A Reliable & Autonomous Robotic In-Pipe Leak Detection System

by

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Submitted to the Department of Mechanical Engineering in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Mechanical Engineering at the Massachusetts Institute of Technology

June 2015

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Abstract
Leaks are the major factor for unaccounted losses in every pipe network around the world (oil, gas or water). In most cases the deleterious effects associated with the occurrence of leaks may present serious economical and health problems. Therefore, leaks must be quickly detected, located and repaired. Unfortunately, most state-of-the-art leak detection systems are of limited applicability, lack in reliability or depend on user experience for data interpretation.

In this dissertation we present a new, autonomous, in-pipe, leak sensing system; the "MIT Leak Detector". The proposed system is able to perform autonomous leak detection in pipes and, thus, eliminates the need for user experience. In addition, the sensing methodology under consideration is independent of pipe material and surrounding medium, thus it is widely applicable. As shown in the experimental section of the thesis, the detection principle proves to be very reliable and sensitive to small leaks in pipes. Last but not least, the robotic system is equipped with intelligence in order to use the acquired sensor signals to estimate the leak size and flow rate without user intervention.

We start the thesis by describing the fundamental concept behind detection and present the proposed design. The detection principle in based on the presence of a pressure gradient in the neighborhood of any leak in a pressurized pipe. This phenomenon is translated into force measurements via a carefully designed and instrumented mechanical embodiment. In addition, an analytic dynamic model of the robotic detector is derived. Further study and analysis show that the proposed system can sense leaks at any angle around the circumference of the pipe by utilizing two force measurements at specific locations. Finally, a prototype is built and experiments are conducted in controlled laboratory conditions in compressed air pipes.

Thesis Supervisor: Kamal Youcef-Toumi
Title: Professor of Mechanical Engineering
To my beloved parents
Mihalis and Zoi,
I would like to express my deepest appreciation and gratitude to my advisor, Professor Kamal Youcef-Toumi. Kamal embraced me from day one at MIT, welcomed me to his group and gave me an exciting research opportunity. I will never forget the day, when I talked to him after class and got the invitation to visit his lab for the first time. Kamal helped me develop both as a person and as a researcher and has been a source of advice and support during my years as a graduate student at MIT. He was never too busy to chat about any little problem and kept advising me through most of my life decisions. In addition, his technical and editorial feedback was essential to the completion of this dissertation. Moreover, Kamal taught me innumerable lessons and insights on the workings of academic research and life in general.

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To conclude, I would like to dedicate this dissertation with all my love and appreciation to my wonderful parents. Thank you for your endless love, support and encouragement. Thank you for being always there for me and for inculcating in me the dedication and discipline to do whatever I undertake well. Thank you for the tremendous sacrifices that you made to ensure that I had an excellent education. Thank you for being always there to chat and guide me through all my decisions. For this and much more, I am forever in your debt.
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<thead>
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<tr>
<td>$f(\cdot)$</td>
<td>Function $f$</td>
</tr>
<tr>
<td>$\dot{f}(\cdot)$</td>
<td>Time derivative of function $f$</td>
</tr>
<tr>
<td>$f_\theta$</td>
<td>Partial derivative of function $f$ wrt to $\theta$</td>
</tr>
<tr>
<td>$f_\psi$</td>
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<tr>
<td>$c_i$</td>
<td>$\cos(i)$</td>
</tr>
<tr>
<td>$\hat{e}_i$</td>
<td>Unit vector along axis $i$</td>
</tr>
<tr>
<td>$\sum_{i=1}^{n}$</td>
<td>Summation from 1 to $n$</td>
</tr>
<tr>
<td>$R(q)$</td>
<td>Rotation matrix as a function of $q$</td>
</tr>
<tr>
<td>$R_y(\psi)$</td>
<td>Matrix of rotation about axis $y$ by $\psi$</td>
</tr>
<tr>
<td>$R_x(\theta)$</td>
<td>Matrix of rotation about axis $x$ by $\theta$</td>
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</tr>
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<td>$E[\cdot]$</td>
<td>Expected value</td>
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<tr>
<td>$</td>
<td></td>
</tr>
<tr>
<td>$(\cdot)^{-1}$</td>
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### Coordinates & Vector Notation

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<td>Position vector of point $J$ wrt to chassis frame</td>
</tr>
<tr>
<td>$\mathbf{p}'_J$</td>
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</tr>
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<td>Velocity vector of point $J$ wrt to chassis frame</td>
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<tr>
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<td>Velocity vector of point $J$ wrt to drum frame</td>
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<td>$\dot{z}_J$</td>
<td>$z$-velocity of point $J$ wrt chassis frame</td>
</tr>
<tr>
<td>$\dot{x}'_J$</td>
<td>$x$-velocity of point $J$ wrt drum frame</td>
</tr>
<tr>
<td>$\dot{y}'_J$</td>
<td>$y$-velocity of point $J$ wrt drum frame</td>
</tr>
<tr>
<td>$\dot{z}'_J$</td>
<td>$z$-velocity of point $J$ wrt drum frame</td>
</tr>
</tbody>
</table>

### Points & Reference Frames

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>$G$</td>
<td>Point on the drum (Gimbal center)</td>
</tr>
<tr>
<td>$G'$</td>
<td>Point on the front plate (Projection of $G$ on front plate)</td>
</tr>
<tr>
<td>$\mathcal{L}$</td>
<td>Point on the front plate (Point where spring is mounted)</td>
</tr>
<tr>
<td>$O$</td>
<td>Origin - Inertial reference frame</td>
</tr>
<tr>
<td>$\mathcal{K}$</td>
<td>Point on the drum</td>
</tr>
<tr>
<td>$\mathcal{K}_1$</td>
<td>Point on the drum</td>
</tr>
<tr>
<td>$\mathcal{K}_2$</td>
<td>Point on the drum</td>
</tr>
<tr>
<td>$\mathcal{K}_3$</td>
<td>Point on the drum</td>
</tr>
<tr>
<td>$\mathcal{K}_4$</td>
<td>Point on the drum</td>
</tr>
<tr>
<td>$A$</td>
<td>Point on the drum</td>
</tr>
<tr>
<td>$B$</td>
<td>Point on the drum</td>
</tr>
<tr>
<td>$Oxyz$</td>
<td>Inertial reference frame</td>
</tr>
<tr>
<td>$Gxyz$</td>
<td>Chassis' reference frame</td>
</tr>
<tr>
<td>$Gx'y'z'$</td>
<td>Drum reference frame</td>
</tr>
</tbody>
</table>
## Detector Notation

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>( r )</td>
<td>Distance between gimbal center and sensor on the drum</td>
</tr>
<tr>
<td>( R )</td>
<td>Radial distance from ( G ) to the point where the leak force is applied</td>
</tr>
<tr>
<td>( l )</td>
<td>Distance from ( G ) to ( G' )</td>
</tr>
<tr>
<td>( l_0 )</td>
<td>Unperturbed length of spring</td>
</tr>
<tr>
<td>( l_{ef} )</td>
<td>Length of membrane</td>
</tr>
<tr>
<td>( \alpha )</td>
<td>Angle of first sensor on the drum</td>
</tr>
<tr>
<td>( \beta )</td>
<td>Angle of second sensor on the drum</td>
</tr>
<tr>
<td>( \alpha^* )</td>
<td>Optimal angle of first sensor on the drum</td>
</tr>
<tr>
<td>( \beta^* )</td>
<td>Optimal angle of second sensor on the drum</td>
</tr>
<tr>
<td>( \kappa_1 )</td>
<td>Angle of point ( K_1 )</td>
</tr>
<tr>
<td>( \kappa_2 )</td>
<td>Angle of point ( K_2 )</td>
</tr>
<tr>
<td>( \kappa_3 )</td>
<td>Angle of point ( K_3 )</td>
</tr>
<tr>
<td>( \kappa_4 )</td>
<td>Angle of point ( K_4 )</td>
</tr>
<tr>
<td>( v_{robot} )</td>
<td>Speed of robot in the pipe</td>
</tr>
</tbody>
</table>

## Pipe & Leak Notation

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>( D )</td>
<td>Pipe diameter</td>
</tr>
<tr>
<td>( p_{High} )</td>
<td>Pressure inside the pipe (line)</td>
</tr>
<tr>
<td>( p_{Low} )</td>
<td>Pressure outside the pipe (ambient)</td>
</tr>
<tr>
<td>( \Delta p )</td>
<td>Difference between line and ambient pressure</td>
</tr>
<tr>
<td>( \phi )</td>
<td>Incidence angle of a leak</td>
</tr>
<tr>
<td>( F )</td>
<td>Normal (radial) force on membrane in case of a leak</td>
</tr>
<tr>
<td>( F_z )</td>
<td>Longitudinal force amplitude in case of a leak</td>
</tr>
<tr>
<td>( F_z )</td>
<td>Longitudinal force vector in case of a leak</td>
</tr>
<tr>
<td>( A_{leak} )</td>
<td>Area (cross-sectional) of leak</td>
</tr>
<tr>
<td>( \mu )</td>
<td>Static friction coefficient</td>
</tr>
<tr>
<td>( M )</td>
<td>Torque amplitude</td>
</tr>
<tr>
<td>( M_x )</td>
<td>( x )-contribution of torque on the drum in case of a leak</td>
</tr>
<tr>
<td>( M_y )</td>
<td>( y )-contribution of torque on the drum in case of a leak</td>
</tr>
<tr>
<td>( M )</td>
<td>Torque vector</td>
</tr>
</tbody>
</table>
## Detector & Analysis Notation

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>( q )</td>
<td>Degree of freedom vector for drum &amp; gimbal</td>
</tr>
<tr>
<td>( n )</td>
<td>Number of springs</td>
</tr>
<tr>
<td>( \kappa )</td>
<td>Enclosed angle of point ( \mathcal{K} )</td>
</tr>
<tr>
<td>( x )</td>
<td>State vector</td>
</tr>
<tr>
<td>( \dot{x} )</td>
<td>Time derivative of state vector</td>
</tr>
<tr>
<td>( \theta )</td>
<td>Rotation of drum about axis ( x )</td>
</tr>
<tr>
<td>( \psi )</td>
<td>Rotation of drum about axis ( y )</td>
</tr>
<tr>
<td>( \dot{\theta} )</td>
<td>Rotational velocity of drum about axis ( x )</td>
</tr>
<tr>
<td>( \dot{\psi} )</td>
<td>Rotational velocity of drum about axis ( y )</td>
</tr>
<tr>
<td>( \ddot{\theta} )</td>
<td>Rotational acceleration of drum about axis ( x )</td>
</tr>
<tr>
<td>( \ddot{\psi} )</td>
<td>Rotational acceleration of drum about axis ( y )</td>
</tr>
<tr>
<td>( \delta \theta )</td>
<td>Change in ( \theta )</td>
</tr>
<tr>
<td>( \delta \psi )</td>
<td>Change in ( \psi )</td>
</tr>
<tr>
<td>( k_{\kappa} )</td>
<td>Stiffness of spring mounted at point ( \mathcal{K} )</td>
</tr>
<tr>
<td>( k )</td>
<td>Stiffness of spring</td>
</tr>
<tr>
<td>( b_{\kappa} )</td>
<td>Strength of linear damper mounted at point ( \mathcal{K} )</td>
</tr>
<tr>
<td>( b )</td>
<td>Strength of linear damper</td>
</tr>
<tr>
<td>( \kappa F_k(x) )</td>
<td>Force of spring mounted at point ( \mathcal{K} )</td>
</tr>
<tr>
<td>( \kappa M_{k,x}(x) )</td>
<td>Torque of spring mounted at point ( \mathcal{K} ) about axis ( x )</td>
</tr>
<tr>
<td>( \kappa M_{k,y}(x) )</td>
<td>Torque of spring mounted at point ( \mathcal{K} ) about axis ( y )</td>
</tr>
<tr>
<td>( \kappa F_b(x) )</td>
<td>Force of linear damper mounted at point ( \mathcal{K} )</td>
</tr>
<tr>
<td>( \kappa M_{b,x}(x) )</td>
<td>Torque of linear damper mounted at point ( \mathcal{K} ) about axis ( x )</td>
</tr>
<tr>
<td>( \kappa M_{b,y}(x) )</td>
<td>Torque of linear damper mounted at point ( \mathcal{K} ) about axis ( y )</td>
</tr>
<tr>
<td>( I_{xx} )</td>
<td>Rotational inertia of drum &amp; gimbal about axis ( x )</td>
</tr>
<tr>
<td>( I_{yy} )</td>
<td>Rotational inertia of drum &amp; gimbal about axis ( y )</td>
</tr>
<tr>
<td>( y )</td>
<td>Output vector</td>
</tr>
<tr>
<td>( y_1 )</td>
<td>First output/measurement</td>
</tr>
<tr>
<td>( y_2 )</td>
<td>Second output/measurement</td>
</tr>
<tr>
<td>( A )</td>
<td>A-Matrix of state space representation</td>
</tr>
<tr>
<td>( B )</td>
<td>B-Matrix of state space representation</td>
</tr>
<tr>
<td>( C )</td>
<td>C-Matrix of state space representation</td>
</tr>
<tr>
<td>( d )</td>
<td>Disturbance vector</td>
</tr>
<tr>
<td>( d_1 )</td>
<td>First disturbance - torque contribution about axis ( x )</td>
</tr>
<tr>
<td>( d_2 )</td>
<td>Second disturbance - torque contribution about axis ( y )</td>
</tr>
<tr>
<td>( \mathcal{O} )</td>
<td>Observability matrix</td>
</tr>
<tr>
<td>( \mathcal{C} )</td>
<td>Controllability matrix</td>
</tr>
<tr>
<td>( \delta y )</td>
<td>Change in output vector</td>
</tr>
<tr>
<td>( \delta \chi )</td>
<td>Infinitesimal rotation vector</td>
</tr>
<tr>
<td>( \delta \chi )</td>
<td>Infinitesimal rotation magnitude</td>
</tr>
</tbody>
</table>
Detector & Estimation Notation (1/2)

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>$w$</td>
<td>Process noise vector</td>
</tr>
<tr>
<td>$v$</td>
<td>Sensor noise vector</td>
</tr>
<tr>
<td>$\hat{x}$</td>
<td>Estimate of state vector</td>
</tr>
<tr>
<td>$d$</td>
<td>Estimate of disturbance vector</td>
</tr>
<tr>
<td>$t^*$</td>
<td>Time of leak trigger</td>
</tr>
<tr>
<td>$\hat{F}_z$</td>
<td>Estimate of leak force</td>
</tr>
<tr>
<td>$\phi$</td>
<td>Estimate of leak incidence angle</td>
</tr>
<tr>
<td>$\hat{A}_{leak}$</td>
<td>Estimate of leak cross sectional area</td>
</tr>
<tr>
<td>$d_{leak}$</td>
<td>Estimate of leak flow rate</td>
</tr>
<tr>
<td>$f_s$</td>
<td>Sampling rate</td>
</tr>
<tr>
<td>$T_s$</td>
<td>Sampling period</td>
</tr>
<tr>
<td>$j$</td>
<td>Discrete counter</td>
</tr>
<tr>
<td>$A_d$</td>
<td>Discrete A-Matrix of state space representation</td>
</tr>
<tr>
<td>$B_d$</td>
<td>Discrete A-Matrix of state space representation</td>
</tr>
<tr>
<td>$C_d$</td>
<td>Discrete A-Matrix of state space representation</td>
</tr>
<tr>
<td>$\hat{x}_{j-1</td>
<td>j-1}$</td>
</tr>
<tr>
<td>$\hat{x}_{j</td>
<td>j-1}$</td>
</tr>
<tr>
<td>$\hat{x}_{j^*j}$</td>
<td>The unbiased state estimate</td>
</tr>
<tr>
<td>$W$</td>
<td>Covariance matrix for process noise</td>
</tr>
<tr>
<td>$V$</td>
<td>Covariance matrix for sensor noise</td>
</tr>
<tr>
<td>$L_j$</td>
<td>Gain Matrix for instant $j$</td>
</tr>
<tr>
<td>$K_j$</td>
<td>Gain Matrix for instant $j$</td>
</tr>
<tr>
<td>$Y_j$</td>
<td>Sequence of measurements up to instant $j$</td>
</tr>
<tr>
<td>$J_j$</td>
<td>Triggering Metric at instant $j$</td>
</tr>
<tr>
<td>$c$</td>
<td>Threshold for triggering metric</td>
</tr>
<tr>
<td>$j^*$</td>
<td>Discrete instant of time $t^*$</td>
</tr>
<tr>
<td>$j_{end}$</td>
<td>Discrete instant of time when triggering metric reaches a maximum</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>Correction factor for orifice equation</td>
</tr>
<tr>
<td>$\rho$</td>
<td>Pipe medium density</td>
</tr>
<tr>
<td>$\bar{F}_z$</td>
<td>Mean estimated leak force</td>
</tr>
<tr>
<td>$\bar{\phi}$</td>
<td>Mean estimated leak incidence angle</td>
</tr>
<tr>
<td>$d_{leak}$</td>
<td>Estimated leak diameter</td>
</tr>
</tbody>
</table>
### Detector & Estimation Notation (2/2)

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\sigma_w$</td>
<td>Standard deviation for process noise</td>
</tr>
<tr>
<td>$\sigma_v$</td>
<td>Standard deviation for sensor noise</td>
</tr>
<tr>
<td>$d_{\text{nom}}$</td>
<td>Nominal leak diameter</td>
</tr>
<tr>
<td>$n_{\text{MC}}$</td>
<td>Monte Carlo iterations</td>
</tr>
<tr>
<td>$P_{00}$</td>
<td>Initial condition for error covariance matrix</td>
</tr>
<tr>
<td>$x_{00}$</td>
<td>Initial condition for state estimate</td>
</tr>
<tr>
<td>$P_{j+1,j}$</td>
<td>Error covariance matrix</td>
</tr>
<tr>
<td>$\hat{R}_j$</td>
<td>Error covariance matrix</td>
</tr>
<tr>
<td>$F$</td>
<td>A matrix used in the detection and estimation</td>
</tr>
<tr>
<td>$b_1$</td>
<td>Damping coefficient for dissipation about axis $x$</td>
</tr>
<tr>
<td>$b_2$</td>
<td>Damping coefficient for dissipation about axis $y$</td>
</tr>
</tbody>
</table>

### System ID and Detector Prototype Notation (2/2)

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\theta_{\text{sus}}$</td>
<td>Angle of suspension leg of the robotic locomotive</td>
</tr>
<tr>
<td>$s$</td>
<td>Laplace variable</td>
</tr>
<tr>
<td>$Y_1(s)$</td>
<td>Transfer function of $y_1$</td>
</tr>
<tr>
<td>$Y_2(s)$</td>
<td>Transfer function of $y_2$</td>
</tr>
<tr>
<td>$D_1(s)$</td>
<td>Transfer function of $d_1$</td>
</tr>
<tr>
<td>$D_2(s)$</td>
<td>Transfer function of $d_2$</td>
</tr>
<tr>
<td>$F_z(s)$</td>
<td>Transfer function of $F_z$</td>
</tr>
<tr>
<td>$K_1$</td>
<td>Constant gain</td>
</tr>
<tr>
<td>$K_2$</td>
<td>Constant gain</td>
</tr>
<tr>
<td>$w_{n,1}$</td>
<td>Natural frequency</td>
</tr>
<tr>
<td>$w_{n,2}$</td>
<td>Natural frequency</td>
</tr>
<tr>
<td>$\zeta_1$</td>
<td>Damping ratio</td>
</tr>
<tr>
<td>$\zeta_2$</td>
<td>Damping ratio</td>
</tr>
<tr>
<td>$q_{\text{leak, measured}}$</td>
<td>Measured leak flow rate</td>
</tr>
<tr>
<td>$q_{\text{leak, nominal}}$</td>
<td>Nominal leak flow rate</td>
</tr>
<tr>
<td>$F_{\text{leak}}$</td>
<td>Nominal leak force</td>
</tr>
<tr>
<td>$F_{\text{theory}}$</td>
<td>Theoretical leak force</td>
</tr>
</tbody>
</table>
Chapter 1

Introduction

In this chapter we discuss the implications and significance of pipe leaks to modern societies. This includes leaks in water, as well as oil and gas pipes. At the end of this chapter we list the contributions of the thesis in detail and then move to the state of the art review in chapter 2.

1.1 Motivation: Why Leak Detection?

Leaks in Water Networks

Water scarcity is the lack of sufficient available water resources to meet the demands of water usage within a region. Water scarcity is already a big problem that affects every continent and millions of people. Nowadays, there are more than 1.2 billion people that lack access to clean drinking water and the problem is going to become more serious in the near future (Fig. 1.1). Preventing leaks from occurring or fixing existing leaks will contribute to the solution of this major global problem.

Water transmission and distribution networks deteriorate naturally with time and subsequently lose their initial water tightness. Causes of leaks in these networks include corrosive environments, soil movement, poor construction standards, fluctuation of line pressure, excessive traffic loads (vibration) and in some cases bad workmanship. A leak inside a city stemming from a defect in the water distribution network can result in large road and building damages as shown in the example of Fig. 1.2.

