Detection of Stiction in Interacting Systems using a Hammerstein Model Approach

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***Abstract*— Automated non-invasive diagnosis and localization of the root cause of oscillations in process plants is a widely held industry goal sought in order to stabilize product qualities and reduce equipment problems and energy costs. As stiction in control valves is one of the leading causes of oscillations in plant variables, detection and localization of valve stiction is a major part of any method for root cause diagnosis. Previous contributions have introduced a number of techniques that seek to achieve this objective, but most of the approaches presented are only applicable for the case of single-input single-output (SISO) processes. The current work seeks to extend one widely used approach, Hammerstein-model-based stiction detection, to the case of interacting plants. Because of the difficult nature of the problem, we first consider the case where a nominal linear plant model is known for the interacting system in question. With these approximate linear dynamics, we introduce an approach to identify in which loop the valve stiction is originating from, under the assumption that only a single valve in the interacting system is afflicted by stiction. The method efficacy is explored using simulation studies. The feasibility of extending the method to the case of unknown plant model via multivariate time-series identification of the linear plant model is then briefly discussed.**

I. INTRODUCTION

In the process industries, oscillations in the values of process variables can have immense economic costs due to equipment wear and increased product variability. Previous industrial surveys have indicated that a large percentage of control loops are affected by oscillations [1], [2]. A major cause for these oscillations is valve stiction (stiction being a term meaning static friction). The control valve is a weak link in the control loop, as it is often the only moving component in many processes [3]. Stiction induced oscillations caused by one control valve may propagate from control loop to control loop until a large portion of the entire plant is affected. Since large industrial processes may have hundreds to thousands of control loops, reliable and noninvasive automated stiction detection would serve as a valuable resource in order to locate the original source of oscillations so that the problem can be eliminated.

With this goal in mind, many valve stiction detection algorithms have appeared in the literature in recent years. Huang et al. [4] suggested that these methods could be classified into (i) descriptive statistic, (ii) pattern recognition, and (iii) model-based approaches. Alternatively, Babji et al. [5] have suggested to classify stiction detection approaches into the categories of (i) shape-based, (ii) frequency-domain based, and (iii) model-based. In each case, the model-based methods referred to are those based on representing the process as a Hammerstein model. This technique was first introduced by [6], and many variants have been introduced since [7], [8], [9], [10], [11].

With few exceptions, the available techniques are focused on single-input single-output (SISO) processes. However, many industrial control loops are interacting, wherein the controlled or manipulated variables from one loop have direct impact on the controlled variables of one or more other loops. In this case, the nonlinear input-output behavior induced by stiction can appear in several loops simultaneously. Choudhury et al. [12] provided several methods for confirmation of valve stiction, two of which should be applicable to interacting systems, and these are (1) putting the controller for the suspected loop with stiction into manual control and see if the stiction induced limit cycles die down or (2) use valve positioner data and compare to the op (controller output) data to check for stiction. A third method presented in the same work was to change the controller gain and observe whether the oscillatory plant signals exhibited a change in frequency, with a change indicating the presence of valve stiction. Haoli et al. [13] have demonstrated that for interacting systems, this gain change method could fail to give the correct indication. A change in any controller gain within the interacting system could cause a shift in the oscillation frequency of the plant signals. Therefore, they proposed a modification of this technique, wherein for an interacting system having several valves where the presence of stiction has been detected but not isolated to a particular valve, every controller gain in the interacting system was changed from its original setting, in order to see in which loop the controller gain change caused the largest magnitude change in oscillation frequency. The valve within the loop whose controller gain change caused the largest frequency shift is deemed to be the source of the stiction induced oscillations within the system.

All of the aforementioned methods that should correctly isolate valve stiction within interacting systems are fairly intrusive (unless a valve positioner was already installed). For instance, the modification of the gain change method presented in [13] requires 2 significant changes in gain for every control loop within the interacting system. Putting the loop in manual to complete the diagnosis is disruptive and possible unsafe [12], so this should be done as rarely as

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possible. An alternative to these methods is to use knowledge of the process topology to create a plant adjacency matrix, which can then be used to isolate the source of oscillation based upon the additional knowledge of which combination of process loops are exhibiting oscillations at the same frequency [14]. This method was designed in order to isolate the source of any type of oscillation whether due to poor tuning, external disturbance, or equipment malfunction or degradation, valve stiction included. However, in some instances, it is possible that the necessary topology information is not fully available or else possible that even with this information, the specific fault and location cannot be resolved completely. Therefore, other techniques for resolving the location of valve stiction in interacting systems should still be useful.

