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IAM: An Intuitive ANFIS-based method for stiction detection

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Abstract. Stiction in control valves is an industry-wide problem which results in degradation of control performance. A new approach to detect the presence of stiction by utilising only the PV-OP data from control loops is proposed using an Adaptive Neuro-fuzzy Inferencing System (ANFIS). Intuitively, the error between the output of an FIS model developed with stiction and a process with stiction would be minimal. When benchmarked against seventeen well-known industrial control loop case studies, the Intuitive ANFIS-based Method (IAM) accurately predicts the presence or absence of stiction in 65% of loops tested.

1. Introduction

Modern chemical plants employ regulatory control strategies that require control loops to be far more integrated than those of yesteryear so that plant economy can be increased. However, control loops which function poorly can affect plant performance targets. Such loops may cause substandard product quality, increased utility wastage as well as increased downtime and frequency of maintenance. Poor control performance itself can be the result of improper controller tuning, plant-model mismatch, and actuator nonlinearity among others. Control valves are the most commonly used actuator and the well-known causes of control valve nonlinearity are backlash, saturation, and stiction [1, 2].

Control valve stiction is a particularly interesting fault. It progressively worsens as the mechanical components of the valve gradually deteriorate throughout their service life. Ideally, the controller output (OP) i.e. the desired valve position will be equal to the actual valve position (VP). However, the response of the control valve will begin to deviate from the required command of the controller due to mechanical wear or deposits on the valve stem. This, in turn, would cause oscillation which accelerates wear and further degrades control performance. The oscillation also tends to propagate downstream from the faulty loop to other control loops resulting in further deterioration of control performance.

Research in control valve stiction is mainly divided into modelling, detection, and quantification of stiction as well as compensation for valve stiction. The end goal is to mitigate the negative effects stiction has on the performance of a control loop. Since there can easily be hundreds or even thousands of control loops in process plants it would be difficult to diagnose every valve for the presence of stiction or detect when a loop abnormally enters a limit cycle. Only when stiction is identified can corrective measures be taken to restore control performance. This would be done either manually by manipulating the control loop parameters or by having the controller reconfigure itself automatically.

Detecting stiction is challenging because of two factors. Firstly, a sticky valve exhibits nonlinear behaviour such that the VP does not precisely map onto the OP. Thus, linear approximation methods of the process would fail. Secondly, aside from the OP, the process variable (PV), and the set-point

(SP), seldom is any other process data available to be utilised. The dynamics of the valve, i.e. the VP, would largely have to be inferred from the PV-OP data. Among the nonlinear system identification methods is a method that uses fuzzy logic and adaptive neural networks [3].

Fuzzy logic is an inferencing system that can be used to map an input space (the input variables) to an output space (the decision) using a set of IF-THEN rules. Each rule comprises of an antecedent which follows the "IF" and a consequent which follows the "THEN". Two main types of fuzzy rules exist: the Mamdani fuzzy rules and the Takagi-Sugeno (TS) fuzzy rules [4]. The key difference between them is that in Mamdani systems, the consequent part is based on fuzzy sets whereas in TS systems it is function-based. This makes TS systems especially useful for nonlinear system modelling.

Jang [3] showed how adaptive neural networks (ANN) can be used to overcome the limitation of ordinary TS systems where human knowledge and experience is needed to develop the fuzzy IF-THEN rule base and tune the membership functions to minimize output error during modelling. Using the backpropagation gradient descent algorithm, the ANN recursively recalculates the output error and sends it back to the input until the error falls below an acceptable threshold. This coupling of fuzzy logic and ANN is known as an Adaptive Neuro-Fuzzy Inferencing System (ANFIS).

This paper is organised in the following manner: Section 2 takes a glance at stiction detection methods and Section 3 breezes through ANFIS applied in stiction detection. Sections 4 and 5 show how the Intuitive ANFIS-based Method (IAM) is developed and used to detect stiction. In Section 6 are the results and the discussion. Sections 7 holds the conclusion.

