Leakage Detection for Pipe Systems with Fuzzy Monitoring Strategy

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***Abstract*— A Pipe is a ubiquitous product in the industries that is used to convey liquids, gases, or solids suspended in a liquid, e.g., a slurry from one location to another. Both internal and external cracking can result in structural failure of the industrial piping system and possibly decrease the service life of the equipment. The chaos and complexity associated with the uncertain behavior inherent in pipeline systems lead to difficulty in detection and localisation of leaks in real-time. The timely detection of leakage is important in order to reduce the loss rate and serious environmental consequences. To address this issue, in this paper an auto regressive with exogenous input (ARX)-Laguerre fuzzy proportional -derivative (PD) observation system is pro-posed to detect and estimate a leak in pipelines. In this work, the ARX-Laguerre model has been used to generate better performance in the presence of uncertainty. According to the results, the proposed technique can detect leaks accurately and effectively.**

Keywords*— *Autoregressive with eXogenous Input Laguerre (ARX-Laguerre); Fuzzy; Pipeline; PD; Controller; PD observer.

I. Introduction

Pipelines are the safest way for transporting crude oil, petroleum products, and natural gas over long distances. Pipelines deliver clear benefits in supporting economic growth as they provide a cheaper means to transport. However, oil and gas pipelines may be significantly damaged due to internal and external defects (e.g., corrosion, dents, gouges, weld defects). Construction and operational defects of pipes can pose major risks to supplies. Pipeline safety is possible using inspection and monitoring techniques which can be either internal or external in nature.

Over the last few years, a number of technologies have been reported to monitor pipelines such as acoustic emission [1-4], fibre optic sensor [5, 6], digital signal processing and mass-volume balance [7]. In [8, 9] an approach for the detection and location of leaks in a pipeline using only measurements at the extremes of the pipe is suggested. In [10] the technique of acoustic pulse reflectometry is proposed for the detection of leaks in pipes. In [11] the cepstrum method is used to analyse a series of different pipe networks, both with and without leaks. Fuzzy logic and artificial intelligence techniques have been used successfully in many real-world applications[12-17]. They have been used for leak detection in water networks as well as in the oil and gas industry. In [18, 19] neural network method is used to fault pattern recognition of pipeline leakage. In [20] and [21] neural network method has been proposed for the purpose of detecting and localizing leakage in pipeline. In [12, 22-24] neural network technique is used for detection of the gas leakage in pipeline. In [20] a fault detection model based on multi-layer neural network using data mining technique is used for pattern recognition in oil pipe networks [24-27].
Various researchers have used observational approaches for fault diagnosis in pipes that are based on different algorithms [28-30]. In [31], a nonlinear adaptive state observer approach is used for timely detection of leakage in pipelines. In [32] second-order sliding mode algorithm is used for estimating the

position of the leak in a pipeline. In [33, 34] an exponentially convergent observer is used for detection of leakage in pipelines.

This paper presents a new approach based on ARX-Laguerre fuzzy PD approach for detection of leakage in pipelines. First, in this study, the ARX-Laguerre technique is used for pipeline modeling. In the second step, the PD observer based on the ARX-Laguerre model is designed to improve leak estimation in the presence of uncertainties. The performance and reliability of the proposed technique is numerically assessed based on simulation results for a pipeline with a leakage. This paper is structured as follows: in the next section the fundamental equations which describe the flow through pipelines are given. Afterwards, the pipeline model equations based on the ARX-Laguerre Technique are given. Then the proposed new technique based on ARX-Laguerre fuzzy PD observer is explained to detect and locate leaks in a pipe. Next, the simulation results are given. Finally, conclusions are provided.

II. Pipeline Modeling

First, Here, we do not consider convective speed changes and compressibility effects in process lines (Γ). The mass flow rate (ρ), the flow in a pipe system (Φ), and the inlet pressure ($\wp_i$) and outlet pressure ($\wp_o$) at pipeline are assumed to be computable. Furthermore, the area of cross section (Å) is fixed along the pipe. The suggested pipeline architecture is illustrated in Figure 1.

