# Integrated Approach to Reliable Leakage Diagnosis

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**Abstract:** A generic and reliable diagnosis framework, for incipient leakages is proposed using an integrated approach combining two entirely different model-free (MF) and model-based (MB) schemes. The primary objective of this vital combination is to ensure a timely monitoring of the critical information about the presence/absence of leakages, and an accurate unfolding-in-time of the complete leakage status. Whereas the model-free approach provides the user with the possibility of an early incipient fault detection via limit checks and some form of knowledge-based (KB) analysis, the model-based approach allows for a Kalman filter (KF)-based detection followed by a parameter identification-based fault isolation. As such the MB approach will provide a confirmation of the detection of any fault flagged by the MF approach. A new model order selection scheme is proposed here to provide a reliable model. Two vital advantages accruing from this integrated approach are a substantial reduction in false alarms and an increased probability of leakage detection. The proposed integrated approach is tested on a physical fluid system, exemplified by a benchmarked two-tank system.

*Keywords: fault diagnosis, leakage fault, Kalman filter, parameter identification, knowledge base.*

## 1. INTRODUCTION

Plant accidents in the COG (Chemical, Oil and Gas) industry, and in other process plants, that are caused by undetected, and therefore unattended to, leakages have been a major cause for concern to the Global Safety and Environmental Agencies which have then been compelled to regulate and enforce existing and emerging safety standards. Leakage can occur in various places of a plant and can be due to various causes. The causes for a leakage in pipes and storage tanks can be attributed to various factors such as faulty joints, aging, excessive loads, holes caused by corrosion and accidents and the like.

Diagnosis of leakage faults in fluid systems is undoubtedly of paramount importance as it relates to key areas such as economy, potential hazards, pollution, and conservation of scarce resources [1-6]. Leakage in pipes and storage tanks occurs due to a variety of causes, such as faulty joints, aging, excessive loads, holes caused by corrosion and accidents and the like. Amongst the various approaches proposed in the literature, such as model-, neural network-, and statistical inference-based approaches, the model-based approach is gaining in popularity thanks to its ability to reliably diagnose incipient leakages.

A model of a process control system is typically highly complex, nonlinear and stochastic, and consequently model-based approaches tend to be computationally burdensome and costly. In critical applications such as those involving hazardous leaks, it is important to ensure that a leak is detected quickly and reliably.

This paper proposes an integrated approach, combining two entirely different schemes, that enjoys the following three attractive attributes: timely detection of faults via the model-free scheme, accurate diagnosis (i.e. accurate detection through Kalman filtering and accurate isolation through parameter estimation), and finally reduction of false alarms and an increase in the leakage detection probability, both of which being achieved through cross-checking between the two entirely dissimilar schemes. As shown in Fig. 2, the tasks of leakage diagnosis are executed in the order of decreasing importance and increasing precision [7] starting with limit checks and a plausibility analysis, which is then followed by a signal-based analysis and a fuzzy logic (FL) fault detection and isolation (FDI) stage. In the FL approach, the nominal fault-free data is computed from the current input-output data using a steady-state observer. The steady-state residuals are then generated by computing the deviations between the observer outputs and the fault-bearing measurements. The fuzzy logic IF-and-THEN rules can then be generated using graphical models relating the system's inputs and outputs. A model-based approach is then used based on the present input-output data and the fault-free model to accurately detect and isolate faults, especially incipient faults. This approach hinges upon the use of a Kalman filter for fault detection and a parameter identification stage for fault isolation.

The final stage provides estimates of the parameters of the various components of the process control system. This helps to implement a cost-effective condition-based monitoring procedure, in that the size of the deviation of the system parameters from their nominal fault-free values will help in reducing false alarms and increasing the probability of leakage detection. This in turn can be incorporated into a larger leakage monitoring scheme that can cater for both a preventive and a corrective type of maintenance.

The paper is organized as follows. In Section II, the process control system is described. Section III describes the modeling of the two tank bench mark model and the leaks. In Section IV, the model-free and model-based approach is described. In Section V, the kalman filter based approach is described. In Section VI, the parametric estimation based approach is described. Finally Section VII deals with the evaluation of the proposed schemes on the physical system and Section 7 contains the conclusion.

