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Blind Identification of Stiction in Nonlinear Process Control Loops

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Abstract— **Stiction in control loops lead to oscillations and loss of productivity. Timely detection of stiction in control valves can be used in scheduling valve maintenance and deployment of compensation techniques to reduce their impact. Several approaches have been proposed for detection of stiction. Data-based approaches use unique shapes of the PV and OP data to identify stiction. Approaches based on nonlinearity detection have also been used to identify stiction. Yet another approach uses a Hammerstein model structure identification for detecting stiction. Most of these approaches are restricted to linear processes. In this paper, possible approaches to detect stiction in nonlinear process control loops are discussed.**

I. INTRODUCTION

Interpretation of measured process signals is an important task in performance monitoring and assessment. Traditional methods used for performance assessment in control loops include: inspection of hardware, logging of the percentage of time control loops are in AUTO mode, and the calculation of the mean and standard deviation of the controlled process variables. A spate of surveys on the performance of control loops [1], [2], [3], [4] 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 [4]. This has to be seen coupled with the fact that PID is the dominant control algorithm in the industry accounting for 97% of the regulatory loops [5]. Further, MPC control algorithms manipulate the set point of lower level PID loops. Hence, poor performances of PID control loops pose a significant problem with huge financial implications. This has led to increasing interest in automated Controller Performance Assessment (CPA) tools in recent years. Deterioration of control performance may have several reasons such as badly tuned controllers, oscillating load disturbance, or nonlinearity in control valves. 20% to 30% of all control loops oscillate due to valve problems caused by static friction or hysteresis [1], [6] resulting in performance deterioration. It was found that over 80% of all valves adjusted by Entech Control Engineering failed dynamic performance standards [3] due to stiction, backlash or oversized design. The task of detecting stiction or other nonlinearities in valves from routine operating data is a challenging task and is an important component in a CPA suite. It has been estimated that detection and diagnosis of control loop degradation could reduce energy cost of the overall process industry by 1% which could amount to as much as $ 300 million per year [4].

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II. PROBLEM DEFINITION

Figure 1 depicts a process control loop with stiction in the control valve. The stiction precedes the valve dynamics and the process transfer function also includes the valve dynamics. The fundamental problem that is being solved is one of identifying the root cause of oscillation 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. [7], [8] proposed a shape analysis of data for stiction identification. [9] proposed the calculation of higher order statistics for identification of nonlinearities, which could also be due to stiction.

Previous attempts at quantifying stiction were mostly based on measures developed from the data characteristics. [8] quantified the stiction as a percentage of the span of the OP data, whereas [10] introduced a quantity called apparent stiction. The maximum width of an ellipse fitted in the *pv-op* plot measured in the direction of *op* is defined as the apparent stiction. [11] 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

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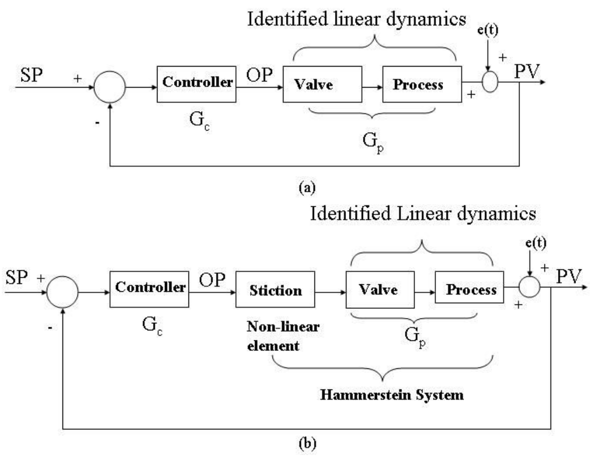

Fig. 1. (a) Regular process control loop, (b) Process control loop in presence of stiction

