INTELLIGENT FAULT DIAGNOSIS USING SENSOR NETWORK

Haris M. Khalid, Rajamani Doraiswami[1]
Systems Engg. Department,King Fahd University of Petroleum and Minerals, Dhahran 31261, KSA
[1]Department of Electrical and Computer Engineering, University of New Brunswick, Fredericton, New Brunswick, Canada
g200702310@kfupm.edu.sa, dorai@unb.ca

Lahouari Cheded
Systems Engg. Department,King Fahd University of Petroleum and Minerals, Dhahran 31261, KSA
cheded@kfupm.edu.sa

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Abstract: An intelligent diagnostic scheme using sensor network for incipient faults is proposed using a holistic approach which integrates model-, fuzzy logic-, neural network- based schemes. In case the system is highly non-linear and there are enough training data available, a neural network based scheme is preferred; where the rules relating the input and output can be derived, a Fuzzy-logic approach is chosen; and where a model is available, a linearized model is employed. These three schemes are integrated sequentially ensuring thereby that critical information about the presence or absence of a fault is monitored in the shortest possible time, and the complete status regarding the fault is unfolded in time. The proposed scheme is evaluated extensively on simulated examples and on a physical system exemplified by a benchmarked laboratory-scale two-tank system to detect and isolate faults including sensor, actuator and leakage ones.

1 INTRODUCTION

Fault is an undesirable factor in any process control industry. It affects the efficiency of system operation and reduces economic benefit to the industry. The early detection and diagnosis of faults in mission critical systems becomes highly crucial for preventing failure of equipment, loss of productivity and profits, management of assets, reduction of shutdowns, condition-based monitoring, product quality, process reliability, economy, potential hazards, pollution, and conservation of scarce resources. In a chemical industry, the release of hazardous chemicals into the environment requires quick action to limit the harmful impact of such a release. Of much concern is the purposeful release of chemicals in order to cause harm. Quickly detecting and identifying an unknown threat caused by a fault is pivotal to limiting harm and possibly saving lives. Because of the large area covered in either a process control industry or water distribution systems, a single technique is not able to monitor all of the activity in the area of concern. For this reason, a precise pool of intelligent approaches is being developed to create a better response plan. There must be a way to process and clearly present an accurate picture of the fault threat. Information about the constraints associated with an early detection of hazardous material in the environment help shape the proposed methodology, and is one of the main motivations for embedding intelligent tools in diagnosis and decision making (R.J. Patton, 2000).

The purpose of this paper is to present and advance a new methodology for the intelligent detection of incipient faults. New methods of assimilating information from highly complex and nonlinear physical systems with various nonlinearities are being developed. Intelligent tools that have the ability to adapt, such as neural networks and fuzzy inference systems, are brought to bear on both of these aims. Data from a benchmarked laboratory-scale two-tank system is used and the proposed approach evaluated.

The faults include sensor, actuator and leakage faults, and they can be classified broadly as either parametric faults or additive ones. An additive fault manifests itself as an additive exogenous signal in the measured data, while a parametric fault induces a variation in the system parameters.

The fault diagnosis scheme can be carried out using a neural network, or fuzzy logic or a model-based technique (L. B. Palma, 2003). While neutral networks can be used to quickly and correctly classify a particular fault, they cannot unravel it and point out its root causes. However, these root causes can be uncovered by supplementing the neural network used by a fuzzy logic scheme, which through the very makeup of its rules, will accurately , albeit more slowly than the neural network, pinpoint the cause(s) that spawned this fault. The synergistic value of this integration will no doubt provide a powerful fault detection scheme. The neural net and fuzzy logic approaches are not geared for the diagnosis of incipient faults, hence the need for, and the inclusion of, a model-based scheme.

2 A SENSOR NETWORK PARADIGM FOR FAULT DIAGNOSIS

A new scheme is proposed here whereby a sensor network paradigm is applied to fault diagnosis. A typical system including a process control system, a water distribution system formed of tanks and network of pipes, a power utility formed of generators and transmission lines, a communication network, and petrochemical industries consisting of a number of control loops, including controllers, sensors and actuators, and various processing plants, as shown in Fig. 1. As such, such a large system will include a sensor network.