## 2. THE PROCESS CONTROL SYSTEM

The mathematical model of a typical process control system consisting of two tanks and a network of pipes is derived relating various key variables such as the reference input to the motor driving the pump, the flow rate, and the height of the liquid in the tank. Because the system's model is nonlinear and since our goal is to detect incipient leakages, that is, to estimate small deviations in the states and the parameters about an operating point, a linearized model is therefore employed.

The signal- (or data-) based analysis is employed as it is simpler and faster to implement and does not require any a-priori knowledge of the model. The limit value checking and plausibility checks are both fast and indicate a possible presence/absence of a leakage. However, it cannot detect incipient leakages. A leakage manifests itself as an abrupt jump in the error signal, flow rate and height data. A knowledge-based scheme is used to locate a change in the slope of the sensor signal.

The inability of the model-free approach to detect incipient leakages calls for the introduction and use of the model-based approach. An essential component of this approach is the Kalman filter which is designed for the linearized plant model. A most popular approach to fault detection is based on the residuals generated by the Kalman filter [8-11]. A suboptimal steady-state Kalman filter, is used here as it is computationally simple and has also been successfully used in a plethora of practical fault diagnosis applications [8-11]. A generalized likelihood ratio is employed to detect the presence or absence of a fault (leakage). The mean of the residual or the mean of its correlation is compared with a specified threshold value, which is determined from both the pre-specified value of the false alarm rate, determined by past records, and the variance of the measurement noise. Because of the difficulty in estimating the probability density function (PDF) of the measurement noise, a Gaussian PDF is assumed here. Since the Kalman filter is not efficient for fault isolation, a further stage, in the form of a parameter identification scheme, is therefore required for fault isolation, hence giving a complete diagnostic picture of the leakage.

The identified model of a physical system may generally have a structure different from that of the mathematical model derived from the physical laws due several reasons such as the presence of noise, nonlinearities and inability to capture faster dynamics of the components. To address this model structural mismatch problem, a combination of a model selection criterion (Akaike Information criterion (AIC)) and the location of the identified poles for different selected model orders is used here to identify the correct model order of the system.

The proposed scheme, embodying both model-free and model-based approaches, is evaluated on a benchmark laboratory-scale process control system using National Instruments LABVIEW. A knowledge-base for leakage diagnosis is deduced from an extensive experimentation and simulation of the model under different leakage scenarios. Model-free and model-based analyses are employed here to detect the leakage. The covariance matrices for the Kalman filter were adapted from the measured data so as to find a compromise between a fast response and a small variance of the noisy residual. A complete model of the system is finally identified using parameter identification for different types of leakage faults and different types of control strategies including ON/OFF, P and PI schemes.

## 3. A TWO-TANK BENCH MARK MODEL

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:

$$\dot{Q}_i = -a_m Q_i + b_m \phi(u) \qquad (1)$$

where $a_m$ and $b_m$ are the parameters of the motor-pump system and $\phi(u)$ is a dead-band and saturation type of nonlinearity. It is assumed that the leakage $Q_\ell$ occurs in tank 1 and is given by:

$$Q_\ell = C_{d\ell}\sqrt{2gH_1} \qquad (2)$$

With the inclusion of the leakage, the liquid level system is modeled by:

$$A_1 \frac{dH_1}{dt} = Q_i - C_{12}\varphi\left(H_1 - H_2\right) - C_\ell \varphi\left(H_1\right) \quad (3)$$

$$A_2 \frac{dH_2}{dt} = C_{12}\varphi\left(H_1 - H_2\right) - C_0 \varphi\left(H_2\right) \quad (4)$$

