20th European Symposium on Computer Aided Process Engineering – ESCAPE20 547
S. Pierucci and G. Buzzi Ferraris (Editors)

Resilient control in view of valve stiction: extension of a Kalman-based FTC scheme

Kris Villez[a] Babji Srinivasan[b] Raghunathan Rengaswamy[b] Shankar Narasimhan[c] Venkat Venkatasubramanian[a]

[a] Laboratory for Intelligent Process Systems, School of Chem. Eng., Purdue University, West Lafayette, IN 47907, USA
[b] Dept. of Chem. Eng., Texas Tech University, Lubbock, TX 79409, USA
[c] Dept. of Chem. Eng., Indian Institute of Technology, Madras, Chennai 600036, India

Abstract

In this contribution we propose an active Fault Tolerant Control (FTC) strategy which enables the isolation and identification of valve stiction and valve blocking, in addition to the additive faults like sensor and actuator biases. The developed method is an extension of the original method proposed by Prakash *et al.* (2002). This method is based on the Kalman filter and is developed under the assumption that the monitored system is Linear Time Invariant (LTI). It has been shown to work well for additive faults such as sensor and actuator biases. Within this method the fault isolation and identification task is based on the Generalized Likelihood Ratio (GLR) test by which the most plausible fault type in a library of faults is selected following estimation of fault parameters.

Keywords: Kalman filter, Valve stiction, Fault isolation, Fault diagnosis

1. Introduction

Valve stiction is a problem that has caught the attention of several research groups in the last decade. Valve stiction is considered one of the most common problems in control loops (Shoukat Choudhury et al., 2004). Its presence leads to rather severe non-linear effects which makes its detection, diagnosis and accommodation a challenging problem. In this work, we evaluate an extended Kalman-based method for on-line diagnosis of several faults in control loops with valves. We show promising results for a range of faults and list several opportunities and threats to our approach.

2. Materials and methods

2.1. Simulated system

A buffer tank system model is used for evaluation of our method. The tank level is measured and is affected by an inflow as a disturbance input and gravitational outflow, which is in turn manipulated by a valve. In the original (continuous, non-linear) system, the outflow relates to the tank level as follows:

$$q(t)_{out} = C \cdot v(t) \cdot \sqrt{x(t)} \qquad \text{(Eqn. 1)}$$

with:

$q(t)_{out}$	outgoing flow rate	$[m^3/s]$
$v(t)$	valve position	$[0-100\,\%]$
$x(t)$	tank level	$[m]$
C	valve constant	$[0.1414\,m^{2.5}/s]$

This system is linearized around its equilibrium point corresponding to an ingoing flow rate of 0.1 m^3/s. This corresponds to a volume of 1 m^3 and a valve position of 5%. Furthermore, the model is discretized in time so to obtain the standard discrete state-space model form, including input disturbances and measurement error:

$$\dot{x}(k) = \Phi \cdot x(k) + \Gamma_v \cdot v(k) + \Gamma_w \cdot w(k)$$
$$y(k) = C \cdot x(k) + D \cdot e(k) \qquad \text{(Eqn. 2)}$$

with: $e(k)$ measurement error
$w(k)$ input disturbance
$\Phi, \Gamma_u, \Gamma_w, C, D$ time-invariant system matrices

This discretized and linearized model is used for all simulations. A PI-controller brings the tank level measurement, y(k), at its set-point by means of manipulation of the valve position, v(k). In nominal operation, the actual valve position is equal to the controller signal, u(k).

2.2. Simulated faults

Four types of faults are simulated. The first type is valve stiction. As soon as this type of fault sets in, the valve is simulated to move only when the difference between the valve position, v(k), and the controller signal, u(k), is larger than a given parameter value. This parameter is called the stiction band. Mathematically, one writes:

$$v(k) = u(k) \quad if\,|(v(k) - u(k))| > b_{stiction}$$
$$v(k) = u(k-1) \quad if\,|(v(k) - u(k))| \leq b_{stiction} \qquad \text{(Eqn. 3)}$$

with: $b_{stiction}$ stiction band

The second type is valve blocking. In this case, the valve does not move at all for any signal sent to the valve as soon as the fault sets in. Now one writes simply:

$$v(k) = v(k-1) \qquad \text{(Eqn. 4)}$$

The third and fourth types of faults are a bias in the valve position and a bias in the level measurement. Now one writes for the valve bias and sensor bias respectively:

$$v(k) = u(k) + b_u \qquad \text{(Eqn. 5)}$$
$$y_{faulty}(k) = y(k) + b_y \qquad \text{(Eqn. 6)}$$