A sensor is modelled by a gain and an additive noise, as given below:

$$y_i = k_{si} y_i^0 + v_i \tag{1}$$

where y_{si}, y_{si}^0 and v_i are the measured sensor output, true or fault-free output and additive noise, respectively. Here the gain is such that $0 \le k_{si} \le 1$, with the degree of the fault ranging from no fault at all for $k_{si} = 1$ to a complete failure for $k_{si} = 0$. The subsystems such as actuators, processors and controllers are denoted by transfer functions, G_i. Many systems consisting of several closed loops, each with its own reference input, can be viewed as a sensor network that can be described by a ring-type topology.

The objective of the sensor network is to diagnose faults in both the sensors, through the gains k_{si} and in the subsystems G_i by monitoring the sensor outputs y_i.

The mathematical relations governing the sensor outputs y_i to the input to G_0, denoted by e are:

$$\begin{aligned} y_1 &= G_0 k_{s0} e + v_0 \\ y_2 &= G_0 G_1 k_{s1} e + v_1 \\ y_3 &= G_0 G_1 G_2 k_{s2} e + v_2 \\ &\;\;. \\ &\;\;. \\ y_i &= G_0 G_1 G_2 \ldots G_{i-1} k_{s(i-1)} e + v_{i-1} \end{aligned} \tag{2}$$

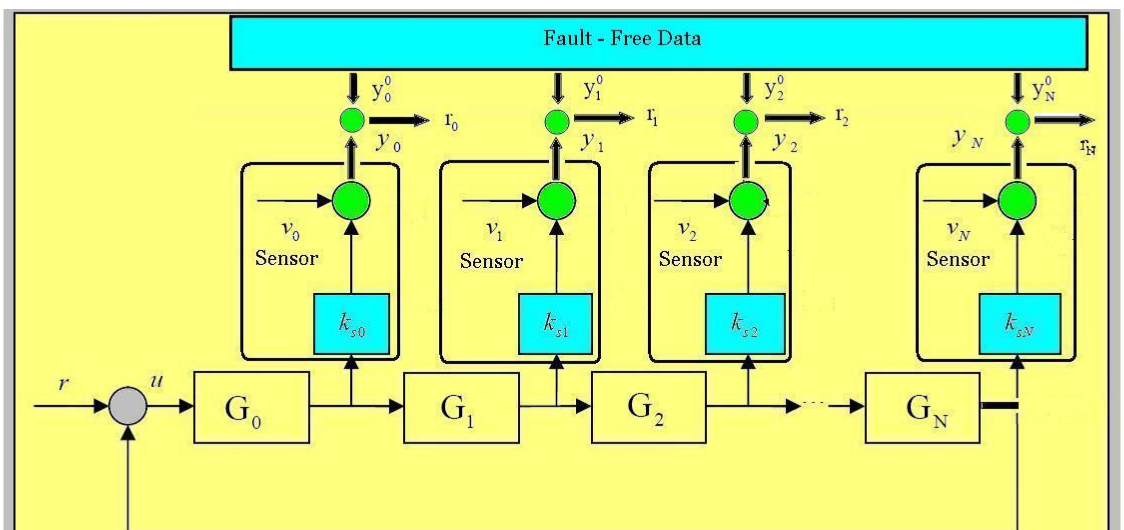

Fig. 1 Sensor Network

where $e = r - y$.