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, $H_1$ is the height of the liquid in tank 1, $H_2$ is the height of the liquid in tank 2, $A_1$ and $A_2$ are the cross-sectional areas of the 2 tanks, g=980 $cm/\sec^2$ is the gravitational constant, $C_{12}$ and $C_o$ are the discharge coefficient of the inter-tank and output valves, respectively. The model of the two-tank fluid control system, shown above in Fig. 1, is of a second order and is nonlinear with a smooth square-root type of nonlinearity. As our focus is on detecting incipient leakages, that is detecting leakage in their nascent state and well before they develop into costly system failures, a powerful fault detection technique, such as Kalman filtering, is required at this stage. To design such a filter, a linearized model of the fluid system is required. To ensure that the functions $\varphi\left(H_1 - H_2\right)$ and $\varphi\left(H_2\right)$ are real and differentiable, we will assume $H_1 > H_2 > 0$. For design purposes, a linearized model of the fluid system is required and is given below in (5) and (6):

$$\frac{dh_1}{dt} = b_1 q_i - (a_1 + \alpha) h_1 + a_1 h_2 \quad (5)$$

$$\frac{dh_2}{dt} = a_2 h_1 - (a_2 - \beta) h_2 \quad (6)$$

where $h_1$, $h_2$ and $Q_i$ are the increments in the nominal (leakage-free) heights $H_1^0$, $H_2^0$ and flow $Q_i^0$,

$$H_1 = H_1^0 + h_1,\ H_2 = H_2^0 + h_2,\ Q_i = Q_i^0 + q_i,\ b_1 = \frac{1}{A_1}, a_0 = \frac{C_{12}}{2\sqrt{2g(H_1^0 - H_2^0)}},$$

$$\alpha = \frac{C_\ell}{2A_1\sqrt{2gH_1^0}},\quad a_1 = \frac{a_0}{A_1}, a_2 = \frac{a_0}{A_2} + \frac{C_0}{2A_2\sqrt{2gH_2^0}}\quad \beta = \frac{C_0}{2A_2\sqrt{2gH_2^0}}$$

and the parameter $\alpha$ indicates the amount of leakage.

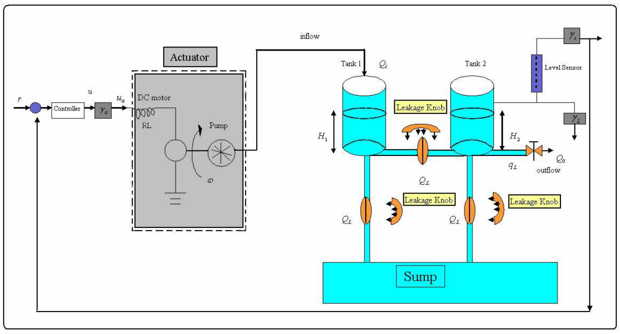

Fig.1: Two-tank fluid control system

A PI controller, with gains $k_p$ and $k_I$, is used to maintain the level of the Tank 2 at the desired reference input $r$.

$$\dot{x}_3 = e = r - h_2$$
$$u = k_p e + k_I x_3 \qquad (7)$$

The state space model is given by:

$$\dot{x} = Ax + Br \qquad (8)$$

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

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

where $q_i$, $q_\ell$, $q_0$, $h_1$ and $h_2$ are the increments in $Q_i$, $Q_\ell$, $Q_o$, $H_1^0$ and $H_2^0$, respectively, the parameters $a_1$ and $a_2$ are associated with linearization whereas the parameters $\alpha$ and $\beta$ are respectively associated with the leakage and the output flow rate, i.e. $q_\ell = \alpha h_1$, $q_o = \beta h_2$.

## 4. MODEL-FREE AND MODEL-BASED APPROACHES

In this work, an integration of model-free and model-based approaches is employed. The tasks of leakage diagnosis are executed in the order of decreasing importance and increasing precision [7] starting with limit checks followed by plausibility analysis, Kalman filter and parameter identification schemes. The parameter identification provides a complete diagnostic picture.

From the system model equations (8) and (9), it can be deduced that the derivative of the height $h_1$ changes with the leakage parameter $\alpha$. This a-priori knowledge is employed to detect the onset of any leakage.

As part of the model-free approach, a fuzzy logic scheme was also used to detect leakages. The fuzzy rules are derived by comparing the actual flow and height measurements to their fault-free steady-state counterparts.