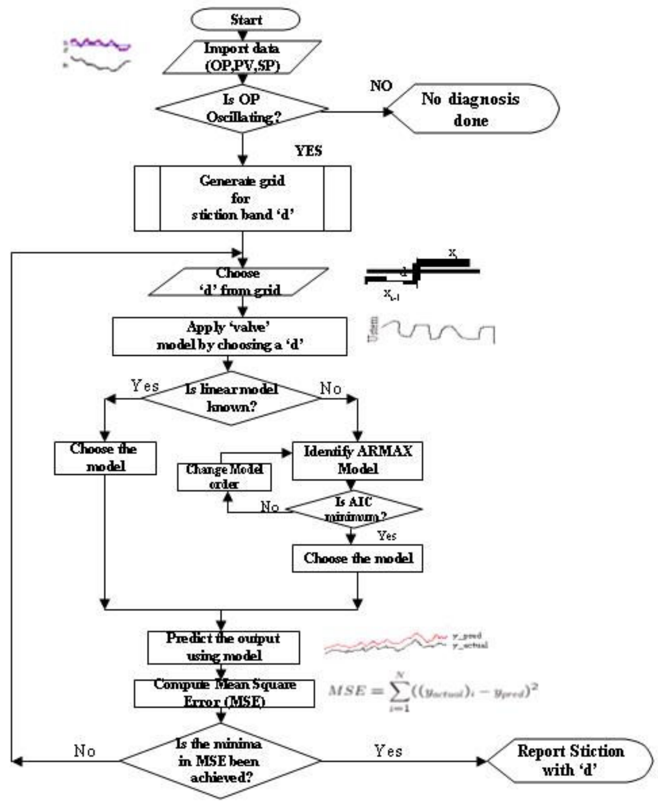

Fig. 2. Solution technique proposed by [11]

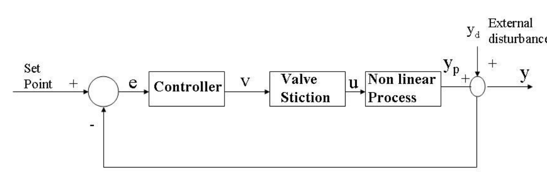

Fig. 3. Nonlinear control loop with stiction

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 [11] is shown in Figure 2. A similar approach but with a two parameter model to quantify stiction is discussed in [12]. Another work using a Hammerstein ID approach with a two parameter model can be found in [13].

The control loop that is being addressed is shown in Figure 3. Based on the 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 pv, which is assumed to be comprised of a process component y_p and a disturbance component y_d, which are additive. N is the process transfer function and u is the valve output, which might not be measured. The valve output u is a function (V) of the op (v) dictated by the stiction phenomenon. In this paper, the identification and isolation of stiction from external disturbances for the system given in equation 1 is addressed.

$$x(t) = \left\{ \begin{array}{ll} x(t-1) & if\ |u(t) - x(t-1)| \leq d, \\ u(t) & otherwise \end{array} \right. \tag{2}$$

III. SOLUTION STRATEGY

Stiction is assumed to be absent when a zero value (within a threshold) is identified for the stiction parameter d, shown in equation 2. A non-zero value denotes the presence of stiction. The estimation of the stiction value is achieved by decoupling the stiction parameter estimation from the estimation of the process dynamics. This is achieved by assuming a value for d in an outer loop and identifying the best fit model for the remaining dynamics. From Figure 3, since the controller parameters θ_c are known, v (op) can be calculated from y. Based on the assumed stiction value d, u can then be calculated from equation 2. For the case where the process model is known, a moving average (MA) model for the disturbance is built. A best fit model based on an AIC criterion is identified. This process is repeated for all the d values and the best fit based on a Total Squared Error (TSE) is identified as the solution. Based on the best fit model, a determination about either the presence or absence of stiction is made.

IV. Case study

A nonlinear polymerization reactor process from [14] is used as a case study. In this case study, 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. The process is described by a second-order Volterra model in the frequency domain as given below

$$\begin{aligned} P_1 &= c_1^T(sI - A_{11})^{-1}b_1 \\ P_2 &= c^T[(s_1+s_2)I - A]^{-1}N(s_1 - A)^{-1}b \end{aligned} \qquad (3)$$

Details on the matrices c, A, N, b can be found in [14].

A. Data used in testing of the proposed approach

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

(i) Oscillations due to external disturbance with no stiction present
(ii) Oscillations induced due to stiction alone
(iii) Oscillations due to both stiction and an external oscillating disturbance

To test the proposed approach, three datasets were generated by using equation 3 as the nonlinear process in Figure 3. A PI controller with $T_c = 1.5873$, $T_i = 4.759$ was used. Data were simulated for scenario (i) using an external sine oscillation disturbance of amplitude 0.1 at a frequency of $0.05Hz$ as y_d. For scenario (ii), a stiction value of $d = 0.14$ was used. For scenario (iii), both the sine oscillation of scenario (i) and a stiction value of $d = 0.15$ were used. The data that are generated are shown in Figure 4.