In this work we will explore the localization of stiction detection on interacting systems using a Hammerstein-model-based detection approach wherein the linear plant model is assumed to be approximately known, and the nonlinear stiction element uses a one-parameter valve model during data-fitting. In the Section 2, the detection approach is described. In Section 3 several simulation examples are used to demonstrate the efficacy of the method as well as to highlight possible pitfalls. Finally, Section 4 contains discussion of the approach and conclusions are provided.

II. STICTION DETECTION APPROACH

This section introduces a stiction detection method for systems with internal interactions between control loops. First, some data-based valve stiction models are introduced which are useful for simulation and detection of stiction. Following this, a Hammerstein model-based stiction detection approach is proposed.

A. Valve stiction modeling

There are two types of valve stiction models, these being (i) physics-based models and (ii) data-driven models. In practical applications, a large number of the parameters required for physics based modelling have unknown value, and so data-driven models are used within stiction detection techniques. The phase plot produced by the data driven models of [15] and [16] is displayed in Fig. 1. These authors used two parameters to characterize a valve's stiction behavior, combined deadband and stickband, denoted S, and slip-jump J. A study by Garcia [17] comparing many types of physics based and data-driven valve models found that the model of [16] gave physically realistic input-output behavior under the simulations performed, and therefore this model is selected as the simulation model used in later sections.

For stiction detection however, a simpler data-driven model is used, this being the one-parameter model, which was used along with the original Hammerstein model-based stiction detection technique [6]. Here valve position $v(t)$ is related to its previous value $v(t-1)$ and the controller output $u(t)$ by the following simple expression,

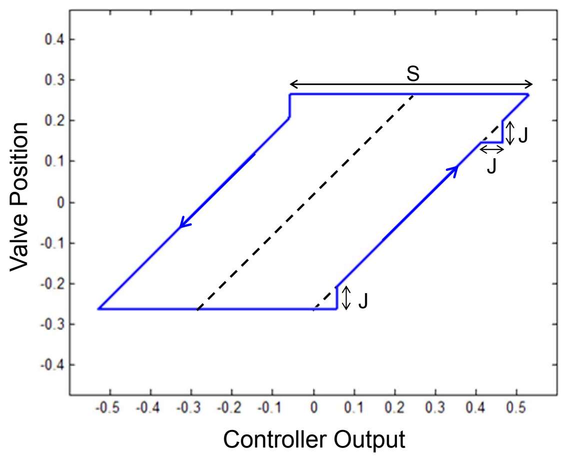

Fig. 1. Idealized phase plot for a valve with stiction

$$v(t) = \begin{cases} u(t), & \text{if } |u(t) - v(t-1)| > d \\ v(t-1), & \text{otherwise} \end{cases}$$

where d is the parameter describing the magnitude of stiction present in the valve.

B. Hammerstein model for interacting system

A Hammerstein model is a block oriented model in which a nonlinear system is broken into two parts: a block containing a static nonlinearity, followed by a block containing linear dynamics. Several of the previous proposed methods for stiction detection rely upon this Hammerstein structure for stiction quantification, with the nonlinear data-driven stiction model contained in the first block, followed by a linear plant model. Then an iterative search is undertaken for identifying the parameters from each the linear and nonlinear blocks, with an outer loop for selecting the valve stiction parameters and an inner loop for identifying the linear dynamics.