As shown in Fig. 3, these fault-free measurements are generated by the steady-state model of the liquid flow system, formed by a bank of steady-state gains, $\{g_i^0\}_{i=0}^N$, which are connected in cascade and which are driven by the steady-state value of the error e. Assuming that the noise term, $v_i$, in the i[th] path is subsumed in the fuzzy membership function, the deviation in the in steady-state output is :

$$r_j = \left( \prod_{i=0}^{j} \left( g_i k_{si} - g_i^0 \right) \right) e^{ss} \quad \forall j = 0,1,2,\ldots,N \qquad (9)$$

where $g_i$ is the steady-state gain of $G_i$. In fault diagnosis terms, the above residual-generation equation may be called the parity equation. Let us now define two fuzzy sets, namely *Z (zero)* and *NZ* (*non-zero)*. For simplicity, we will consider the case of a single fault, i.e. when only one device can be faulty at any given time. Let us first define the i[th] path in the sensor network as the path that originates from the signal e and ends at the i[th] sensor output $y_i$. Since faults propagate forward from e to y and in order to discriminate whether a fault exists in the i[th] subsystem $G_i$ or its associated sensor $k_{si}$, two fuzzy rules are needed to reflect the flow of information along the successive (i-1)[st] and i[th] paths. In this case, the required fuzzy rules may take on the following form:

*Rule 1:* If $r_{i-1} \in Z$ and $r_i \in NZ$ then there is a fault in the subsystem $G_i$ and/or the sensor $k_{si}$

*Rule 2:* If $r_{i-1} \in Z$, $r_i \in NZ$ and $r_{i+1} \in Z$ then there is a fault in the sensor $k_{si}$

It is clear from the above two rules that if Rule 1 is true and Rule 2 is false for all i, then $G_i$ is faulty.

## 5. KALMAN FILTER

The Kalman filter is designed for the normal leakage-free operation. The model of the leakage-free system, that is when $\alpha = 0$, is given by equation (10-11) where y is the output, e.g. height or flow rate, $(A_0, B_0, C_0)$ are obtained from the discretized model of $(A, B, C)$ for the leakage-free case, $w(k)$ and $v(k)$ are zero-mean, white plant and measurement noise signals, respectively, with covariances (equation 12-13):

$$x(k+1) = A_0 x(k) + B_0 u(k-d) + w(k) \quad (10)$$
$$y(k) = C_0 x(k) + \upsilon(k) \qquad (11)$$

$$Q = E\left[w(k)w^T(k)\right] \quad (12)$$
$$R = E\left[v(k)v^T(k)\right] \quad (13)$$

The plant noise, $w(k)$, is a mathematical artifice introduced to include uncertainty in the *a priori* knowledge of the plant model. The larger its covariance is, the less accurate is the model $(A_0, B_0, C_0)$ and the smaller its covariance is, the more accurate the model becomes. The Kalman filter is given by:

$$\hat{x}(k+1) = A_0\hat{x}(k) + B_0u(k-d) + K_0\left(y(k) - C_0\hat{x}(k)\right) \quad (14)$$

$$e(k) = y(k) - C_0\hat{x}(k) \quad (15)$$

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

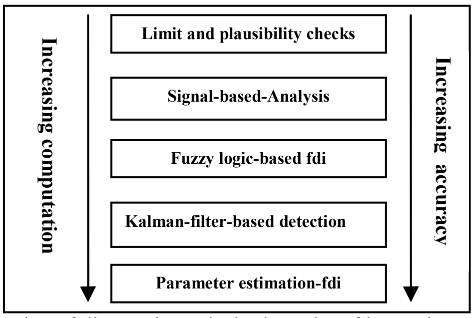


Fig. 2 Execution of diagnostics tasks in the order of increasing computation and accuracy

