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

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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.

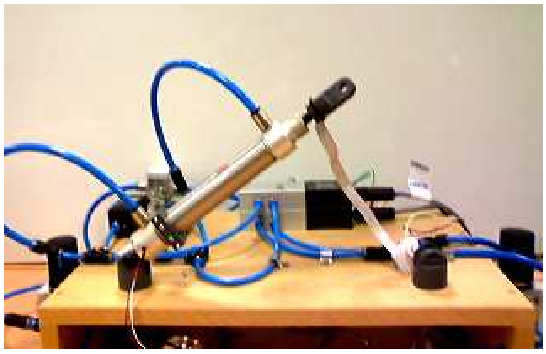

Fig. 1. Single pneumatic actuator test-rig

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

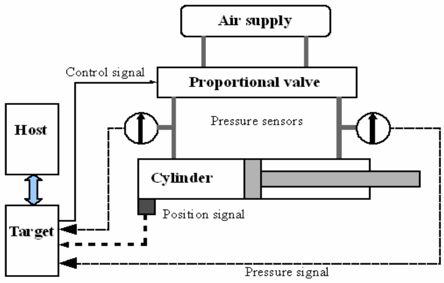

Fig. 2. Schematic of experimental set-up

analysis and plotting of results. Whereas 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 PNUEMATIC 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).

$$\dot{P}_p = -\frac{\gamma A P_p}{V_{p0}}\dot{x} + K\frac{\gamma R T_s}{V_p}v \qquad (1)$$

$$\dot{P}_n = \frac{\gamma A P_n}{V_n}\dot{x} - K\frac{\gamma R T_s}{V_n}v \qquad (2)$$

$$\ddot{x} = \frac{A}{M}(P_p - P_n) - \frac{F_f}{M}\Delta\dot{x} \qquad (3)$$

Where M is the piston mass, A is the bore area, P_p is the pressure in chamber p, P_n is the pressure in chamber n, V_p is the air volume in chamber p, V_n is the air volume in chamber in n, γ is the ratio of specific heat, R is the universal gas constant, T_s 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_f represents the viscous friction coefficient and coulomb friction force. K is the servo valve constant.

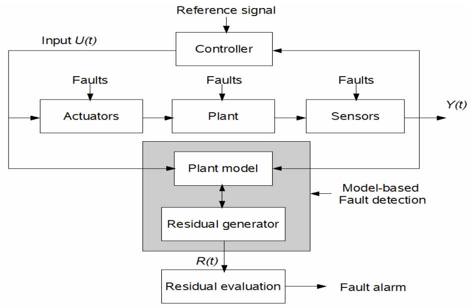

Fig. 3. Conceptual structure of FDI scheme

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

$$C(s) = \frac{0.12s + 0.1}{s} \qquad (4)$$

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 likehood 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

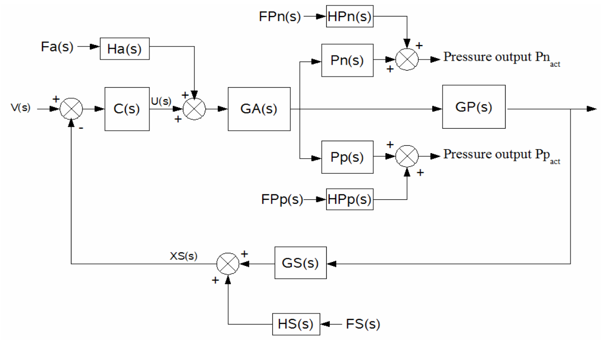

Fig. 4. Pneumatic closed loop scheme with intended faults

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.