The previously introduced methods pertained to SISO systems, which we now propose to extend to the case of interacting multiple-input multiple-output (MIMO) systems. Fig. 2 displays the assumed block form of the system under the Hammerstein assumption for the case of a 2×2 MIMO system. Controller outputs u_1 and u_2 enter the nonlinear element and are modified by data-driven valve models V_1 and V_2 into valve positions v_1 and v_2. The linear dynamics then transform the valve position into measured outputs y_1 and y_2. Under the assumption of only one valve having stiction at a time, either V_1 or V_2 will be a nonlinear transformation, while the other simply acts as a pass-through of the controller signal.

Previous works used several types of models to identify the linear dynamics, including ARMAX (auto-regressive moving average with exogenous input) ([6], [11], [10]), extended ARMAX [9], and low-order model with time delay [8]. Possible multivariate extensions of these models include VARMAX (vector-ARMAX) or matrix transfer

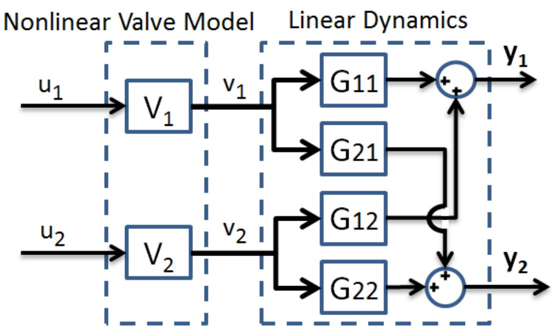

Fig. 2. Example Hammerstein stiction model for a 2×2 system

function models. In this work, we assume that a VARX (vector auto-regressive) approximation of the continuous-time multivariate system dynamics is available. Using the same one parameter valve stiction model as [6], we propose the following stiction location procedure for multivariate interacting systems:

1) Obtain a positive detection of stiction within the interacting system using one of the previously existing techniques.
2) Assume the valve in Loop i has stiction and the other valves do not. Perform steps 2-6 for each $i = 1 \ldots n$ where n is the number of control loops in the system considered.
3) Perform a grid search over estimated stiction parameter $\hat{d}_i$ from 0 to $d_{i,max}$, where $d_{i,max}$ is defined $u_{i,max} - u_{i,min}$, while holding $(\hat{d}_j = 0,\ j \neq i)$.
4) At each value of $\hat{d}_i$, transform u_i to linear plant input v_i using the one parameter valve model. Each of the other inputs $u_j, j \neq i$, enters the plant unaltered ($v_j = u_j$) since currently no stiction is assumed in the other valves.
5) Transform the plant inputs by the approximate VARX model to obtain plant output estimates $\hat{y}_k$, $k = 1 \ldots n$. Calculate the mse (mean-squared error) for each plant output, which is $mse(\hat{y}_k) = (y_k - \hat{y}_k)^2$ where y_k is the measurement signal of plant output k.
6) Calculate the MSE index, defined by $I_{mse}(\hat{d}_1, \ldots, \hat{d}_n) = \sum_{k=1}^{n} \dfrac{mse(\hat{y}_k)}{var(y_k)}$ for the current set $\hat{d}_i > 0$, $\hat{d}_j = 0$ ($\forall j \neq i$), where $var(y_k)$ is the variance of plant output signal k.
7) After looping through steps 2-6 for $i = 1 \ldots n$, select the valve most likely to contain stiction and the estimated severity based on the lowest value of $I_{mse}(\hat{d}_1, \ldots, \hat{d}_n)$. Since the search space consisted of having of only one nonzero stiction parameter $\hat{d}_i$ at a time, the minimum will correspond to stiction in a single valve.

III. SIMULATION RESULTS

To test the efficacy of the proposed method, simulation studies were carried out using Matlab and Simulink. For an example 2×2 MIMO system, we considered the distillation