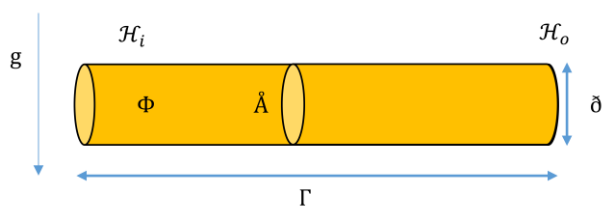

Figure 1. The suggested pipeline architecture

The differential equation describing the dynamic behavior of a fluid in a duct is based on the mass, momentum and the conservation of energy. Newton's 2nd law of motion ($F = ma$), when implemented to a control volume generated the following momentum equation[35, 36],

$$\frac{\partial \mathcal{H}}{\partial t} + \frac{a^2}{g\text{Å}}\frac{\partial \Phi}{\partial x} = 0 \tag{1}$$

in which a represents the speed of the wave inside a fluid filled elastic duct. The wave velocity depends on the elastic properties of the fluid and pipe. The pressure head ($\mathcal{H}$) and flow rate (Φ) change as functions of position and time, $\mathcal{H}(x,t)$ and $\Phi(x,t)$, respectively, so that, $x \in [0,\Gamma]$, where Γ represents the length of the duct. When the flow rate is small enough, you get the following equation of momentum,

$$\frac{\partial \Phi}{\partial t} + \text{Å}g\frac{\partial}{\partial x}\mathcal{H} + \frac{\Im\Phi^2}{2ð\text{Å}} = 0 \tag{2}$$

Now we can create a model of the pipe applying (1) and (2). These equations need to be solved, however getting analytical solutions is not easy. Because of this, different methods need to be used to solve these equations like characteristics and finite difference approaches [37]. Here, the finite difference approach is implemented such that (1) and (2) are discretized to obtain a system of ordinary differential equations. The considered finite difference approach discretizes the whole pipe into N smaller sections[37, 38].

The computational domain $z \in [0,\Gamma]$ is divided up into three smaller domains $\{s_k\} \coloneqq \{0, s_{leak}, \Gamma\}$, so that z_{leak} indicates the location of leak, see Figure 2. The leak flow rate can be measured by $\Phi_{leak} = C_d\text{Å}_{leak}\sqrt{2g}\sqrt{\mathcal{H}(s_{leak},t)}$, such that C_d represents efflux coefficient, and Å_{leak} the cross-sectional area along the leak path. The leak flow rate can be calculated by $\Phi_{leak} = \Lambda\sqrt{\mathcal{H}(s_{leak},t)}$, in which $\Lambda = C_d\text{Å}_{leak}\sqrt{2g}$. The behaviour of a dynamic pipeline network can be described by an ordinary differential equation system,

$$\begin{aligned} \dot{\Phi}_1 &= \frac{g\text{Å}}{s}(\mathcal{H}_1 - \mathcal{H}_2) - \frac{\Im{\Phi_1}^2}{2ð\text{Å}} \\ \dot{\mathcal{H}}_{leak} &= \frac{c^2}{g\text{Å}s}(\Phi_1 - \Phi_2 - \Lambda\sqrt{\mathcal{H}_{leak}}) \\ \dot{\Phi}_2 &= \frac{g\text{Å}}{\Gamma - s}(\mathcal{H}_2 - \mathcal{H}_3) - \frac{\Im\Phi_2^2}{2ð\text{Å}} \end{aligned} \tag{3}$$