3 FUZZY LOGIC-BASED FAULT DIAGNOSIS

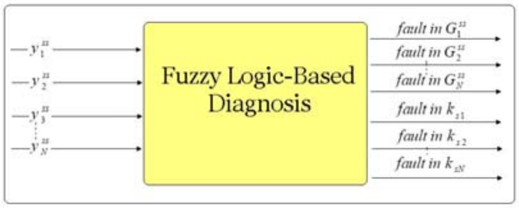

Fig. 2 Fuzzy Logic-Based Fault Diagnosis Scheme

The fuzzy fault diagnosis scheme uses the steady-state values of the sensor outputs, y_i, denoted by y_i^{ss}. A change in the gain k_{si} or a change in the steady-state gain of the transfer function G_i, denoted by G_i^{ss}, is indicative of a fault in the i-th sensor and i-th subsystem, respectively (see Fig.2). Assuming that the noise term is subsumed in the fuzzy membership function, the steady-state model takes the form:

$$y_i^{ss} = G_0^{ss} G_1^{ss} G_2^{ss} ... G_{i-1}^{ss} k_{s(i-1)} e \quad (3)$$

Let us now define linguistic variables such as *zero*, and *non-zero*. For simplicity, we will consider the case where only one device can be faulty at any given time, i.e. the fault is assumed to be simple. In this case, the fuzzy rules may take the following form:

Rule 1: If y_i^{ss} is non-zero, then there is a fault in the steady-state gain G_0^{ss} or G_1^{ss} or G_2^{ss} or…or G_i^{ss} or ith sensor gain k_{si}

Rule II: If y_i^{ss} is zero, then there is no fault in the subsystem's steady-state gain G_0^{ss} or G_1^{ss} or G_2^{ss} or…or G_i^{ss} or ith sensor gain k_{si}

Rule III: If y_i^{ss} is zero and $y_{s(i+1)}$ is non-zero then there is a fault in subsystem G_{i+1}^{ss} or sensor $k_{s(i+1)}$

Rule IV: If y_i^{ss} is non-zero and $y_{s(i+1)}$ is zero then there is a fault in sensor k_{si}

These rules may be generalized to multiple faults.

4 NEURAL NETWORK-BASED FAULT DIAGNOSIS

A fault in the sensor, k_{si}, and or in a subsystem, G_i, can also be diagnosed by using a neural network, as shown in Fig.3. The inputs to the neural network are the spectrum of the coherence between the fault-free and measured sensor outputs.

$$c\left(y_i^0(j\omega), y_i(j\omega)\right) = \frac{\left|y_i^0(j\omega)\, y_i^*(j\omega)\right|^2}{\left|y_i^0(j\omega)\right|^2 \left|y_i(j\omega)\right|^2} \quad (4)$$

where ω is the frequency in rad/sec, and $c\left(y_i^0(j\omega)y(j\omega)\right)$ is the coherence spectrum. If there is no fault, then $c\left(y_i^0(j\omega)y(j\omega)\right) = 1$ for all frequencies. If the measured and fault-free outputs are incoherent with each other at some frequencies, then the coherence spectrum will be less than 1 at those frequencies.

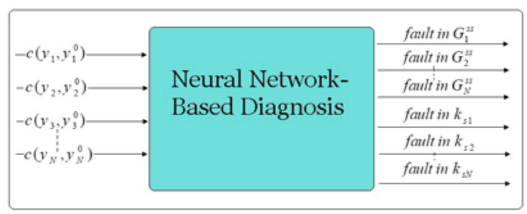

Fig. 3 Neural Network-Based Fault Diagnosis Scheme

5 MODEL-BASED FAULT DIAGNOSIS

A bank of Kalman filters is employed to detect faults. An i-th Kalman filter will be driven by the signal $e(k)$, and the output of the i-th sensor output y_i,

$$\begin{aligned} x_i(k+1) &= A_i x_i(k) + B_i e(k-d) + K_i\left(y_i(k) - \hat{y}_i(k)\right) \\ \hat{y}_i(k) &= C_i \hat{x}_i(k) \end{aligned} \quad (5)$$

where d is the delay, $\hat{x}_i$ is the estimate of the state, x_i, (A_i, B_i, C_i) is the state-space model of the system with input $e(k)$ and the sensor output, $y_i(k)$. The above-defined Kalman filter is applied to the following transfer function model of the collection of *i* sub-systems:

$$y_i = G_0 G_1 G_2 ... G_{i-1} k_{s(i-1)} e + v_{i-1} \quad (6)$$

5.1 Kalman Filter Design

Let us consider a generic Kalman filter for a system with input u and output, y. The Kalman filter is designed for the normal fault-free operation. The model of the fault-free system is given by:

$$\begin{aligned} x(k+1) &= A_0 x(k) + B_0 u(k-d) + w(k) \\ y(k) &= C_0 x(k) + v(k) \end{aligned} \quad (7)$$