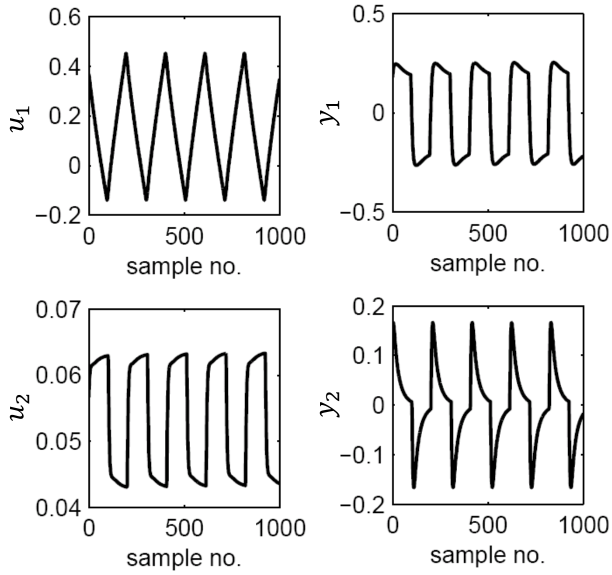

Fig. 3. Simulated controller and process outputs for the Wood and Berry system under the case $(S_1, J_1) = (0.6, 0.06)$

column model of [18]. The original continuous time transfer function model is used to simulate the plant, and two PI controllers were added. To simulate valve stiction, the model of [16] was used because of favorable characteristics of the model discussed in [17]. Within one valve model, the parameter set (S, J) was set to nonzero values to simulate stiction, while for the other loop, the valve parameters remained at $(S, J) = (0, 0)$. Simulations were run for 1000 seconds with sampling at a frequency of 1 Hz. In each case, a set-point change was used to excite the loop and no other external disturbances or nonlinearities were added.

Fig. 3 shows the controller and process outputs when the parameter sets $(S_1, J_1) = (0.6, 0.06)$ and $(S_2, J_2) = (0, 0)$ are used. Stiction induced oscillations are present in all plant signals, even though the valve in loop 2 had no stiction simulated. If considering the control loops separately, loop 1 takes on the classic appearance of a nonintegrating process under PI control that has stiction, with triangular wave controller output (u_1) and approximately rectangular wave process output (y_1). However, the effects of the valve nonlinearity will also appear in loop 2, and it can be shown that using SISO Hammerstein stiction detection on this loop will result in positive detection even though stiction is absent from the second valve.

An approximate linear model of the process was generated by taking a zero-order hold discretization of the original continuous time transfer function model to produce a discrete transfer function model, and then converting this into VARX form. Using the controller output data from Fig. 3, and assuming stiction sequentially in one loop at a time, predicted outputs $\hat{y}_1$ and $\hat{y}_2$ were generated for a range of stiction parameters on each valve.

Fig. 4 shows the mean-square error for each output with

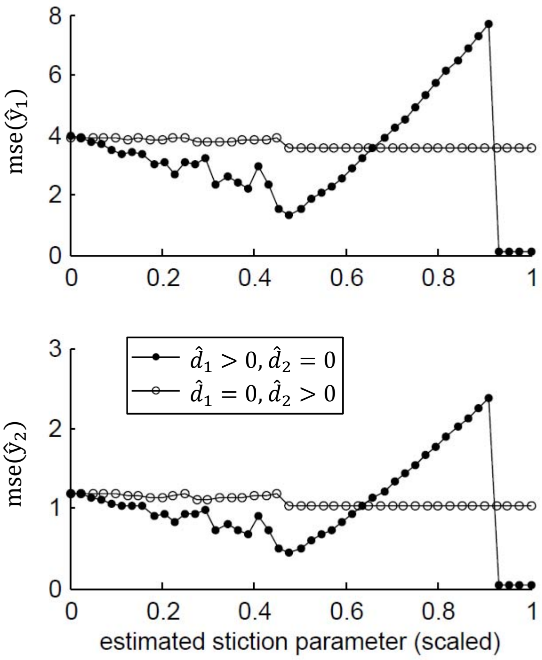

Fig. 4. MSE of each predicted output for the Wood and Berry system under the case $(S_1, J_1) = (0.6, 0.06)$

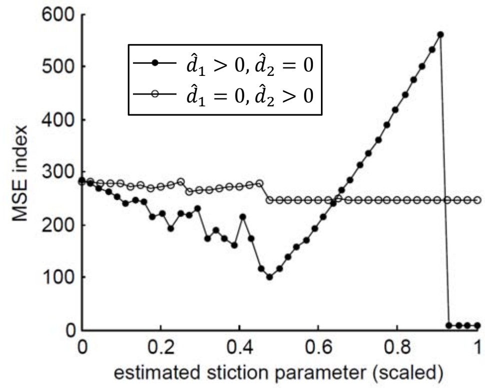

Fig. 5. MSE index computed for the Wood and Berry system under the case $(S_1, J_1) = (0.6, 0.06)$