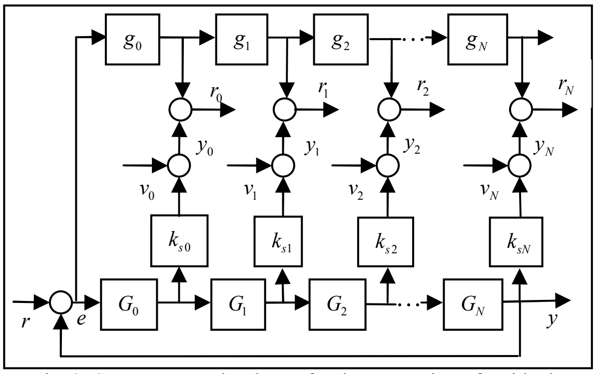

Fig. 3: Sensor Network scheme for the generation of residuals

Since the system model has a pure time delay $d$, the latter 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 $(A_0, B_0, C_0)$. The fusion is based on the a-priori information of the plant covariance, Q, and the measurement noise covariance, R. When Q is small, implying that the model is more accurate, the state estimate is obtained by weighting the plant model more than the measurement model. In this case, the Kalman gain, $K_0$, will be small. On the other hand, when R is small, implying that the measurement model is more accurate, the state estimate is obtained by weighting the measurement model more than the plant model. In this case, the Kalman gain, $K_0$, will be large. For leakage diagnosis, it is important to design the Kalman filter so that an acceptable compromise is obtained between fast detection and a good sensitivity to small (incipient) leakages.

A statistical decision-theoretic approach was used to decide between two hypotheses:

$$H_O : e(k) = v(k) \quad (16)$$
$$H_1 : \; e(k) = v(k) + c \quad (17)$$

Where $c$ is some constant. A likelihood ratio test is used, with the assumption that $v(k)$ is a white Gaussian noise, to discriminate between the presence or absence of a leakage. The discrimination rule is as follows:

$$|e(k)| \begin{cases} \geq \sigma & leakage \\ < \sigma & no\ leakage \end{cases} \quad (18)$$

Where $\sigma$ is a pre-specified threshold.

## 6. PARAMTERIC IDENTIFICATION BASED

The Kalman filter is not well suited for fault isolation. As such, a separate parameter estimation scheme is needed for this purpose. This scheme is used to estimate the model parameters of the complete process control system, comprising the motor, pump, tanks and valves. By estimating the parameters, the status of all such devices can be known and be used as part of a larger plan for some condition-based monitoring activities.

A discrete-time model of the fluid system relating the height and the input u takes the form:

$$y(k) = \varphi^T(k)\theta + v(k) \quad (19)$$

Where $\varphi$ is a data vector formed of the input and the output, and $\theta$ is the transfer function coefficient vector of the model, and $v(k)$ is the noise. A recursive least-squares method is used to estimate $\theta$.

First an offline estimate of $\theta$, denoted by $\widehat{\theta}^0$, is obtained when there is no leakage. This estimate is then employed in the Kalman filter model. Various system orders are chosen and for each order, the coefficient vector $\theta$ is identified. The Akaike Information Criterion (AIC) and the estimate of the pole locations are both used to guide the choice of an appropriate final model order. Note here that when the leakage is detected, an estimate of $\theta$, denoted by $\hat{\theta}$, is obtained online. As time progresses, the deviations ($\hat{\theta} - \widehat{\theta}^0$) will give a profile of the system parameter changes, thus providing a means of monitoring and revealing the complete diagnostic picture of the process. In identifying a model of a physical system, the structure of the model may not be identical to that of the mathematical model derived from the physical laws due to various factors including the presence of noise and fast dynamics [12]. In this section, a direct approach based on exploiting the *a-priori* knowledge of the location of the poles of the system's discrete-time equivalent is employed. To appreciate the proposed scheme, the mapping relating the poles of the continuous-time and the discrete-time equivalent models is reviewed hereunder.

The poles of the discrete-time model, i.e. $\lambda_d$ are related to those of the continuous-time model, i.e. $\lambda_c$, by $\lambda_d = e^{\lambda_c T_s}$ where $T_s = 1/f_s$ is the sampling period and $f_s$ is the corresponding sampling frequency. We will now state and give a brief proof to the following new proposition:

***Proposition**: Given that the system to be identified is of a low-pass nature and regardless of the location of the continuous-time system's poles, then the poles of its discrete-time equivalent will lie in the right half of the z-plane ($Z^+$) iff the sampling frequency is more than twice the Nyquist rate* $(2f_c)$.

