Comparison of two model based residual generation schemes for the purpose of fault detection and isolation applied to a pneumatic actuation system

This item was submitted to Loughborough University's Institutional Repository by the/an author.


Additional Information:

- This is a conference paper, it was presented at SafeProcess 2009 [© IFAC]. The definitive version is available at: http://www.ifac-papersonline.net/

Metadata Record: https://dspace.lboro.ac.uk/2134/4970

Version: Accepted for publication

Publisher: © IFAC

Please cite the published version.
This item was submitted to Loughborough’s Institutional Repository (https://dspace.lboro.ac.uk/) by the author and is made available under the following Creative Commons Licence conditions.

For the full text of this licence, please go to: http://creativecommons.org/licenses/by-nc-nd/2.5/
Comparison of two model based residual generation schemes for the purpose of fault detection and isolation applied to a pneumatic actuation system


* Control Systems Group, Loughborough University. Loughborough. Leicestershire. UK.
** SEIC, BAE Systems, Holywell Park, Loughborough. Leicestershire. UK.

Abstract: This paper discusses research carried-out on the development and validation (on a real plant) of a parity-equation and Kalman filter based fault detection and isolation (FDI) system for a pneumatic actuator. The parity and Kalman filter equations are formulated and used to generate residuals that, in turn, are analysed to determine whether faults are present in the system. Details of the design process are given and the experimental results are compared. The results demonstrate that both approaches can successfully detect and isolate faults associated with the sensors, actuators (servo-valves and piping) and the pneumatic cylinder itself. The work is part of a BAE SYSTEMS sponsored project to demonstrate advanced control and diagnosis concepts on an industrial application.

Keywords: Fault detection; isolation; residuals; modeling; pneumatic; parity equations; Kalman filter

1. INTRODUCTION

Early detection of developing faults can allow maintenance work to take place before a system malfunctions, possibly causing damage, or complete shutdown of the system/plant. This increases system availability, and potentially reduces costs by eliminating costly repairs resulting from system failures. Designing schemes for the detection and diagnosis of faults is becoming increasingly important in engineering due to the complexity of modern industrial systems and growing demands for quality, cost efficiency, reliability, and more importantly the safety issue (Al-Najjar, 1996). In safety/mission critical applications, fault detection can be combined with reconfiguration (after a fault) to achieve fault tolerant control allowing the system to complete its function in a way that is sub-optimal but does achieve the design objective.

Model-based Fault Detection and Isolation (FDI) uses the principles of analytical redundancy to first detect deviations from normal behaviour in a system, and then to isolate the particular component that has a fault. Typically, model-based analytical estimates are compared with measured variables to generate residuals. The residuals will be zero mean when the system is operating normally and will exceed a threshold when a fault arises. There are a number of approaches to model-based residual generation. For example, observer-based approaches including Kalman Filters (Frank, 1990), parity relations approaches (Gertler and Singer, 1990) and parameter estimation (Patton et al 2000), Isermann, (1997). Useful surveys of these and other useful FDI methods can be found in Patton (1997), Iserman (1984), Willsky (1976), and Venkatasubramaniam et al (2003). However, most of the fault tolerant literature available deals with systems in a purely theoretical way or uses simulations to demonstrate the methods. Although many of the concepts work well in theory it is clear that there have been limited real industrial applications particularly of the more advanced techniques.

Fig. 1. Single pneumatic actuator test-rig

The work described in this paper is part of an on going project which aims to demonstrate FDI as part of a fault tolerant control system on a Stewart-Gough platform comprising six pneumatic actuators. The first phase of the work has focussed on modelling, control and FDI applied to a single actuator (see figure 1).

This paper reports results obtained from the experiment on the rig so that a comparison can be made between the parity equation and Kalman filter approach to FDI. The paper is organised as follows, in section 2 the experimental set-up is described; section 3 summarises the mathematical model of the pneumatic system, which is used as the foundation of the control and FDI design; section 4 describes the FDI approach and how the parity equations and Kalman filter schemes are applied to the pneumatic system; Section 5 presents and discusses the results and compares the two FDI schemes; and, finally, conclusions are drawn and future work is discussed in section 6.

2. EXPERIMENTAL SET-UP

The experimental set-up is illustrated in Figure 2. The diagram shows the xPC Target computer, linked by TCP/IP to a host computer. The host computer controls the experiments and allows recording of the data for offline
Fig. 2. Schematic of experimental set-up

The target provides the real-time control platform and includes Digital to Analogue and Analogue to Digital Converters (DAC/ADC). The control voltage to the valve is provided from the DAC and the ADC allows the sensor signals to be sampled and fed into the control and FDI algorithms. The position signal is measured via a Linear Resistive Transducer (LRT) mounted in the cylinder rear section. The pressure signal is acquired using pressure sensors located between the proportional valve and the cylinder chambers.