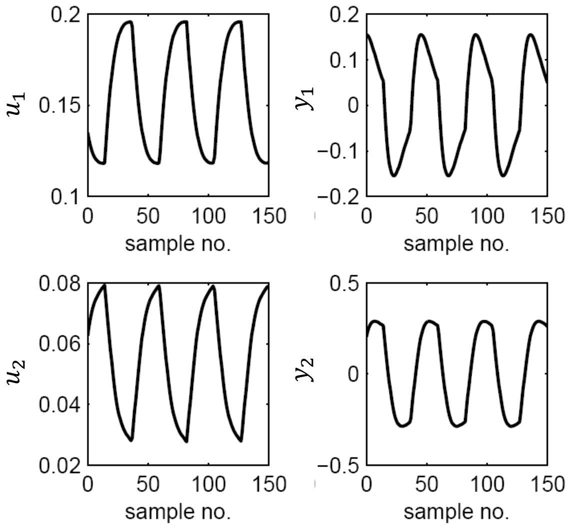

Fig. 6. Simulated controller and process outputs for the Wood and Berry system under the case $(S_2, J_2) = (0.05, 0.05)$

stiction assumed on each valve sequentially (one valve with stiction, the other without) during detection. The pointed lines on each plot represent the mean square error (mse) resulting from assuming stiction in the first valve and no stiction in the second, while the circled lines provide the mse when stiction is assumed to be present only in the second valve. On the plots, each estimated stiction parameter ($\hat{d_1}$ in the case of the pointed line, $\hat{d_2}$ in the case of the circled line) is scaled by the span of the corresponding op signal so that the results can be presented together. For both estimated outputs $\hat{y}_1$ and $\hat{y}_2$, the minimum mean squared error is achieved when $\hat{d_1} > 0.6$ ($\hat{d_2} = 0$) (on the plots $\hat{d_1} = 0.6$ corresponds to approximately 0.9 when scaled by span of the op). Since the minimum value of mse is obtained for each output when assuming stiction in valve 1 (pointed line), the method is correctly indicating stiction in this valve.

In this case, the results from each plot in Fig. 4 agree, and so the plot of I_{mse} in Fig. 5 reflects this, having a minimum value for $\hat{d_1} \geq 0.6$ (≥ 0.9 on the plot after scaling by d_{max}) and $\hat{d_2} = 0$. Therefore, it is concluded that stiction is correctly detected in the valve within loop 1 for this case. Interestingly, the indicated values of the stiction parameter ($\hat{d_1} \geq 0.6$) correspond to the case where the valve is completely immobile for the duration of the predicted series. This result is probably due to different valve models being used during simulation and detection.

The simulation was again repeated, this time with stiction simulated in the valve in loop 2 with stiction parameter magnitudes of $(S_2, J_2) = (0.05, 0.05)$ ($(S_1, J_1) = (0, 0)$). This is a special case where the deadband and stickband are equal, which provides input-output behavior quite similar to the one-parameter model used during identification. The data from this simulation is presented in Fig. 6, wherein each plant signal is vaguely sinusoidal. Again, the stiction detection proceeded according the method of the previous section. The mse for each output is plotted separately in Fig. 7. For each output, minimum mse was obtained for the parameter set ($\hat{d_1} = 0$, $\hat{d_2} = 0.048$) (on the plots, this value of $\hat{d_2}$ is scaled to approximately 0.37). Here, as could be expected in this special case, the result achieved gives $\hat{d_2} \approx S = J$. The agreement of the results between each of the plots in Fig. 7 is also reflected in the MSE index in Fig. 8, wherein the same parameter set is identified.