$$XS(s)=[GS(s)+HS(s)FS(s)][GA(s)U(s)\ GP(s)+Ha(s)Fa(s)] \quad (5)$$

$$Pn_{act}=[U(s)GA(s)+Ha(s)Fa(s)][Pn(s)+HPn(s)FPn(s)] \quad (6)$$

$$Pp_{act}=[U(s)GA(s)+Ha(s)Fa(s)][Pp(s)+HPp(s)FPp(s)] \quad (7)$$

$$U(s)=C(s)(V(s)-XS(s)) \quad (8)$$

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,

$$R_1=XS(s)-GS(s)GP(s)GA(s)U(s)=HS(s)FS(s)+Ha(s)Fa(s) \quad (9)$$

$$R_2= Pn_{act} - U(s)GA(s)Pn(s)=Ha(s)Fa(s)+HPn(s)FPn(s) \quad (10)$$

$$R_3= Pp_{act} -U(s)GA(s)Pp(s)=Ha(s)Fa(s)+HPp(s)FPp(s) \quad (11)$$

To represent the pneumatic process shown in Figure 4, *GA(s)* is modelled by the equations (1), (2) and *GP(s)* by equation (3). It is assumed that the fault and sensor transfer functions are all instantaneous i.e. *Ha(s)*, *HS(s), HPn(s)*, *HPp(s), Pn(s), Pp(s)* and *GS(s)* =1.

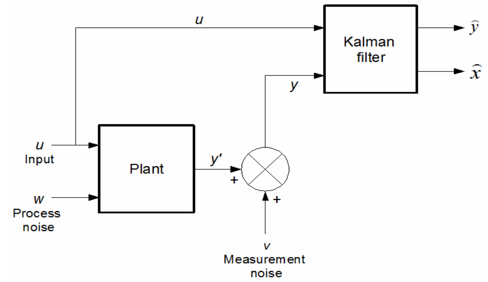

Figure 5: Schematic of the Kalman filter estimator

5.3. Dedicated observer approach (Kalman filter)

Many authors have approached the FDI problem by directly starting with a single or banks of observers see for example Frank and Ding (1997). The basic idea of the observer approach is to reconstruct the outputs of the system from the measurements or subsets of measurements with the aid of observers or Kalman filters using the estimation error or innovation (Frank, 1990). This estimation error or innovation is used as a residual for the detection and isolation of faults. Primarily, the Kalman filter is not used to obtain an estimate of the states but is implemented to generate residuals which are sensitive to faults. Kalman filters are used for the stochastic case, as noise has to be considered See e.g. Kalman, (1960) for more details. In general, A Kalman filter incorporates all information that can be provided to it. It processes all available measurements regardless of their precision, to estimate the current value of the variable of interest. Given a system:

$$\dot{x} = Ax + Bu + Gw \quad \text{(State equations)} \quad (12)$$

$$y = Cx + Du + Hw + v \quad \text{(Measurement equation)} \quad (13)$$

where u is the input, w is the process noise, v is the measurement white noise with $E(ww^T)=Q$, and $E(vv^T)=R$. It is also assumed that the state and measurement noise is uncorrelated, that is, $E(wv^T)= 0$.

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

$$\dot{\hat{x}} = A\hat{x} + Bu + L(y - C\hat{x} - Du) \quad (14)$$

and

$$\hat{y} = C\hat{x} + Du \quad (15)$$

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.

$$\dot{X}\begin{bmatrix}\dot{P}_d\\ \dot{x}\\ \ddot{x}\end{bmatrix} = \begin{bmatrix}0 & 0 & a-b\\ 0 & 0 & 1\\ \frac{A}{M} & 0 & -\frac{F_f}{M}\end{bmatrix}\begin{bmatrix}P_d\\ x\\ \dot{x}\end{bmatrix} + \begin{bmatrix}c-d\\ 0\\ 0\end{bmatrix}$$

$$y_{pos} = \begin{bmatrix}0 & 1 & 0\end{bmatrix}\begin{bmatrix}P_d\\ x\\ \dot{x}\end{bmatrix}$$

$$y_{P_d} = \begin{bmatrix}1 & 0 & 0\end{bmatrix}\begin{bmatrix}P_d\\ x\\ \dot{x}\end{bmatrix} \qquad (16)$$

Where:

$$P_d = P_p - P_n,\ a = -\frac{\gamma A P_p}{V_p},\ b = \frac{\gamma A P_n}{V_n},\ c = K\frac{\gamma R T_s}{V_p},\ d = -K\frac{\gamma R T_s}{V_n}$$