3. MODELLING OF PNEUMATIC SYSTEM

One of the main problems in pneumatic actuator position control is the highly non-linear behaviour of the system. This makes it difficult to apply linear controller synthesis methods. Moreover, due to the non-linearity, the parameters of these equations are usually very difficult to identify. However, using an approximation of the model, allows the application of linear controller synthesis methods. (Chillari et al, 2001). Early attempts to analyse pneumatic control systems was reported by Shearer (1956). This was further extended by Burrows (1969), and Scavarda et al (1987). The relationship between the air mass flow and the pressure changes in the chambers is obtained using energy conservation laws (first law of thermodynamics), and the force equilibrium is given by Newton’s second law. The pneumatic system can be modelled by the following equations, see for example Grewal et al (2008).

\[ p_v = -\frac{\gamma A P_{v} x}{V_{v}} \dot{x} + K \frac{\gamma RT_{v}}{V_{v}} \]  

(1)

\[ p_v = \frac{\gamma A P_{v} x}{V_{v}} \dot{x} - K \frac{\gamma RT_{v}}{V_{v}} \]  

(2)

\[ \ddot{x} = \frac{A}{M} (p_v - P_m) - \frac{F}{M} \Delta \dot{x} \]  

(3)

Where \( M \) is the piston mass, \( A \) is the bore area, \( P_v \) is the pressure in chamber \( v \), \( P_m \) is the pressure in chamber \( m \), \( V_v \) is the air volume in chamber \( v \), \( V_m \) is the air volume in chamber \( n \), \( \gamma \) is the ratio of specific heat, \( R \) is the universal gas constant, \( T_v \) is the operating temperature, \( \dot{m}_p \) is the mass flow rate into chamber \( p \), and \( \dot{m}_n \) is the mass flow rate into chamber \( n \). \( x \) is the position of the piston, \( F_p \) represents the viscous friction coefficient and coulomb friction force. \( K \) is the servo valve constant.

Fig. 3. Conceptual structure of FDI scheme

4. PNEUMATIC SYSTEM CONTROL

This paper is not concerned with control of the actuator so full details are not given. However, the controller is based on the model described in section 3 using classical frequency domain design.

The control objectives of the pneumatic system are:

- Settling time is less then 0.4 sec.
- Maximum 10% overshoot.
- Maximum 3% steady state error.
- Gain margin 6dB.
- Phase margin 60 degrees

All the requirements above are satisfied using the following PI controller

\[ C(s) = \frac{0.12s + 0.1}{s} \]  

(4)

5. DESIGN OF THE FDI SCHEME

5.1. FDI Approach

Figure 3 shows the generic structure of the model-based fault detection scheme. The method consists of detecting faults on the process, which includes actuators, components and sensors, based on measuring the input signal \( U(t) \) and the output signal \( Y(t) \). The detection method uses models to generate residuals \( R(t) \). The residual evaluation examines the residuals for the likelihood of faults and a decision rule is applied to determine if faults have occurred. Referring to the pneumatic system depicted in Figure 2 (and with reference to Figure 3) the proportional valve would be described as the actuator and the pneumatic cylinder would be described as the plant. The sensors are self-evident. In this paper the process model can be based on either parity equations or Kalman filters. Both are discussed below.

5.2. The Parity Equation Method

The parity equation method was first proposed by Chow and Willsky, (1984) using the redundancy relations of the dynamic system. The basic idea is to provide a proper check of the parity (consistency) of the measurements for the monitored system. Parity equations are rearranged and usually transformed variants of the input-output or space-state models of the system (Venkatasubramaniam et al 2003). In effect this means making use of known mathematical models that describe the relationships between system variables. In theory, under normal operating conditions, the
residual or value of the parity equations is zero. However, in real situations, the residuals will be nonzero. This is due to measurement and process noise, model inaccuracies and faults in sensors, actuators and plant(s). The idea of the parity approach is to rearrange the model structure to achieve the best fault isolation (i.e. so that the effect of faults is far greater than that of the other uncertainties). The residual generator scheme used hereafter is based on a model-based methodology using the parity space approach. The desired properties for the residual signal are $r(t) \neq 0$ if $f(t) \neq 0$. Where $r$ is the residual and $f$ is the fault. The residual is generated based on the information provided by the system input and output signals and the plant equation. Figure 4 shows the pneumatic control loop scheme, which contains the following elements: The controller $C(s)$, the proportional valve $GA(s)$, the pneumatic actuator $GP(s)$, and the sensor $GS(s)$. The proportional valve fault $Fa(s)$ and the sensor fault $FS(s)$ can have dynamics, which are modelled by the transfer functions $Ha(s)$, and $HS(s)$. In addition to the position (feedback) sensor, pressure sensors are included in the system to read pressure from each chamber of the actuator. These are not included in the closed loop system, and are shown as $Pp(s)$ and $Pn(s)$ respectively. With the pressure sensor faults, shown as $FPp(s)$ and $FPn(s)$, again having dynamics modelled by the transfer functions $HPp(s)$ and $HPn(s)$. Using the description of the system shown in Figure 4 the following relationships (equations) can be derived.