Suppose that both inlet and outlet pressures, $\mathcal{H}_1$ and $\mathcal{H}_3$, respectively, are known and have been defined using external means such as a pump. The pressure $\mathcal{H}_2$ and the inlet and outlet flow rate (Φ_1 and Φ_2, respectively) of the leakage point are considered to be variables. From the continuity equation we can write,

$$\Phi_1 = \Phi_{leak} + \Phi_2 \tag{4}$$

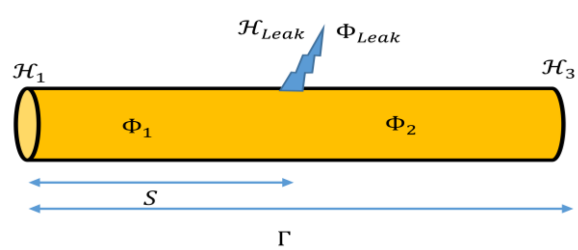

Figure 2. The suggested pipeline architecture

III. Pipeline Modeling based on the ARX-Laguerre Technique

For many years pipeline play a huge role in oil and gas industries as they significantly reduce transport costs. Leakage inspection in transmission pipelines is crucially significant for safe operation. In general, there are various fault detection methods, each with different potentials, however the selection of proper leak detection technique is difficult. This is particularly important when they deal with various types of uncertainties of conditions. To deal with this problem we introduce a fuzzy ARX-Laguerre PD observer in Section 4. First, in this study, the ARX-Laguerre technique is used for pipeline modeling. In the second step, the PD observer based on the ARX-Laguerre model is designed to improve leak estimation in the presence of uncertainties. The proposed model-based ARX-Laguerre orthonormal method is represented by developing its coefficients associated to the flow input and flow output, Fourier coefficients, and Laguerre-based orthonormal function as follows [29]:

$$M_0(s) = \sum_0^{i_a} \lambda_{n.a}\left(\sum_{j=1}^{\infty} \ell_a * M_0(s)\right).x_{n.M_0}(s) + \sum_0^{i_b} \lambda_{n.b}\left(\sum_{j=1}^{\infty} \ell_b * M_i(s)\right).x_{n.M_i}(s) \tag{5}$$

in which $M_0(s)$, $(\lambda_{n.a}\ and\ \lambda_{n.b})$, (i_a, i_b) (ℓ_a, ℓ_b),$*$, $M_i(s)$, $X_{n.M_0}(s)$ and $X_{n.M_i}(s)$ represent the pipe outflow, Fourier coefficients, the order of the system, Laguerre orthonormal function, convolution product, pipe inflow, exhaust filter, and entrance filter, respectively. By expanding the ARX model on Laguerre orthonormal bases the following state-space model can be obtained,

$$\begin{cases} M(s+1) = [AM(s) + B_y\big(y(s) + \alpha_s(k)\big) \\ \qquad +B_u u(s)] \\ \qquad y(s) = (S)^T M(s) + B_s \alpha_s(s) \end{cases} \tag{6}$$

in which, $M(s), y(s), u(s)$, $\alpha_s(s)$ represent the state vector, calculated output, control input, and sensor defect respectively. A, B_y, B_u , B_s as well as S represent matrices of coefficients. The flowchart of the proposed methodology is shown in Figure 3.

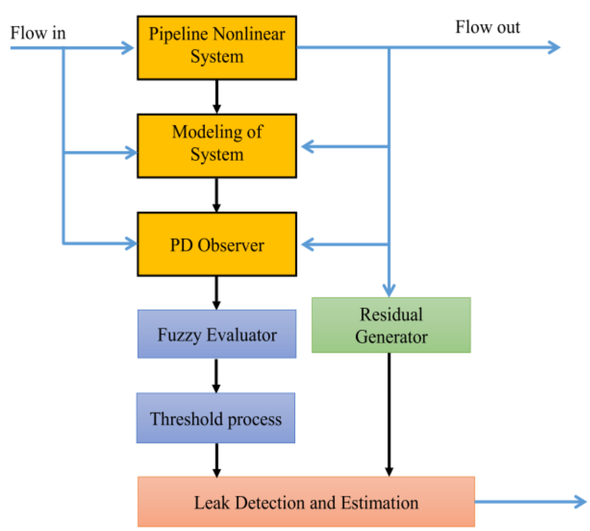

Figure 3. The flowchart of the proposed methodology

IV. ARX-Laguerre Fuzzy PD Observation Technique

In this section the ARX-Laguerre fuzzy PD observation system is proposed to detect and estimate a leak in pipelines.