In designing the Kalman filter approach only the sensed outputs are considered. These are position and pressure difference outputs. Figure 6 illustrates the Kalman filter set up; where the residuals (R_4 and R_5) are given by the two separate Kalman filters. The residual equations are:

$$R_4 = y_{pos} - C_{pos}\hat{x}_1 \qquad (17)$$

$$R_5 = y_{P_d} - C_{P_d}\hat{x}_2 \qquad (18)$$

Where

$$C_{pos} = \begin{bmatrix}0 & 1 & 0\end{bmatrix},\ C_{P_d} = \begin{bmatrix}1 & 0 & 0\end{bmatrix}$$

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 $|R_i(t)| > J_i(t)$ 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:

$$R_{i\,RMS}(k) = \sqrt{\frac{\sum_{j=k-N}^{k} R_{ij}^{2}}{N}} \qquad i = 1,2,3,4,5 \qquad (19)$$

Where $R_i(k)$ 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 and R_3), are given in equations (9), (10) and (11). The Kalman filter residuals (R_4 and R_5) are given by equations (16), (17) and (18).

Table 1. Fault signatures for the various faults

Residuals	Faults			
	Actuator	Plant	Position sensor	Pressure sensor
R_1	1	1	1	0
R_2	1	1	0	1
R_3	1	1	0	1
R_4	1	1	1	0
R_5	1	1	0	1

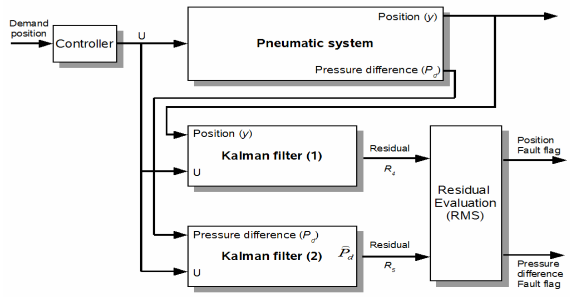

Figure 6. Overview of the Kalman filter scheme

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.

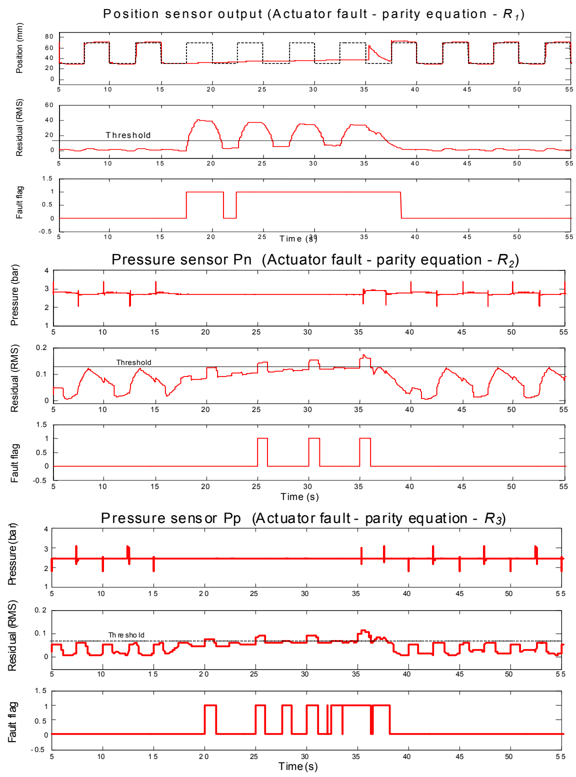

Fig. 7. Actuator fault Fa (s) parity equation results- actual plant output-position sensor (top), Pressure sensor Pn (middle), Pressure sensor Pp (lower).

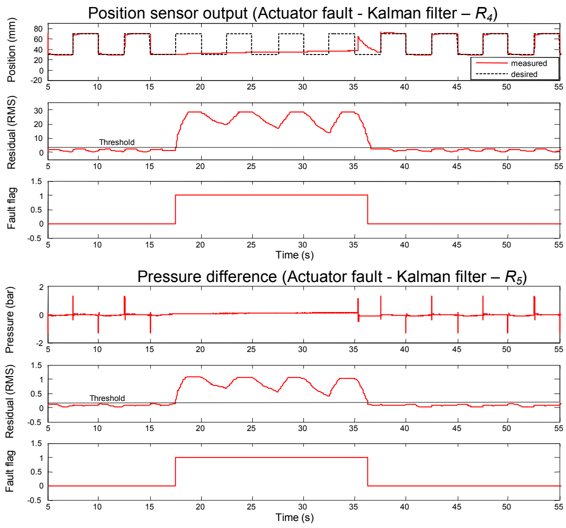

Fig. 8. Actuator fault, Kalman filter results- actual plant output-position sensor (top), pressure difference outputs (lower)

