. The more difficult third scenario is where both stiction and an external oscillating disturbance are present, with the process being nonlinear. The result for this case is shown in Figure 9. In this case also, not only is stiction detected but the magnitude of stiction is also accurately estimated. From these observations, it clear that the proposed solution approach works well in detecting and isolating the root cause of oscillation in nonlinear SISO loops.

6. VALIDATION USING DATA FROM PHYSICAL STICTION MODEL

The aim of this section is to verify how the proposed approach works when process data is generated by considering physical stiction model instead of single parameter stiction model. The physical stiction model that was used for this simulation is the same as the one used by Srinivasan et al. [2008]. The various parameters that were used for the physical stiction model are given in Table 1.

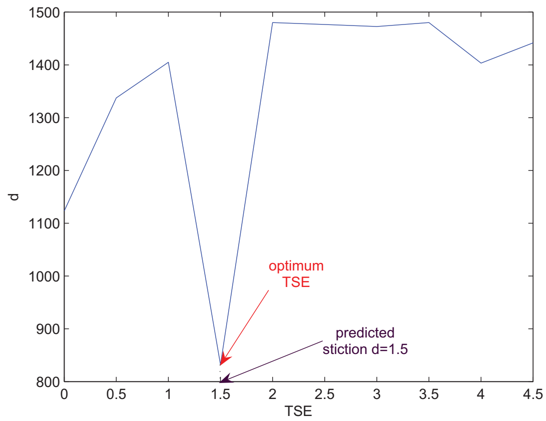

Fig. 9. Result for the case of both stiction and an external oscillating disturbance case

Table 1. Valve Parameters

Parameter	Description	Value
P	Applied Actuator Pressure	psi
A	Effective Diaphragm Surface area	100 in^2
m	Mass of Stem and Plug	3 lb
K	Spring rate	300 lbf/in
b	Viscous coefficient	0.15 lb/s
F_c	Coulomb friction	24 lbf
F_s	Static friction	34 lbf
v_s	Stribeck constant	0.01 in/s

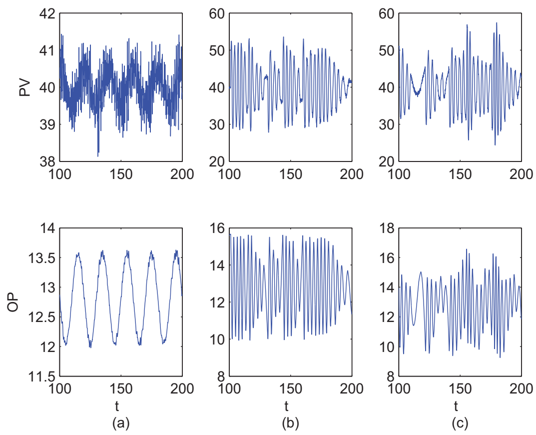

Fig. 10. Data set 2 for (a) No stiction (b) Stiction alone (c) Stiction and external oscillation

Data were simulated for scenarios (a) and (c) using an external sine oscillation disturbance of amplitude 5 at a frequency of $0.3142 rad/sec$ as y_d. A PI controller with $K_p = 0.01$, $T_i = 0.5$ was used for this data generation. The data that are generated are shown in Figure 10.

This data are tested using the proposed approach and the results are given in the Table 2. As seen, the absence or presence of stiction is predicted correctly in all the scenarios as indicated by a zero or non zero d value respectively. However the d parameter estimated for scenarios b and c are not the same as one would expect because of the use of the physical stiction model in generating the data. The reason for this is that the single parameter stiction model used in the detection algorithm is only an approximation of the physical stiction model. Nonetheless, stiction detection is not compromised.

Table 2. Validation Results

Scenario	Predicted stiction
No stiction case	d=0
Stiction alone case	d=3
Stiction and disturbance case	d=0.5

7. DISCUSSION

The proposed approach takes advantage of the fact that the stiction nonlinearity is discontinuous, whereas the process transfer function is continuous for stiction detection. It was shown that it might be possible to detect and isolate stiction in some cases in nonlinear SISO control loops when the process model is not known. However, extensive studies are needed before any definite conclusions can be drawn. There are several possible extensions to the proposed approach. The obvious ones include the use of two parameter stiction model for stiction quantification, the use of optimization algorithms such as GA for estimating the stiction parameters and validation with industrial data. Also, further theoretical work is needed to formalize the approach proposed in this paper.

8. CONCLUSIONS AND FUTURE WORK

In this paper, the problem of detection of stiction and isolation of stiction from external oscillations in nonlinear process control loops was addressed for the unknown model case. While Nallasivam and Rengaswamy [2008] have demonstrated the solution strategy for known nonlinear model case, almost no work exists in the case of unknown nonlinear processes. A solution approach for the unknown model case was proposed. The advantages and the limitations of the proposed approach were discussed.

It is essential to analyze the theoretical basis of the proposed method for using Volterra models. In addition, it would be interesting to study the use of Volterra second-order models to higher order nonlinear systems or linear systems. The former results in under-modeling of the original process while the latter results in over-modeling of the underlying linear process. We are in the process of developing a theoretical basis to analyze these interesting phenomena [Nallasivam et al. [2009]]. In future, the efficacy of the proposed approach along with the underlying theory needs to be further validated with other examples for different types of disturbances and different stiction models.

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