A. *Modeling of Dynamic System by ARX-Laguerre*

Let us consider the linear ARX state space model with disturbances illustrated by following equation to formulate the dynamic fault detection problem,

$$\begin{cases} M(s+1) = [A\ M(s) + B_u u(s)] \\ \ \ y(s) = (S)^T M(s) + B_s \alpha_s(s) \end{cases} \tag{7}$$

We define the ARX model on Laguerre base as follows [39, 40]:

$$\begin{aligned} y(k) &= \textstyle\sum_0^{N_a-1} S_{(n,p)} x_{(n,y)}(s) + \sum_0^{N_b-1} S_{(n,b)} x_{(n,u)}(s) \\ X(k) &= [x_{(n,u)}(s) \quad x_{(n,y)}(s)] \\ x_{(n,y)}(s) &= L_n^a(k, \xi_p) * y(s) \\ x_{(n,u)}(s) &= L_n^b(k, \xi_b) * u(s) \end{aligned} \tag{8}$$

in which $y(k)$, $u(k), K_{(n,s)}$, (N_a, N_b), $x_{(n,y)}(s)$, $x_{(n,u)}(s)$ and $(L_n^a(s, \xi_a), L_n^b(s, \xi_b))$ represent the pipe outflow, pipe inflow, Fourier coefficients, exhaust filter, entrance filter, and Laguerre orthonormal function, respectively.

Using (8), the following state-space model can be obtained in the presence of failures of the sensor as well as disturbances,

$$\begin{cases} M_s(s+1) = [AM_s(s) + B_y\big(y_s(s) + \alpha_s(s)\big) + \\ \qquad B_u u(s)] \\ \qquad y(s) = (S)^T M_s(s) + B_s \alpha_s(s) \end{cases} \tag{9}$$

The fault of the sensor is calculated using the following formula,

$$\begin{aligned} e_y(s) &= y_s(s) - y(s) \\ e_M(s) &= \begin{bmatrix} M_{s(n,u)}(k) - M_{(n,u)}(s) \\ M_{s(n,y_s+\alpha_s)}(k) - M_{(n,y)}(s) \end{bmatrix} \end{aligned} \tag{10}$$

such that

$$\begin{aligned} M_{s(n,y_s+\alpha_s)}(s) \neq x_{(n,y)}(s) \to M_s(s) \neq M(s) \\ \to y_s(s) \neq y(s) \to e_y(s) \neq 0. \end{aligned} \tag{11}$$

Pipe with fault can be recognized using (11). The fuzzy PD observation method using the ARX-Laguerre technique is used for diagnosing fault in pipe.

B. *Fault Diagnosis*

In this study the ARX-Laguerre fuzzy PD observation system is proposed to identify sensor defects in pipes. We define the proposed technique by following formulas in the presence of failures of the sensor in the pipe,

$$\begin{cases} \hat{M}(s+1) = A\hat{M}(s) + B_y\big(\hat{y}(s) + \hat{\alpha}_s(s)\big) + \\ B_y u(s) + K_p e(s) \\ e_s(s) = (q_s(s) - \hat{q}_s(s)) \\ \quad \hat{\alpha}_s(s+1) = \hat{\alpha}_s(s) + K_{d_s}(e_s(s+1) \\ \quad +e_s(s) + e_s(s-1)) \\ \quad \hat{y}(s+1) = (S)^T \hat{M}(s+1) + \beta_s \hat{\alpha}_s(s) \end{cases} \tag{12}$$

where $\hat{M}(s)$ represents the state vector, $\alpha_s(s)$ sensor defect and $\hat{y}(s)$ the output of the system. In accordance with (12), in this paper, we particularly study three main cases and types of faults in pipe.