Leaks in water distribution systems can result in financial losses for the water authorities, potential risks to public health, as well as environmental burden associated with wasted energy (Fig. 1.3). Thus, nowadays, such problems have led to the introduction of stricter penalties against water authorities for ignoring leakage. Moreover, all these problems have provided the necessary incentives for the investment in better leak detection technology and enhanced leak reduction strategies.
Figure 1.1: Projected global water scarcity for the year 2025. Note the large regions in the map with significant water scarcity.
Figure 1.2: This leaking underground pipe blew an 8m diameter hole in the road, blowing bitumen and kerbing into the air. Fortunately no-one was hurt. The burst water pipe that caused this massive sink hole in the road was 300mm in diameter.

The financial cost associated with water loss is not new and is perhaps the most obvious complication of leakage. There is a clear correlation between a utility’s income and water that fails to reach customers’ homes. Lai [43] conducted one of the first “global” surveys, that reported water loss figures from several different countries and cities. They discovered that these figures varied significantly, from a low of 9% in Germany to a high of 43% in Malaysia, with most countries falling into the range of 20-30%.

In a similar fashion Brothers [6] estimated average water loss in North American networks to be about 20%, most of this being leakage. Vickers [69] reports water losses in USA municipalities to range from 15 to 25%. Finally, the Canadian Water Research Institute [50] reports that on average 20% of the treated water is wasted due to losses during distribution.

In addition to water loss, leaks are costly in terms of energy consumption. Colombo and Karney studied the correlation and performed a preliminary evaluation of the relative importance of energy waste via leakage [18]. In their study a computer program is used to simulate the energy costs of leaks on representative distribution networks.

Last but not least, any defect, opening or leak on the pipe walls can result in the admission of contaminants into the water supply (especially during hydraulic transients). Kirmeyer et al. [39], and Karim et al. [33] collected and tested soil and water samples in the immediate vicinity of water mains at eight locations in six US states. They found that often these soils contain potentially harmful bacteria and pathogens such as coliform (detected in 58% and 70% of water and soil samples, respectively) and fecal coliform bacteria (detected in 43% of the water and 50% of the soil samples).

**Leaks in Oil & Gas Networks**

In addition to water losses, there are thousands of miles of natural gas and oil pipelines around the globe, that are poorly maintained. Thus, a significant portion of these natural resources is lost through leakage annually (Fig. 1.4). In some cases, high-volume transmission pipelines are monitored for evidence of leaks using various techniques (see chapter 2). However, in most cases leaks are detected only after a significant volume of oil or gas is already lost from the pipelines. The cost of leaks in oil and gas networks is huge and is usually associated with financial losses and environmental as well as human-life threats.

Gas distribution companies were reported to be releasing 69 billion cubic feet of natural gas to the atmosphere according to [61]. This quantity is almost enough to meet the state of Maine’s gas needs for a year and equal to the annual carbon dioxide emissions of about six million automobiles. According to the same study,
Worldwide, up to 60% of water is lost due to leaky pipes—to the tune of US$14 billion every year.

30% of the pipes are between 40 and 80 years old in water systems that serve 100,000 or more people.

In the United States alone, an average of 700 water main breaks occur every day—that's 240,000 per year.

A faucet that drips just once per second wastes 2,700 gallons of water annually.

Water use has been growing at more than 2x the rate of population increase in the last century.

The total estimated cost to fix U.S. water systems is $335 billion over 20 years.

Figure 1.3: An interesting water infographic from IBM.
consumers in the US paid at least $20 billion from 2000-2011 for gas that was unaccounted for and never used due to leaks. However, leaks in these networks result in serious accidents (explosions), e.g., the fatal pipeline explosion in San Bruno, California in 2010 [71]. This incident started with a leak in a buried pipeline and resulted in a big explosion in an urban area that killed eight people. California regulators have imposed $1.4 billion in penalties against Pacific Gas & Electric for the explosion.

Figure 1.4: An interesting gas infographic for the state of Massachusetts, USA.
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Chapter 2

Background

In this chapter we review the most prominent leak detection techniques and discuss their advantages and drawbacks. At the end of the chapter we list the limitations of the existing solutions and present our proposed approach.

2.1 State of the Art Systems

The state of the art systems for pipe monitoring need to be divided into some main categories. Pipe health monitoring techniques include methods for inspecting the integrity of pipes and assisting in some cases in the prevention of leaks and damages to the pipe material. This is done by inspecting pipe walls for voids or preliminary cracks. On the other hand, once a leak has been created, leak detection techniques need to be utilized for leak identification and localization. Leak detection methodologies can be further divided into out-of-pipe and in-pipe methods, as summarized in Fig. 2.1. In the next paragraphs, we present the most prominent solutions of each family of methods.

2.1.1 Pipe Health Monitoring

It is always preferable to prevent leaks from occurring, than fixing them once they happen (preventing is better than curing in a sense). Thus, there exist various Non-Destructive Testing (NDT) methods for pipe-health monitoring. Most NDT systems use sonar, electromagnetic or optical sensors to search for defects on the pipe walls [47]. In all cases an in-pipe moving system is needed and the wall thickness is scanned for voids, cracks or any other defects (Fig. 2.2). One of the major drawbacks is the difficulty in interpreting the results and in most cases significant user experience is necessary.

In case of sonar sensors, an ultrasonic signal is transmitted, reflected off the pipe walls, and received again by the sonar head. The on-board processor uses the wave time of flight to calculate the distance to the pipe wall and reconstruct an internal profile of the pipe walls. Acoustic resonance can be also used to get
an estimation of the remaining wall thickness of cast iron pipes, as well as for the detection of pipe joints, valves, and bends. However, a major disadvantage of ultrasonic devices is their inability to inspect both the flooded part of the pipe and the dry part simultaneously (in case of liquids), because the optimal operating frequencies in water/oil and air are different.

Electromagnetic systems for pipe-health monitoring include in most cases a Magnetic Flux Leakage (MFL) sensor. This sensor is based on measuring the disturbances of the magnetic flux with a hall-effect device. Disturbances on the flux are caused by cracks, voids, or corrosion pits in the pipe material. Drawbacks of these methods include the high power requirement needed. This can be a limiting factor for in-pipe untethered autonomous systems, that carry their own power sources on board. Moreover, inspection is usually slow and the systems become bulky (Fig. 2.3).

Optical sensors range from lasers to cameras. The first ones can provide a very good accuracy in the estimation of the pipe geometry, and hence detection of many different pipe deformations are possible. In addition, one is able to find a number of different cameras available for in-pipe inspection robots, e.g. the fish-eye concept. Disadvantage of this method includes the fact that visual inspection cannot be done when the pipes are in operation and filled with various liquid media (water, oil). Not to mention, that the pipe environment is usually very dark, so a regular camera would not work without proper illumination.
Figure 2.2: Pipe Health Monitoring device from Pure Technologies [55]. System is equipped with electromagnetic sensors, high-speed profiling SONAR and high definition digital pan-tilt-zoom closed circuit television (CCTV).

Figure 2.3: The world’s largest MFL system from EMTEK Electromechanical Technologies Inc. [23].
2.1.2 Out-of-Pipe Methods

When leaks have already occurred, other methods need to be utilized for leak detection. Mays [45] and Hunaidi [29] report on various techniques for leak detection in water pipes. First, water losses can be identified from water audits. The difference between the amounts of water produced by the water company and the total amount of water recorded by the usage meters indicates the amount of lost water.

District metering offers a slightly higher level of insight into water losses than bulk accounting by isolating sections of the distribution network (into districts), measuring the amount of water entering the district and comparing the amount of water recorded by meters within the district. While the amount of unaccounted water gives a good indication of the severity of water leakage in a distribution network, metering gives no information about the locations of these losses.

Acoustic leak detection is normally used to identify and locate leaks. Acoustic methods consist of listening rods, aquaphones and geophones [29]. These devices make contact with valves or hydrants or even try to listen for leaks on the ground directly above the pipes. To operate a listening device an experienced user is required. The user carries the equipment above ground, tries to follow the pipe map and at the same time is focused on pinpointing a “high-amplitude” acoustic signal with a headset or a monitor (Fig. 2.4).

All listening devices are based on the same ”sensing” technique, since all of them are using sensitive materials, such as piezoelectric elements to sense leak-induced sounds and/or vibrations. Those sensing elements are usually accompanied by some signal amplifiers and filters to make the leak signal stand out [30]. Drawbacks of these methods include the necessary experience needed for the operator and the limitation in scalability to the large network range, since the procedure is slow.

The state of the art in acoustic leak detection techniques are the leak noise correlators (Fig. 2.5). Those devices are more efficient, get more accurate results and depend less on user experience than the listening devices [31]. This method includes the installation of two sensors on either side of the leak along a pipeline. In most cases, either vibration sensors (e.g. accelerometers), or acoustic sensors (e.g. hydrophones) are used at two distinct pipe locations (usually in openings within a water distribution network, such as fire hydrants) that of course need to bracket the location of the suspected leak.

If the leak is located somewhere between the two measurement points but not in the middle, then there is a time lag between the measured leak signals by the two distinct sensors. This time lag is pinpointed by the cross-correlation function of the leak signals. The location of the leak can be easily calculated using a simple
Figure 2.4: Leak detection in water pipelines using the Sewerin Aquaphone A100. [62]
algebraic relationship using the time lag, the distance between the sensors and the propagation velocity of the wave signal in the pipe \cite{24,56}. A typical leak noise correlator system is shown in Fig. 2.5. However, a number of difficulties are encountered during the application of the method to plastic pipes and the effectiveness is doubtful \cite{5,27}. This happens because sound does not propagate well in plastic pipes, because of the large dissipation rate in the material.

Figure 2.5: Typical Leak Noise Correlators. Sensor A, Sensor B and Correlator device from *Dantec Measurement Technology* \cite{20}.

In a similar fashion to leak noise correlators, *PipeTech* \cite{53} recently developed a system able to detect leaks in pipes by using pressure sensors mounted in key locations throughout the pipe network. These sensors are able to pick the transients in case of a ”leak event/birth”. This is done by continuously monitoring the pressure profile of the pressure sensors and using machine learning algorithms to identify leak events and estimate leak position. The technology is still at the early stage and looks promising. However, no one can guarantee the detection of existing leaks in the network (old/existing leaks). Moreover, in order for the system to be able to detect small leaks, the network needs to be heavily instrumented with pressure sensors.

Other techniques include imposing transient pressure waves along with appropriate network models for leak detection and localization \cite{32,68}. This is based on the comparison of the transient response with leaks, to the nominal response without any leak in order to identify and characterize defects on the pipe.
walls. Inverse transient formulation involves collecting pressure data during the occurrence of transient events followed by minimization of the difference between observed and estimated parameters. The estimated parameters are calculated through hydraulic transient solvers [19, 70]. The method has shown success in detecting leaks in laboratory conditions under high leak flow rates. Karney studied the applicability and effectiveness of inverse transient analysis to the detection of leaks in real water distribution systems [34]. This method constitutes a low-cost and easy-to-implement alternative; however its feasibility has yet to be fully established in actual field conditions. In addition, there are risks of introducing controlled transients into the distribution system. Although those transient methods looked very promising, interpretation of measured data is not trivial. Not to mention, successful experimental results are hard to find in the literature [17].

Several non-acoustic methods like infrared thermography, tracer gas technique and ground-penetrating radar have been reported in the literature of leak detection [28, 30]. Those methods have the advantage of being insensitive to pipe material and operating conditions. Nevertheless, a map of the network is needed, user experience is necessary and the methods are in general slow. We present more details on each one of them in the following paragraphs.

Tracer Gas Technique involves the injection of a non-toxic, insoluble in water, gas, into an isolated pipe section. The gas is then pressurized and able to exit the pipe through a leak opening and then, being lighter than air, permeates to the surface through the soil and pavement. The leak is located by scanning the ground surface directly above the pipe with a highly sensitive gas detector (Fig. 2.6). The method cannot be applied to live operating pipelines, as they have to be completely drained before the injection of the gas. Moreover, the method can be hard to apply in pipes that are buried deep into soil.

The principle behind the use of thermography for leak detection in water-filled pipes is that water leaking from an underground buried pipe is changing the thermal field of the adjacent soil. The resulting temperature gradients can be picked up by the corresponding equipment, e.g. infrared cameras. The method requires scanning of the pipe network above ground and the procedure is almost the same as in the Tracer Gas Technique. An experienced user is required to walk, following the map of the network and searching for leaks in the pipe network. A major limiting factor of this method apart from being slow, is the fact that there are many cases when the map of the network and the precise position of pipes is unknown or not accurately updated.

The Ground-Penetrating Radar technique uses a radar that can detect voids in the soil created by leaking water as it circulates near the pipe, or segments of the pipe which appear to be buried deeper than they are because of the increase
of the dielectric constant of adjacent soil saturated by leaking water. GPR waves are partially reflected back to the ground surface when they encounter an anomaly in dielectric properties, for example, a void [28]. An image of the size and shape of the object is formed by radar time-traces obtained by scanning the ground surface. The time lag between transmitted and reflected radar waves determines the depth of the reflecting object. A typical GPR device is presented in Fig. 2.7. In general the output data are usually hard to interpret and an experienced operator is needed.

### 2.1.3 In-Pipe Methods

In the area of in-pipe inspection systems, there are many examples of prior-art robotic systems for use in underground piping. Most of them are however optimized for water- and sewer-lines, and meant for inspection, repair and rehabilitation. Some examples are shown in Fig. 2.8. As such, they are mostly tethered; utilizing cameras and other specialized tooling and are usually designed to operate in empty pipes that aren’t pressurized.

Three of the more notable exceptions are the autonomous Kurt I system from GMD used for sewer monitoring [38], the tethered gas main cast-iron pipe joint-sealing robot CISBOT from ULC [66] and the GRISLEE robot [59] (Fig.
Figure 2.7: The RADIODETECTION RD1000 Portable Ground Penetrating Radar System.

Figure 2.8: Some state-of-the-art leak inspection robots as discussed in [7].
2.9). The latter is a coiled-tubing tether deployed inspection, marking and in-situ spot-repair system.

![Figure 2.9: Top Left: Un-tethered Autonomous Kurt I, Top Right: CISBOT, Bottom: GRISLEE. These systems are discussed in [7]](image)

There are also robots that have been developed for in-pipe inspection such as corrosion, cracks or normal wear and damage. State of the art robots are usually four-wheeled, camera carrying and umbilically controlled. Most of them are however focused on oil or sewer-mains. One of the most successful steps in building such a robot was developed by Schemas at the Carnegie Mellon University [58] with his untethered Explorer robot. The system is a long-range, leak-inspection robot, working in real-gas-pipeline conditions and is being controlled by an operator in real-time through wireless Radio Frequency (RF) technology. The operator is constantly looking to a monitor and is searching for leaks visually via a camera.
The design of the system is shown in Fig. 2.10.

Figure 2.10: The Explorer (in-pipe) robot for gas pipes. The system has a modular design with many degrees of freedom and suitable actuation mechanisms between the modules. The system is shown on a pipe for reference.

Kwon built a reconfigurable pipeline inspection robot with a length of 75 mm and a modular exterior diameter changing from 75 mm up to 105 mm [42]. Controlling the speed of each one of the three caterpillar wheels independently provides a steering capability to the system. This is one of the very few in-pipe systems that are able to comply to different pipe diameters. Moreover, the system has demonstrated satisfactory performance in empty pipes.

Most of the state-of-the-art leak detection robots are able to travel along horizontal pipelines and only a small fraction of them can cope with complicated pipeline configurations, e.g. T-junctions, elbows etc. Even if some of them manage to cope with that, they usually require a complete shut-down of the network and deployment of the system in an empty pipe such as the MRINSPECT [16].

On the other hand, the Smartball is a mobile device that can identify and locate small leaks in water pipelines larger than 254 mm (10") in diameter constructed of any pipe material [41], as shown in Fig. 2.11. The system is able to perform inspection when the pipes are filled with liquid/water and the network is still in operation. The free-swimming device consists of a porous foam ball that envelops a water-tight, aluminum sphere containing the sensitive acoustic
instrumentation. This device is capable of inspecting very long pipes but cannot handle complicated pipeline configurations, because it is completely passive.

Bond presents a tethered system (Sahara) that pinpoints the location and estimates the magnitude of the leak in large diameter water transmission mains of different construction types [4]. Carried by the flow of water, the system can travel through the pipe and in case of a leak, the leak position is marked on the surface by an operator, who is following the device (Fig. 2.12). The system is tethered and thus all range limitations apply in this case. Both the Smartball and Sahara, being passive, cannot actively maneuver inside complicated pipeline configurations. Moreover, both systems rely on acoustics for leak detection and user experience is needed for signal interpretation.

Our group developed a passive in-pipe inspection system for water distribution networks using acoustic methods [15]. It is designed to operate in small pipes. The merits of the in-pipe acoustic leak detection under different boundary conditions are reported in [9, 36]. Although, there seems to be some promise in such an approach, the method can fail when pipes are made out of plastic material [48, 49]. This happens because sound dissipates very quickly in plastic pipes compared to pipes made out of metal or other materials.

\section*{2.2 Summary of Limitations of Existing Solutions}

In general, as mentioned in the previous sections, most of the existing solutions fall short in one or more of the following categories. We summarized their limitations in the points to follow:

- Most methods are not effective for small leaks in plastic pipes. For instance, methods that rely on acoustics are not reliable enough for small leaks and even less reliable in the case of leaks in plastic pipes. This happens because sound dissipates quickly in pipes made of plastic. Thus, sound waves cannot travel long distances compared to what these waves can do in metallic pipes.

- Most of the existing solutions depend on the pipe operating conditions, e.g. pipe material, depth of bury, flow conditions, soil type and line pressure. Some methods require the pipe to be under high pressure to get good Signal to Noise Ratio (SNR) for acoustic signals. In other cases, if the pipes are buried deep into the soil, noise might not be able to propagate to the surface.

- In many cases a skilled operator is needed for leak detection and data interpretation. In such cases no automation is possible.

- Most of the solutions are not effective for complicated pipeline configurations. Some of the systems are completely passive and cannot actively maneuver
Figure 2.11: A typical leak detection survey with the Smartball. When the ball travels close to the leak location, the signal level gets significantly increased and leaks are identified.

Image from http://www.puretechltd.com/
inside the pipes. In other cases the systems are very bulky and, thus, unsuitable for complicated pipeline configurations, e.g. elbows, bends, etc.

- Many systems require the complete drainage of the pipe medium for the drone to enter and perform pipe inspection. In all these cases the systems are not capable of live inspection (inspection of pipes while the supply to the user is still on), because the network or the sections need to shut down prior to insertion/deployment of the leak detection equipment.

- Almost all the existing leak detection systems are extremely slow in operation, making them unsuitable for long networks. Note that the existing city networks are sometimes very long. In some cases they exceed 10,000km in total length of pipes, e.g. water distribution network of New York City.

- There are cases where the pipe map is not available or has errors because it might not be accurately updated after changes or modifications. In those cases, all methods that require an accurate map, can fail.
2.3 Proposed Approach

Past experience has shown that in-pipe inspection is much more accurate and less sensitive to random events and external noise. This is because the leak detection equipment/drone will come closer to the leak source. On the other hand, in-pipe systems face some challenges associated with design, maneuvering, communication, power and integration [47].

Unlike state-of-the-art in-pipe systems, that rely on acoustics or visual inspection for leak identification, our proposed detection concept is based on the fact that any leak in a pipeline alters the pressure and flow field of the working medium. More specifically, the fundamental principle behind detection is based on identifying the existence of a localized pressure gradient. This pressure gradient is apparent in all pressurized pipes in the vicinity of leaks/openings. The phenomenon is independent of pipe size and/or material and more importantly, is apparent in various fluid media, which makes the detection method widely applicable (gas, water pipes, etc). More details about the proposed solution's concept, design and analysis follow in the next chapters in this thesis.

For this particular work we are interested in small leaks, that can be considered the most dangerous ones. Small leaks, that cannot be detected by most of the existing methods, can go undetected for long periods of time. These can result in significant financial losses and can have other complications as discussed in chapter 1. By small sized leaks we mean leaks that are "mm" in size, operating under "low" pressures. Any pressure below 1bar $\approx 14psi$ is considered "low" for the water or gas industry. Thus, for this work the design goal is to develop a solution that can detect and pinpoint leaks of "mm" in size and even under pressures less than 1bar $\approx 14psi$. 
Chapter 3

Proposed Detection Concept

In this third chapter of the thesis the proposed detection concept is presented. The concept is based on a local pressure gradient in the vicinity of leaks in pressurized pipes. Finally, an overview of the proposed solution will be discussed towards the end of this chapter.