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 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_3 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_4 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_5) exceeds 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 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 affect 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

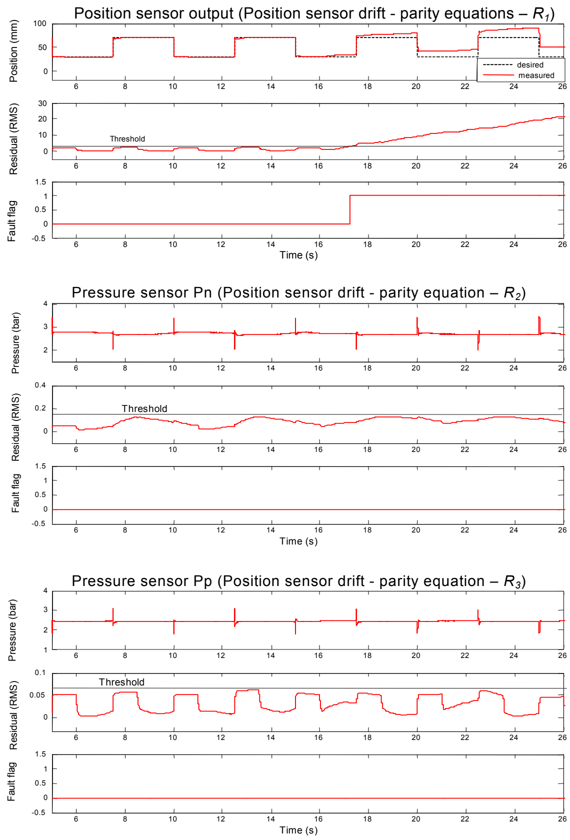

Fig. 9. Position sensor faults, parity equation results- actual plant output-position sensor (top), Pressure sensor Pn (middle), Pressure sensor Pp (lower)

position and pressure difference Kalman residuals (R_4 and R_5) 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

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.

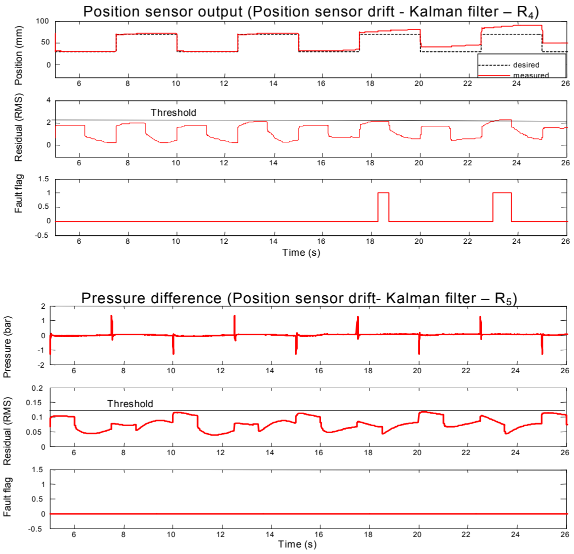

Figure 10. Position sensor drift fault, Kalman filter results - actual position sensor (top), Pressure difference outputs (lower)

6.2.2. Kalman filter - Sensor drift fault

From Figure 10 the same drift fault has been applied. Using the Kalman filter scheme, the RMS residual R_4 exceeds its threshold at 18.2s and the fault is raised within 0.5ms. The fault flag is raised for approximately 0.5s then returns to a false state. This is due to the residual R_4 falling below the threshold. Residual R_5 does not activate/cross its respective threshold and the fault flag remains false.

6.2.3. Discussion - Sensor drift fault

Applying the drift bias to the position sensor has an effect on the plant parity residual (R_1), this raises the fault flag. The fault has no affect on the pressure sensor parity residuals (R_2 and (R_3). The fault affects the position RMS residual R_4 and there is no affect on the pressure difference RMS residual R_5. Comparing RMS residuals R_1 and R_4 (position outputs) The Parity equation approach when compared with the Kalman filter scheme has a faster fault detection response time. Again indicating the faults can be isolated. These results concur with the fault signatures detailed in Table 1.