2. Control Valve Stiction

A well-regarded definition of control valve stiction based on empirical observations is given by Choudhury et al [5]. Stiction is described by two variables; S which represents the sum of the deadband and the "stickband", and J which represents "slip-jump". When a force acts on a valve stem, it is initially held in place (stuck) by static friction. This causes an accumulation of potential energy. As the force increases, the friction is eventually overcome, and the valve stem slips and jumps due to an abrupt release of kinetic energy. The valve stem may then overshoot the position commanded by the controller thus requiring the controller to issue a signal for it to reverse direction. When the valve moves back and forth repeated, the process undergoes what is known as a limit cycle.

Stiction detection methods conventionally capitalise on the limit cycle pattern, the signal waveform shape, or employ some form of nonlinearity detection [6]. The method described in this paper is better classified as a model-based method. Daneshwar and Noh [7] have explored the use of fuzzy logic for stiction detection. They model the nonlinear dynamic part of a process with stiction using the OP and VP obtained from a smart valve. Arumugam and Panda [8] appear to have used ANFIS for detection but they do not clearly demonstrate how the ANFIS is trained nor how the amount of stiction present is determined.

3. ANFIS for System Identification

The essential mathematics behind fuzzy logic is given here with the goal of showing how fuzzy logic can be applied in system identification. This is a high-level overview of fuzzy logic taken from Mehran's [9] exposition of the subject. The basic structure of a Mamdani fuzzy rule can be represented by (1). When used for modelling, the TS fuzzy rule is written as (2).

$$\begin{aligned}&\text{IF} \quad u_1 \text{ is } M_1 \text{ AND } u_2 \text{ is } M_2 \text{ AND } u_3 \text{ is } M_3\\ &\text{THEN} \quad y_1 \text{ is } M_a, y_2 \text{ is } M_b\end{aligned} \tag{1}$$

$$\begin{aligned}&\text{IF} \quad y(k) \text{ is } M_1 \text{ AND } y(k\text{-}1) \text{ is } M_2 \text{ AND } y(k\text{-}2) \text{ is } M_3 \text{ AND } u(k) \text{ is } M_4 \text{ AND } u(k\text{-}1) \text{ is } M_5\\ &\text{THEN} \quad y(k+1) = F(y(k), y(k\text{-}1), y(k\text{-}2), u(k), u(k\text{-}1))\end{aligned} \tag{2}$$

where u_1 to u_3 are input variables; M_1 to M_5 are fuzzy input sets; AND is a logic operator; y_1 and y_2 are output variables; M_a and M_b are fuzzy output sets; $y(k)$, $y(k\text{-}1)$ and $y(k\text{-}2)$ are the output of the system at time k, k-1 and k-2 respectively; $u(k)$ and $u(k$-1) are the input of the system at time k and k-1 respectively; $y(k+1)$ is the output of the system; and $F(\cdot)$ is an arbitrary function.

Fuzzy rules make up part of a fuzzy inferencing system called the rule base which can have many such rules. Together with the rule base, the database which defines the membership functions of the fuzzy sets make up the knowledge base. In ANFIS, ANN is used to develop the IF-THEN rules and membership functions. The decision-making unit performs inferencing operations whereas the fuzzification and defuzzification interfaces transform crisp input to degrees of match and then to crisp output as shown in figure 1.

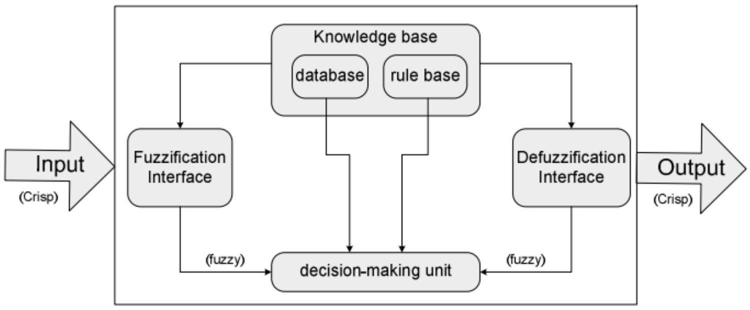

Figure 1. The structure of a fuzzy inferencing system (FIS) [3].

4. Development of the FIS model

To develop an FIS model for a process with stiction, simulated controller output (OP) data and process variable (PV) data are obtained from a feedback control process model with a sticky valve [10, 11]. The Choudhury valve stiction model is used in this scenario as it is sufficiently accurate. As per the Choudhury model, the stiction parameters are defined as “deadband plus stickband”, S = 3 and “slip-jump”, J = 1. Three thousand PV-OP data points are obtained over a period of 3,000 timesteps.