For the simulation of the system with these faults, one uses equations (1) with equations (4-5) in the case of fault types 1-3 and one replaces y with y_{faulty} as measurements in the case of fault type 4. In the case of valve faults, only the desired valve position, u, is available for inference (v is hidden). For the sensor fault, only y_{faulty} is available (y is hidden). Note that fault types 1, 2 and 4 are characterized by their start time and a magnitude parameter (stiction band or bias). Valve blocking (fault type 3) is only characterized by the start time.

2.3. Kalman-filter based Fault Detection and Diagnosis

A Kalman-filter based technique for Fault Tolerant Control exists and has been shown successful for detection, diagnosis and accommodation of process faults (Prakash *et al.*, 2002). Although the framework is general, the method has been tested particularly for additive linear faults such as the valve and sensor bias in our simulations (fault type 3 and 4). Central to the method is the use of a Kalman filter to generate prediction residuals, i.e., the deviations between actual and predicted measurements. In essence, the fault diagnosis part in this method follows from the (deterministic) simulation of each hypothesized fault after which the fault scenario with the highest likelihood (based on the Kalman-filter) is selected. Several advantages result from the system's linearity and the additive and linear properties of the considered faults. First, the problem of identification of maximum likelihood bias parameters is reduced to a simple linear regression for a given start time of a fault. Also, the likelihood associated with the given fault parameter conditional to the considered time window of observations, follows in one direct step. Therefore, no advanced optimization techniques are necessary and for a given start time of a fault, a unique solution exists.

In the original work, the start time of a fault follows from the fault detection part of the method. The method which is based on a sequential testing is a fast way to obtain a rough estimate of the fault start time. This is not necessary the best to do as the actual fault start time may differ and may affect fault isolation and identification. For this reason, we evaluate a different strategy where every possible (discrete) time within a certain time window before fault confirmation is evaluated as a start time for the fault.

2.4. Extension for valve blocking and valve stiction

The particular problem of detecting and diagnosing valve blocking and valve stiction has not been tackled from the model-based angle described above. Therefore, the 'library' of faults is extended with valve stiction and valve blocking as follows.

Valve stiction and valve blocking are both of a deterministic nature, just like the bias faults. No other parameter than the start time needs to be evaluated for valve blocking. In the case of valve stiction, one needs to estimate the band stiction parameter in addition to the start time. Conditional to a stiction band value and a fault start time, one can evaluate what the true valve position is in a considered time window by applying equations (3) to the series of valve position signals. The expected response of the system is otherwise linear so one can calculate of the likelihood of the observations conditional to the evaluated scenario (stiction time + band parameters) with the Kalman filter.

For band stiction higher than a certain minimal value, the actual simulation will be the same as for a stuck valve. Indeed, if the band stiction is high enough, the valve will not move at all, thus making the two scenarios phenomenologically the same. On the positive side, one can recognize this situation by simply checking whether the valve position changes for the evaluated band stiction value and fault start time during a considered window. The situation that the two faults are not separable is thus detectable.

3. Results

In what follows, simulation results will be shown for faults introduced at sample 76. Figure 1 shows the simulated data for valve stiction. It can be seen that the true valve position fails to follow the demanded valve position. It can also be seen that the valve gets stuck at different positions for periods of time. As a result, control performance degrades as a oscillatory response of the level follows, as is typical for valve stiction problems. Similar oscillations occur in the state estimation errors and the prediction residuals.

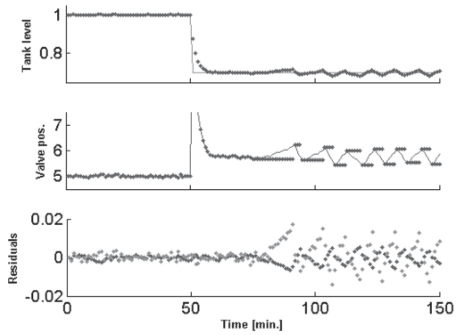


Figure 1: Valve stiction scenario - data. Top: Tank level set-point (─), and measurement y(k) (●). Middle: Valve control signal $u_{signal}(k)$ (─) and position $u_{real}(k)$ (●). Bottom: Kalman estimation and prediction errors ($r_x(k)$ (blue), $r_y(k)$) (red)).