Where (A_0, B_0, C_0) are the system matrices obtained from the fault-free system model, $w(k)$ and $v(k)$ are the zero-mean white plant and measurement noise signals, respectively, with covariances:

$$Q = E\left[w(k)w^T(k)\right], \text{ and } R = E\left[v(k)v^T(k)\right] \quad (8)$$

The plant noise, $w(k)$, is a mathematical artifice introduced to account for the uncertainty in the *a-priori* knowledge of the plant model. The larger the covariance Q is, the less accurate the model (A_0, B_0, C_0) is and vice versa.

The Kalman filter is given by:

$$\begin{aligned} \hat{x}(k+1) &= A_0 \hat{x}(k) + B_0 u(k-d) + K_0\left(y(k) - C_0 \hat{x}(k)\right) \\ e(k) &= y(k) - C_0 \hat{x}(k) \end{aligned} \quad (9)$$

where d is the delay and $e(k)$ the residual.

The system model has a pure time delay which is incorporated in the Kalman filter formulation. The Kalman filter estimates the states by fusing the information provided by the measurement $y(k)$ and the *a-priori* information contained in the model, (A_0, B_0, C_0). This fusion is based on the *a priori* information of the plant and the measurement noise covariances, *Q*, and *R*, respectively. When *Q* is small, implying that the model is accurate, the state estimate is obtained by weighting the plant model more than the measurement one. The Kalman gain, K_0, will then be small. On the other hand, when *R* is small implying that the measurement model is accurate, the state estimate is then obtained by weighting the measurement model more than the plant one. The Kalman gain, K_0, will then be large in this case.

The larger K_0 is, the faster the response of the filter will be and the larger the variance of the estimation error becomes. Thus, there is a trade-off between a fast filter response and a small covariance of the residual. An adaptive on-line scheme is employed to tweak the *a- priori* choice of the covariance matrices so that an acceptable trade-off between the Kalman filter performance and the covariance of the residual is reached.

5.2 Fault Isolation

Let e_i be the residual of the i-th Kalman filter. A fault in G_0, G_1 G_2 …or G_i or k_{si} is indicated if the absolute mean of the residual exceeds a specified threshold σ_{th} .

Let us define a 2(N+1) by1 vector of zeros and ones.

$$b_i = \left[g_0 \quad g_1 \quad g_2 \quad \dots \quad g_N \quad | \quad \kappa_0 \quad \kappa_1 \quad \kappa_2 \quad \dots \quad \kappa_N\right] \quad (10)$$

$$g_i = \begin{cases} 0 & no \;\; fault \; in \; G_i \\ 1 & fault \; in \; G_i \end{cases} \quad (11)$$

$$\kappa_i = \begin{cases} 0 & no \;\; fault \; in \; k_{si} \\ 1 & fault \; in \; k_{si} \end{cases} \quad (12)$$

Case I:

If the absolute mean of the i-th residual exceeds the threshold σ_{th}, then b_i will be:

$$b_i = \left[1 \;\; 1 \;\; 1 \;\; X \quad X....X \;\; | \;\; X \;\; X \;\; 1 \;\; X \;\; X...X\right] \quad (13)$$

where X is a don’t care value (0 or 1).

If the absolute mean of the (i+1)-st residual does not exceed the threshold σ_{th}, then b_{i+1} will be:

$$b_{i+1} = \left[0 \;\; 0 \;\; 0 \;\; 0 \quad X....X \;\; | \;\; X \;\; X \;\; X \;\; 0 \;\; X...X\right] \quad (14)$$

The intersection between the 2 binary sets b_i and b_{i+1}, amounting to an element-wise binary logical ANDing of these 2 sets, will then clearly indicate that the sensor k_{si} is the faulty one.