## 7. EVALUATION ON A PHYSICAL SYSTEM

The evaluation of the proposed scheme has been on the physical system as shown in Fig. 1.

### *7.1 Model-Free Approach*

As a starting point, various leakage degrees were introduced into the system in an open-loop setting, and the flow and height data were recorded as shown in Fig. 3. The limit checks, plausibility and knowledge-based analysis were carried out resulting in the following remarks: the height and flow are within the physical limits. Moreover, the five degrees of leakage introduced into the system, namely no-leakage, small, medium, large and very large, can also be clearly identified from the height profile in Fig. 4(a).

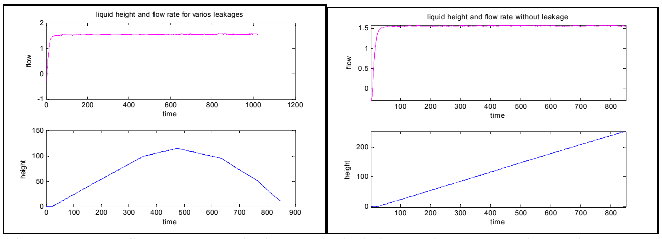

Fig. 4 Input flow rate and the tank height under (a) various degrees of leakage (b) no leakage.

We will use a fuzzy logic rules to detect a leakage fault. The fuzzy IF-and-THEN rules for the two-tank fluid system are derived using the sensor network for the physical two-tank fluid system as shown in Fig. 3. For the leakage detection problem, the equivalent of Fig. 3, 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 $\gamma_\ell$ which is used to quantify the amount of flow lost from the first tank. Thus the net outflow from tank 1 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 labeled $G_2 = G_2^0(1-\gamma_\ell)$. The feedback sensor, modeled by the gain $k_{sf}$, is used to quantify the amount of plant output $y$ fed back to the controller, and is modeled by the last block $G_3$ of Fig. 3, i.e. $G_3 = k_{sf}$. An additional sensor, termed as the redundant sensor of gain $k_{s2}$, is used here to discriminate between the leakage and feedback sensor fault. 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, labeled $k_{s0} = 1$, 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.

### *7.2 Kalman Filter Based Evaluation*

First the leakage-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. Even though the theoretical model is of a higher order, the fast dynamics of the motor, pump, sensors are all dealt with by the AIC criterion. With no leakage, the identified model is essentially an integrator (and thus unstable) with a delay (see Fig. 4(b)).

Using the leakage-free model together with the covariance of the measurement noise, R, and the plant noise covariance, Q, the Kalman filter model is 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, $K_0$.

$$\hat{x}(k+1) = A_0\hat{x}(k) + B_0 u(k-d) + K_0\left(y(k) - C_0\hat{x}(k)\right) \quad (22)$$

$$e(k) = y(k) - C_0\hat{x}(k) \quad (23)$$

where $A_0 = 1$, $B_0 = 0.0033$ and $K_0 = 25$

(Note that the height profile is essentially a linear one).

The Kalman filter was evaluated under different leakage scenarios for various types of controllers: ON-OFF, P, PI and PID controllers, as shown in Figs. 6(a) -6(d).

### *7.3 Parametric Estimation Based Evaluation*

The model of the entire system was identified for different leakage magnitudes. A discrete-time model of the fluid system relating the height and the input u takes the form of:

$$y(k) = \varphi^T(k-1)\theta + v(k-1) \quad (24)$$

where $\theta$ and $\varphi(k-1)$ are the parameter and the past data vectors, respectively.