\[ \begin{align*}
XS(s) &= [GS(s)+HS(s)FS(s)][GA(s)U(s) GP(s)+Ha(s)Fa(s)] \\
PP_{act} &= [U(s)GA(s)+Ha(s)Fa(s)][Pn(s)+HPn(s)FPn(s)] \\
PP_{act} &= [U(s)GA(s)+Ha(s)Fa(s)][Pp(s)+HPp(s)FPp(s)] \\
U(s) &= C(s)(V(s)-XS(s))
\end{align*} \tag{5} \tag{6} \tag{7} \tag{8} \tag{9} \tag{10} \tag{11}
\]

With the current experimental set-up the pneumatic plant output can only be measured with the position sensor. Therefore the sensor and plant faults cannot be isolated. Residuals are formulated from equations (5) to (7) as follows,

\[ \begin{align*}
R_1 &= XS(s)-GS(s)GP(s)GA(s)U(s)+HS(s)FS(s)+Ha(s)Fa(s) \\
R_2 &= PP_{act} - U(s)GA(s)Pn(s)+Ha(s)Fa(s)+HPn(s)FPn(s) \\
R_3 &= PP_{act} - U(s)GA(s)Pp(s)+Ha(s)Fa(s)+HPp(s)FPp(s)
\end{align*} \tag{12} \tag{13} \tag{14} \tag{15}
\]

To represent the pneumatic process shown in Figure 4, $GA(s)$ is modelled by the equations (1), (2) and $GP(s)$ by equation

\[ \begin{align*}
\hat{x} &= AX + Bu + Gw \quad \text{(State equations)} \\
y &= Cx + Du + Hw + v \quad \text{(Measurement equation)}
\end{align*} \tag{16}
\]

An optimal estimate of $y'$, $\hat{y}$ can be provided by the Kalman filter equations:

\[ \hat{x} = A\hat{x} + Bu + L(y - C\hat{x} - Du) \tag{17} \]

\[ \hat{y} = C\hat{x} + Du \tag{18} \]

Where in practice the weightings for process and measurement noise (Q and R respectively) are chosen heuristically using engineering judgement to provide a trade-off between sensitivity to faults, and the likelihood of false alarms. The Kalman filter gain $L$ is determined by solving an algebraic Riccati equation. This estimator uses the known inputs $u$ and the measurement $y$ to generate the output and state estimates $\hat{y}$ and $\hat{x}$. The Kalman estimator is depicted in Figure 5. Using Equations (1)-(3) the pneumatic system can be represented in state space form. The equations have been manipulated to ensure observability of all states. Equation 16 shows the state space representation.
Table 1. Fault signatures for the various faults

<table>
<thead>
<tr>
<th>Residuals</th>
<th>Actuator</th>
<th>Plant</th>
<th>Position sensor</th>
<th>Pressure sensor</th>
</tr>
</thead>
<tbody>
<tr>
<td>R₁</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>R₂</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>R₃</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>R₄</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

5.4. Residual Evaluation and Thresholds

The purpose of residual evaluation is to generate a fault decision by processing the residuals. A fault decision is the result of all the tasks fault detection, isolation, and identification (Kiencke and Nielsen, 2005). Residual evaluation is essentially to check if the residual is responding to a fault. The residual evaluation can in its simplest form be a thresholding of the residual, i.e. a fault is assumed present if \( |R_{ij}(t)| > J(t) \) where \( J(t) \) is the threshold, or moving averages of the residuals. Another method may consist of statistical sequential probability ratio testing (Patton et al., 2000). In the present case the residuals are processed to acquire the root mean square (RMS) of the value over a moving window of \( N \) samples (Dixon, 2004) as shown:

\[
R_{\text{RMS}}(k) = \sqrt{\frac{1}{N} \sum_{i=1}^{N} R_{ij}^2} \quad i, j = 1, 2, 3, 4, 5
\]

Where \( R_{ij}(k) \) is the value of the residual at the \( k\)th sample. Subsequently, the residual RMS value is compared with a predetermined fault detection threshold. Table 1 shows the fault signatures using the parity equations and Kalman filter approaches of the pneumatic system for various faults. These signatures arise from the formulation of parity equations and the structure of the observer scheme. Where the parity equations residuals \( (R_1, R_2 \text{ and } R_3) \), are given in equations (9), (10) and (11). The Kalman filter residuals \( (R_4 \text{ and } R_5) \) are given by equations (16), (17) and (18).