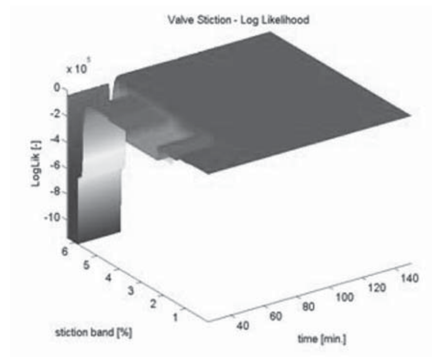
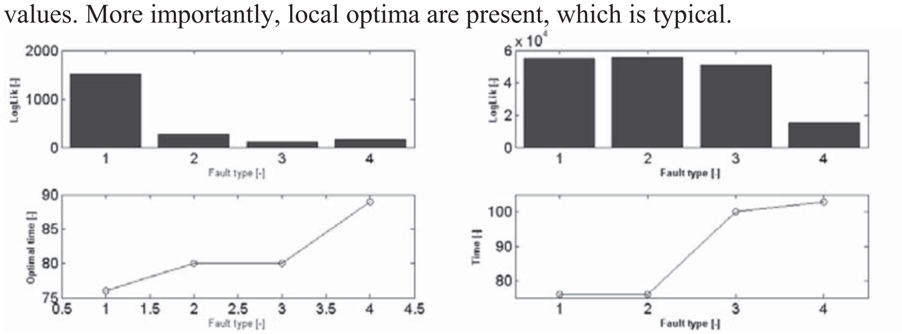


Figure 2: Valve stiction scenario – Log-Likelihood of valve stiction scenario as function of start time and stiction band.

Figure 2 shows the Generalized Likelihood Ratio (GLR) as found for valve stiction, evaluated for a range of band stiction values (resolution 0.01%) and all considered (discrete) fault start times (26 to 150). It can be seen that a large portion of the surface plot is flat, meaning that the likelihood is rather insensitive to the fault parameter values. More importantly, local optima are present, which is typical.



(a) (b)

Figure 3: (a) Valve stiction scenario (b) Valve blocking scenario – fault diagnosis. Maximal Generalized Likelihood Ratio values for all considered fault types and corresponding optimal fault start times.

Figure 3a shows the fault diagnostic results. It is seen that the maximal GLR values are large for any fault. In addition, fault type 1 (valve stiction) delivers the highest GLR value found thus leading to a correct identification of valve stiction as the root cause. It is noted that the optimal fault start time for valve blocking (fault type 2) is relatively close to the one for valve stiction (fault type 1). This suggests that the optimal start time for valve blocking may be a good initial guess to start the optimization for valve stiction.

Next, the valve blocking scenario is evaluated. Here, at sample 76, the valve gets stuck and remains at its position for the remainder of the simulation. This leads to an offset in the tank level and increasing discrepancy between desired valve position and increasing state estimation and prediction residual magnitudes (not shown).

Figure 3b shows the results for the fault diagnosis task in the valve blocking scenario. Also here, the largest GLR is found for the correct fault, namely fault type 2 (valve blocking). In addition, the correct fault start time is found and the optimal start time for valve stiction and blocking are the same. It is noted that the maximal GLR for valve stiction is slightly lower than the one for valve blocking. It is in fact possible to make them equal if one considers scenarios with valve stiction bands so high that the valve doesn't move anymore. Such solutions were automatically discarded. However, valve stiction and blocking remain inseparable without further information. In the discussion section some ideas on how to tackle this issue are provided.

Also valve bias and sensor bias scenarios were investigated. In both cases, state estimation and prediction show performance degradation, the correct fault is found as well as the start time (no results shown). For the sensor bias scenario, the log-likelihood for each fault type is shown as function of time in Figure 4. Plotted values are maximal with respect to other parameters. The most important observation drawn from this graph is that the fault start time is important for correct fault diagnosis. Indeed, at any other time than the correct start time of the fault, fault type 3 (valve bias) would be erroneously preferred over the correct fault type (4, sensor bias). The profiles for fault type 3 and 4 are relatively smooth which may facilitate automated optimization although local optima are present. For presence or evaluation of fault types 1 and 2, the nonlinear estimation problem is more severe.