B. Discussion on the previous approaches for use with the dataset

Just from observing the OP and PV data from Figure 4, it is obvious that the clear qualitative patterns that result in the case of linear processes are not preserved in the nonlinear case. This might lead to difficulties in identifying stiction in this case using qualitative pattern matching approaches such as the one proposed in [7]. The model-based approach proposed by [11] is also not likely to work for this case. The data shown in Figure

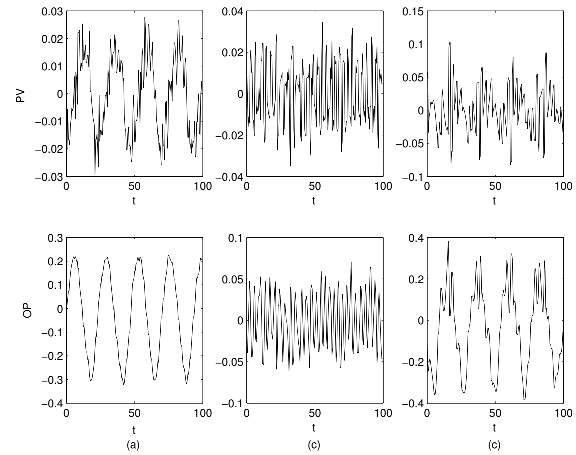

Fig. 4. Data for (a) No stiction (b) Stiction alone (c) Stiction and external oscillation

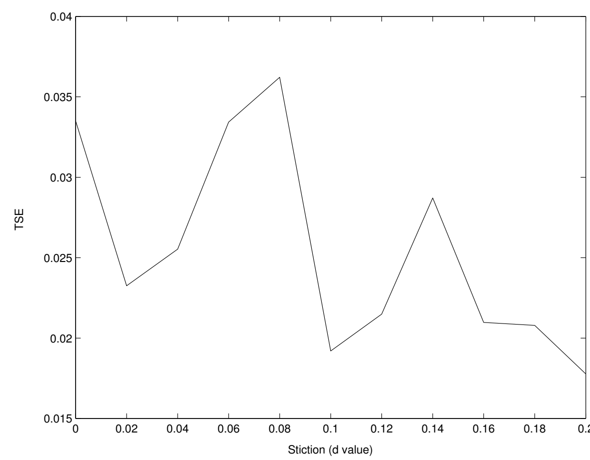

Fig. 5. Result for the approach of [11]

4(a) for the no stiction case is tested using the approach suggested in [11] (approach shown in Figure 2). The resulting d vs TSE plot is shown in Figure 5. The observation of multiple minima for the d identification problem from the work of [11] is reinforced in Figure 5. However, as expected, the value of d is incorrectly identified. In other words, stiction is detected where it is not present.

V. Results

The dataset (Figure 4(a)), where the approach of [11] failed and the two other datasets (Figures 4(b) and 4(c)) are used to test the performance of the proposed approach. The results are shown in Figures 6-8. From Figure 6, it is clear that the scenario is correctly diagnosed as being a no stiction case. The minimum TSE is achieved at $d = 0$. It can be seen from Figure

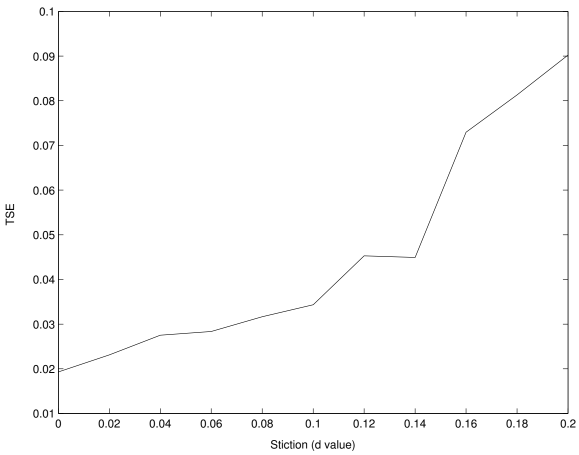

Fig. 6. Result for the no stiction case (known model)