Case II:

If the absolute mean of the ith residual does not exceed the specified threshold σ_{th}, then b_i will be:

$$b_i = \begin{bmatrix} 0 & 0 & 0 & X & X....X & | & X & X & 0 & X & X...X \end{bmatrix} \quad (15)$$

If the absolute mean of the (i+1)-st residual exceeds the specified threshold σ_{th}, then b_{i+1} will be:

$$b_{i+1} = \begin{bmatrix} 1 & 1 & 1 & 1 & X....X & | & X & X & X & 1 & X...X \end{bmatrix} \quad (16)$$

This shows that the intersection between the 2 binary sets b_i and b_{i+1}, amounting to an element-wise binary logical ANDing of these 2 sets, will then clearly indicate that either the sensor $k_{s(i+1)}$ or subsystem $G_{s(i+1)}$ is the faulty one.

6 EVALUATION OF THE PROPOSED SCHEME

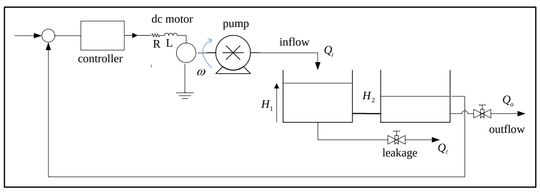

Fig. 4 Two-tank Fluid System

An evaluation of the proposed scheme for fault diagnosis was performed on a benchmark laboratory-scale process control system using National Instruments LABVIEW as shown in Fig 4. Fault diagnosis in a fluid system has enjoyed an increasing importance and popularity in recent years from the points of view of economy, safety, pollution, and conservation of scarce resources (Marco Ferrente, 2008) (Zhang Sheng, 2004)(Doraiswami, 1996) (R.J. Patton, 2000)(Astrom et.,al, 2001) (C. De Persis, 2000)(H. Hammouri, 2002) (K.M. Kinnaert, 1999).

The proposed scheme is used to detect and isolate a fault by a sequential integration of model-free and model-based approaches.

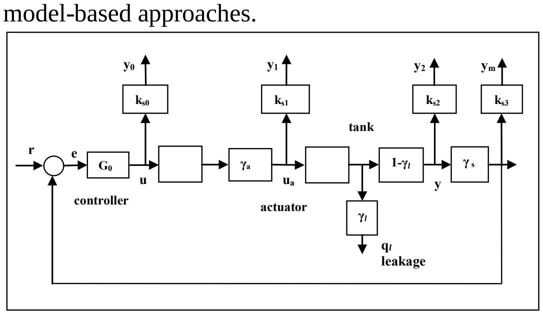

Fig. 5 Fluid system subject to a leakage

We will use a set of fuzzy logic rules to detect a leakage. The fuzzy IF and THEN rules for the two-tank fluid system are derived using the sensor network shown in Fig.1. For the fault diagnosis problem, the equivalent of Fig. 1, is shown in Fig. 5 whose various sub-systems and sensor blocks are all explained below. First, note that the first two blocks in Fig. 5, i.e. G_0 and $G_1 = G_1^0 \gamma_a$, represent the controller and the actuator sub-systems, respectively. As shown in Fig. 5, the leakage is modelled by the gain γ_ℓ which is used to quantify the amount of flow lost from the tank. Thus the net outflow is quantified by the gain $(1-\gamma_\ell)$. Since the two blocks G_2^0 and $(1-\gamma_\ell)$ cannot be dissociated from each other, they are fused into a single block labelled $G_2 = G_2^0(1-\gamma_\ell)$. The feedback sensor, modelled by the gain k_{sf}, is used to feed the plant output y back to the controller, and is modelled by the last block G_3 in Fig. 3, where $G_3 = k_{sf}$. An additional sensor, termed as the redundant sensor of gain k_{s2}, is used here to discriminate between faults in the height sensor and feedback sensor. Even though the control input u does not necessitate a separate sensor to monitor its output as it is freely available from the digital controller (G_0), a separate unit gain, labelled $k_{s0} = 1$, is attributed to it. Similarly, the last sensor, used to monitor the feedback sensor output, is also attributed a unit gain, i.e. $k_{s3} = 1$. The reason for adding these two unit gains to Fig. 5 is motivated by our desire to make the overall sensor network structure for the leakage detection problem fit in well within the general sensor network-based fault detection paradigm shown in Fig. 3. By doing so, the two fuzzy rules (Rules 1 and 2 given earlier) can be readily applied to Fig. 5. The four residuals, r_0, r_1, r_2 and r_3, are the deviations between the fault-free and fault-bearing measurements of the control input , flow rate, height from the redundant sensor, and height from the feedback sensor, respectively.