3.1 Detection from the Inside of the Pipe

In the neighborhood of a leak opening there is a fluidic region that is characterized by a rapid change in static pressure, dropping from $p_{\text{High}}$, inside the pipeline, to $p_{\text{Low}}$ in the surrounding medium resting outside (Fig. 3.1). This fact essentially generates a "suction region". Numerical studies showed that the radial pressure gradient close to the leak is large in magnitude and drops quickly as distance increases [2]. More details on these numerical studies are presented in chapter 4.

As mentioned earlier, our goal is to develop a system that is able to identify leaks based on the radial pressure gradient [3, 57]. Such a system will be less subjective to false positives (compared to acoustic or visual methods) and less dependent on user experience. This is because of the fact that the pressure gradient under discussion is apparent only when a leak has occurred in the pipe. Finally, by developing suitable estimation algorithms and triggering metrics, the detection procedure can become completely automated as shown in our recent publication in [11] and discussed in detail in chapter 6.

However, since a leak can happen at any angle $\phi$ around the circumference, observability would require a series of pressure sensors installed around the perimeter of the pipe. Nevertheless, directly measuring the pressure at each point in order to calculate the gradient is not effective and should be avoided. To overcome the complexity of such an attempt, we introduce a more efficient concept that is discussed in the next section.

The system overview of the MIT Leak Detector is presented in Fig. 3.2. The system is deployed inside a pipeline via existing insertion points in the network.
Figure 3.1: Numerical study of the static pressure distribution in the vicinity of a $3mm$ leak in a gas pipe. For this particular case $\Delta p = 5\text{bar}$. Similar trends are observed in studies with other media in pressurized pipelines, e.g. oil, water. In this particular case we see that there is region of fluid close to the pipe walls that gets significantly affected by the existence of the leak.
The complete system consists of a robotic locomotive to move inside the pipes, electronics for on-board processing and communication capabilities with base stations [72, 73]. Details of the proposed system are given in the coming chapters of this thesis, with emphasis on the leak detection module.

### 3.2 Detection Concept

A schematic of the proposed detection concept is shown in Fig. 3.3. To capture leaks at any angle $\phi$ around the circumference of the pipe, a circular membrane is utilized. The membrane is moving close to the pipe walls at all times complying to small diameter changes, irregularities and other defects on the pipe walls, e.g. accumulated scale. The membrane is supported from one end by a rigid body, called drum (Fig. 3.3 [a]). The drum is allowed to rotate about its center point $G$ (about any axis) by design. The latter is allowed by a gimbal mechanism. Finally, the drum is suspended by springs and, thus, remains always in the neutral position, when not externally perturbed by leaks.
In case of a leak, the membrane is pulled towards it. This happens because the membrane is pulled by the radial drop in pressure mentioned earlier (Fig. 3.3 [b]). Upon touching the wall of the pipe and covering the leak, the pressure difference $\Delta p$ creates a normal force $F$ on the membrane. We can write that:

$$F = \Delta p A_{\text{leak}}$$  \hspace{1cm} (3.1)

where $A_{\text{leak}}$ stands for the cross-sectional area of the leak, which can be of any shape.

As the system continues to travel along the pipe, a new force, $F_z$, is generated. This force is a result of friction and contact mechanics between the membrane and the pipe walls. Thus, $F_z$ is related to the normal force, $F$, by a friction/contact mechanics model, say $F_z = \mu F$. $\mu$ is the static friction coefficient between the pipe walls and the membrane. By using Eq. (3.1) we can see that $F_z$ depends on the gauge pressure and the size of the opening, since:

$$F_z = \mu \Delta p A_{\text{leak}}$$  \hspace{1cm} (3.2)

In general, in case of a leak incidence in a pipeline, the flow rate through the leak will increase as $A_{\text{leak}}$ and/or gauge pressure $\Delta p$ increases.

At the next time instant, $F_z$ generates an equivalent force and torque on the drum, $M$. This torque pushes the drum to rotate about some axis passing through its center point $G$, while orientation of the axis depends on the angle $\phi$ of the leak around the circumference (Fig. 3.3 [c]). The effects of $M$ on the drum can then be sensed by installing force sensors on the detector. Finally, $F_z$ only vanishes when the membrane detaches from the leak and the drum travels back to neutral position, because of the existence of linear springs (Fig. 3.3 [d]).

In the next section we describe the detailed design of the proposed system that utilizes the concepts presented here to effectively identify leaks in pipes. The proposed system can identify a leak by measuring forces on the drum. *Essentially the problem has switched from identifying a radial pressure gradient (at any angle around the circumference of the pipe), to measuring forces on a mechanical system (gimbal & drum).*

### 3.3 Proposed Solution

The proposed solution’s final design (solid model) is depicted in Fig. 3.4 and also Fig. 3.5. The system is an in-pipe, robotic solution that is able to carry around the leak detection system under discussion in this thesis. More details about the design of both the robotic locomotive and the leak detector are given in the rest of
Figure 3.3: The detection concept: [a] "Approach Phase": The detector is moving from left to right. [b] "Detection Phase A": The membrane is pulled towards the leak due to the suction caused by the drop in pressure. [c] "Detection Phase B": The membrane touches the walls and covers the leak. As the system moves along the pipe a new force, $F_z$ is generated. Resulting torque $M$ moves the drum. [d] "Detaching Phase": Membrane detaches from the leak and the drum bounces back to neutral position. Note the inertial reference frame $Oxyz$. 
Figure 3.4: A 3D view of the complete proposed robotic system inside a 100mm ID pipe for reference. The robotic locomotive sits in the front and is connected to the leak detection module via an appropriate interface.
the chapters of this thesis. As discussed before, the key contributions of the thesis lie in the analysis, modeling, instrumentation and design of the leak detector.

A 3D solid model of the proposed detector is presented in Fig. 3.6. The drum [b] is depicted in red (solid color) and the membrane [a] in dark grey (transparent color). The drum is suspended by a wheeled system. The wheels and the suspension legs [f] are mounted on the front/rear plates [e]. The purpose of the wheels and the suspension legs is to keep the detector always in the middle (collinear with the longitudinal axis of the pipe) during inspection.

A key fact with this proposed design is the gimbal mechanism consisting of two different parts (parts [b] and [c] in Fig. 3.7). This mechanism allows the drum to pivot about axes x and y at point G independently. Finally, the system dimensions are such that the membrane leaves a small clearance (<2mm) from the walls of the pipe.

In addition, the drum is suspended by four springs [h] as shown in Fig. 3.7. The purpose of those springs is to drive the drum back to neutral position after the detection phase is over and prepare it for a new detection. The pre-loading of each of those four springs can be independently regulated with help of four setscrews [g]. Finally, the whole system is mounted on a shaft, which essentially represents the chassis of the system [d].

Forces are measured by force sensors. Two such sensors are placed on the drum, behind two of the springs (at distance $r = 17.5mm$ and angles equal to $\alpha = \pi/4$ and $\beta = 3\pi/4$, measured about z axis on the $x-y$ plane, see Fig. 3.6). As it is shown in chapter 5, such placement of sensors on the drum provides leak-observability to the detector, i.e. occurrence of a leak at any angle $\phi$ (input/disturbance to the detector), results in changes in the measurements. The latter statement implies that there is no "blind spot" on the detector, i.e. a leak at any angle $\phi$, will result in some unique output signals from the sensors.

Figure 3.5: The side view of the complete robotic solution is depicted here.
Figure 3.6: 3D solid model of the proposed detector. Side and front view in a pipe. Details: [a] Membrane, [b] Drum, [e] Front Plate and [f] Suspension Legs.
Figure 3.7: A 3D assembled view of the detector is shown at the bottom right corner. The exploded view of the proposed design is presented and all key components are laid out. Supporting wheels and suspension legs are skipped for simplicity. Details: [a] Membrane, [b] Drum, [c] Gimbal, [d] Shaft/Chassis, [e] Front/Rear Plates, [g] Spring caps with setscrews, [h] Springs.
Chapter 4

A Localized Pressure Gradient

As briefly mentioned in the previous chapter, any small leak in a pressurized pipeline will force the pipe medium to leak out of the pipe at a specific leak flow rate. As one would expect, there is a small neighborhood of the fluid (liquid or gas) region that is affected (as shown in Fig. 3.1). In this chapter we study the alterations in the flow and pressure distribution because of the existence of leaks in pipelines in detail via simulations and experiments. The localized pressure gradient discussed in this chapter is the key element behind our proposed leak detection approach in this thesis.

4.1 Preliminary CFD Simulations of Leaking Pipes

To study the phenomenon of leaking pipelines and understand the alterations in pressure and flow patterns because of leaks, we set up Computational Fluid Dynamics (CFD) simulations. The goal of this preliminary analysis is to understand some trends behind the pressure gradient under discussion. The software we used is Ansys Fluent 14.5. The problem we tried to simulate in each of the following cases in this chapter is exactly the one sketched in Fig. 4.1.

More specifically, we modeled a circular pipe of ID equal to $D = 4'' = 101.6\text{mm}$. The size is selected on purpose and because of the fact that all prototypes built for the purpose of this thesis are optimized for 4" pipes. However, similar CFD results can be obtained for pipes of different diameters, as long as the pipe diameter remains much larger than the leak’s characteristic size (e.g. the leak diameter or length).

For the analysis we assumed that the thickness of the pipe wall is equal to $6.5\text{mm}$. This is again not a random selection, but agrees with the standard pipe dimensions used in the industry. As shown in the next couple of paragraphs, we study different leak geometries (slit, circles) in this chapter. In each one of the following cases, the pipe was "filled" with pressurized medium (liquid or gas correspondingly). The latter was escaping through the leak opening to the sur-
CHAPTER 4. A LOCALIZED PRESSURE GRADIENT

Figure 4.1: Simple sketch of leaking pipeline. A small opening in the pipe walls forces the fluid to exit from the pipe to the surrounding medium. Note the pressure difference between the inside and the outside of the pipe. The frame of reference for this chapter is "centered" around the leak position in the pipe.

The surrounding medium, as shown in Fig. 4.1. The surrounding medium was assumed to be air (leak was open to air) in all cases. Without loss of generality we assumed that $p_{\text{Low}} = 0$ for each simulation, and $p_{\text{High}}$ was equal to the gauge pressure in each case. Finally, the pipe length and the associated fluid region is modeled to be 0.5m long, as shown in Fig. 4.1. We need to mention at this point, that similar studies have been conducted recently by Dr. Khalifa in [35]. His results agree very well with our results in this chapter.

### 4.1.1 Preliminary Study of Slit-shaped Leak

**Medium:** Air

We start the analysis by considering a slit-shaped leak as the one showed in Fig. 4.2. For this preliminary study we assume the slit to be 10mm in length and 2mm in thickness. We start by modeling the geometry in Solidworks, and to do that we had to generate the model of the fluidic region inside the pipe of Fig. 4.1. The fluidic region we modeled is shown in Fig. 4.3, since the pipe geometry would not be needed for CFD. In this initial study, air is modeled as the in-pipe flowing medium.

Our next step is to mesh the geometry. To generate an appropriate mesh we consider 207,728 triangular elements, with a refined region close to the leak for better precision at the region of interest. The final mesh used for the simulation study is shown in Fig. 4.4. Finally, we set the boundary conditions (BC) for the
Figure 4.2: A longitudinal crack/slit on a metallic pipe, as the one we study in this section.

Figure 4.3: The modeled fluidic region of the 10mm X 2mm slit simulation.
The generated mesh of the fluidic region for the simulation of the slit-shaped leak.

To qualitatively study the results of the simulations, we plot the static pressure distribution along axis $z$ for different distances below the leak in Fig. 4.5. The locus of the points shown here are lines lying $1\text{ mm}$, $2\text{ mm}$ and $3\text{ mm}$ below the leak along axis $z$ correspondingly ($x = 0$). We can see here that pressure drops significantly (up to almost 20%) close to the leak and at a distance of $1\text{ mm}$ away from it. However the magnitude of the pressure drop decreases very quickly with distance as shown in Fig. 4.6. One can easily observe that some small distance away from the leak (e.g. $5\text{ mm}$), the pressure drop is almost negligible and the line pressure has fully recovered to the nominal value. These qualitative results show that the phenomenon is indeed local and the pressure gradient is "visible"
in a small neighborhood around the leak incidence.

**Medium: Water**

In this subsection, we conduct the same simulation for the case of pipes filled with water (instead of air). Again, the simulation results are very similar to the case of air and the relative pressure distribution looks very similar to the one shown in Fig. 4.5 and Fig. 4.6.

In order to compare the results between the air and water cases, we can look at Fig. 4.7. In this figure one can see the comparison in the different values of the relative static pressure distribution between the two cases, namely air versus water. There is a very good match between the values of the two cases. However, there is small deviation in the tail of the plot. The difference at the tail exists because leaks in water pipes induce significant losses in the actual line pressure and the pressure does not fully recover to $p_{High}$ after the leak incidence. The losses in the air pipes are much lower, mostly because of the relatively lower viscosity and density of the medium.

*The previous result shows that the air and water cases are very similar.* On other words, results obtained for the case of water can be extrapolated for air and vice versa. This statement is more accurate for points/regions very close to the leak location and less accurate at regions further away from the leak.

### 4.1.2 Preliminary Study of Circular Leak

**Medium: Air**

In this section we study and simulate a leak of a different shape, namely a circle as the one showed in Fig. 4.8. For this study we assume the leak to be $3mm$ in diameter. A similar simulation setup procedure is followed in this case, and the final generated mesh includes 342,772 triangular elements, with a refined region close to the leak. We use the same BC as in Table 4.1 and the $k - \epsilon$ solver as before.

After running the CFD simulation we get qualitatively similar results to the previous cases. More specifically we found out that there that there is a region close to the opening, that is highly affected by the leak on the wall. We plot the static pressure distribution in the pipe and focus on the region close to the leak as shown in Fig. 4.9. Pressure drops inside this region gradually and quickly, from high values inside the pipe to lower pressures outside the pipe. In general, *the pressure gradient is again apparent in pressurized pipelines for circular leaks as it was for longitudinal leaks (cracks/slits).*
Figure 4.5: The relative static pressure distribution (actual pressure at each point divided by $p_{\text{High}}$) along lines underneath the leak. The locus of points close to the leak show a drop in pressure close to the opening.

Figure 4.6: The relative static pressure distribution (actual pressure at each point divided by $p_{\text{High}}$) along lines underneath the leak. Pressure drop is almost negligible away from the leak, indicating that it is a local effect.
Figure 4.7: Comparison of pressure drop between air and water media. Qualitatively, pressure behaves in a very similar way in both cases. Pressure (head) losses in water pipes are more significant when leaks occur, so pressure in the pipe cannot fully recover after leak incidences.

Figure 4.8: A circular leak on a metallic pipe, as the one we study in this section.
Medium: Water

In this section we simulate the same circular leak, but now for the case of water inside the pipe. In this case we assumed a circular leak/crack of 4\textit{mm} (slightly larger) in diameter. The mesh includes 342,772 triangular elements, with a refined region close to the leak. We use the same BC as in Table 4.1 and the same \(k - \epsilon\) solver as before. Results show very similar trends to the previous cases, as demonstrated in Fig. 4.10 and Fig. 4.11.

To summarize, in all of the simulated cases, both in air and water pipes, with either rectangular or circular leaks, one is able to observe an apparent pressure gradient close to the leak openings. The pressure gradient is very large in magnitude close to the opening, and drops quickly with distance as one moves away from the leak. Based on these observations, we designed and developed a novel leak detection technique that "senses" this localized pressure gradient in a unique and smart way. In the next sections, we plan to identify the existence of this gradient experimentally and compare the experimental results to the ones obtained from simulation for a comparison that completes this chapter.

Some more CFD simulations and analysis of small leaks in pipelines are presented in our publication in [2]. Moreover, our ideas on the development of a novel leak detection system based on this pressure gradient concept are summarized in
two patents [3, 57] and also further discussed later in this thesis.

Figure 4.10: Numerical study of the static pressure distribution in the vicinity of a 4mm leak in a pipe filled with compressed water. In this study $\Delta p = p_{High} - p_{Low} = 5bar$.

### 4.2 Experimental Validation of Pressure Gradient

In order to validate the existence of the pressure gradient in real pipelines, experiments are conducted. Our tests include pipes with leaks of circular and slit shapes, that were filled with water. Very similar trends and results can be observed for experiments in air (gas) pipes. These experimental results have been obtained with the help of Kabir Suara from KFUPM and are also documented in [64].

#### 4.2.1 Experiments on Slit-shaped Leak

Initially we start by setting up experiments in leaking pipelines, where the defect is like a crack, similar to the one studied earlier in simulations. The main objective of these experiments is to characterize the pressure gradient around a thin slit-
shaped leak and, in addition, compare the results to the results obtained from CFD.

The experimentation includes taking measurements of pressure at various locations along the axial direction (axis z) of the pipe at two different distances (0.5mm and 1mm) away from the pipe wall (at $x = 0$). For all the experiments that follow, the line pressure was kept constant at $p_{High} = 2.07bar$ (30psi). Additionally, the experiments are carried out with approximately no ambient flow in the pipe, except for the flow induced by the leak in the pipe.

Our experimental setup is shown in Fig. 4.12. It consists of a 100mm ID (4") 2.2m long plexiglas pipe section. The setup is connected to the municipal water supply on one end with a hose, while the other end handles the draining of water. As one is able to see in the same figure, there is a T-connection installed in the test section. This serves as an insertion point for devices and pressure sensors to be deployed or removed from the test section. Additionally, a pressure gage is mounted closed to the inlet to monitor the line pressure of the test section. A flow valve at the outlet is used for line pressure regulation.

For the coming paragraphs we consider a slit-shaped leak (crack). The leak is artificially generated and its dimensions are 0.6mm in width and 12mm in length. Fig. 4.13 shows the close up view of the generated slit and water jetting.
out through the slit during experimentation.

In order to experimentally validate the existence of the pressure gradient, the pressure has to be measured at various locations close to the leak. To do that, we designed and built a device that carries a differential pressure sensor along the pipe and can move it with precision relatively to the pipe wall/leak location. The solid model of this device along with some explanation of different parts is shown in Fig. 4.14. The device (sensor holder) was 3D printed and is made out of ABS plastic. This sensor holder can move inside the pipe as the user directs it. This happens with the help of magnets that are being moved by the operator from the outside of the pipe.

The differential pressure sensor used in this experiment is the Omega PX26-015GV [52]. This pressure sensor permits both sides of the diaphragm to handle liquids. One end of the sensor is exposed to line pressure and the pressure in the vicinity of the leak is at the other end. The sensor determines the difference between those two pressures and produces an output signal. The sensor produces 100mV output in full scale, which corresponds to the maximum allowable differential pressure of 15psi = 1.034bar. We calibrated the sensor gage using dead weight and got a slope of 1psi/kNm⁻²; thus, no adjustment was required for the pressure gage. The calibration of the differential pressure sensor gave a slope 6.667 mV/psi; this ratio was used in the conversion of digital outputs to equivalent differential pressures during experimentation.
Figure 4.13: Close up view of the generated slit and picture of water jetting out through the slit.
Sec. 4.2. Experimental Validation of Pressure Gradient

Ball-transfers touching the pipe walls at all times

Pressure Sensor

Carriage for precise sensor upwards/downwards movement

Wheels for in-pipe locomotion

Figure 4.14: Solid model of the sensor holder unit that we use for pressure measurements close to the cracks in our lab setup.

<table>
<thead>
<tr>
<th>Boundary Condition (BC)</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inlet Surface BC</td>
<td>$p_{High} = 30\text{psi} = 2.07\text{bar}$</td>
</tr>
<tr>
<td>Outlet Surface BC</td>
<td>$p_{High} = 30\text{psi} = 2.07\text{bar}$</td>
</tr>
<tr>
<td>Leak Surface BC</td>
<td>$p_{Low} = 0\text{psi}$</td>
</tr>
<tr>
<td>Wall Surface BC</td>
<td>Wall - No Slip</td>
</tr>
</tbody>
</table>

Table 4.2: Boundary Conditions for the CFD study of the slit-shaped (crack) leak on the pipe.

In order to perform a fair comparison between the experimental measurements and simulation, similar conditions are simulated in *Ansys Fluent* to produce the CFD counterparts of these experiments. After this is done, the differential pressure results of the computational study are compared to that obtained from experiments. The boundary conditions selected for the CFD simulation are presented in Table 4.2.

Fig. 4.15 compares the experimental and computational results of the differential pressure at a distance equal to 0.5mm away from the wall near the 0.6mm x 12mm crack. Fig. 4.16 shows the result at 1mm away from the wall. *One can observe that the computational results are very close to the experimental results*
in both cases. More specifically, in the case of 1mm away from the leak, both the experimental and the computational results are almost identical (less than 3% deviation). The small deviation lies, among other factors, in the fact the existence of the pressure sensor in the flow field close to the leak, changes the pressure distribution slightly in a way that is not predicted by the simulation.