The simulated PV-OP data is scaled from a range of -1 to 1. Feature scaling overcomes the inability of the FIS to generate accurate output data if the range of input values differ significantly from the range of values used when modelling the FIS. The absolute value of the maximum and minimum values of the data sets may not be equal leading to an uneven spread of positive and negative values. This does not pose a problem for this simulation.

The following steps closely follow a tutorial example available on the MATLAB website for modelling a nonlinear dynamical system using ANFIS [12]. To determine which input variables should be used to develop the FIS model, a heuristic approach called sequential forward search (SFS) is used. Feature selection using this approach seeks to minimize the mean square error (MSE) by gradually adding features thus creating different permutations of the input variables.

Before running the SFS algorithm (seqsrch.m in MATLAB), the PV-OP data is delayed hence creating ten input candidates as shown in (3). The PV data is delayed by one to four timesteps and the OP data is delayed by one to six timesteps. The input candidates are then truncated leaving each with 2,994 datapoints.

$$\begin{bmatrix} Y_{k-1} \\ \vdots \\ Y_{k-4} \\ U_{k-1} \\ \vdots \\ U_{k-6} \end{bmatrix} = \begin{bmatrix} y_6 & y_7 & \cdots & y_{k-1} \\ y_5 & y_6 & \cdots & y_{k-2} \\ y_4 & y_5 & \cdots & y_{k-3} \\ y_3 & y_4 & \cdots & y_{k-4} \\ u_6 & u_7 & \cdots & u_{k-1} \\ u_5 & u_6 & \cdots & u_{k-2} \\ u_4 & u_5 & \cdots & u_{k-3} \\ u_3 & u_4 & \cdots & u_{k-4} \\ u_2 & u_3 & \cdots & u_{k-5} \\ u_1 & u_2 & \cdots & u_{k-6} \end{bmatrix} \tag{3}$$

The number of input candidates and the number of time steps to delay each dataset is chosen arbitrarily. To reduce the tendency for overfitting, conventional validation is implemented by using only the first half of the PV-OP data set for training. The second half is used for checking. Cross-validation is not used as sufficient data points are available for training and checking.

The SFS function is used to select the permutation of the best four input candidates. Four is the maximum number of input candidates which the function can determine. The number of membership functions (MFs) for SFS is set to three and the number of epochs is set to ten. Beyond three MFs, MATLAB warns that it may run out of memory as the rule base is large. Beyond ten epochs, the MSE does not decrease. An alternative feature selection method which could be used is exhaustive search (exhsrch.m). This method runs through all possible permutations of input candidates but is more time consuming and might not yield better results than SFS.

Once the SFS determines the optimal permutation of input candidates, the FIS is generated using the ANFIS GUI. The four input candidates selected by the SFS algorithm and the PV data are used. Again, the first half of the data is used for training and the other half for checking. A FIS model is generated using the grid partitioning method with three generalized bell-shaped MFs assigned to each of the four inputs. The output is assigned a constant membership function. The parameter estimation of the MFs is done using the hybrid method which combines backpropagation and least squares estimation. Error tolerance is set to 0.01 and training is run for thirty epochs.

5. Diagnosing Loops using the Intuitive ANFIS-based Method (IAM)

Once the FIS model is developed, other loops can be tested by comparing the PV data from loops being investigated and with the FIS output when it is fed with PV-OP data from the same loop.

Intuitively, since the FIS has been developed using stiction data, the FIS output will be similar to the PV data from a loop undergoing stiction.

To generate the output data using the FIS model, the PV-OP data from a loop being investigated is scaled from -1 to 1. Then, it is delayed by the same number of instances as the data used to generate the model. For example, if the input candidates used to generate the FIS were $u(t\text{-}1)$, $u(t\text{-}3)$, $y(t\text{-}5)$ and $y(t\text{-}6)$, the same input candidates are generated from the loop's PV-OP data. The input candidates are then fed to the FIS model to get the FIS output.