A recursive least-squares estimation of $\theta$ is given below as:

$$\hat{\theta}(k+1)=\hat{\theta}(k)+K(k+1)\left[y(k+1)-\varphi^{T}(k)\hat{\theta}(k)\right] \quad (25)$$

$$K(k+1)=P(k+1)\varphi(k)\left[\varphi^{T}(k)P(k)\varphi(k)+1\right]^{-1} \quad (26)$$

$$P(k+1)=\left[I-K(k+1)\varphi^{T}(k)\right]P(k) \quad (27)$$

where $\hat{\theta}$ is the estimate of $\theta$.

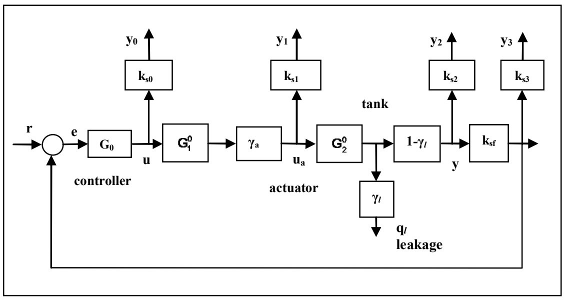


Fig. 5: Sensor Network scheme for the generation of residuals

The estimate of the parameter $\theta$ gives the complete diagnostic picture of the system. The leakage magnitude is estimated from the estimate $\hat{a}$ of $a$, which is one of the elements of the vector $\theta$.

$$\hat{a}=\begin{cases}1 & no\ leakage\\ \alpha & leakage:\alpha<1\end{cases} \quad (28)$$

The leakage magnitude increases with the value of $\alpha$.

## 8. CONCLUSION

The proposed scheme for the incipient leakage diagnosis in a process control system, using two totally different approaches, namely model-free and model-based ones, was successfully evaluated on both simulated and physical systems. The results are certainly encouraging. The proposed leakage diagnosis scheme was found to be robust to measurement noise and system nonlinearities. The Kalman filter and parameter identification schemes based on approximate linearized model were also found to be satisfactory. The integration of the model-free and model-based approaches enjoys a number of attractive features, such as a reduction of false alarms leading to an increase in the leakage detection probability, an increased reliability of detecting incipient leakages through the cross-checking between the two approaches used. Endowed with these advantages, and if integrated into a larger condition-based monitoring setup, the proposed scheme would improve the effectiveness of the latter. Overall the results obtained so far are certainly encouraging to pursue this research further by considering scenarios of multiple leakages occurring in a typical network of pipelines analyzed within a sensor network-based paradigm. It should however be pointed out that very small leakages were difficult to evaluate as the measurement noise variance was relatively large. Current efforts are under way to address this problem by considering a combination of more powerful model-free denoising techniques, such as wavelets, and an extended Kalman filter scheme to accommodate the effects of any plant nonlinearities.

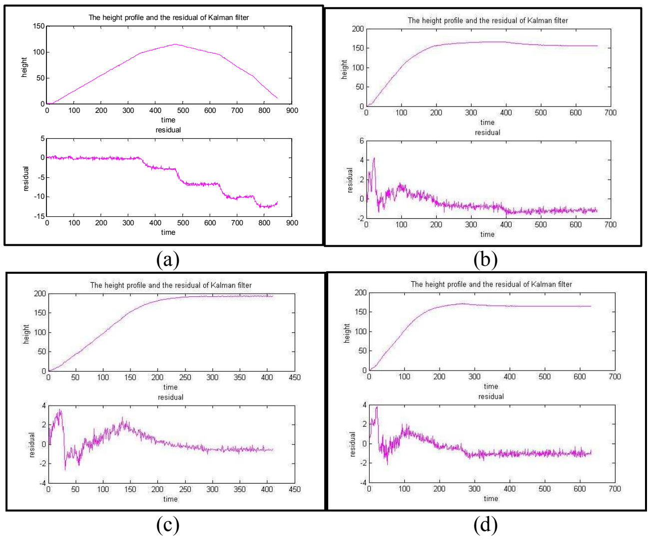


Fig 6. Kalman filter results under various leakage magnitudes for (a) ON-OFF Controller: for Flow and Heights. (b) P Controller: for Flow and Height. (c) PI Controller: for Flow and Height. (d) PID Controller: for Flow and Height.

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