As a conclusion, one can claim that results of experimental and computational methods are in a good agreement. The previously described pressure gradient is apparent in all leaking pipelines close to the leak opening as suspected. This is a fundamental result that we will use throughout this thesis in order to develop a new, autonomous and reliable leak detection methodology. Before we move on the next chapter, where we start describing the detector and its associated analysis, we conclude this chapter by repeating the same experiments for leaks of circular shape for completeness.

![Differential Pressure along leak](image)

Figure 4.15: Differential pressure distribution along slit; 0.5mm below the wall; 30psi = 2.07bar line pressure.

### 4.2.2 Experiments on Circular Leak

The objective of the final experimental investigation in this case is to characterize the pressure gradient around an artificially generated circular leak. This is achieved by measuring the pressure at various locations along the axial direction...
close to the leak location and at two different distances (0.5\textit{mm} and 1\textit{mm}) from the pipe wall. More specifically, we measure the differential pressure along the pipe with an interval of 2\textit{mm} between two adjacent measurements.

In this case the leak size is comparable to the sensor size and thus, the sensor itself affects the measurement significantly. To overcome that, we install a thin tube (sensor tap) on one side of the differential pressure sensor. A sensor tap is essentially a metallic tube of 2.2\textit{mm} diameter. The tap allows the sensor to rest further away from the leak position, while the end of the thin tube is close to the desired position of measurement. Since the thin tube is much thinner than the sensor itself, the measurements are going to be affected less by the placement of the sensor inside the flow field.

All experiments are again conducted at $p_{\text{High}} = 30psi = 2.07bar$ line pressure. Moreover, the experiments are carried out with approximately no flow, except for the flow induced by the simulated leaks in the pipes. These boundary conditions along with a circular leak are simulated in CFD, and the differential pressure results of the computational study are compared with that from the experiment. Again, the BC of this simulation study are the same ones as before, namely the same as in Table 4.2.

As mentioned before, the original objective of this section is to compare the
results of the experimental work with those obtained using computational fluid dynamics. The plot shown in Fig. 4.17 compares the experimental and computational results for a 2.2mm hole at 1.5mm above the wall. The graph shows good agreement between the different points.

![Differential Pressure along leak](image)

**Figure 4.17:** Differential pressure distribution away from leak: 2.2mm circular leak; 1.5mm above the wall; 30psi = 2.07bar line pressure.

For the 4mm leak case (Fig. 4.18), we get similar results as the case of the 2.2mm leak case. Again the simulation and experimental values show good agreement. However, when the sensor is moving away from the leak along the z axis, the results from the two methods match better, as shown in Fig. 4.17, and Fig. 4.18.
Figure 4.18: Differential pressure distribution away from leak: 4mm circular leak; 1.5mm above the wall; 30psi = 2.07bar line pressure.
In chapter 3 we initially presented the proposed detection system. In this section of the thesis, we derive an analytic dynamic model of the proposed robotic detector. The complete nonlinear model is complex and is linearized accordingly to study further in this chapter. Observability and sensitivity analysis result in the optimal placement of sensors on the drum. Finally, with the final selected configuration the detector becomes input/leak-observable. Most of the results discussed in this chapter are published in [10,12,14] and more recently in [13].

5.1 Dynamic Modeling

In the coming paragraphs we derive analytic models (nonlinear and linear) for the proposed autonomous robotic sensor. We start by discussing the kinematics of the mechanism under discussion and then use the kinematics in the derivation of the equation of motion.

5.1.1 Kinematics

To start our analysis we initially discuss the kinematics of the proposed mechanism. Let us assume that the Degrees of Freedom (DoF) of the drum & gimbal are \( q = [\theta \ \psi]^T \). Angles \( \theta \) and \( \psi \) measure the rotation of the drum about axis \( x \) and \( y \) respectively with respect to the chassis’ frame (see Fig. 3.7 for the corresponding frames of reference on the drum). Fig. 5.1 shows the drum under discussion in the original and a perturbed configuration.

With this notation the rotation matrix [60] from the body fixed frame (drum)
Figure 5.1: [Up] The drum under discussion in the original position. At this posture the body fixed (drum) and chassis fixed frames coincide. [Down] The drum is now perturbed about point $G$. Note that the body fixed frame is now rotated with respect to the chassis fixed frame.
Let us assume a vector $\mathbf{p}'_K$ denoting the point $K$ on the drum with respect to the body fixed frame (drum). If $\kappa$ is the enclosed angle and $r_\kappa$ the length of the vector (distance $KG$) we can write:

$$
\mathbf{p}'_K = \begin{bmatrix}
    x'_K \\
    y'_K \\
    z'_K
\end{bmatrix} = r_\kappa
\begin{bmatrix}
    c_\kappa \\
    s_\kappa \\
    0
\end{bmatrix}
\tag{5.2}
$$

We can write that $\mathbf{p}_K = R(q)\mathbf{p}'_K$ for the transformation of the vector to the chassis’ frame. This transformation (using Eq. (5.1, 5.2)) gives:

$$
\mathbf{p}_K = \begin{bmatrix}
    x_K \\
    y_K \\
    z_K
\end{bmatrix} = r_\kappa
\begin{bmatrix}
    c_\kappa c_\theta + s_\kappa s_\theta s_\kappa \\
    c_\kappa s_\theta s_\kappa \\
    c_\kappa s_\kappa - s_\kappa c_\kappa
\end{bmatrix}
\tag{5.3}
$$

Taking derivatives with respect to time:

$$
\dot{\mathbf{p}}_K = \begin{bmatrix}
    \dot{x}_K \\
    \dot{y}_K \\
    \dot{z}_K
\end{bmatrix} = r_\kappa
\begin{bmatrix}
    -s_\psi c_\kappa \dot{\psi} + c_\psi s_\theta s_\kappa \dot{\psi} + s_\psi c_\theta s_\kappa \dot{\theta} \\
    -s_\psi c_\theta s_\kappa \dot{\psi} - s_\psi s_\theta s_\kappa \dot{\theta} - c_\psi c_\kappa \dot{\psi} \\
    -s_\psi s_\theta s_\kappa \dot{\psi} + c_\psi c_\theta s_\kappa \dot{\theta} - c_\psi c_\kappa \dot{\psi}
\end{bmatrix}
\tag{5.4}
$$

Now that we have established the basic foundation for the next sections, we can proceed with the derivation of the (dynamic) equations of motion of the detector.

### 5.1.2 Dynamic Modeling - Equations of Motion

#### Nonlinear Governing Equations

We discussed in chapter 3 that a force $\mathbf{F}_z = -F_z \hat{e}_z$ is being applied on the drum at leak positions. Here we use $\hat{e}_z$ to represent the unit vector along axis $z$ and

---

1$^1_{c_i}$ stands for $\cos(i)$ and $s_i$ stands for $\sin(i)$ correspondingly. Similar notation is used throughout this thesis for simplicity.
similar notation is followed throughout the thesis. This force is then generating a torque about point \( G \), the center of the gimbal mechanism, which is equal to (see Fig. 5.2):

\[
M = F_z R \hat{\phi} = -F_z R S \phi \hat{e}_x + F_z R C \phi \hat{e}_y
\]

\begin{equation}
(5.5)
\end{equation}

In the previous notation \( R \) is the radial distance from the point of the membrane/drum that the force \( F_z \) is applied, to the center of rotation \( G \) (Fig. 5.2). For this work we assume \( R \) is approximately equal to 50mm (since the detector is designed to operate in 100mm ID pipes). This torque represents the input/disturbance to the dynamic model that is derived in this chapter. Note that \( \hat{e}_\phi \) is the unit vector along the axis of rotation of the drum, while \( \hat{e}_r \), is normal to \( \hat{e}_\phi \) and in the radial direction (Fig. 5.2).

Let us start the analysis by defining the state vector \( \mathbf{x} = [\theta \ \dot{\theta} \ \psi \ \dot{\psi}]^T \). We need to start by modeling the springs. To do that we assume that a spring of stiffness \( k_\kappa \) is mounted between points \( \mathcal{K} \) on the drum and point \( \mathcal{L} \) on the front plate (Fig. 5.3). According to the kinematic analysis, the coordinates of point \( \mathcal{K} \) with respect to the chassis’ reference frame are given by Eq. (5.3). The latter coordinates are dependent on the position/deflection of the drum. On the other hand the coordinates of point \( \mathcal{L} \) are fixed and equal to:

\[
\mathbf{p}_\mathcal{L} = \begin{bmatrix} x_{\mathcal{L}} \\ y_{\mathcal{L}} \\ z_{\mathcal{L}} \end{bmatrix} = \begin{bmatrix} r_{\mathcal{K}} C_{\kappa} \\ r_{\mathcal{K}} S_{\kappa} \\ l \end{bmatrix}
\]

\begin{equation}
(5.6)
\end{equation}

In the previous notation we implied that \( \mathcal{GK} = \mathcal{G'L} = r_{\kappa} \) and also \( \mathcal{GG'} = l \). Point \( \mathcal{G'} \) is the projection of point \( \mathcal{G} \) on the front plate of the detector as seen in Fig. 5.3.

The spring force can be calculated as:

\[
\kappa F_k(x) = k_\kappa \{ \mathcal{KL} - l_0 \} \\
= k_\kappa \{ [(x_\kappa - x_{\mathcal{L}})^2 + (y_\kappa - y_{\mathcal{L}})^2 + (z_\kappa - z_{\mathcal{L}})^2]^{1/2} - l_0 \}
\]

\begin{equation}
(5.7)
\end{equation}

where the parameters in the previous equation can be calculated using Eq. (5.3, 5.6). For an analytic derivation please refer to the Appendix A at the end of the thesis. Here \( l_0 \) represents the unperturbed length of the spring.
Figure 5.2: Forces acting on the drum in case of a leak and the corresponding force $F_z$. A 3D view as well as a front view (side) is shown. Note the body (drum) fixed and the chassis frames of reference.
Figure 5.3: Points $G'$, $L$ on the front plate of the detector and points $G$, $K$ on the drum that are discussed in this section. The chassis fixed reference frame $Gxyz$ is drawn on the drum for completeness. The parts are drawn in exploded view, as in Fig. 3.7.

As the drum deflects from neutral position, the spring generates equivalent torques about $x$ and $y$ axes respectively:

\[ \kappa M_{k,x}(x) = -\kappa F_k(x)y_K \]
\[ = -\kappa F_k(x)c_\theta s_\kappa \]  \hspace{1cm} (5.8)

\[ \kappa M_{k,y}(x) = \kappa F_k(x)x_K \]
\[ = \kappa F_k(x)(c_\psi c_\kappa + s_\psi s_\kappa) \]  \hspace{1cm} (5.9)

In the previous derivation we used Eq. (5.3) to evaluate the quantities/coordinates.

Next, we assume that there is a linear dashpot of strength $b_K$ at point $K$ (same point and parallel to the spring element we modeled earlier). We also assume that the force of dissipative nature that the dashpot produces as the drum moves is of the form:

\[ \kappa F_k(x) = -b_K(\dot{x}_K + \dot{y}_K + \dot{z}_K) \]  \hspace{1cm} (5.10)

where the parameters in the previous equation can be calculated from Eq. (5.4). In a similar fashion, we can now calculate the resulting torques about $x$ and $y$. 

...
In the previous derivation we used Eq. (5.3) to evaluate the quantities/coordinates. The idea of adding linear dashpots to the model is to compensate for the viscous losses observed in the prototyped robotic detector, as shown later in the thesis.

We can now extend this framework to come up with the complete nonlinear equations of motion of a drum, that is able to rotate about two axes (2 DoFs) connected to \( n = 4 \) springs and dashpots at different points (\( \mathcal{K}_i \)). The governing equations of such a mechanical system that is subject to a leak force \( F_z \) (disturbance action) as described by Eq. (5.5) can be given by:

\[
\begin{align*}
I_{xx} \ddot{\theta} + \sum_{i=1}^{4} \{ \kappa_i M_{b,x}(x) + \kappa_i M_{k,x}(x) \} &= M_x = -F_z R s_{\phi} \\
I_{yy} \ddot{\psi} + \sum_{i=1}^{4} \{ \kappa_i M_{b,y}(x) + \kappa_i M_{k,y}(x) \} &= M_y = F_z R c_{\phi}
\end{align*}
\]

\( I_{xx} \) and \( I_{yy} \) are the moments of inertia of the drum & gimbal about axes \( x \) and \( y \) respectively. To derive those equations of motion, Eq. (5.7-5.12, 5.5) are used. From now on, let us assume that all springs are of identical stiffness \( k \) and all linear dashpots have the same strength \( b \), for simplicity.

We claim in this thesis, that by placing two force sensors at points \( A \) and \( B \) (equal distance \( r \) from \( G \), enclosed angles \( \alpha \) and \( \beta \) respectively) and measure the corresponding spring forces behind those points, we achieve complete input-observability on the detector. This statement is justified in the next sections. By measuring the forces behind those points, our model can be updated in terms of the measured quantities/outputs:

\[
y = \begin{bmatrix} y_1 \\ y_2 \end{bmatrix}
\]

where:

\[
\begin{align*}
y_1 &= -k \{ [(x_A - rc_\alpha)^2 + (y_A - rs_\alpha)^2 + (z_A - l)^2]^{1/2} - l_0 \} \\
y_2 &= -k \{ [(x_B - rc_\beta)^2 + (y_B - rs_\beta)^2 + (z_B - l)^2]^{1/2} - l_0 \}
\end{align*}
\]
Note that the minus sign stems from the fact that we measure the effect of the spring force on a sensor, which is of equal magnitude but opposite sign than the original spring force.

In the specific detector we designed and prototyped for this work, we placed \( n = 4 \) springs at points \( K_1, K_2, K_3 \) and \( K_4 \). Those points find themselves at equal distances \( r = 17.5mm \) from the center of the gimbal, \( G \). More specifically, the enclosed angles were designed to be equal to:

\[
\begin{align*}
\kappa_1 &= \pi/4 \\
\kappa_2 &= 3\pi/4 \\
\kappa_3 &= 5\pi/4 \\
\kappa_4 &= 7\pi/4
\end{align*}
\] (5.17)

The reader may refer to Fig. 3.7 for the detailed design of the detector and Fig. 5.2 for a sketch of these four points on the drum.

**Linearized Equations of Motion**

In this section we linearize the equations of motion in order to simplify and study them further. Linearizing the equations around the "neutral state" of the gimbal and drum can be justified by the fact the drum moves very little when perturbed by a leak disturbance. This happens because forces stemming from leaks are usually small in magnitude and also because the final prototyped detector is equipped with stiff springs. Thus, the drum does not move too much when externally perturbed by leaks.

For small values of \( x = [\theta \dot{\theta} \psi \dot{\psi}]^T \) (small motions of the drum) we can linearize Eq. (5.8, 5.9) and also Eq. (5.11, 5.12) and get:

\[
\begin{align*}
\kappa M_{k,x}(x) &\approx kr^2(s^2 \theta - s_c c_p \psi) \\
\kappa M_{k,y}(x) &\approx kr^2(c^2 \psi - s_c c_p \theta) \\
\kappa M_{b,x}(x) &\approx br^2(s^2 \dot{\theta} - s_c c_p \dot{\psi}) \\
\kappa M_{b,y}(x) &\approx br^2(c^2 \dot{\psi} - s_c c_p \dot{\theta})
\end{align*}
\] (5.18-5.21)

Note that to derive the previous equations, we assumed that the springs are not preloaded for simplicity, i.e. \( l = l_0 \). In addition we can linearize the measurements from the force sensors (Eq. (5.14-5.16)) and get:

\[
y \approx \begin{bmatrix} kr(s_\alpha \theta - c_\alpha \psi) \\ kr(s_\beta \theta - c_\beta \psi) \end{bmatrix}
\] (5.22)
For a complete derivation of the linearized equations of motion please refer to Appendix A at the end of this thesis. Combining Eq. (5.13) with Eq. (5.18-5.21) and using Eq. (5.22) we can write the system of equations in matrix form, namely:

\[
\dot{x} = Ax + Bd \quad (5.23)
\]

\[
y = Cx \quad (5.24)
\]

where the system matrices are given in Eq. (5.26-5.28). Note here that the disturbance vector from the occurrence of leaks at the circumference can be written as:

\[
d = \begin{bmatrix} d_1 \\ d_2 \end{bmatrix} = \begin{bmatrix} -F_x R \sin \theta \\ F_x R \cos \phi \end{bmatrix} \quad (5.25)
\]

We need to mention here that with the specific selection of enclosed angles (Eq. (5.17)), the dynamics become uncoupled for the \( \theta, \psi \) motions. This is because elements \( A_{2,3}, A_{2,4} \) and \( A_{4,1}, A_{4,2} \) in Eq. (5.26) become identically equal to zero. The latter fact is very important, because, as the linear model now predicts, the drum is able to pivot about axes \( x \) and \( y \) independently, i.e. no coupling exists between the two motions.

\[\textbf{5.2 Analysis}\]

In the previous section we derived an analytic dynamic model for the proposed detector. In the coming paragraphs we study the model in detail and gain more insight about its controllability, observability and sensitivity properties.
5.2.1 Controllability & Observability

The properties of the system described in Eq. (5.23-5.24, 5.26-5.28) are discussed here. We claimed earlier that with the specific measurements/outputs described by Eq. (5.22), the detector can achieve leak-observability. However, we need to justify the selection of values for parameters $\alpha$ and $\beta$.

To do so, we start by calculating the corresponding observability matrix [51]:

\[
\mathcal{O} = \begin{bmatrix}
C \\
CA \\
CA^2 \\
CA^3
\end{bmatrix}
\]  \tag{5.29}

The complete derivation is tedious but straightforward and requires plugging in Eq. (5.26, 5.28) into Eq. (5.29). By deriving the observability matrix, we can see that the system is indeed completely observable under most of the cases for the angles $\alpha$ and $\beta$ (observability matrix is full rank). However, there are some special cases that make the system unobservable. More specifically, when placing the two force sensors in the locus of points that are shown in Fig. 5.4, the detector becomes unobservable. To retain full observability one needs to place a sensor at point $A$ and then select another point $B$ at an angle $\beta$ such that ("Observability Rule"):

\[
\beta \neq \alpha + m\pi \text{ for } m = -1, 0, 1
\]

Now we introduce the check for system controllability [51]. The configuration of the proposed detector, that is described by the linear governing equations presented in the previous section, makes the system fully controllable (controllability matrix is full rank for the corresponding linear system). Again the complete derivation of the controllability matrix is tedious and straightforward and skipped in this thesis for simplicity. However, one can calculate the matrix by substituting Eq. (5.26, 5.27) into:

\[
C = [B \ AB \ A^2B \ A^3B]
\]  \tag{5.30}

Observability is a measure for how well internal states of a system can be inferred by knowledge of its measurements. Our detector being controllable means that the external disturbances can move the internal states of a system from any initial state to any other final state in a finite time interval. Finally, by having a system that is both controllable and observable, the system becomes input-observable. Input observability simply means that a change in inputs/disturbances in a dynamic system can reflect itself in the change of measurements (outputs) [26]. This is something desirable for the proposed detector.

Thus, one needs to select values for parameters $\alpha$ and $\beta$ that make the detector input/leak-observable, by following the Observability Rule. However, if
the inputs are observable, as they are in our case, the question is how to reconstruct the inputs. By doing so one may be able to recover information about the magnitude of leaks that is very useful for the operation of the robotic detection. Reconstruction of inputs/disturbances, has been investigated by researchers in the past [26] and is applied on the MIT Leak Detector in [11].

### 5.2.2 Sensitivity

After studying the observability and the controllability of the MIT Leak Detector, we now know how to instrument the system to make it leak-observable. However, we still need to justify the selection of the parameters \( \alpha \) and \( \beta \). To do that, we study the sensitivity of the sensor readings to changes in the leak disturbances. Our goal is to design a detector with leak-observability and with maximum sensitivity.

Starting from Eq. (5.22) we can get:

\[
\delta y = \begin{bmatrix} k r (s_\alpha \delta \theta - c_\alpha \delta \psi) \\ k r (s_\beta \delta \theta - c_\beta \delta \psi) \end{bmatrix}
\]  

(5.31)

An infinitesimal rotation about axis along the unit vector \( \hat{e}_\phi \), of magnitude \( \delta \chi \)
can be written in vector form as $\delta \chi = \delta \chi \hat{e}_\phi$. Equivalently we can write:

$$\delta \chi = \delta \chi s_\phi \hat{e}_x + \delta \chi c_\phi \hat{e}_y$$

(5.32)

Substituting back to Eq. (5.31) gives:

$$\delta y = \begin{bmatrix} -k\delta \chi r (s_x s_\phi + c_x c_\phi) \\ -k\delta \chi r (s_\beta s_\phi + c_\beta c_\phi) \end{bmatrix}$$

(5.33)

Maximizing the above relations will maximize the sensitivity of the detector. By doing so we get for the "optimal" parameters ("Optimality Rule"):

$$\begin{cases} \alpha^* = \phi + m\pi & \text{for } m = 0, 1 \\ \beta^* = \phi + m\pi & \text{for } m = 0, 1 \end{cases}$$

This results show that maximum sensitivity is achieved when the sensors are placed either at the same angle as the leak, $\phi$, or $\pi$ away from it. Unfortunately, one cannot control where the leak will happen, since it can occur anywhere around the circumference of the pipe. Thus, placement of the sensors cannot be predetermined explicitly in order to increase sensitivity of the readings. Final selected values for parameters $\alpha$ and $\beta$ are equal to:

$$\begin{cases} \alpha = \pi/4 \\ \beta = 3\pi/4 \end{cases}$$

(5.34)

With this selection we guarantee observability, since our design follows the "Observability Rule" derived in the previous section. In addition, by placing the two sensors at orthogonal directions, we make sure that the maximum sensitivity areas of the two sensors on the drum do not overlap and are well spread out on the perimeter of the drum. A schematic of the sensitivity of each sensor on the drum is shown in Fig. 5.5.