A final simulation example uses a 3×3 MIMO transfer function simulation model obtained from [19]. Valve stiction was simulated in loop 1 using the same two parameter model as before and parameters ($S_1 = 0.06$, $J_1 = 0.04$). The simulated output was sampled at 1 Hz for 1200 seconds. Again, stiction detection occurs using the approach of the

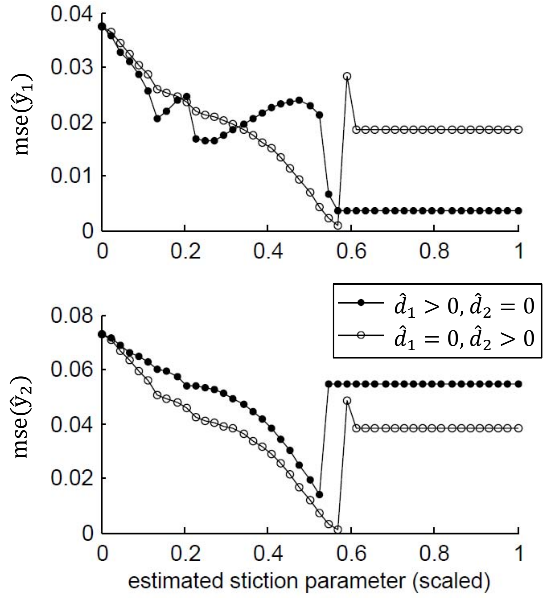

Fig. 7. MSE of each predicted output for the Wood and Berry system under the case $(S_2, J_2) = (0.05, 0.05)$

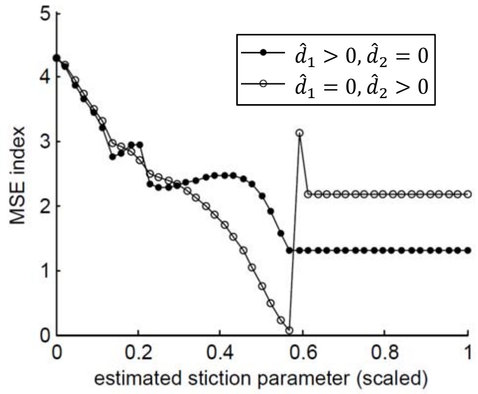

Fig. 8. MSE index computed for the Wood and Berry system under the case $(S_2, J_2) = (0.05, 0.05)$

previous section, with an approximate model generated by taking a zero-order hold of the original transfer function model. Fig. 9 presents results from attempting to identify stiction on each valve. For each output, the lowest mse is obtained by assuming $(\hat{d}_1, \hat{d}_2, \hat{d}_3) = (0.54, 0, 0)$ (scaled values).

The MSE index was calculated, with the results in Fig. 10. A correct localization to the valve in loop 1 is provided with the minimum I_{MSE} reached at $(\hat{d}_1, \hat{d}_2, \hat{d}_3) = (0.54, 0, 0)$ (scaled by span of op). The MSE index is useful for selection of a final detection in cases where the results for each output considered separately do not agree, although this case was not found in any of the simulation results of this section.

IV. DISCUSSION AND CONCLUSIONS

The results of the previous section indicate that performing localization of stiction detection in interacting multivariate systems using approximately known model information shows promise. The results of each detection were correct, with appreciable margin between correct and erroneous detection. These relatively convincing results in the case where an approximately known model is available, lead us to the next question, which is the ability of this method to work when a model is not available and would have to be identified, in which case model structure (order) and time delays would have to be estimated too. The additional task of estimating multivariate linear dynamics from the closed-loop data will have unknown effect on the reliability of the method. The reliability could decrease if the parameter