7. CONCLUSIONS

In this paper studies conducted for fault detection in a closed loop system for an industrial application have been described. Parity equations and the Kalman filter approach have been used to generate residuals for the purpose of fault detection. Disconnection and drift faults have been considered and applied to the pneumatic system. A comparison was made between the two methods. The output results show that using the described parity equation and Kalman filter methods; fault detection was possible from the available measurements. However, certain faults were only detected and not isolated when using the residual generator methods. From the experimental results it is shown that system level knowledge has been developed and used to check plant and sensors for problems, to detect and identify faults as they develop. An important reason for selecting the parity equation and Kalman filter residual generation methods was 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

Al-Najjar, B. (1996). Total quality maintenance: An approach for continuous reduction in costs of quality products. *Journal of Quality in Maintenance Engineering*, **2**, pp. 2-20.

Burrows, C. R. (1969). Non-linear pneumatic servomechanism. PhD Thesis, University of London, UK.

Chillari, S., Guccione, S., and Muscato, G. (2001). An experimental comparison between several pneumatic position control methods. *Proceedings of the 40th IEEE conference on Decision and Control.* Florida, USA, pp. 1168- 1173.

Chow, E. Y., and Willsky, A.S (1984). Analytical redundancy and design of robust failure detection systems. *IEEE Trans. on Aut. Control* **29** (7), 603-614.

Dixon, R (2004). Observer-based FDIA: application to an electromechanical positioning system. *Control Engineering Practice* 12, pp. 1113-1125.

Frank, P. M. (1990). Fault diagnosis in dynamic systems using analytical and knowledge-based redundancy: A survey and some new results. *Automatica*, **26,** pp. 459-474.

Frank, P.M., and Ding, X. (1997). Survey of robust residual generation and evaluation methods in observer-based fault detection systems. *J. Proc. Cont.* **7**, (6), pp. 403-424.

Gertler, J., and Singer, D (1990). A new structural framework for parity equation based failure detection and isolation. *Automatica*, **26**, pp. 381-388.

Grewal, K. S., Dixon, R., and Pearson. J. (2008). Development of a fault tolerant actuation system- modelling and validation. *Actuator 08, 11th international conference on new actuators,* pp, 469-472.

Isermann, R. (1984). Process fault detection based on modelling and estimation methods- A survey. *Automatica*, **20**, pp. 387-404.

Isermann, R. (1997). Supervision, Fault-Detection and Fault Diagnosis methods- An Introduction, *Control Engineering Practice*, **5**, (5), pp. 639-652.

Kalman, R. E. (1960). Anew approach to linear filtering and prediction problems. *ASME Transactions on Journal of Basic Engineering.* 82-D, 35-45.

Kiencke, U., and Nielsen, L (2005). *Automotive Control Systems: For Engine, Driveline, and Vehicle*. Springer. USA.

Patton, R.J (1997). Fault-tolerant control: The 1997 situation. *Proceedings of the third symposium on fault detection, supervision and safety for technical processes (SAFEPROCESS'97)*. **3,** pp, 1029-1052.

Patton, R.J., Frank, P.M., and Clark, R.N. (2000). *Issues in fault diagnosis of dynamic systems.* Springer Verlag. London

Scavarda, S., Kellal, A., and Richard, E. (1987). Linearized models for electropneumatic cylinder servo valve system. *Proceedings of the 3rd International conference on Advanced Robotics.* France. pp. 149-160.

Shearer, J. L. (1956). Study of pneumatic processes in he continuous control of motion with compressed air I and II, *Tran. AMSE,* pp. 233-249.

Venkatasubramanian, V., Rengaswamy, R., Yin, K., and Kavuri, S.N. (2003). A review of process fault detection and diagnosis. Part I: Quantitative model-based methods. *Computers and Chemical Engineering*, **27**, pp. 293-311.

Willsky, A. S. (1976). A survey of design methods for failure detection in dynamic systems. *Automatica,* 12, 601-611.