The FIS output is then compared with the loop PV data by calculating the mean absolute error (MAE) given by (4), where x loop PV data, y is the FIS output, and n is the number of data points.

$$\mathrm{MAE} = \frac{\sum_{i=1}^{n} |y_i - x_i|}{n} \tag{4}$$

The MAE is the mean of the absolute distance between each point of the loop PV data with the corresponding point of the FIS output. Other error metrics such as the mean squared error (MSE) and the root mean square error (RMSE) were also tested during this study. However, they do not yield apparent performance benefits over the MAE. Furthermore, the MAE is conceptually simpler.

To select an appropriate error threshold which can be used to identify stiction, the ninety-four industrial control loops published by Jelali and Scali [13] were examined. By looking at the literature on stiction detection, the goal was to identify loops which have stiction present to a high degree of certainty. A complication that arises here is that the stiction detection methods have a high tendency of misdiagnosis. Therefore, between authors, little consensus exists on the presence of stiction in many of the control loops. This poses a problem for the threshold selection. If the threshold is set too high, it will result in too many false negatives. And if it is set too low, there will be too many false positives.

A timely publication of a review paper by Capaci and Scali [6] supported the selection of an appropriate threshold. They have identified five loops which are evidently present with stiction. (The nomenclature used when referring to data sets and detection methods henceforth is consistent with that used by Jelali and Huang [14] and later by Capaci and Scali [6].) The loops are CHEM 1, CHEM 10, CHEM 12, CHEM 23, and CHEM 26 [14]. Using the method explained above, the MAE is obtained for each of these five loops.

Ultimately, the MAE of loop CHEM 10 which is 0.63 is selected as the threshold. The reason for this is three-fold. Firstly, Jelali and Scali have said that CHEM 23 and CHEM 26 are only likely to be having stiction. Secondly, all stiction detection methods reviewed by Capaci and Scali identify this loop to have stiction. Although some methods could not be used on CHEM 10, there are no false negatives. The YAMA and YAMA+ tests failed to identify stiction in CHEM 01 and CHEM 12 respectively. Thirdly, the MAE of CHEM 10 is the highest among the five loops indicating that this method needs to allow for that much of error to work.

One hundred and fourteen industrial control loops were available to the authors via the International Stiction Database (ISDB) [14] but only seventeen were analysed in this study because there is no consensus on whether the rest of the loops have been accurately labelled with stiction being present or otherwise.

Of the twenty-six loops listed by Capaci and Scali, the five loops used during the process of selecting the threshold were omitted from stiction analysis as including them would be self-serving. The four other loops omitted are CHEM 3, CHEM 33, CHEM 34 and PAP 7 because Capaci and Scali [6] could not reach a global consensus on those four loops. They recommend that additional tests be carried out to identify the type of nonlinearity present there.

6. Results and Discussion

The IAM can correctly indicate the presence (or absence) of stiction in eleven out of the seventeen loops tested. Of the six failures, one is a false negative (indicating stiction when it is not actually present) and the remaining five are false positives. The results are tabulated in table 1.

Table 1. Results of stiction analysis issued by the IAM

LOOP	STICTION[a]	MAE	RESULT	STATUS	OTHER[b]
CHEM 02	YES	0.22	YES	PASS	9
CHEM 05	*YES*	*1.03*	*NO*	***FAIL***	*9*
CHEM 06	YES	0.24	YES	PASS	9
CHEM 11	YES	0.23	YES	PASS	8
CHEM 24	YES	0.46	YES	PASS	10
CHEM 29	YES	0.50	YES	PASS	7
CHEM 32	YES	0.13	YES	PASS	8
MIN 01	YES	0.28	YES	PASS	9
PAP 02	YES	0.17	YES	PASS	9
PAP 05	YES	0.21	YES	PASS	7
CHEM 04	NO	0.96	NO	PASS	5
CHEM 13	*NO*	*0.25*	*YES*	***FAIL***	*9*
CHEM 14	NO	0.46	YES	**FAIL**	1
CHEM 16	NO	0.45	YES	**FAIL**	1
CHEM 58	NO	0.27	YES	**FAIL**	4
PAP 04	NO	0.74	NO	PASS	3
PAP 09	NO	0.26	YES	**FAIL**	8

[a] Presence of stiction according to Capaci and Scali **[6]**
[b] The number of other methods to accurately detect presence (or absence) of stiction. A total of fourteen other methods are compared.