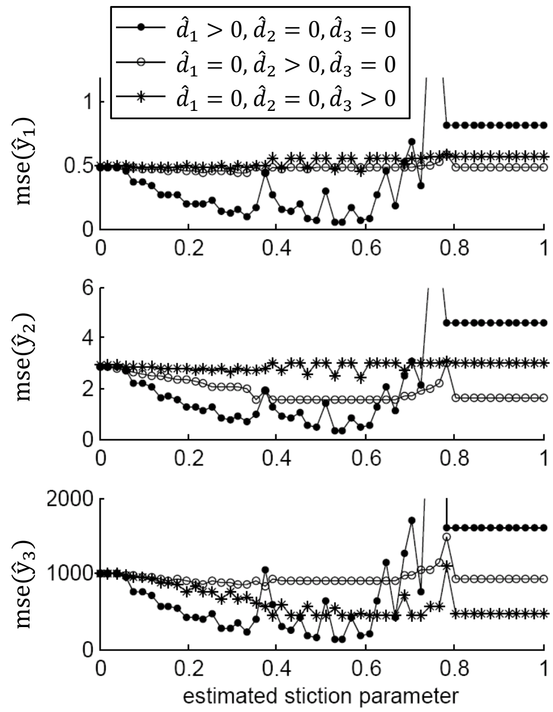

Fig. 9. MSE of each predicted output for the Ogunnaike and Ray system under the case $(S_1, J_1) = (0.06, 0.04)$

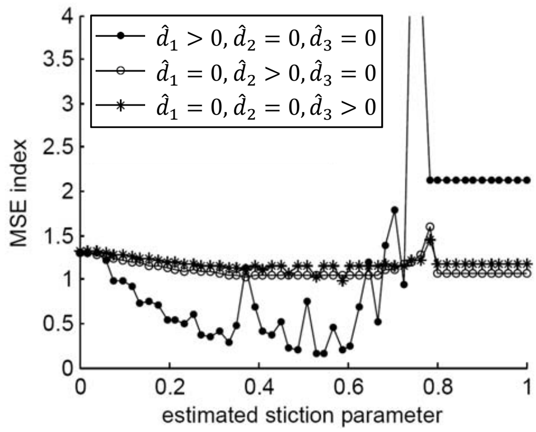

Fig. 10. MSE index computed for the Ogunnaike and Ray system under the case $(S_1, J_1) = (0.06, 0.04)$

estimates converge far from true values, but the use of simultaneous linear model identification could also provide the flexibility to reduce errors due to plant or disturbance changes compared to the case of using previously determined dynamics. One possible way to decrease error may be to use a valve model for detection which is more able to capture the input-output behavior of the valve generating the data (in this study, the detection valve model is a one-parameter and the simulation model was a 2 parameter type). For practical applications, it would be necessary to know which valve model provides the most similar input-output characteristics as the sticky valve in the closed loop. There is some disagreement in the literature in this regard, with recent work [20] suggesting that a suitable valve model should have the valve reaching a stationary state during each sampling period, which is in contrast to the assumption in many previous works wherein the valve was assumed to stay in motion across sampling periods.

Extensive studies on industrial data-sets [21] have shown that, at best, the currently existing automated data-based techniques should be relied on as a screening mechanism in order to identify which subset of control valves should be selected for more invasive tests in order to confirm valve stiction. This conclusion is because of the limited accuracy of the non-invasive techniques studied. This is still a valuable role for this type of technique to serve as it can greatly reduce the time and effort of plant personnel in locating the source of oscillations. In this role, it is essential that a stiction detection technique should have a low false negative rate, to avoid eliminating the sticky valve from consideration. Of course, reducing the number of false positives is also beneficial as it will reduce the number of invasive tests necessary in order to locate the valve with stiction that is the root cause of the oscillations. In a similar way, the currently proposed technique is not meant to provide a definite answer as to which valve contains stiction, but it can provide the most probable location for plant personnel to begin more invasive testing.

Future work can proceed in several directions, such as dropping the assumption that a nominal plant model is available for use. In the SISO case, it is known that the presence of stiction provides sufficient excitation for the closed-loop identification of plant models [6]. For the MIMO case, it would be necessary to fit a multivariate linear model, such as a VARX, VARMAX, or matrix transfer function model. Even in the SISO case, fitting linear dynamics is a computationally intensive procedure, which must be repeated at a large sampling of stiction parameters, so it is unknown if the multivariate case is feasible to be completed in a timely manner. A final challenge is industrial validation of the proposed approach, which will require obtaining data sets from the correct type of process (interacting) with enough additional information (the condition of each control valve in the system, knowledge of disturbances, controller tunings, plant models) to properly test the diagnosis technique.

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