Finally, to derive the previous result and come up with the optimal values for the parameters, we kept the spring stiffness $k$ and the radial distance of the sensors $r$ constant. However, one can easily infer that increasing either $k$ or $r$ will increase the sensitivity of the readings to inputs/disturbances.

With this specific configuration (outputs/measurements) we guarantee observability, and since the system is also controllable, input/leak-observability. More specifically, points $A, B$ coincide with points $K_1, K_2$ (Fig. 5.2) on the drum.
Figure 5.5: This figure demonstrates the sensitivity of each sensor \( y_1, y_2 \). On the left figure one can see the sensitivity colormap on the drum for the first sensor, while on the right figure the equivalent sensitivity colormap for the second sensor. A combination of those two sensors will provide full coverage at the perimeter of the drum.

### 5.3 Final Model

By selecting the enclosed angles given in Eq. (5.17) and sensor angles given in Eq. (5.34) the system matrices are significantly simplified to:

\[
A = \begin{bmatrix}
0 & 1 & 0 & 0 \\
-\frac{2}{l_{xx}} kr^2 & -\frac{2}{l_{xx}} br^2 & 0 & 0 \\
0 & 0 & 0 & 1 \\
0 & 0 & -\frac{2}{l_{yy}} kr^2 & -\frac{2}{l_{yy}} br^2
\end{bmatrix}
\]

(5.35)

\[
B = \begin{bmatrix}
0 & 0 \\
\frac{1}{l_{xx}} & 0 \\
0 & 0 \\
0 & \frac{1}{l_{yy}}
\end{bmatrix}
\]

(5.36)

\[
C = \begin{bmatrix}
kr s_{\pi/4} & 0 & -krc_{\pi/4} & 0 \\
kr s_{3\pi/4} & 0 & -krc_{3\pi/4} & 0
\end{bmatrix}
\]

(5.37)

This is the model of the detector that we use for the rest of this work. The system is controllable, observable as well as leak-observable as shown and discussed earlier in this chapter.
Chapter 6

Detector: Algorithms for Leak Parameters Estimation

In this chapter we discuss an algorithmic scheme we developed for the estimation of important quantities during inspection with the proposed leak detection robotic system. We found out during experimentation, that simply obtaining a binary signal (leak, no leak) is not enough, and thus, we developed this new estimation scheme that enables the real-time calculation of leak characteristic quantities. More specifically, as discussed in this chapter, with the utilization of the proposed scheme, the system is able to estimate the flow rate and size, associated with a leak, without any human intervention in a completely autonomous fashion.

6.1 Estimation Scheme

The primary goal of the detector is the reliable and effective detection of leaks. In addition, the estimation of the leak size and flow rate are also important and will give extra valuable information to the operator. However, from Eq. (5.23), one can see that the information behind the leaks is "hidden" in \( \mathbf{d} \), a variable that we do not have access to (is not measurable directly, since it stems from the leak disturbances). The accessible variable is of course the one coming from the outputs/measurements in our model, namely \( \mathbf{y} \) in Eq. (5.24).

A block diagram representation of the proposed scheme is shown in Fig. 6.1. Disturbances/inputs stemming from leaks (\( \mathbf{d} \)) perturb the detector and result in outputs/measurements (\( \mathbf{y} \)) on the sensors. By using a suitable "Input Reconstruction" (Simultaneous Input and State Estimator - SISE) algorithm, we can reconstruct the states (\( \hat{\mathbf{x}} \)) and the inputs/disturbances stemming from leaks (\( \hat{\mathbf{d}} \)). By doing so, we are able to get an estimate of the "original leak disturbances" and use the estimates in order to calculate important leak quantities.

In parallel to that we use a carefully tuned "Triggering Metric" in order to
successfully pinpoint leaks at times $t^*$ during inspection. Finally, in case of leaks at times $t^*$, we can feed the reconstructed inputs/disturbances to the "Leak Force & Size Estimators" and get an estimate of the magnitude of the leak by calculating the leak force $\hat{F}_z$, the incidence angle $\hat{\phi}$, the leak cross-sectional area $\hat{A}_{\text{leak}}$ and the leak flow rate $\hat{q}_{\text{leak}}$. Those quantities, and especially $\hat{A}_{\text{leak}}$ and $\hat{q}_{\text{leak}}$, are very important for leak detection, since they provide a measure of the size of the actual leak. In what follows we go into more details into each one of the blocks of Fig. 6.1. Note that the whole scheme runs at a fixed sampling rate $f_s$. We can write that $t(j) = jT_s$, where $j$ represents a discrete counter and $T_s = 1/f_s$ is the corresponding sampling period.

### 6.1.1 Input Reconstruction

For the discussion that follows in this section we consider a linear, discrete-time system:

$$x_{j+1} = A_d x_j + B_d d_j + w_j$$  \hspace{1cm} (6.1)

$$y_j = C_d x_j + v_j$$  \hspace{1cm} (6.2)

where $A_d$, $B_d$ and $C_d$ represent the discrete counterparts of the matrices presented in Eq. (5.35-5.37). $x_j \in \mathbb{R}^4$ is the state vector, $d_j \in \mathbb{R}^2$ is the input/disturbance
vector and \( w_j \in \mathbb{R}^4 \) is the associated process noise. In a similar fashion \( y_j \in \mathbb{R}^2 \) represents the output vector and \( v_j \in \mathbb{R}^2 \) the corresponding measurement noise. Our objective is to design a recursive filter of the form:

\[
\begin{align*}
\hat{x}_{j|j-1} &= A_{d}\hat{x}_{j-1|j-1} \\
\hat{d}_{j-1} &= L_j(y_j - C_{d}\hat{x}_{j|j-1}) \\
\hat{x}_{j|j}^* &= \hat{x}_{j|j-1} + B_{d}\hat{d}_{j-1} \\
\hat{x}_{j|j} &= \hat{x}_{j|j}^* + K_j(y_j - C_{d}\hat{x}_{j|j}^*)
\end{align*}
\]

Let \( \hat{x}_{j-1|j-1} \) be an unbiased estimate of \( x_{j-1} \), \( \hat{x}_{j|j-1} \) is biased due to the unknown input to the true system. Finally \( \hat{x}_{j|j}^* \) is the unbiased state estimate.

The goal is to make a minimum variance unbiased (MVU) estimation of the system's states and disturbances, given a sequence of measurements \( Y_j = \{y_0, y_1, y_2, \ldots, y_j\} \). We solve the problem by utilizing a filter similar to the one designed by Gillinjs & De Moor for simultaneous state and input estimation [25]. Their work is based on previous work by Kitanidis [40] and Darouach & Zasadzinski [21] to joint MVU input and state estimation.

We assume here that process and measurement noise are mutually uncorrelated, zero-mean, white random signals with known covariance matrices, \( W = E[w_jw_j^T] \) and \( V = E[v_jv_j^T] \) respectively. As proven in our paper [12] and in chapter 5, the pair \( (C, A) \) is observable, thus the pair \( (C_{d}, A_d) \) should also be observable. Moreover the main assumption that \( rank(C_{d}B_{d}) = rank(B_{d}) = 2 \) holds in this case and thus the Darouach & Zasadzinski and the Kitanidis assumptions are satisfied. In order to successfully complete the filter design, the matrices \( L_j \in \mathbb{R}^{2x2} \) and \( K_j \in \mathbb{R}^{4x2} \) need to be selected for each discrete instant \( j \).

According to Gillinjs & De Moor [25], the complete algorithm for the calculation of the gain matrices \( L_j \) and \( K_j \) is presented in the "State & Input Reconstruction Block" in Fig. 6.2.

### 6.1.2 Triggering Metric

As mentioned earlier, we install force sensors on the drum and measure the outputs at all times. In order to successfully trigger alarms in case of leaks, while at the same time reject unnecessary noise (coming from turbulence in the pipe and maybe other factors), we propose the use of the following metric:

\[
J_j = \|y_j\| = \sqrt{y_{1,j}^2 + y_{2,j}^2}
\]

More specifically, a leak incidence is identified at \( j^* \) iff:
Initialization: $P_{0|0}, \hat{x}_{0|0}$

Update/Propagate Error Covariances

$P_{j|j-1} = A_d P_{j-1|j-1} A_d^T + W$
$\hat{R}_j = C_d P_{j|j-1} C_d^T + V$

Calculate Matrices

$L_j = (F^T \hat{R}_j^{-1} F)^{-1} F^T \hat{R}_j^{-1}$
$K_j = P_{j|j-1} C_d^T \hat{R}_j^{-1}$
where: $F = C_d B_d$

Update Estimates

$\hat{x}_{i,j-1} = A_d \hat{x}_{i-1|j-1}$
$\hat{d}_{j-1} = L_j (y_j - C_d \hat{x}_{j|j-1})$
$\hat{x}_{j|j}^* = \hat{x}_{j|j-1} + B_d \hat{d}_{j-1}$
$\hat{x}_{j|j} = \hat{x}_{j|j}^* + K_j (y_j - C_d \hat{x}_{j|j}^*)$

$P_{j|j} = P_{j|j-1} - K_j C_d P_{j|j-1} + [B_d - K_j F][F^T \hat{R}_j F]^{-1}[B_d - K_j F]^T$

Figure 6.2: Algorithm for simultaneous input and state estimation based on the work of Gillinjs & De Moor [25].
In other words, an alarm is triggered whenever $J$ exceeds a threshold $c$, where $c$ is a predefined constant. The free parameter $c$ needs to be selected by the operator in order to neglect noise and avoid false alarms. At the same time large values of $c$ will lower the sensitivity of the detection. Thus, $c$ needs to be carefully tuned before inspection.

$c$ is a value that depends on many parameters. For example the higher the line pressure inside the pipe, the higher one can set the value of $c$. Higher values of $c$ favor the rejection of higher noise levels, but at the same time reduce the sensitivity of detection, since small leaks will be ignored. A good trade-off between sensitivity and noise rejection needs to be experimentally identified for each case before inspection. Moreover, for clean pipes with small deviations in pipe diameter one can use a small value for $c$. But for the opposite case, one will need higher values for the threshold, since any bump of the membrane on the pipe walls needs to be rejected automatically and not be treated as a leak incidence.

Finally we need to mention here that the end of the leak incidence (instant $j_{\text{end}}^*$) occurs when the metric $J$ stops being "upwards sloping". This happens when $\frac{d^2J_{\text{end}}^*}{dt^2} < 0$ and $J_{\text{end}}^*$ becomes a local maximum, i.e. $F_{z}$ is maximized and $F_{z,j_{\text{end}}^*}$ is the local maximum value.

\section{6.1.3 Leak Size Estimation}

In order to estimate the magnitude (and the incidence angle) of a leak in case of an alarm, we utilize the "Leak Force Estimator" in Fig. 6.1. Since the reconstructed inputs are provided by the corresponding block and the connection between the quantities is deterministic as described in Eq. (5.25), we can then use the following formulas to calculate the associated estimates as follows:

$$\hat{F}_{z,j} = \sqrt{\hat{d}_{1,j}^2 + \hat{d}_{2,j}^2} \frac{R}{R} \quad (6.8)$$

$$\hat{\phi}_{j} = \text{atan2}(-\hat{d}_{1,j}, \hat{d}_{2,j}) \quad (6.9)$$

The latter equations show the importance of the Input Reconstruction algorithms. Without them, we would not have access to the reconstructed inputs/disturbances and the estimation of the quantities in Eq. (6.8, 6.9) would not be possible.
Moreover, by using Eq. (3.2) and a measurement of the pressure $\Delta p$, we can estimate the cross-sectional area of the leak by writing (inverse of Eq. (3.2)):

$$\hat{A}_{\text{leak},j} = \frac{\hat{F}_{z,j}}{\mu \Delta p}$$

(6.10)

If we assume that the leak is circular in shape, we can estimate the leak diameter by using:

$$\hat{d}_{\text{leak},j} = \sqrt{\frac{4\hat{A}_{\text{leak},j}}{\pi}}$$

(6.11)

If the leak is not circular (for example it is a long slit-crack), the previous equation gives as the diameter of an "equivalent" leak of circular shape. Finally, we can estimate the leak flow rate through the opening by writing [46] (orifice equation):

$$\hat{q}_{\text{leak},j} = \gamma \sqrt{\frac{2\Delta p}{\rho}} \hat{A}_{\text{leak},j}$$

(6.12)

In the last equation $\rho$ represents the density of the pipe medium and $\gamma$ is a correction factor to compensate for the shape factor in case of flow via an orifice.

For completeness we mention here that by averaging the estimated quantities over a small time window $[j^*,j_{\text{end}}]$ for each leak incidence/alarms $i$, we can get the mean estimated leak quantities, namely $\hat{F}_{z,i}$ and $\hat{\phi}_i$. Last, we need to calculate the maximum value of the leak force (right before the membrane detaches from the leak) in order to accurately calculate the rest of the leak quantities, namely $\hat{A}_{\text{leak},i}, \hat{d}_{\text{leak},i}$ and $\hat{q}_{\text{leak},i}$. The latter implies that these quantities are being evaluated at the instant $j^*_{\text{end}}$.

Finally, we need to note that for the application of the leak estimation scheme one needs to know the parameters $\gamma$ and $\mu$ a priori. As shown towards the end of this thesis, one needs to perform a specific set of experiments in order to identify the values of these parameters. Once this is done successfully, we can then apply the complete estimation scheme to real experimental data and estimate leak characteristic quantities.

### 6.2 Monte Carlo Simulation of Proposed Estimation Scheme

In this section we perform simulations in order to verify the efficacy of the proposed Leak Detection & Estimation Scheme discussed in the previous section. As shown by the end of this chapter, the proposed scheme is very efficient and leak characteristics are identified reliably within reasonable ranges of process and
Initialization: $P_{0|0}, \hat{x}_{0|0}$

Update/Propagate Error Covariances

$P_{j|j-1} = A_d P_{j-1|j-1} A_d^T + W$

$\tilde{R}_j = C_d P_{j|j-1} C_d^T + V$

Calculate Matrices

$L_j = (F^T \tilde{R}_j^{-1} F)^{-1} F^T \tilde{R}_j^{-1}$

$K_j = P_{j|j-1} C_d^T \tilde{R}_j^{-1}$

where: $F = C_d B_d$

Update Estimates

$x_{j|j-1} = A_d \hat{x}_{j-1|j-1}$

$\hat{\dot{x}}_{j-1} = L_j (y_j - C_d \hat{x}_{j|j-1})$

$\hat{x}_{j|j} = \hat{x}_{j|j-1} + K_j (y_j - C_d \hat{x}_{j|j-1})$

$\hat{\dot{x}}_{j|j} = \hat{\dot{x}}_{j|j-1} + K_j (y_j - C_d \hat{x}_{j|j-1})$

$P_{j|j} = P_{j|j-1} - K_j C_d P_{j|j-1} + [B_d - K_j F][F^T \tilde{R}_j F]^{-1} [B_d - K_j F]^T$

Calculate Triggering Metric

$J_{j|j-1} = ||y_{j-1||}$

Is $J_{j|j-1} \geq c$ and $\frac{dJ_{j|j-1}}{dt} > 0$?

Trigger

Leak Force Estimator

$\hat{F}_{z,j-1} = \sqrt{\hat{d}_{1,j-1}^2 + \hat{d}_{2,j-1}^2}$

$\phi_{j-1} = \text{atan}2(-\hat{d}_{1,j-1}, \hat{d}_{2,j-1})$

Leak Size Estimator

$\hat{A}_{\text{leak},j-1} = \frac{\hat{F}_{z,j-1}}{\mu \Delta p}$

$\hat{\dot{A}}_{\text{leak},j-1} = \sqrt{4 \hat{A}_{\text{leak},j-1} / \pi}$

$\hat{\dot{q}}_{\text{leak},j-1} = \gamma \sqrt{2 \Delta p / \rho \hat{A}_{\text{leak},j-1}}$

Figure 6.3: A algorithmic representation of the proposed Detection & Estimation scheme.
measurement noise. Later in this thesis, we apply the proposed scheme to real experimental data with great efficiency as well.

As we mentioned in the previous section, the proposed leak detection and estimation scheme is model-based. For that purpose, we will use the model structure obtained at the end of chapter 5. For each simulation we assumed a different level of process and measurement noise. More specifically, we assume a standard deviation of process noise equal to $\sigma_w$ and a standard deviation of sensor noise equal to $\sigma_v$. Then we define the covariance matrices to be:

$$W = (\sigma_w * R)^2 \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{6.13}$$

$$V = (\sigma_w)^2 \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \tag{6.14}$$

Note that the standard deviation of the process noise has units of $N$, and is multiplied with a moment-arm (drum radius $R$ in order to get converted to torque in Eq. (6.13). For each noise level the simulation was iterated $n_{MC} = 3000$ times. Results follow in the next sections.

6.2.1 Structure of Monte Carlo Simulations

To perform each iteration the following steps are followed:

1. A leak is assumed to occur on the pipe wall. The angle of the leak incidence with respect to the leak detector is random and uniformly selected in the range $[0 : 2\pi)$.

2. Because of the leak, as the robot moves inside the pipe with speed $v_{robot}$, the membrane of length $l_{eff}$ is perturbed accordingly. This is imposed by allowing a leak force to act on the leak detector. The leak force is equal to $F_z = 2N$.

3. A leak force of that magnitude ($F_z = 2N$) for a line pressure equal to $\Delta p = 10psi = 0.69bar$, corresponds to a leak diameter of $d_{nom} = \sqrt{\frac{4F_z}{\pi \mu \Delta p}} = 3.45mm$. This is the nominal leak diameter considered for the simulations. We also assumed the coefficient of friction to be equal to $\mu = 3.1$. The selection of this value is justified in chapter 9.
4. To generate the signals (outputs from the sensors as a result of the afore-
mentioned leak) a linear simulation is performed using the model described
in Eq. (5.23-5.24) and Eq. (5.35-5.37). Some of the parameters used in this
model are summarized in Table 6.1.

5. Prior to the simulation, process noise is added to the leak torques. Moreover,
measurements get corrupted by additional sensor noise. A specific level (co-
variance) of measurement and process noise is assumed, as discussed before,
for each set of simulations.

6. The signals are filtered using a first order low-pass filter with tunable cutoff
frequency.

7. The Leak Detection & Estimation Algorithm is applied and the leak char-
acteristic quantities are estimated and compared to the "actual/nominal"
values \(d_{\text{nom}} = 3.45\text{mm}, F_z = 2N\) and the randomly selected leak incidence
angle \(\phi\).

8. Moreover, the scheme is able to estimate the associated leak flow rate using
Eq. (6.12) and assuming \(\gamma = 0.6228\). The selection of this value is justified
in chapter 9.

9. The process is repeated \(n_{MC} = 3000\) times in order for the Monte Carlo
simulation to complete.

Some of the values used in the Monte Carlo simulations are summarized in
Table 6.1. For the input reconstruction block of the scheme, a slightly different
model is used than the one described in step #4. More specifically, we used
the model that we obtained from the system identification experiments on the
prototyped leak detector. The analytic model derived is presented in chapter 8
and discussed in detail. This introduced some slight deviation between the model
used for dynamic simulation (output/measurement generation) and the model
used for the input reconstruction, allowing for some model uncertainty in the
simulations.

### 6.2.2 Results

**First Iteration / Case Study**

Initially we start by presenting the results of a single iteration in order to show
how the process flows. For this initial iteration the angle of the leak incidence is
equal to \(\phi = 25^\circ\). Moreover, for this case we assumed \(\sigma_v = .1\%\) and \(\sigma_w = 1\%\).
CHAPTER 6. DETECTOR: ALGORITHMS FOR LEAK PARAMETERS ESTIMATION

Parameter | Value | Notes
---|---|---
$F_z$ | 2N | Simulated leak force
$\mu$ | 3.1 | Static friction coef.
$d_{nom}$ | 3.45mm | Nominal leak diameter
$\Delta p$ | 10psi = 0.7bar | Line pressure
$R$ | 50mm | Drum radius
$r$ | 20mm | Distance between gimbal center and sensor
$l_{eff}$ | 12mm | Membrane length
$v_{robot}$ | 0.38m/s | Robot speed
$f_s$ | 3000Hz | Sampling rate
$c$ | 0.8 | Threshold for trigger
$I_{xx}$ | $0.9882e^{-6}Kg m^2$ | Rot. Inertia about x
$I_{yy}$ | $0.9794e^{-6}Kg m^2$ | Rot. Inertia about y
$b_1$ | 1.5Nms | Damping coef. about x
$b_2$ | 2Nms | Damping coef. about y
$k$ | 2738.98N/m | Spring stiffness
$\gamma$ | 0.6228 | Orifice equation correction factor

Table 6.1: Parameters used for the Monte Carlo simulations.