In case $\alpha_s \neq 0$, $\hat{\alpha}_s(s) \neq \alpha_s(s)$ we have:

$$(y(s+1) - \hat{y}(s+1) \neq 0) \& (M(s+1) - \widehat{M}(s+1)) \neq 0 \implies$$

$$[M_1^T(s+1) \quad M_2^T(s+1)]^T - \left[\widehat{M}_{1,\alpha_s}^T(s+1) \quad \widehat{M}_2^T(s+1)\right]^T \neq 0 \implies M_{(n,y)}(s) - \widehat{M}_{(n,y+\alpha_s)}(s) \neq 0 \tag{13}$$

Also, in case $\alpha_s \neq 0$ as well as $\hat{\alpha}_s(s) = \alpha_s(s)$, we have:

$$(y(s+1) - \hat{y}(s+1) \neq 0) \& (M(s+1) - \widehat{M}(s+1)) \neq 0 \implies M_{(n,y)}(s) - \widehat{M}_{(n,y+\alpha_s)}(s) \neq 0 \tag{14}$$

In accordance with (14), in case the pipe includes sensor and pump failures, the signals received from pump and joint variable can identify the defects. Signal sensor faults are:

$$\hat{\alpha}_s = \alpha_s \rightarrow r_1 = w - \widehat{w} \gg 0 \tag{15}$$

To increase the signal estimation accuracy and to modify the performance of fault estimation of the ARX-Laguerre PD technique, optimal fuzzy observer coefficients, K_{p_s}, and K_{d_s} are applied which are defined as follows:

$$K_{d_s} = K_{p_s} . T_{d_s} \tag{16}$$

where T_{d_s}, represent the derivative gain for sensor failure, respectively. Following (14), we have:

$$K_{i_s} = \frac{(K_{p_s})^2}{\beta_s K_{d_s}} \tag{17}$$

Normalization of the above equation can be done by the formula described below,

$$K'_{p_s} = \frac{K_{p_s} - K_{p_s(min)}}{K_{p_s(max)} - K_{p_s(min)}} \in [0,1], K'_{d_s} = \frac{K_{d_s} - K_{d_s(min)}}{K_{d_s(max)} - K_{d_s(min)}} \in [0,1], 2 \leq \beta_s \leq 5 \tag{18}$$

such that $\beta = \frac{\sum_i \alpha(x_i) . x_i}{\sum_i \alpha(x_i)}$ represents a membership function.

V. Simulation Results

In this section we evaluate our proposed technique on a pipe model under the leak condition in the presence of failures of the sensor in the pipe. In order to check the efficiency of the proposed ARX-Laguerre fuzzy PD observation technique for fault detection conditions.

Pipe under fault condition. In this case, the duct functions under fault circumstances. The duct has two kinds of defects simultaneously, the sensor defect and the pump defect.

The input-output signals from sensor in the pipe with fault state can be computed as follows:

$$r(\phi) = \phi - \hat{\phi} \rightarrow r(\phi) = \phi - (\phi_{Observer} + \alpha_s) \gg 0 \tag{19}$$

where,

$$\phi_{1_{\alpha_s}}(m) = \begin{cases} 0.6, & 10 \leq t \leq 25 \\ 0, & otherwise \end{cases} \tag{20}$$

The sensor signal for the pipe under fault condition is shown in Figure 4.