6.1 Fault Diagnosis using a Model-free approach

A sequential integration of an artificial neural network (ANN) and a fuzzy logic (FL) approach is employed here to isolate faults.

Fuzzy-logic approach: The features were chosen to be the steady-state values of the control input, u_{ss}, measured flow flw_{ss} and height h_{ss} values and their fault-free counterparts, u_{ss}^0, flw_{ss}^0 and h_{ss}^0, respectively. The fuzzy logic rules pertinent to this case are similar to those described earlier.

The steady-state gain relating flw_{ss} and u_{ss} is given by:

$$flw_{ss} = G_0^{ss} G_1^{ss} u^{ss} \quad (17)$$

The steady-state gain relating h_{ss} and u_{ss} is given by:

$$h_{ss} = G_0^{ss} G_1^{ss} G_2^{ss} u^{ss} \quad (18)$$

Where $G_0^{ss}, G_1^{ss}, G_2^{ss}$ are the steady-state gains of the actuator, the transfer function relating the control input to the flow, and the transfer function relating the flow to the height, respectively.

The fuzzy IF-and-THEN rules given in the previous section can isolate a leakage from faults in the actuator, flow and height (or level) sensor.

Neural network approach: A neural network is driven by the coherence spectrum between the measured height h and the corresponding fault-free one h^0. This coherence spectrum is defined by:

$$c\left(h^0(j\omega), h(j\omega)\right) = \frac{\left|h^0(j\omega)h^*(j\omega)\right|^2}{\left|h^0(j\omega)\right|^2 \left|h(j\omega)\right|^2} \quad (19)$$

The neural network is trained to classify four possible faults, namely a fault in the actuator, a fault in the level sensor, a fault in the flow sensor, and a leakage.

The fuzzy approach is then integrated sequentially with the neural network-based fault classification approach to complete the required fault isolation scheme. The Neural Network-based classifier precedes the Fuzzy Logic-based one, with the former providing a fast fault classification, followed by a fuzzy logic block to unravel the real cause(s) of the fault. The fault magnitude is estimated from the changes in the settling time, $\Delta t_s = t_{ss}^0 - t_{ss}$, whereas its onset is indicated by the changes in the height profile.

Figs 6-8 give the profiles of the flow, height and the coherence spectrum. Fig. 6 shows height profiles in the presence of leakages of different magnitudes occurring when the fluid level system is operated in both an open-loop and a closed-loop configuration. For the open-loop case, one can readily deduce both the onset and amount of the leakage from the height/flow profile. The leakage flow has five sections corresponding to the following five degrees of no-leakage, small, medium, large and very large leakage. However, by its very nature, the closed-loop PI controller hides the fault and hence makes it difficult to visually detect it.