The IAM was compared against fourteen other stiction detection methods. The comparison is tabulated in table 2. Of the fourteen methods, only the results for HAMM2 and HAMM3 tests were available for all seventeen loops. Some methods could not issue verdicts for certain cases due to various reasons and are considered to have failed to detect stiction in those cases. If no verdicts were made available for some loops, it is also considered that the methods failed there as the ISDB has been openly available since 2009.

Table 2. Synthesis of the verdicts issued by stiction detection methods

	IAM	RELAY [15]	HAMM2 [16]	BIC [10]	HIST [17]	HAMM3 [18]	CURVE [19]	SLOPE [20]	ZONES [20]	YAMA+ [21]	CORR [22]	YAMA [23]	AREA [24]	FUZ [7]	BRA [25]
NRI	**11**	12	12	11	10	10	9	9	9	9	8	7	5	4	1
False +ve	**1**	0	1	0	3	1	3	3	4	0	0	2	5	0	0
False -ve	**5**	4	4	4	2	6	2	0	1	1	2	1	1	0	0
UNC/NA /NIV/XX	**0**	1	0	2	2	0	3	5	3	7	7	7	6	13	16
NRI (%)	**65**	71	71	65	59	59	53	53	53	53	47	41	29	24	6

NRI: number of right indications; UNC: uncertain or unknown; NA: not applicable; NIV: verdict not issued; XX: not applicable to type of loop

Considering the number of right indications (NRI) alone, IAM having eleven NRI is on par with BIC. HIST and HAMM3 come close with ten NRI each. RELAY and HAMM2 have twelve NRI each but RELAY does not work on one loop. The IAM has five false negatives and one false positive. As seen in table 2, generally methods with a higher number of false positives tend to have a lower number of false negatives and vice versa.

Figures 2 and 3 are typical plots of the output generated during the tests. Looking at the failed loops, CHEM 5 and CHEM 13 are probably the most jarring as most other methods succeed here. Figure 2 shows the scaled PV vs. t plot for the test on CHEM 5 which is a flow control loop with stiction. The high MAE can be attributed to the generated PV being slightly out of phase from the actual and the wider range of values generated compared to the actual PV.

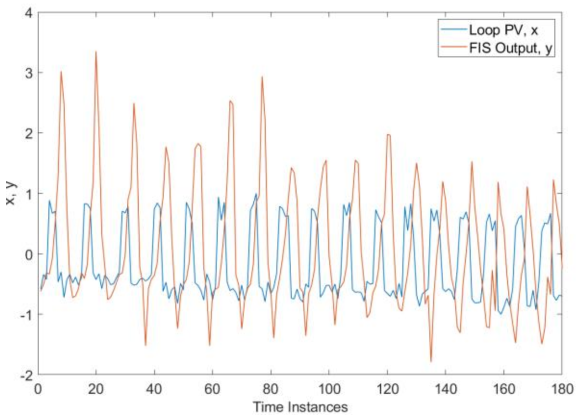

Figure 2. CHEM 5, a false negative.

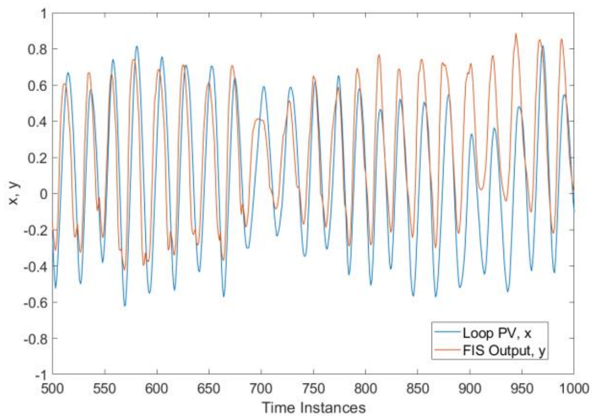

Figure 3. CHEM 13, a false positive.

7. Conclusion

This paper details a novel method to detect stiction using ANFIS. The IAM can correctly diagnose 65% of loops tested and does not require much pre-processing or filtering of the data. Further studies could investigate developing the FIS model using different sets of stiction data or by simultaneously using multiple FIS models do diagnose or even quantify stiction in a loop.

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