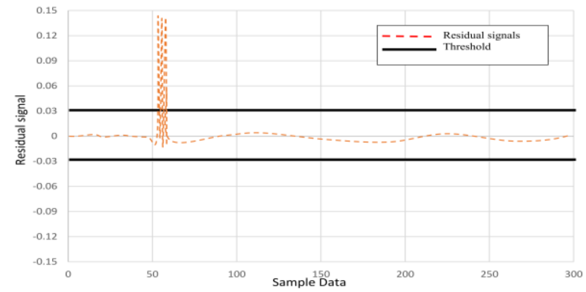

Figure 4. The sensor signal for the pipe under fault condition

The effectiveness of the proposed technique for fault estimation under fault condition is shown Figures 5. The error between the predicted output and the expected output based on the proposed technique under fault condition is shown in Figures 6.

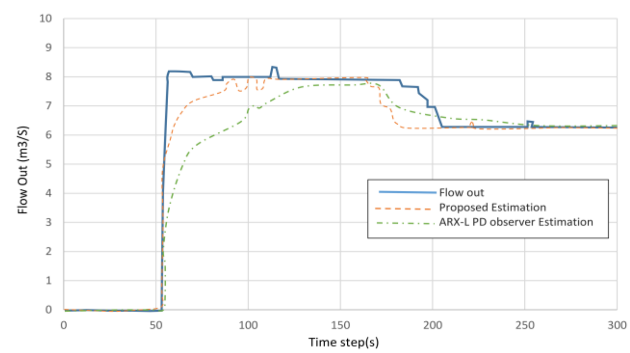

Figure 5. The effectiveness of the proposed technique for fault estimation under fault condition

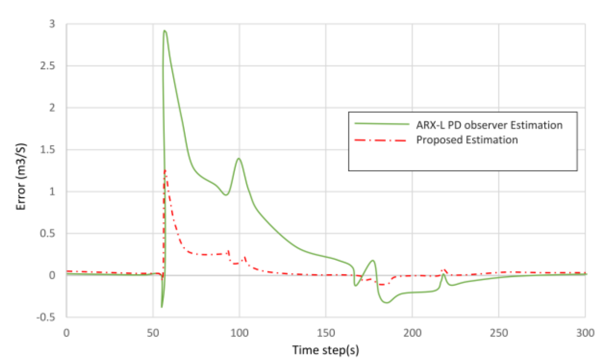

Figure 6. The error between the predicted output and the expected output based on the proposed technique under fault condition

The effectiveness of the proposed technique for fault estimation at leakage point is shown in Figures 7. It can be seen from this figure that our proposed method detects fault in less time in comparison with PD observer technique.

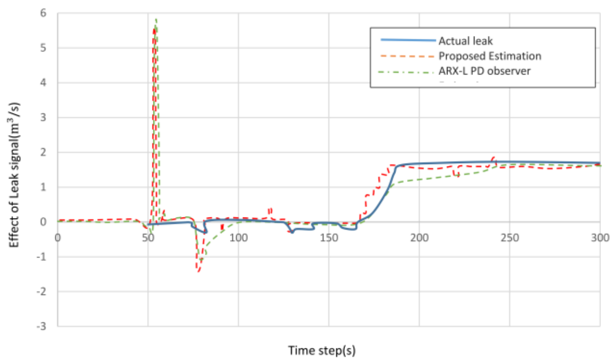

Figure 7. The effectiveness of the proposed technique for fault estimation at leakage point in pipe

VI. Conclusions

The task of precise defect detection in the pipeline system is a formidable challenge due to the uncertainties in leak signal. To better deal with uncertainties in the leak signal, in this paper, an ARX-Laguerre PD-observer is introduced to perform fault diagnosis in the pipeline system. First, in this study, the ARX-Laguerre technique is used for pipeline modeling. In the second step, the PD observer based on the ARX-Laguerre model is designed to improve leak estimation in the presence of uncertainties. The performance of the proposed algorithm is tested on numerical simulation. According to the results, the proposed technique can accurately locate the leakage point. In the future, the proposed observation method will be used to enhance the performance of fault diagnosis when the uncertainties are in the form of Z-numbers.

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