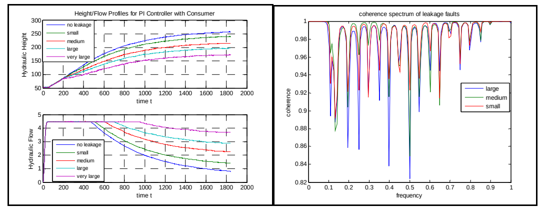

Fig.6: Height/Flow Profile/Coherence under leakage faults

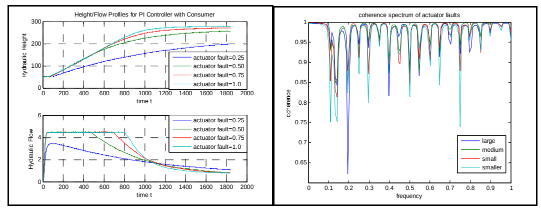

Fig.7: Height/FlowProfile/Coherence under actuator faults

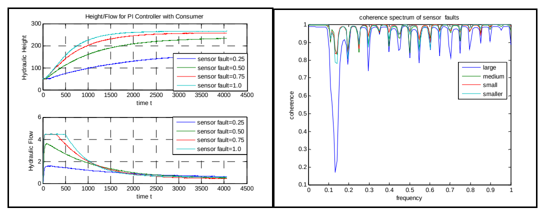

Fig.8: Height/Flow Profile/Coherence under level sensor faults

6.2 Model of the Fluid System

A benchmark model of a cascade connection of a dc motor and a pump relating the input to the motor, *u*, and the flow, Q_i, is a first-order system expressed by:

$$\dot{Q}_i = -a_m Q_i + b_m \phi(u) \quad (20)$$

where a_m and b_m are the parameters of the motor-pump system and $\phi(u)$ is a dead-band and saturation-type nonlinearity. The Proportional and Integral (PI) controller is given by:

$$\begin{aligned} \dot{x}_3 &= e = r - h_2 \\ u &= k_p e + k_I x_3 \end{aligned} \quad (21)$$

where k_p and k_I are gains and r is the reference input.

With the inclusion of the leakage, the liquid level system is modelled by (Astrom et al., 2001):

$$A_1 \frac{dH_1}{dt} = Q_i - C_{12}\varphi\left(H_1 - H_2\right) - C_\ell \varphi\left(H_1\right) \tag{22}$$

$$A_2 \frac{dH_2}{dt} = C_{12}\varphi\left(H_1 - H_2\right) - C_0 \varphi\left(H_2\right) \tag{23}$$

where $\varphi(.) = sign(.)\sqrt{2g(.)}$, $Q_\ell = C_\ell \varphi\left(H_1\right)$ is the leakage flow rate, $Q_0 = C_0\varphi\left(H_2\right)$ is the output flow rate, H_1 and H_2 are the liquid heights in tanks 1 and 2, respectively, A_1 and A_2 are the cross-sectional areas of tanks 1 and 2, respectively, g=980 $cm/\sec^2$ is the gravitational constant, C_{12} and C_o are the discharge coefficients of the inter-tank and output valves, respectively. The linearized model of the entire system formed of the motor, pump, and the tanks is given by:

$$\dot{x} = Ax + Br \quad y = Cx \tag{24}$$

$$x = \begin{bmatrix} h_1 \\ h_2 \\ x_3 \\ q_i \end{bmatrix}, A = \begin{bmatrix} -a_1 - \alpha & a_1 & 0 & b_1 \\ a_2 & -a_2 - \beta & 0 & 0 \\ -1 & 0 & 0 & 0 \\ -b_m k_p & 0 & b_m k_I & -a_m \end{bmatrix}, \tag{25}$$

$$B = \begin{bmatrix} 0 & 0 & 1 & b_m k_p \end{bmatrix}^T, C = [1 \quad 0 \quad 0 \quad 0]$$

Where q_i , q_ℓ , q_0 , h_1 and h_2 are respectively the increments in Q_i , Q_ℓ , Q_o , H_1^0 and H_2^0 , a_1 , a_2 , α and β are parameters associated with linearization, α is associated with leakage and β is the output flow rate, $q_\ell = \alpha h_1$, $q_o = \beta h_2$.

6.3 Evaluation of the Fault Detection using a Bank of Kalman Filters

A bank of two Kalman filters is used here, one with input u(k) and the flow-sensor output, and the other with input u(k) and the height-sensor output

First the fault-free model of the system is identified using a recursive least-squares identification scheme. The order of the estimated model was iterated to obtain an acceptable model structure using a combination of the AIC criterion and the identified pole locations.