6. EXPERIMENTAL RESULTS

In order to demonstrate and compare the FDI scheme using parity equations and Kalman filter approaches a number of experiments were carried out on the pneumatic system. The faults presented are actuator and position sensor faults. The demand input to the system is a square wave input with amplitude of 20mm at a frequency 0.2 Hertz. The starting point of the piston is at mid position (50mm).

6.1. Actuator fault

A fault \( Fa(s) \) (see Fig.4) is applied to the proportional valve. The fault injected is that the control signal has been disconnected. This is physically achieved by means of a switch. Figure 7 shows the time history of this experiment (actuator fault) for the parity equation scheme. Figure 8 shows the time history of this experiment (actuator fault) for the Kalman filter scheme.

![Fig. 6. Overview of the Kalman filter scheme](image)

![Fig. 7. Actuator fault Fa(s) parity equation results- actual plant output-position sensor (top), Pressure sensor Pn (middle), Pressure sensor Pp (lower).](image)
Fig. 8. Actuator fault, Kalman filter results- actual plant output-position sensor (top), pressure difference outputs (lower)

6.1.1. Parity equations - Actuator fault

From Figure 7, at approximately 17.5s the fault is applied. From residual $R_1$ the fault is detected within 0.5ms and the fault flag is raised within 1ms and remains raised until the fault is removed from the system at 35s. At 21.5s the residual RMS value falls below the threshold, this is due to the position output coinciding with the model output. This trend is apparent throughout the fault period. At 37.5s the fault flag returns to the false state when the RMS value falls below the threshold. Residual $R_2$ exceeds its respective threshold at 25s. The fault flag is raised for approximately 1s then returns to a false state. This is due to the residual falling below the threshold. The fault flag returns to a false state within 1s when the fault is removed. Residual $R_2$ exceeds its respective threshold at 20s. The fault flag is raised for approximately 1s then returns to a false state. This is due to the residual falling below the threshold. When the fault is removed the fault flag returns to a false state at 37s.

6.1.2. Kalman filter - Actuator fault

Applying the same fault scenario as above, Figure 8 illustrates the outputs for the Kalman filter approach. From residual $R_1$ the fault is detected within 0.5ms and the fault flag is raised within 1ms and remains raised until the fault is removed from the system and subsequently; at 35s the fault is removed. At 36s the fault flag returns to the false state when the RMS value falls below the threshold. The pressure difference residual ($R_2$) crosses its respective threshold at 17.5s. Where the fault flag is raised within 0.5ms of the residual crossing its respective threshold, and remains raised until the fault is removed. When the fault is removed the fault flag returns to a false state within 0.5ms of the residual falling below its respective threshold.

6.1.3. Discussion - Actuator fault

Applying the disconnection fault to the control signal of the proportional valve has an effect on the actuator fault parity residual ($R_1$), this raises the fault flag. The fault has an effect on the pressure sensor parity residuals ($R_2$ and $R_3$). Both position and pressure difference Kalman residuals ($R_2$ and $R_3$) are affected by the actuator fault and their fault flags are raised. From both methods the Kalman approach tracks the fault better with a faster fault detection response time. Overall, it is clear that the parity equations and the Kalman filter approach can detect an actuator fault. However, using both methods an actuator or plant fault cannot be isolated. This agrees with the fault signatures detailed in Table 1. It should be noted that the Kalman filter residuals are less intermittent during the fault periods (i.e. the fault flags are not resetting until the fault is passed). However, adaptive thresholds could overcome this for the parity approach.

6.2. Position sensor faults

Fig. 9, Position sensor faults, parity equation results- actual plant output-position sensor (top), Pressure sensor Pn (middle), Pressure sensor Pp (lower)

Harsh working conditions along with the gradual build up of dirt on the sensor and faulty circuitry can cause the effect of position sensor drift. Figure 9 shows the time history for the parity equation scheme. Figure 10 shows the time history of these experiments for the Kalman filter scheme.

6.2.1. Parity equations – Sensor drift fault

From Figure 9 at 17s a drift bias is added to the position signal. Although sensor drift can be a slow process i.e. possibly over a period of hours, for this work adding a drift bias within a period of approximately 9s has accelerated the effect of sensor drift. This is so the fault can be detected and isolated without running the experiment for long periods. From the RMS residual $R_1$ the drift fault is detected at 17.5s and the fault flag is raised within 0.6ms. The RMS residuals $R_2$ and $R_3$ do not activate/cross their respective thresholds.
the relative simplicity of the layout and application of the model equations. Suggested future work will be focussed on applying other types of faults, which can include blocked pipes between proportional valve and pneumatic cylinder, and leaking pressure pipes. Beyond this the work will be extended for a full Stewart platform.

REFERENCES