The MATLAB code used to simulate this case study is given in Appendix B for completeness.

As the robot moves inside the pipe, the membrane of the detector starts to be affected and gets pulled at $t = 5s$. The sensors pick up the drum movement and capture the signals of the forces behind the springs. Signals captured by the sensors are plotted in Fig. 6.4. One can observe that the force on sensor #1 is reduced, while the force on the other sensor is increased after and during the leak incidence. This happens because the drum moves in a very specific direction, because in this case the leak incidence angle is $\phi = 25^\circ$. Note here that the outputs are already corrupted with sensor noise in Fig. 6.4. However the standard deviation of the sensor noise is small in this case. This simply means that the sensors behave reliably (SNR is high).

During the simulation, the triggering metric is being calculated continuously. At some point, the triggering metric exceeds the threshold set at $c = 0.8$ and a leak alarm is triggered. The plot of the triggering quantity over time is shown in Fig. 6.5.

In parallel to the calculation of the triggering metric, the input reconstruction block provides the reconstructed inputs/disturbances. Those quantities are very important, as mentioned earlier in this chapter, since they can provide the
Figure 6.4: The outputs for the single iteration simulation. For this case $\phi = 25^\circ$.

Figure 6.5: The triggering quantity that corresponds to the outputs shown in Fig. 6.4. The threshold is plotted for comparison.
Figure 6.6: The reconstructed inputs/disturbances for the case of the single iteration with $\phi = 25^\circ$.

important information about leak characteristic quantities. The reconstructed disturbances are plotted in Fig. 6.6. One is able to see, that at the leak incidence, the first disturbance goes negative (this is the torque about axis $x$), while the second one becomes positive (this is the torque about axis $y$). This is what one would expect for a leak incidence at an angle of $\phi = 25^\circ$.

Now, using the Eq. (6.8, 6.9), we can estimate the leak force and the leak incidence angle from the reconstructed disturbances. The output of the algorithm is plotted in Fig. 6.7. Qualitatively we can see that the estimated quantities at $t = 5s$, when the leak happens, are pretty close to the nominal values (for this case $\phi = 25^\circ$ and $F_x = 2N$).

Finally, as mentioned in earlier sections of the chapter, we can calculate the leak characteristic quantities over a small time window after the leak trigger. By doing this we get the results presented in Table 6.2. Note that for the estimation of the leak flow rate we assumed that the pipe medium is air of density $\rho = 1.225kg/m^3$.

**Monte Carlo Results**

In this section we present the results of the Monte Carlo simulations. More specifically, we repeated the iterations 3000 times for each noise level and recorded
Figure 6.7: The reconstructed force signal and leak incidence angle estimate.

<table>
<thead>
<tr>
<th>Nominal Value</th>
<th>Estimated Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\vec{F}_z = 2N$</td>
<td>$\vec{F}_z = 2.0121N$</td>
</tr>
<tr>
<td>$\phi = 25^\circ$</td>
<td>$\phi = 24.8748^\circ$</td>
</tr>
<tr>
<td>$d_{nom} = 3.45mm$</td>
<td>$d_{leak} = 3.4621mm$</td>
</tr>
<tr>
<td>-</td>
<td>$A_{leak} = 9.4139mm^2$</td>
</tr>
<tr>
<td>-</td>
<td>$\dot{q}_{leak} = 31.179gal/min$</td>
</tr>
</tbody>
</table>

Table 6.2: Results for the leak estimated quantities.
the results. In each case we estimated the leak quantities and compared them to the nominal/actual values each time and calculated the error. The MATLAB code used for the Monte Carlo analysis is given as reference in Appendix C.

In Table 6.3 we present the results of the estimation of the leak diameter. More specifically, we show the different calculated standard deviation of the error in the estimation of the leak diameter for each case. We varied the process and sensor noise in each case. As one is able to observe, the standard deviation remains small for reasonably small noise levels. As the sensor noise increases, the results get less reliable, even for relatively larger values of process noise (Fig. 6.8). This is expected, as a noisy sensor will corrupt the measurements and the estimation of the different quantities. As long as the sensor noise remains small (< 0.50%), the estimation is performing well. We mention here that the mean of the error of the diameter estimation is, as expected, zero. The latter implies that the estimation is indeed unbiased.

Good estimation results are demonstrated in Table 6.4 for the standard deviation of the error in the force quantity. The standard deviation remains small for reasonable level of sensor noise as before. Similar trends can be observed for the estimation of the incidence angle in Table 6.5. The corresponding plots are shown in Fig. 6.9 and Fig. 6.10.

In general one can claim that the proposed leak detection and estimation scheme performs well, even at low pressures. The simulated pressures here are small, resulting in a small force on the drum. At higher pressures, forces are larger and signals stand out even more. Nevertheless, all leak characteristic quantities are estimated reliably and in most cases the estimates are very close to the nominal values. As the Monte Carlo analysis demonstrated, the performance of the scheme heavily depends on level of process and measurement noise as expected (for a constant line pressure). For relatively low levels of such noises, the scheme performs very well, even for small sized leaks at very low pressures.
Table 6.3: Standard Deviation of the error in the Diameter Estimation for the Monte Carlo Simulations for different levels of sensor and process noise. The units here are in [mm]. A 3D plot of this table is shown in Fig. 6.8.

<table>
<thead>
<tr>
<th>$\sigma_w$</th>
<th>$\sigma_v$</th>
<th>0.01%</th>
<th>0.03%</th>
<th>0.05%</th>
<th>0.1%</th>
<th>0.25%</th>
<th>0.50%</th>
<th>1%</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.01%</td>
<td>0.0013</td>
<td>0.0043</td>
<td>0.0083</td>
<td>0.0233</td>
<td>0.1221</td>
<td>0.3809</td>
<td>0.8436</td>
<td></td>
</tr>
<tr>
<td>0.05%</td>
<td>0.0013</td>
<td>0.0043</td>
<td>0.0084</td>
<td>0.0241</td>
<td>0.1214</td>
<td>0.3811</td>
<td>0.8642</td>
<td></td>
</tr>
<tr>
<td>0.1%</td>
<td>0.0013</td>
<td>0.0044</td>
<td>0.0088</td>
<td>0.0244</td>
<td>0.1274</td>
<td>0.3841</td>
<td>0.8652</td>
<td></td>
</tr>
<tr>
<td>0.5%</td>
<td>0.0016</td>
<td>0.0045</td>
<td>0.0084</td>
<td>0.0238</td>
<td>0.1250</td>
<td>0.3816</td>
<td>0.8494</td>
<td></td>
</tr>
<tr>
<td>1%</td>
<td>0.0025</td>
<td>0.0048</td>
<td>0.0089</td>
<td>0.0235</td>
<td>0.1194</td>
<td>0.3812</td>
<td>0.8537</td>
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</tr>
<tr>
<td>3%</td>
<td>0.0065</td>
<td>0.0075</td>
<td>0.0102</td>
<td>0.0245</td>
<td>0.1183</td>
<td>0.3752</td>
<td>0.8654</td>
<td></td>
</tr>
<tr>
<td>5%</td>
<td>0.0105</td>
<td>0.0111</td>
<td>0.0132</td>
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<td>0.8731</td>
<td></td>
</tr>
<tr>
<td>10%</td>
<td>0.0200</td>
<td>0.0205</td>
<td>0.0218</td>
<td>0.0305</td>
<td>0.1221</td>
<td>0.3818</td>
<td>0.8757</td>
<td></td>
</tr>
</tbody>
</table>

Table 6.4: Standard Deviation of the error in the Force Estimation for the Monte Carlo Simulations for different levels of sensor and process noise. The units here are in [N]. A 3D plot of this table is shown in Fig. 6.9.

<table>
<thead>
<tr>
<th>$\sigma_w$</th>
<th>$\sigma_v$</th>
<th>0.01%</th>
<th>0.03%</th>
<th>0.05%</th>
<th>0.1%</th>
<th>0.25%</th>
<th>0.50%</th>
<th>1%</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.01%</td>
<td>0.0016</td>
<td>0.0050</td>
<td>0.0097</td>
<td>0.0275</td>
<td>0.1521</td>
<td>0.5316</td>
<td>1.4245</td>
<td></td>
</tr>
<tr>
<td>0.05%</td>
<td>0.0016</td>
<td>0.0050</td>
<td>0.0098</td>
<td>0.0285</td>
<td>0.1515</td>
<td>0.5309</td>
<td>1.4682</td>
<td></td>
</tr>
<tr>
<td>0.1%</td>
<td>0.0016</td>
<td>0.0051</td>
<td>0.0103</td>
<td>0.0289</td>
<td>0.1587</td>
<td>0.5361</td>
<td>1.4738</td>
<td></td>
</tr>
<tr>
<td>0.5%</td>
<td>0.0019</td>
<td>0.0052</td>
<td>0.0099</td>
<td>0.0281</td>
<td>0.1556</td>
<td>0.5339</td>
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<tr>
<td>1%</td>
<td>0.0029</td>
<td>0.0056</td>
<td>0.0104</td>
<td>0.0278</td>
<td>0.1484</td>
<td>0.5304</td>
<td>1.4519</td>
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</tr>
<tr>
<td>3%</td>
<td>0.0076</td>
<td>0.0087</td>
<td>0.0119</td>
<td>0.0289</td>
<td>0.1472</td>
<td>0.5198</td>
<td>1.4736</td>
<td></td>
</tr>
<tr>
<td>5%</td>
<td>0.0123</td>
<td>0.0130</td>
<td>0.0155</td>
<td>0.0298</td>
<td>0.1530</td>
<td>0.5146</td>
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<tr>
<td>10%</td>
<td>0.0234</td>
<td>0.0240</td>
<td>0.0255</td>
<td>0.0359</td>
<td>0.1518</td>
<td>0.5312</td>
<td>1.4540</td>
<td></td>
</tr>
</tbody>
</table>
Table 6.5: Standard Deviation of the error in the Incidence Angle Estimation for the Monte Carlo Simulations for different levels of sensor and process noise. The units here are in [deg]. A 3D plot of this table is shown in Fig. 6.10.

<table>
<thead>
<tr>
<th>$\sigma_w$</th>
<th>$\sigma_v$</th>
<th>0.01%</th>
<th>0.03%</th>
<th>0.05%</th>
<th>0.1%</th>
<th>0.25%</th>
<th>0.50%</th>
<th>1%</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.01%</td>
<td>0.1383</td>
<td>0.7598</td>
<td>1.5471</td>
<td>4.3652</td>
<td>18.3240</td>
<td>42.8658</td>
<td>60.2673</td>
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</tr>
<tr>
<td>0.05%</td>
<td>0.1794</td>
<td>0.6977</td>
<td>1.5881</td>
<td>4.2279</td>
<td>18.7265</td>
<td>42.2288</td>
<td>60.3830</td>
<td></td>
</tr>
<tr>
<td>0.1%</td>
<td>0.1457</td>
<td>0.5949</td>
<td>1.4809</td>
<td>4.5536</td>
<td>19.1956</td>
<td>41.5638</td>
<td>59.5589</td>
<td></td>
</tr>
<tr>
<td>0.5%</td>
<td>0.1392</td>
<td>0.7142</td>
<td>1.3273</td>
<td>4.3286</td>
<td>19.2372</td>
<td>41.6448</td>
<td>59.5649</td>
<td></td>
</tr>
<tr>
<td>1%</td>
<td>0.1848</td>
<td>0.5822</td>
<td>1.4760</td>
<td>4.1976</td>
<td>18.7796</td>
<td>40.4829</td>
<td>58.1447</td>
<td></td>
</tr>
<tr>
<td>3%</td>
<td>0.2169</td>
<td>0.8192</td>
<td>1.5436</td>
<td>4.6787</td>
<td>20.0138</td>
<td>42.0748</td>
<td>58.9691</td>
<td></td>
</tr>
<tr>
<td>5%</td>
<td>0.3563</td>
<td>0.7728</td>
<td>1.3976</td>
<td>3.6991</td>
<td>19.1773</td>
<td>42.0681</td>
<td>60.7995</td>
<td></td>
</tr>
<tr>
<td>10%</td>
<td>0.7078</td>
<td>1.0112</td>
<td>1.6491</td>
<td>4.5204</td>
<td>18.6860</td>
<td>41.4602</td>
<td>58.4106</td>
<td></td>
</tr>
</tbody>
</table>

Figure 6.8: Standard Deviation of the error in the Diameter Estimation for the Monte Carlo Simulations for different levels of sensor and process noise. The units here are in [mm].
Figure 6.9: Standard Deviation of the error in the Force Estimation for the Monte Carlo Simulations for different levels of sensor and process noise. The units here are in [N].
Figure 6.10: Standard Deviation of the error in the Angle Estimation for the Monte Carlo Simulations for different levels of sensor and process noise. The units here are in [deg].
Chapter 7

Complete System Design

We present the final system design in this chapter. We start the discussion by presenting the design of the robotic locomotive we built for the purposes of experimentation. The complete robotic leak detection solution we propose in this thesis consists of a robotic locomotive (carrier) and the previously presented and analyzed leak detection module. Later in the chapter we discuss the detailed design of the robotic detector, before we move to the actual prototype development in the next chapter.

7.1 System Overview

The complete system consists of two modules, i.e. the carrier (robotic locomotive) and the detector (Fig. 7.1). The detector analysis and concept are discussed in detail in previous chapters. The carrier provides the locomotion of the system inside the pipe. The two subsystems are connected via a link, that allows the relative rotation between the two modules.

In this work, the system is optimized to operate in 100mm ID gas pipes. However, all concepts discussed in this thesis can be scaled and slightly altered, in order to accommodate pipes of different sizes and perform inspection in pipes carrying other fluid media, e.g. water. For the 100mm prototype developed in this thesis, the dimensions of the final designed system are presented in Fig. 7.2. In the coming section we introduce some design details of the carrier module, that is responsible for the locomotion of the system inside the pipeline. Some of the details here are initially presented in [10, 14].

7.2 Carrier Module

The carrier module is responsible for the reliable locomotion of the systems inside the pipes. The system carries actuators, sensors, power and also electronics for signal processing and communications. A 3D solid model of the carrier along with
Figure 7.1: Side view of complete leak detection system. [Top]: Solid Model. A pipe section is drawn for reference. [Bottom]: The actual developed prototype inside a 100mm ID pipe.

Explanations of its main subsystems is presented in Fig. 7.3.

The module’s locomotion is materialized via a pair of traction wheels (OD = 1 3/16” ≈ 30.1mm) (Fig. 7.3). Those two wheels are touching the lower end of the wall. In addition, the system is suspended by four legs with passive rollers from the upper walls as shown in the same figure.

Each suspension wheel has a spring loaded pivot. The angle $\theta_{sus}$ of each pivot point on each suspension wheel is regulated in a passive way and is providing the required compliance to the carrier. That compliance is very important, since it enables the module to align itself properly inside the pipe, overcome misalignments or defects on the pipe walls or even comply with small changes in the pipe.
Figure 7.2: The complete system design along with some basic dimensions.
diameter. With this design, the carrier module can stably cruise inside straight pipelines, even if they have slight and smooth deviations in the nominal ID. This can occur because of pure manufacturing standards, large design tolerances or because of accumulated dirt or dust.

The main actuator of the module is a 20W brushed DC Motor from Maxon under model number "339150" [44]. The motor is connected to the traction wheels via a set of gears with ratio 5:1. In order to regulate speed, an incremental rotary encoder (50 counts) from US Digital [67] is used and the speed loop is closed. Both disk and hub are shown in Fig. 7.3. Finally, all electronics, communication modules and batteries are housed inside the carrier module.

### 7.3 Detector

The complete design of the detector is shown in Fig 7.4. We presented the side view of the proposed detection system in Fig. 3.6 and the exploded view of the detector in Fig. 3.7 in previous chapters. The exploded view is shown again in Fig. 7.5 for completeness.

As discussed before, the appropriate placement of two force sensors on the drum results in complete leak/disturbance observability. The sensors are mounted on the drum, behind the springs as described in previous chapters and shown also in Fig. 7.6.
Figure 7.4: The solid model of the final design of the detection module.
Figure 7.5: A 3D assembled view of the detector is shown at the bottom right corner. The exploded view of the proposed design is presented and all key components are laid out. Supporting wheels and suspension legs are skipped for simplicity. Details: [a] Membrane, [b] Drum, [c] Gimbal, [d] Shaft/Chassis, [e] Front/Rear Plates, [g] Spring caps with setscrews, [h] Springs.
Figure 7.6: The solid model of the final design of the detection module. In this case the force sensors are drawn in place for reference. One can see the sensing area in blue color. The springs are touching the sensing area of the sensors and forces are measured accordingly. Note that the supporting wheels have been removed from the model in this case.
Chapter 8

Prototype Development

In this chapter we discuss the prototype development of the complete leak detection system. Of course we put emphasis on the detection module, that is discussed in detail throughout this thesis. After building a detector prototype, we conduct system identification experiments to understand the dynamics under consideration and obtain an accurate model needed for the Leak Detection & Estimation Scheme discussed in chapter 6. Moreover, we validate experimentally the leak-observability concepts discussed in chapter 5.

8.1 Prototype Development

In this section we discuss the development of the carrier module, the architecture behind the electronics and the development of the detection module.

8.1.1 Carrier Module

As far as the carrier module is concerned, most of the parts were 3D printed using a Fortus 250mc 3D printer from Stratasys and made out of ABS material [63]. The carrier module prototype is shown in Fig. 8.1.

The main actuator of the module is a 20W brushed DC Motor. The motor is connected to the traction wheels via a set of gears with ratio 5:1. In order to regulate speed, an incremental rotary encoder (50 counts) is used and the speed loop is closed. Both disk and hub are shown in detail in Fig. 7.3. Finally, all electronics, communication modules and batteries are housed inside the carrier module and are discussed in the coming paragraphs.

8.1.2 Electronics Architecture

Derived from our design requirements, the robot should be able to perform the following tasks:

- Move and regulate the speed inside pipes
Figure 8.1: The carrier module prototype is shown here.
- Identify leaks by measuring signals from two force sensors at relatively high sampling rates.

- Communicate with the "Command Center" (computer) wirelessly

The system's architecture is developed to meet these requirements and is shown in Fig. 8.2. To perform the aforementioned tasks two micro-controllers are used. Micro-controller #2 is dedicated to speed regulation and micro-controller #1 is performing real-time leak sensing.

The workflow is the following: The user specifies a motion command on the computer. The computer sends out the motion command including desired speed and desired position to the robotic leak detection system. After the WiFi transceiver on the robot receives the command, it delivers the command to micro-controller #2. Micro-controller #2 performs closed loop speed control in order to regulate the speed of the system. At the same time it calculates speed (by measuring the signal from the encoder) and commands the system to stop if it reaches the end of the pipe section (or any other point along the pipe as specified by the operator).

Parallel to micro-controller #2, micro-controller #1 is responsible for leak detection and for sending out sensor data to the WiFi transceiver. This micro-controller receives signals from the two force sensors installed on the detector. At the same time it receives the measured position from the encoder mounted on the carrier. It compiles the correlated force sensor data with position data and sends them out through the WiFi transceiver. The WiFi receiver on the command center then receives the data, decomposes them and supplies them to the user via the graphical user interface on the computer.

The WiFi transceiver that we selected is an Xbee Pro 900MHz RF module [22]. We use two Arduino Pro Mini 328 5V/16MHz [1] and the motor driver under codename VNH5019 from Polulu [54]. The motor is powered by a 11.1V 350 mAh 65C Li-polymer battery. The electronics are powered by a thin 3.7V 400mAh Li-ion battery separately. The whole system (Carrier and Detector) can run for 30mins with this configuration, performing leak inspection and locomotion inside pipelines. The final electronics bundle is shown in Fig. 8.3. The "open" carrier module with all the electronics in the Electronics / Battery Box is shown in Fig. 8.4.

### 8.1.3 Detector

A prototype of the proposed detector was manufactured. To do this, most of the parts were built using a Fortus 250mc 3D printer from Stratasys and made out of ABS material [63]. The prototype is shown in Fig. 8.5. A complete side view
of the prototype detection module is shown in Fig. 8.6. Additionally, the shaft (part [d] in Fig. 3.7) was manufactured from aluminum. The springs that we used were rated at 1.49N/mm.

Finally, for the force measurements we used two FlexiForce Sensors for leak detection from Tekscan (Model #A301 – 25) [65]. They are powered at 5V and a resistor of 180kΩ is used for the required inverting op-amp circuit. These sensors are mounted on points A and B on the drum as described earlier. Last, we need to mention here that the membrane was made out polyurethane film of 0.030” \( \approx 0.76 \text{mm} \) thickness.