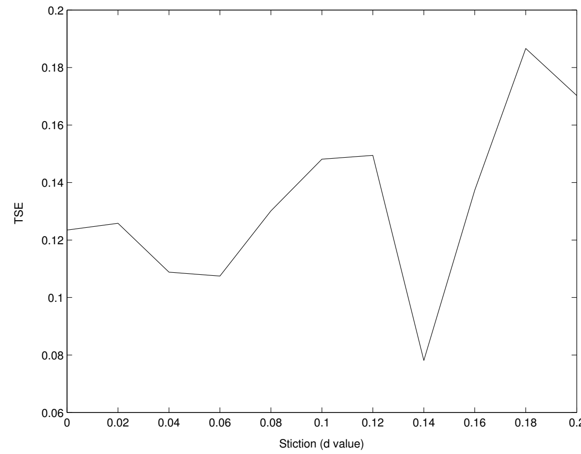

Fig. 7. Result for the stiction case (known model)

7, the case of stiction is also correctly identified with an accurate estimation of the stiction level. The third scenario is a challenging case where both stiction and an external oscillating disturbance are present, with the process being nonlinear. The result for this case is shown in Figure 8. In this case, not only is stiction detected but the magnitude of stiction is also accurately estimated (0.15 estimated as 0.14).

Figure 9 shows the final estimation of the disturbance in the inner loop. Figure 9(a) is the estimate for scenario (i). It can be clearly seen that an oscillatory disturbance is estimated. This further confirms the diagnosis of external disturbance as the root cause when placed in conjunction with a $d = 0$ estimate. Figure 9(b) shows the estimate for scenario (ii), which clearly shows no oscillation. This corroborates the fact that the oscillation is due to stiction (a non-zero d was also estimated for this case). Figure 9(c) shows oscillations, which indicates the presence of both stiction and an external oscillating disturbance. From these results it can be clearly seen that the proposed approach works well in the known model case in detecting and isolating the root cause of oscillation in SISO loops.

VI. 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. While there are several approaches that have been discussed for the linear case, almost no work exists in the case of nonlinear process control loops. A solution approach for the known model case was proposed. A solution to the unknown model case can be developed using the same framework; however, this will be a more

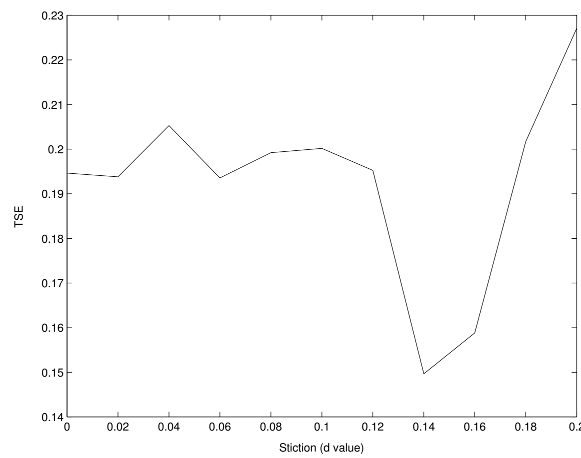

Fig. 8. Result for the case of both stiction and an external oscillating disturbance (known model)

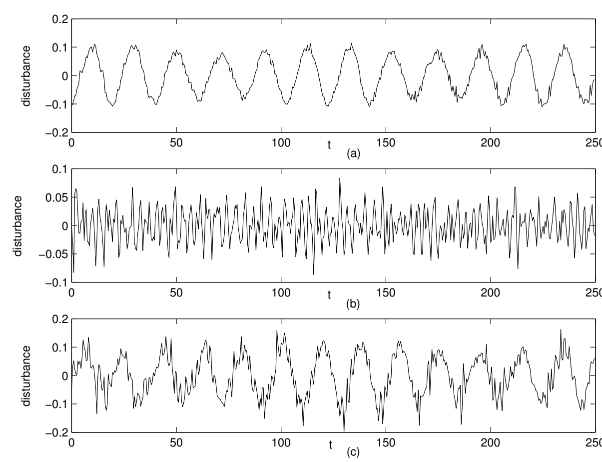

Fig. 9. Estimation of the disturbance for the three datasets

challenging problem. The unknown model scenario can be elegantly solved in the linear case because of the separation in achievable accuracy through the linear and nonlinear components of the model; this principle fails to be of use in the nonlinear process case. Some perturbation signal might be necessary for model discrimination.

The results presented in this paper used a simple one parameter model for both generating the simulation data and also in the detection approach. The effectiveness of the proposed approach needs to be first verified with data generated from a mechanistic first principles model for stiction. Further, the proposed approach should be tested with industrial data. In future, the efficacy of the proposed approach for the known model case needs to be further validated with other examples, different types of disturbances and different stiction models.

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