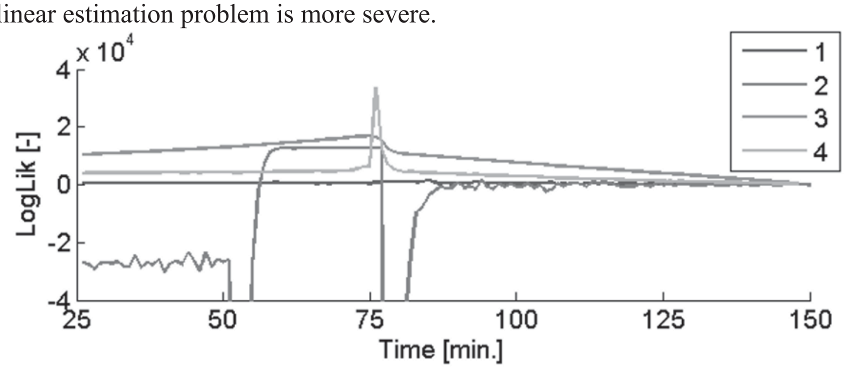


Figure 4: Sensor bias scenario – maximal Log Likelihood as function of time for each fault type (1 to 4).

4. Discussion

In the presented work, a Kalman-based method for fault diagnosis has been evaluated by means of 4 different scenarios with one fault occurrence. Shown results indicate that it is possible to identify the correct faults under certain circumstances. As such, the method is promising for on-line diagnosis of valve-based control loops.

Nevertheless, several remarks are in place with respect to the shown results. First, we have only shown results for fault diagnosis although the original work by the authors provides monitoring as well. In particular, we have assumed that any of the simulated faults is always detected and confirmed at the same, given time instant. This eliminates any effect of fault detection performance on the fault diagnosis performance. However, it may be so that certain fault types are detected faster than others and this may in turn affect the speed of the diagnosis task as well as its accuracy given that the amount of available data may then differ.

For all fault scenarios and all considered faults, the log-likelihood profiles exhibit local optima with respect to time. This is most severe when valve stiction or valve blocking faults are present or evaluated. In our current approach, all possible time instants within a certain window were considered. However, improved optimization strategies for the time parameter may be possible. For one, consider that the optimal start times for valve stiction and blocking were close in both the valve stiction and the valve blocking scenario. Finding the optimal time for either fault may constitute as a fair guess for the other and may therefore reduce computational costs. For valve stiction, the additional band stiction parameter has severe non-linear effects on the likelihood as well. In contrast, for bias faults (valve bias, sensor bias), a unique and global optimum is always found by generalized regression, though conditional to the start time of the fault.

As a last point, consider the problem of separating valve stiction and valve blocking. This is not always possible as a valve stiction scenario with band stiction so high that the valve doesn't move is phenomenologically the same as valve blocking. Additional information is necessary to do so. For this purpose, one may consider to wait for a longer period and collect more data up to a point that valve stiction or valve blocking is ruled out. Such a passive approach to fault diagnosis may be enhanced by modifying the control signal sent to the valve. Srinivasan and Rengaswamy (2008) suggest a two-move strategy by which pulses in the control signal are generated to make the valve move in case of valve stiction. A similar strategy may be taken for diagnostic purposes. Indeed, if valve stiction is present the valve will move if the applied pulse is large enough. If the valve is blocked, it will never move. Such is clearly an active strategy.

5. Conclusion

In this contribution, first results from a study on on-line diagnosis for valve faults are shown and discussed. It is made clear that several faults within a valve-based control loop can be separated under certain conditions. Such faults include valve stiction, valve blocking, valve bias and sensor bias.

Despite the preliminary character of this study, several important remarks were made in view of future research. For example, severe non-linearity of the band stiction estimation problem and of the fault start time was discussed. Further research will therefore be aimed at the search for a better estimation method. In addition, it is worthwhile to further investigate how the separation of valve stiction and valve blocking by means of passive or active collection of informative data can be achieved.

References

Shoukat Choudhury, M.A.A., Thornhill, N.F. and Shah, S.L. (2005). Modelling valve stiction. *Control Eng. Pract.,* **13,** 641–658.

Prakash, J., Patwardhan, S.C. and Narasimhan, S. (2002). A supervisory approach to Fault-Tolerant Control of Linear Multivariable Systems. *Ind. Eng. Chem. Res.,* **41,** 2270–2281.

Srinivasan, R. and Rengaswamy, R. (2008). Approaches for efficient stiction compensation in process control valves. *Comput. Chem. Eng.*, **32,** 218–229.