### 8.2 Detector System ID and Observability

In this section we perform system identification experiments on the prototyped robotic leak detection module and derive an analytic dynamic model that we use for the rest of this thesis. Note that an accurate model is essential for the application of the proposed Leak Detection & Estimation Scheme discussed in chapter 6.
8.2.1 System Identification

Initially, we wanted to test whether the system behaves like a second order system, as claimed in chapter 5 for each of the two "uncoupled" DoF. If this is the case, we expect the transfer functions from disturbances to output forces to be of the form:

\[
\begin{align*}
Y_1(s) & = -Y_3(s) - \frac{w_{n,1}^2}{K_1 R s^2 + 2 \zeta_1 w_{n,1} s + w_{n,1}^2} \\
D_1(s) & = -F_2(s)R_{\phi} \\
Y_2(s) & = -Y_3(s) - \frac{w_{n,2}^2}{K_2 R s^2 + 2 \zeta_2 w_{n,2} s + w_{n,2}^2} \\
D_2(s) & = -F_2(s)R_{\phi} \\
Y_1(s) & = \frac{w_{n,1}^2}{K_1 R s^2 + 2 \zeta_1 w_{n,1} s + w_{n,1}^2} \\
D_1(s) & = -F_2(s)R_{\phi} \\
Y_2(s) & = \frac{w_{n,2}^2}{K_2 R s^2 + 2 \zeta_2 w_{n,2} s + w_{n,2}^2} \\
D_2(s) & = -F_2(s)R_{\phi}
\end{align*}
\]

This can be proven by manipulating Eq. (5.23, 5.24) along with Eq. (5.35-5.37) and transforming them into standard transfer function form.

In order to evaluate the various parameters involved in the previous equations we performed system identification experiments. This was done by imposing impulsive in nature torques about axes x and y independently and trying to fit second order models to the output signals using least-squares error minimization. The results showed that the system indeed behaves like a second order system for
Figure 8.4: The Electronics/Battery Box with all the necessary electronics sitting next to the Carrier Module.

<table>
<thead>
<tr>
<th>Name of Variable</th>
<th>Estimated Value via SysID</th>
</tr>
</thead>
<tbody>
<tr>
<td>$K_1$</td>
<td>16.88</td>
</tr>
<tr>
<td>$w_{n,1}$</td>
<td>485.81 rad/sec</td>
</tr>
<tr>
<td>$\zeta_1$</td>
<td>0.099</td>
</tr>
<tr>
<td>$K_2$</td>
<td>16.88</td>
</tr>
<tr>
<td>$w_{n,2}$</td>
<td>509.72 rad/sec</td>
</tr>
<tr>
<td>$\zeta_2$</td>
<td>0.126</td>
</tr>
</tbody>
</table>

Table 8.1: System ID values

each of the two DoFs (Fig. 8.7).

The estimated parameters from the system identification experiments are summarized in Table 8.1. Reverting Eq. (8.1) to standard state-space representation and using the identified quantities from Table 8.1, the new matrixes shown in Eq. (8.2-8.4) can be derived. The model described by the matrices in Eq. (8.2-8.4) is the one that characterizes the dynamics of the leak detection module and is the one that we are going to be using in the coming sections during the application of the detection and estimation scheme.
Figure 8.5: A side view of the MIT Leak Detector prototype is shown in this picture. Suspension wheels and membrane are not installed yet for simplicity.
Figure 8.6: A side view of the MIT Leak Detector prototype is shown in this picture. Suspension wheels and membrane are shown here for completeness.

\[ A = \begin{bmatrix} 0 & 1 & 0 & 0 \\ -2.3601e^5 & -96.0937 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & -2.5982e^5 & -128.6032 \end{bmatrix} \] (8.2)

\[ B = \begin{bmatrix} 0 & 0 \\ 1 & 0 \\ 0 & 0 \\ 0 & 1 \end{bmatrix} \] (8.3)

\[ C = \begin{bmatrix} 3.9844e^6 & 0 & -4.3862e^6 & 0 \\ 3.9844e^6 & 0 & 4.3862e^6 & 0 \end{bmatrix} \] (8.4)

**8.2.2 Observability Demonstration**

To illustrate input-observability of the proposed mechanism we demonstrate the reaction signals captured from the two force sensors. The detector prototype was mounted on a stiff metallic structure and impulsive in nature forces/torques were generated at different angles \( \phi_i = \pi i/4 \) for \( i = 0, 1...7 \). These impulsive forces were generated with the help of a solenoid. The detector mounted on the stiff structure is shown in Fig. 8.8.
Figure 8.7: Comparison between model predicted outputs and in-situ measurements. Models were fitted via least-square error minimization. An impulse at $\phi = 90^\circ$ was imposed and outputs were recorded.
Figure 8.8: The prototype of the detector is mounted on a stiff structure and with the help of a solenoid, impulsive forces/torques are applied on the drum at different positions around the circumference.

Results are shown in Fig. 8.9. These include the reaction signals captured by the force sensors mounted on the drum to the impulsive forces applied on the drum at different positions. The selection of impulsive inputs was done on purpose and because of the fact that most leak signals look like short-duration step inputs (or else impulse inputs) [10]. Some initial experimental leak detection results of the proposed detector and robot are presented in [14] and [8].

In the experiments presented in this section, we imposed impulsive inputs to the drum at different angles around the circumference and observed the captured output signals. We can see that each distinct input/disturbance (at $\phi_i$) results in a distinct combination of output signals, as expected. The latter statement implies that the system is leak-observable, as proven in chapter 5. Any leak incidence at any angle, $\phi$, will result in a unique signature in the outputs/measurements. By
utilizing the dynamics and the signals one will be able to reconstruct the inputs and estimate the magnitude of the leak. The latter is discussed in chapter 6 and preliminary results are shown in our recent publication in [11].

Finally, we need to point out that results in Fig. 8.9 show performance of the system that looks like second order for the two DoFs. However, there is some weak coupling between the motions, that we neglected in our linearized model. For example, the impulse response at an angle of $\phi = \pi/4$ gives some minor vibrations for $y_2$. However, the linear model would have predicted no excitation of the second output. Nevertheless, the coupling is very weak and the system’s performance is captured by the linear model for the most part, as initially predicted.
Figure 8.9: Experimental demonstration of the input-observability of the proposed robotic detector. Impulsive forces at different angles on the drum are applied and output forces are measured with force sensors installed on points A and B. For all figures [a]-[h] output from sensor at point A, y₁ is depicted in black dashed line, while output from the second sensor at point B, y₂ is depicted in red solid line. For each different input (at an angle φ₁) a distinct combination of output signals is observed. This demonstrates input-observability.
Chapter 9

Experimental Results

In this chapter we initially go over the experimental setup that was used to perform leak detection experiments. Our goal in this chapter is to validate all concepts and designs presented in this thesis via experiments. More specifically, leak detection experiments are performed and the efficacy of the proposed solution is demonstrated. Leak are correctly identified and after application of the Leak Detection & Estimation Scheme, important characteristics are reliably calculated for each leak incidence.

9.1 Experimental Setup

The experimental setup we use in this thesis is shown in Fig. 9.1. As mentioned before, the system is optimized to operate in 100mm ID pipes, and thus, our experimental setup consists of pipes of that specific size. In what follows we go into more details of the experimental setup used for the validation of the proposed solution.

The one end of the setup is connected to an end-cap. The end-cap can open and close with the help of bolts in order to insert and remove the leak detection prototype inside the pipe. Of course, the end-cap can only be removed when the pipe is not pressurized. Once the leak detection prototype is inside the pipe, as shown in Fig. 9.2, we can pressurize the pipe. To do that we turn on a valve that is sitting on the other end of the setup and is connecting the pipe with the compressed air supply (compressor). By regulating the opening of this valve and having one or multiple leaks open in the pipe, we can regulate the line pressure in the setup. If there is no leak in the pipe, the pipe pressure and the supply pressure will equilibrate at about \(60\text{psi} = 4.14\text{bar}\). This is the maximum pressure that our setup can reach.

Once the robotic system is deployed in the pipe and the end cap is sealed, it moves along the pipe from [Start] to [End]. Its job is to move inside the section, autonomously regulate its speed according to the user input (command signals
are being transmitted wirelessly to the robot) and identify the leaks along the way (sensor signals are being transmitted wirelessly to the control station, as discussed earlier). We artificially generated leaks on the pipe walls for the scope of experimentation. All our leaks are small in size and are discussed in detail in the appropriate sections. Finally, we can close leaks at will, by sealing them with a tight black rubber band. For instance, in Fig. 9.1 leak #1 is covered/sealed and leak #2 is opened/active. A red tape is put on the pipe in place of each leak so that one can identify them easily.

In summary, after the leak detection system is in place inside the pipe section, it can move in a straight line back and forth. We let the robot move inside the pipe, automatically detect leaks, and report its findings wirelessly to a control station (PC). We need to mention here that the motion (direction, speed) of the robot is controlled through the control station wirelessly. In the next paragraphs, signals captured by the leak detector during controlled leak detection experiments will be shown and discussed.

### 9.2 Experimental Investigation of Parameters $\mu$ and $\gamma$

As shown in chapter 6, in order to be able to utilize the complete leak identification and estimation scheme we need to know the values of two important parameters. Those are:

- The coefficient of friction, between the membrane and the pipe wall, $\mu$
- The flow rate correction factor, $\gamma$.

In the coming paragraphs, we discuss the experimental investigation and parameter identification of these two important quantities. After knowing their

![Figure 9.1: The experimental setup. The robotic detector moves along the pipe from [Start] to [End] and performs leak detection.](image-url)
Figure 9.2: The *MIT Leak Detector* prototype is shown in this picture. The system consists of the robotic locomotive and the leak detection module.

values, we can perform experimentation with the proposed leak detection solution and apply the proposed Leak Detection & Estimation Scheme proposed in this thesis to estimate important leak characteristic quantities.

### 9.2.1 Parameter $\mu$

In order to measure the friction coefficient, we set up static friction experiments in the pipe. More specifically, we 3D printed a solid piece, with one surface that conforms to the pipe walls (is circular with diameter slightly smaller than the pipe ID). We then mounted the membrane (polyurethane sheet, the same material that is used on the actual leak detection module) on the circular surface of the 3D printed part and put it inside the pipe. The other end of the part is straight, and is used to add/remove loads in order to increase/decrease the normal force for the static friction experiment.

For each experiment we push the part along the longitudinal direction of the pipe. The part is in each case in contact with the pipe walls through the membrane. For each experiment we monitored the required pushing force. At the moment when the part/membrane starts to move inside the pipe, the maximum/static friction force is observed and recorded. We then vary the load on the 3D printed part by adding/removing small weights and record the required force for each
<table>
<thead>
<tr>
<th>Experiment #</th>
<th>Weight [g]</th>
<th>Weight [N]</th>
<th>Max Push. Force [N]</th>
</tr>
</thead>
<tbody>
<tr>
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<td>1.407</td>
<td>3.1</td>
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<tr>
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<tr>
<td>3</td>
<td>227.3</td>
<td>2.203</td>
<td>5.4</td>
</tr>
<tr>
<td>4</td>
<td>227.3</td>
<td>2.203</td>
<td>5.3</td>
</tr>
<tr>
<td>5</td>
<td>143.4</td>
<td>1.407</td>
<td>3.6</td>
</tr>
<tr>
<td>6</td>
<td>143.4</td>
<td>1.407</td>
<td>3.6</td>
</tr>
<tr>
<td>7</td>
<td>178</td>
<td>1.746</td>
<td>4.5</td>
</tr>
<tr>
<td>8</td>
<td>178</td>
<td>1.746</td>
<td>4.6</td>
</tr>
<tr>
<td>9</td>
<td>227.3</td>
<td>2.230</td>
<td>5.2</td>
</tr>
<tr>
<td>10</td>
<td>227.3</td>
<td>2.230</td>
<td>5.5</td>
</tr>
<tr>
<td>11</td>
<td>304.1</td>
<td>2.983</td>
<td>8.4</td>
</tr>
<tr>
<td>12</td>
<td>304.1</td>
<td>2.983</td>
<td>8.2</td>
</tr>
<tr>
<td>13</td>
<td>388</td>
<td>3.806</td>
<td>8.8</td>
</tr>
<tr>
<td>14</td>
<td>388</td>
<td>3.806</td>
<td>9.3</td>
</tr>
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<td>15</td>
<td>427.7</td>
<td>4.196</td>
<td>10.2</td>
</tr>
<tr>
<td>16</td>
<td>427.7</td>
<td>4.196</td>
<td>10.9</td>
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<tr>
<td>17</td>
<td>406.8</td>
<td>3.991</td>
<td>11.2</td>
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</tr>
<tr>
<td>19</td>
<td>691.1</td>
<td>6.780</td>
<td>19.9</td>
</tr>
<tr>
<td>20</td>
<td>691.1</td>
<td>6.780</td>
<td>24.5</td>
</tr>
<tr>
<td>21</td>
<td>647.1</td>
<td>6.348</td>
<td>26.4</td>
</tr>
<tr>
<td>22</td>
<td>647.1</td>
<td>6.348</td>
<td>24</td>
</tr>
<tr>
<td>23</td>
<td>490.7</td>
<td>4.814</td>
<td>14.5</td>
</tr>
<tr>
<td>24</td>
<td>490.7</td>
<td>4.814</td>
<td>14.9</td>
</tr>
</tbody>
</table>

Table 9.1: Experimental Data for the estimation of $\mu$.

experiment. By repeating the experiment a couple of times and recording the maximum required pushing force each time, we can generate the Table 9.1. We can then plot the results in Fig. 9.3 and fit a line among the points. The slope is equal to the optimal estimate for the friction coefficient. *It turns out that in this case, the estimate of $\mu$ is equal to 3.115. This is the value we are going to be using for the rest of the thesis.*

We need to mention here, that in case of different pipe material or different membrane material, the estimation of the friction coefficient needs to take place again. This value is only valid for the specific selection of both membrane (polyurethane) and pipe material (pvc). In the next section we discuss the estimation of the flow rate coefficient $\gamma$ in detail.
9.2.2 Parameter $\gamma$

As mentioned before, $\gamma$ represents the correction factor in the calculation of the leak flow rate. Depending on the shape of the leak opening and the leak geometry characteristics, $\gamma$ can take values in between 0 and 1. A good reference for the parameter under discussion is shown in [46].

In order to estimate the parameter $\gamma$ for our case, we applied different pressures in the pipe (by regulating the inlet valve) and measured the leak flow rate through the leak with a flow sensor. The actual sensor we used is the OMEGA FMA5528A [52]. We also calculated the nominal leak flow rate for each case using Eq. (6.12). A line was fitted to the data shown in Table 9.2 and presented in Fig. 9.4. As shown there, the parameter $\gamma$ is estimated to be equal to 0.623 for our case.

9.3 Leak Detection & Estimation Results

As mentioned in chapter 8, the prototype of the complete robotic system was 3D printed using a Fortus 250mc 3D printer from Stratasys and most of the parts were made out of ABS material [63]. Finally, for the force measurements we used two Tekscan A301 force sensors with a modified op-amp circuit [65]. We used a
<table>
<thead>
<tr>
<th>Experiment #</th>
<th>$\Delta p$ [psi]</th>
<th>$q_{\text{leak}}^{\text{Measured}}$ [l/min]</th>
<th>$q_{\text{leak}}^{\text{Nominal}}$ [l/min]</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.11</td>
<td>13.9</td>
<td>20.31</td>
</tr>
<tr>
<td>2</td>
<td>0.16</td>
<td>16.8</td>
<td>24.50</td>
</tr>
<tr>
<td>3</td>
<td>0.22</td>
<td>19.7</td>
<td>28.73</td>
</tr>
<tr>
<td>4</td>
<td>0.42</td>
<td>26.7</td>
<td>39.63</td>
</tr>
<tr>
<td>5</td>
<td>0.71</td>
<td>33.3</td>
<td>51.61</td>
</tr>
<tr>
<td>6</td>
<td>0.07</td>
<td>11.0</td>
<td>16.20</td>
</tr>
<tr>
<td>7</td>
<td>0.1</td>
<td>14.1</td>
<td>19.37</td>
</tr>
<tr>
<td>8</td>
<td>0.3</td>
<td>22.0</td>
<td>35.55</td>
</tr>
<tr>
<td>9</td>
<td>0.27</td>
<td>19.6</td>
<td>31.82</td>
</tr>
<tr>
<td>10</td>
<td>0.39</td>
<td>24.5</td>
<td>38.25</td>
</tr>
<tr>
<td>11</td>
<td>0.53</td>
<td>27.6</td>
<td>44.59</td>
</tr>
<tr>
<td>12</td>
<td>0.66</td>
<td>31.1</td>
<td>49.76</td>
</tr>
<tr>
<td>13</td>
<td>0.89</td>
<td>35.9</td>
<td>57.78</td>
</tr>
<tr>
<td>14</td>
<td>1.15</td>
<td>40.2</td>
<td>65.68</td>
</tr>
<tr>
<td>15</td>
<td>1.39</td>
<td>43.4</td>
<td>72.21</td>
</tr>
<tr>
<td>16</td>
<td>1.57</td>
<td>45.2</td>
<td>76.74</td>
</tr>
</tbody>
</table>

Table 9.2: Experimental Data for the estimation of $\gamma$.

Figure 9.4: Plot of the values presented in Table 9.2. A line fit is shown here. The slope of the line is equal to the optimal estimate of the parameter $\gamma$. 
feedback resistor of 47kΩ and the calibration function was equal to:

\[ \text{Reading}[V] = 0.3501 \cdot \text{Force}[N] + 1.0204 \]

The sampling rate was fixed at \( f_s = 300Hz \). Signals on the sensors were band-pass filtered to remove high frequency noise as well as dc components before postprocessing. Cut-off frequencies that we used were set to 10Hz and 120Hz correspondingly. Moreover, system identification experiments were conducted before the experiments in order to learn the dynamics and are shown in chapter 8. The discrete counterparts for the matrices described in Eq. (8.2-8.4) that are needed in the State & Input Reconstruction portion of the algorithm are given below:

\[
A_d = \begin{bmatrix}
0.1184 & 0.0018 & 0 & 0 \\
-418.9330 & -0.0522 & 0 & 0 \\
0 & 0 & 0.0777 & 0.0016 \\
0 & 0 & -418.8791 & -0.1296
\end{bmatrix} \quad (9.1)
\]

\[
B_d = \begin{bmatrix}
0 & 0 \\
0.0018 & 0 \\
0 & 0 \\
0 & 0.0016
\end{bmatrix} \quad (9.2)
\]

\[
C_d = 10^6 \cdot \begin{bmatrix}
3.9844 & 0 & -4.3862 & 0 \\
3.9844 & 0 & 4.3862 & 0
\end{bmatrix} \quad (9.3)
\]

## 9.3.1 Case Study

In this section we present the results of successful leak detection and characteristics’ estimation for the case of a small leak on the pipe. More specifically, we artificially generated a circular leak/opening of diameter equal to 3.5mm. Then, we pressurized the pipe section to \( \Delta p = 10psi = 0.69\) bar. In order to test the robotic detector we let the system move inside the pipe with a speed of 0.285m/s (\( \approx 1km/h \)). The signals that were captured from the force sensors, as the robot passed by the leak, are shown in Fig. 9.5. The triggering metric was calculated in real-time (Fig. 9.6). It is clear that the leak signal stands out very clearly, i.e. the SNR is high. For this experiment we set the free parameter (alarm threshold) to \( c = 0.8 \), as illustrated in the same figure. When the metric exceeded \( c \) for the first time, a leak alarm was triggered (instant \( j^* \)).

Using the input reconstruction algorithm the robot automatically reconstructed the disturbances. Those estimated signals are presented in Fig. 9.7. Finally, using the reconstructed inputs, the system calculated the estimates of the incidence
Figure 9.5: Measured signals from the force sensors as the detector travels by the circular leak.

Figure 9.6: The calculated triggering metric $J$ for this case. The metric exceeds the threshold $c = 0.8$, and thus, a leak alarm is triggered. The leak is successfully identified at instant $j^*$. The instant when the metric reaches its maximum value is $j_{end}$. 
angle and leak force, as described in Fig. 6.3. The results are presented in Fig. 9.8.

Using the estimated quantities shown in Fig. 9.8, the algorithm calculated the mean value of the angle to be equal to \( \hat{\phi} = 118.6^\circ \) (the real angle is \( \phi = 120^\circ \)). Now, the maximum force observed in Fig. 9.8 is \( \max(F_z) = 2.0469 N \). Finally, using Eq. (3.2) we can calculate the theoretical value \( \max(F_{\text{theory}}) = 2.05 N \). The latter value matched very well the one obtained from experiments. The theoretical value can be calculated using the known size of the leak \( d_{\text{nom}} = 3.5 mm \), the pressure inside the pipe \( (\Delta p = 10 psi = 0.69 \text{bar}) \) and the coefficient of friction between the membrane and the pipe walls, that is equal to \( \mu = 3.1 \), as described in the previous section.