The identified model is essentially a second-order system with a delay even though the theoretical model is of a fourth order. Using the fault-free model together with the covariance of the measurement noise, R, and the plant noise covariance, Q, the Kalman filter model was finally derived. As it is difficult to obtain an estimate of the plant covariance, Q, a number of experiments were performed under different plant scenarios to tune the Kalman gain, K_0 .

$$\hat{x}_i(k+1) = A_i\hat{x}_i(k) + B_i u_i(k-d) + K_i\left(y_i(k) - C_i\hat{x}_i(k)\right) \tag{26}$$

$$r_i(k) = y_i(k) - C_i\hat{x}(k) \qquad i = 1,2 \tag{27}$$

where x_i is the state, r_i is the residual, (A_i, B_i, C_i) is the state-space model of the first subsystem relating the control input $u(k)$ to the flow output $y_i(k)$. The transfer function for the first subsystem (A_1, B_1, C_1) relating the control input $u(k)$ to the flow output $y_1(k)$.

$$y_1(z) = G_0(z)G_1(z)u(z) \tag{28}$$

where G_0 is the actuator transfer function and G_1 is the transfer function relating the actuator output to the flow. (A_2, B_2, C_2) is the state-space model for the second subsystem relating the control input $u(k)$ to the height $y_2(k)$. The transfer function for the second subsystem (A_2, B_2, C_2) relating the control input $u(k)$ to the height output $y_2(k)$

$$y_2(z) = G_0(z)G_1(z)G_2(z)\,u(z) \tag{29}$$

where G_2 is the transfer function relating the flow to the height.

In this case, four possible fuzzy rules can be derived, two of which are stated in the following:

- If $\left|\frac{1}{N}\sum_{i=1}^{N} r_1(i)\right| > \sigma_{thr}$, then there is a fault in G_0 (subsystem 0) or G_1 (subsystem 1) or in the flow-sensor,
- If $\left|\frac{1}{N}\sum_{i=1}^{N} r_2(i)\right| > \sigma_{thr}$, then there is a fault in G_0 (subsystem 0) or G_1 (subsystem 1) or G_2 (subsystem 2) or in the height-sensor (level-sensor).

The Kalman filter bank was evaluated under different fault scenarios for an ON-OFF controller, a P controller, and a PI controller, as shown in Fig.9.

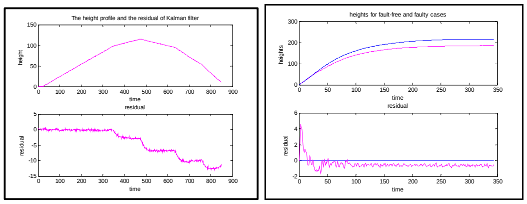

Fig. 9. Kalman filter results for an On-Off and PI Controller: for Flow and Height under various leakage magnitudes

Comments: The model of the fluid system is nonlinear, complex and stochastic. A simplified linearized model which contains only the dominant poles (as it was difficult to identify the fast dynamics) was used in the design of the Kalman filter bank. Results from the evaluation on the physical system shows that the Kalman filter bank is robust in modelling uncertainties including nonlinearities and neglected fast dynamics, while at the same time being sensitive to incipient faults.

7 CONCLUSION

The proposed intelligent fault diagnostic scheme based on a sequential integration of model-free and model (Kalman)-based approach was found promising when applied to a benchmarked laboratory-scale two-tank system. The model-free approach detects a presence of a possible fault from the integration of both neural network and fuzzy logic approaches. Results from the evaluation on the physical system shows that the Kalman filter bank is robust in modeling uncertainties including nonlinearities and neglected fast dynamics, while retaining its sensitivity to incipient faults. The integration of fuzzy-logic and neural networks proved itself to be a robust way of providing a quick and reliable indication of a fault based on steady-state measurements and height profile.

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