Finally, the system has all the required information to estimate the leak diameter using Eq. (6.10, 6.11). In this case we got \( \hat{d}_{\text{leak}} = 3.492 mm \), while the real value was \( d_{\text{nom}} = 3.5 mm \). Note that for this calculation we used \( \rho = 1.225 \text{kg/m}^3 \) for the air medium inside the pipe. Finally, in this case the estimated leak flow rate was equal to \( q_{\text{leak}} = 31.7 \text{gal/min} \). This quantity was estimated using Eq. (6.12) by setting \( \gamma = 0.6228 \), as previously discussed. This value is consistent with the literature for bores of similar geometry [46].
9.3.2 Other Experiments

In this last part, we present some further experimental results to demonstrate the efficacy of the proposed leak detection system. For this part we changed the line pressure inside the pipe (so we essentially varied $\Delta p$) as well as changed the angle $\phi$ of the leak around the circumference. Moreover, we varied the speed of detection and filled the experimental matrix as shown in Table 9.3. Note that the first row in the table describes the experiment (case study) that we presented in the previous section for completeness.

The results in this matrix show that the leak detection and estimation scheme works reliably. All leaks were identified and accurately estimated (estimation error is relatively small for all cases). The good performance of the detection system and the proposed algorithm is demonstrated in the good match between nominal and estimated quantities in Fig. 9.9 and Fig. 9.10.

The Leak Detection & Estimation Scheme performed well even under low pressures, e.g. 5psi as shown in experiments #6 and #7 in Table 9.3. At such low pressures, the SNR for each leak incidence is lower, resulting in degraded performance in the estimation of the leak quantities. Nevertheless, even at such low pressures, the estimation of the leak diameter is very good and very close to the actual value as shown in Fig. 9.10. As a result we can claim that our system is very reliable for high pressures. However, our system can still reliably detect
and estimate all important leak characteristic quantities even at pressures smaller than 10psi as shown in here.
Table 9.3: Experimental Results Summary for 12 Cases

<table>
<thead>
<tr>
<th>Experiment #</th>
<th>$\Delta p$ [psi]</th>
<th>$c$</th>
<th>Speed [m/s]</th>
<th>$max(\dot{F}<em>2)</em>{\text{theory}}$ [N]</th>
<th>$max(\dot{F}_2)$ [N]</th>
<th>$\phi$</th>
<th>$\dot{\phi}$</th>
<th>$\dot{d}_{\text{leak}}$ [mm]</th>
<th>$e_{\text{leak}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>10</td>
<td>0.8</td>
<td>0.285</td>
<td>2.06</td>
<td>2.05</td>
<td>120</td>
<td>119</td>
<td>3.49</td>
<td>-0.16%</td>
</tr>
<tr>
<td>2</td>
<td>10</td>
<td>0.8</td>
<td>0.38</td>
<td>2.06</td>
<td>2.25</td>
<td>105</td>
<td>114</td>
<td>3.44</td>
<td>4.60%</td>
</tr>
<tr>
<td>3</td>
<td>8</td>
<td>0.8</td>
<td>0.19</td>
<td>1.54</td>
<td>1.59</td>
<td>100</td>
<td>99</td>
<td>3.44</td>
<td>-1.69%</td>
</tr>
<tr>
<td>4</td>
<td>7.5</td>
<td>0.7</td>
<td>0.285</td>
<td>1.54</td>
<td>1.61</td>
<td>85</td>
<td>90</td>
<td>3.57</td>
<td>2.08%</td>
</tr>
<tr>
<td>5</td>
<td>7.5</td>
<td>0.7</td>
<td>0.38</td>
<td>1.54</td>
<td>1.62</td>
<td>65</td>
<td>70</td>
<td>3.59</td>
<td>2.56%</td>
</tr>
<tr>
<td>6</td>
<td>7.5</td>
<td>0.7</td>
<td>0.19</td>
<td>1.54</td>
<td>1.44</td>
<td>60</td>
<td>60</td>
<td>3.38</td>
<td>-3.37%</td>
</tr>
<tr>
<td>7</td>
<td>5</td>
<td>0.6</td>
<td>0.19</td>
<td>1.03</td>
<td>0.82</td>
<td>50</td>
<td>50</td>
<td>3.13</td>
<td>-10.7%</td>
</tr>
<tr>
<td>8</td>
<td>5</td>
<td>0.6</td>
<td>0.285</td>
<td>1.03</td>
<td>1.08</td>
<td>50</td>
<td>51</td>
<td>3.59</td>
<td>2.49%</td>
</tr>
<tr>
<td>9</td>
<td>6</td>
<td>0.6</td>
<td>0.38</td>
<td>1.23</td>
<td>1.28</td>
<td>45</td>
<td>40</td>
<td>3.56</td>
<td>1.85%</td>
</tr>
<tr>
<td>10</td>
<td>9</td>
<td>0.8</td>
<td>0.38</td>
<td>1.85</td>
<td>1.84</td>
<td>80</td>
<td>91</td>
<td>3.49</td>
<td>-0.29%</td>
</tr>
<tr>
<td>11</td>
<td>9</td>
<td>0.7</td>
<td>0.285</td>
<td>1.85</td>
<td>1.89</td>
<td>75</td>
<td>85</td>
<td>3.54</td>
<td>1.05%</td>
</tr>
<tr>
<td>12</td>
<td>7.5</td>
<td>0.7</td>
<td>0.285</td>
<td>1.54</td>
<td>1.43</td>
<td>65</td>
<td>73</td>
<td>3.37</td>
<td>-3.71%</td>
</tr>
</tbody>
</table>
Figure 9.9: A graphical comparison between the nominal and the estimated leak force values for each one of the 12 experiments of Table 9.3.

Figure 9.10: A graphical comparison between the nominal and the estimated leak diameter value for each one of the 12 experiments of Table 9.3. The size of the leak diameter is shown in [mm].
Chapter 10

Conclusion and Recommendations

Here we discuss the concluding remarks of the work that was conducted in this thesis. Moreover, we finish the chapter by adding some comments on the ongoing and recommendations for future work.

10.1 Summary / Conclusions

In this thesis a detection system for in-pipe robotic inspection is proposed. Initially, an analytic dynamic model of the system is derived and then simplified by linearization. In addition, the system is designed to be both controllable and observable and thus, input observable with the minimal amount of sensors installed. As part of this thesis, a prototype of the proposed detector is built, in order to validate the models and the observability concepts discussed.

The system can detect leaks in a reliable and autonomous fashion. It is able to trigger alarms in case of leaks by acquiring very good signals from the two installed sensors, even at pressures lower than 10 psi. Higher pressures will generate larger forces and after these forces perturb the drum, the SNR becomes even better.

Moreover, a complete leak identification & estimation scheme for the MIT Leak Detector is proposed in this thesis. Using the proposed scheme the robot is not only able to identify leaks in pipes, but also to reconstruct the leak disturbances, estimate the associated leak forces and sizes and calculate the incidence angles (with respect to the body orientation). Finally the leak flow rate can be calculated without any user input. This information is very important for the operator and provides useful insight about the defects on the pipe walls during inspection. To the best of our knowledge, the system discussed in this thesis, is the first and only one able to provide all this information to the operator during leak detection.

Experimentation showed that the leak detection system proposed works reliably and that the underlying concept is very promising. The system is able to identify and pinpoint small leaks ("mm" in size) at low pressures (for indus-
try standards). Moreover, the scheme works well and the estimated quantities matched the real/nominal values very closely. In addition, the actual leak sizes were estimated accurately as well. We need to state here that in all experiments the pressure was kept low (maximum value is $10psi = 0.69bar$). However, the system works even better when the pressure is higher (the higher the line pressure, the higher the SNR).

10.2 List of Thesis Contributions

In this section we list the thesis contributions in bullet form. In this thesis we:

1. Proposed a novel leak detection concept based on a localized pressure gradient (Chapter 3).
2. Demonstrated the feasibility of the concept via CFD simulations and experiments (Chapter 4).
3. Designed a new leak detection system based on the proposed concept (Chapter 3, Chapter 7).
4. Instrumented the detection system in an optimal way via modeling and analysis of sensitivity, observability and controllability (Chapter 5).
5. Developed algorithms for leak characteristic estimation using the proposed leak detection system (Chapter 6).
6. Built prototype for experimentation (Chapter 8).
7. Conducted successful leak detection & estimation experiments (Chapter 9).

10.3 Performance Envelope

As discussed earlier in this thesis, our leak detection system is able to reliably detect small leaks in pipes under low pressures. However, in this section we try to set the limits of the system’s performance.

- The system is able to detect small leaks in pipes. By small we mean that the characteristic length of the leak, e.g. the leak length, is much smaller than the diameter of the pipe. The system, specifically developed as part of this work as a proof of concept, is optimized for 100mm ID pipes. Thus, we focus on leaks of a couple of "mm" is size.
It should be clear, that the system is able to detect bigger leaks easier. The larger the crack under constant pressure, the larger the forces that perturb the drum will be.

- The system is able to detect small leaks in pipes under pressures down to 5psi as shown in the previous chapter. There is no upper limit on the line pressure for the operation of the system. Actually it will perform much better and provide much more accurate and reliable results at higher pressures.

- The leak detection system proposed in this thesis assumes a clean pipe with very small deviations from the nominal ID. However, we are currently developing a system that is able to cope with accumulated scale, dirt or changes in the pipe diameter in the pipe for the next generation of the prototype. We discuss more about this in the next and final section of this thesis.

- The leak detection system proposed and developed here is optimized for 100mm ID gas pipes. The leak detection principles and most of the discussions in this thesis can be slightly modified for different pipe sizes and also different media (water, etc).

- The leak detection system needs to be inserted in the pipe via a special insertion point. This insertion point can be attached to existing sections in the pipe network or can be made by customizing some of the existing sections.

- The leak detection system presented in this thesis is able to cope with all standard pipe sections, connections, T-junctions, elbows, etc. In addition, it can autonomously maneuver in the network, however it cannot actively steer towards a specific direction at T-junctions (it goes through them straight). To perform active steering, a steering mechanism/actuation needs to be deployed in the design of the robotic locomotive.

### 10.4 Ongoing Work and Future Recommendations

We are now working on the refinement of the design of the detector to make it able to accommodate changes/deviations in the ID of the pipe, e.g. accumulated scale. This includes the development of a compliant drum, in contrast to the rigid one we showed in this thesis (as shown in Fig. 7.5). The compliance will allow the drum to adjust its shape to different diameters or different anomalies in the pipe geometry and make the system widely applicable to real-pipe conditions. A first prototype of the compliant drum system developed at the Mechatronics Research Laboratory at MIT is shown in Fig. 10.1. More details can be found in [37].
Next, we would like to look into the possibility of developing a detection system with improved sensitivity, able to detect even the smallest of leaks at very low pressures (less than 5psi). To achieve that, we would need to study the detection system further and optimize material properties and design parameters, e.g. membrane material properties (bending stiffness and coefficient of friction with the pipe walls), rotational inertia of the drum, stiffness of the springs mounted on the drum and others.

Another interesting research question could be: "How can the system autonomously learn the parameters $\mu$ and $\gamma$, used in the Leak Detection & Estimation Scheme"? Ideally, we would like to have the system estimate these on the fly without having to perform experiments a priori. It would be very helpful to develop an estimation scheme that performs this "learning step" without any user intervention at all.

Moreover, a future suggestion would be to extend the experimental matrix to a wide range of leak sizes and pressures in order to see how the system behaves under different circumstances. In addition, researchers in our laboratory plan to develop prototypes of the proposed detection system optimized for liquid pipes (water, oil, etc) and test the concepts and the effectiveness of the systems in these media as well.

Finally, we plan to develop a more dexterous robotic locomotive for in-pipe maneuvering and locomotion. The one discussed in this thesis is able to move inside pipelines autonomously and traverse bends and elbows, but it cannot actively steer at T or Y-Junctions. A more dexterous robotic carrier with this extra steering feature is highly desirable for a real pipe survey in a real pipe network.
Figure 10.1: The initial prototype of the compliant drum. Various configurations are demonstrated for completeness. The drum is able to passively comply to diameter changes as the system moves inside the pipe.
Appendix A

Appendix: Model Linearization

Starting with Eq. (5.7) we can write:

\[ \kappa F_k(x) = k \kappa \{ \overline{KL} - l_0 \} \]

where:

\[
\overline{KL} = [(x_K - x_L)^2 + 
+ (y_K - y_L)^2 + (z_K - z_L)^2]^{1/2} \\
= [2r_K^2 + l^2 - 2r_K(c_Kx_K + s_Ky_K) - 2lz_K]^{1/2} \tag{A.1}
\]

In the previous derivation we used the fact that \( x_K^2 + y_K^2 + z_K^2 = r_K \). Substituting Eq. (5.3, 5.6) into the previous equation we get:

\[
\overline{KL} = [2r_K^2 + l^2 - 2r_K^2(c_\psi c_\kappa + s_\psi s_\theta \kappa c_\kappa + c_\theta s_\kappa^2) - \\
- 2lr_K(c_\psi s_\theta \kappa - s_\psi c_\kappa)]^{1/2} \tag{A.2}
\]

Now we need to linearize the previous nonlinear equation for small deviations from the neutral state, i.e. \( \theta << 1, \psi << 1 \). We need to mention at this point that for linearization we will use the standard Taylor series expansion formula:

\[
f(\theta, \psi) \approx f(\theta_0, \psi_0) + (\theta - \theta_0)f_\theta(\theta_0, \psi_0) + \\
+ (\psi - \psi_0)f_\psi(\theta_0, \psi_0) + ...
\] \tag{A.3}

where in our case we have:

\[
f(\theta, \psi) = \overline{KL}(\theta, \psi) = h(\theta, \psi) \tag{A.4}
\]

\[
h(\theta, \psi) = 2r_K^2 + l^2 - 2r_K^2(c_\psi c_\kappa^2 + s_\psi s_\theta \kappa c_\kappa + \\
+ c_\theta s_\kappa^2) - 2lr_K(c_\psi s_\theta \kappa - s_\psi c_\kappa) \tag{A.5}
\]

\[
\theta_0 = 0 \tag{A.6}
\]

\[
\psi_0 = 0 \tag{A.7}
\]
So, now by applying the chain rule we get:

\[ f_\theta(\theta, \psi) = \frac{1}{2\sqrt{h(\theta, \psi)}} h_\theta(\theta, \psi) \]  
(A.8)

\[ f_\psi(\theta, \psi) = \frac{1}{2\sqrt{h(\theta, \psi)}} h_\psi(\theta, \psi) \]  
(A.9)

while:

\[
\begin{align*}
    h_\theta(\theta, \psi) &= -2r_k^2(s_\psi c_\theta s_\kappa - s_\theta s_\kappa^2) - \\
    &\quad -2lr_\kappa c_\psi c_\theta s_\kappa \\
    h_\psi(\theta, \psi) &= -2r_k^2(-s_\psi c_\kappa^2 + c_\psi s_\theta s_\kappa) + \\
    &\quad + 2lr_\kappa(s_\psi s_\theta c_\kappa + c_\psi c_\kappa) 
\end{align*}

(A.10)

Combining all the equations into the Taylor expansion formula we get:

\[
\overline{\Phi}(\theta, \psi) \approx l - r_\kappa s_\theta + r_\kappa c_\kappa \psi + ... 
\]  
(A.12)

Going back to Eq. (A.1) and assuming that \( l = l_0 \), we can get:

\[
\kappa F_k(x) \approx -k_\kappa r_\kappa (s_\kappa \theta - c_\kappa \psi) 
\]  
(A.13)

Now starting from Eq. (A.13), multiplying with the appropriate moment-arm quantity (like in Eq. (5.8, 5.9)) and neglecting nonlinear terms, one is able to derive the approximate linear formulas described in Eq. (5.18, 5.19).

The situation is much simpler for the damping terms. For those we start with Eq. (5.10) and can write:

\[
\kappa F_\theta(x) = -b_\kappa m(\theta, \psi) 
\]  
(A.14)

where:

\[
m(\theta, \psi) = \dot{z}_\kappa + y_\kappa + z_\kappa 
\]  
(A.15)

Substituting the coordinates from Eq. (5.4) into the previous formula, assuming small deviations from the neutral state \( \theta \ll 1, \dot{\theta} \ll 1 \) and \( \psi \ll 1, \dot{\psi} \ll 1 \) and keeping only linear terms one can get:

\[
m(\theta, \psi) \approx s_\kappa \dot{\theta} - c_\kappa \dot{\psi} 
\]  
(A.16)

Finally, by combining Eq. (A.14, A.16), multiplying with the appropriate moment-arm quantity (like in Eq. (5.11, 5.12)) and neglecting nonlinear terms, one is able to derive the approximate linear formulas described in Eq. (5.20, 5.21).
Appendix B

Appendix: MATLAB Code for Case Study

```matlab
% This mfile is built in order to simulate the complete Leak Detection & Estimation Scheme for the MIT Leak Detector. 
% %
% % Initialize
% clc;
clear all;
close all;
global Ixx Iyy b1 b2 k D R kapal kappa2 kappa3 kappa4 r alpha beta

%% User Inputs
phi = 25; % incidence angle [deg]
Fz = 2; % leak force (force on detector) [m]
mu = 3.1; % effective friction coefficient
Dp = 10*6894.757; % pressure in pipe ...
    [psi*conversion = Pa]
gamma = 0.6228;
dnom = sqrt(Fz*4 / (pi*mu*Dp))*1000; % Nominal size of leak in mm
R = 50e-3; % radial distance of drum [m]
leff = 12e-3; % effective length of membrane [m]
vrob = 0.38; % robot speed for leak detection ...
    [m/s]
fs = 3000; % sampling rate [hz]
sigma_v = .1/100; % sd of sensor noise
sigma_w = 1/100; % sd of process noise [N]
```
APPENDIX B. APPENDIX: MATLAB CODE FOR CASE STUDY

wlp = 2*pi*150; % Low pass cutoff freq
whp = 2*pi*10; % High pass freq
filt_LP = 1; % True for LP filter on
filt_HP = 0; % True for HP filter on

c = .8; % Triggering threshold
plottrigger = 1; % True in order to plot incidence ...

% Define Mechanical Parameters of Detector
Ixx = 0.9882e-5;
Iyy = 0.9794e-5;
b1 = 1.5;
b2 = 2;
k = 2738.98;

% Angles and Positions of Supports (Springs -- Dashpots)
kapal = 45 + (5)*rand(1) - 5/2;
kapa2 = 45 + 90 + (5)*rand(1) - 5/2;
kapa3 = 45 + 90 + 90 + (5)*rand(1) - 5/2;
kapa4 = 45 + 90 + 90 + 90 + (5)*rand(1) - 5/2;

% Angles and Positions of Force Sensors
r = 40/2*1e-3;
alpha = kapal;
beta = kapa2;

% Create Leak Inputs

t = [0:1/fs:10];

% Calculate pulse length td
td = leff / vrob;
pulselength = round(fs*td);

% Input disturbance from leak
u = zeros(2,length(t));

u(1,ceil(end/2):ceil(end/2)+pulselength) = -Fz*R*sind(phi); ...
% 20 datapoints correspond to 

u(2,ceil(end/2):ceil(end/2)+pulselength) = Fz*R*cosd(phi);

% Add process noise
w = random('norm',0,sigma_w*R,2,length(t));

u = u + w;

% MIT Leak Detector Dynamics & Simulation

[A_det,B_det,C_det,D_det] = linear.dynamics;
detector = ss(A_det,B_det,C_det,D_det);

% Simulate System responses
x0 = [0 0 0 0];
% Define leak detection model and simulate for measurements
Y = lsim(detector,u,t);
%add sensor noise
v = random('norm',0,sigma_v,2,length(t));
sen1_N = Y(:,1) + v(1,:)';
sen2_N = Y(:,2) + v(2,:)';

%%%%% Band-Pass Filtering
Tcon = 1/wlp; %Low pass filter t constant
dt = 1/fs; %Time step
start_point = 1;
end_point = length(sen1_N);
s = tf('s');
G.hp = s/(s+whp); %High Pass filter TF
GD.hp = c2d(G.hp, dt); %High Pass filter TF in Z domain
a.hp = pole(GD.hp); %Pole of the High Pass filter TF

%Low pass filtering
if filt_LP == 1
  sen1.N.lp(1) = sen1.N(1);
sen2.N.lp(1) = sen2.N(1);
  for i = 2 : end_point
    sen1.N.lp(i) = (sen1.N(i)*dt + Tcon*sen1.N.lp(i-1)) / ...
                   (dt + Tcon);
    sen2.N.lp(i) = (sen2.N(i)*dt + Tcon*sen2.N.lp(i-1)) / ...
                   (dt + Tcon);
  end
  sen1.N = sen1.N.lp;
sen2.N = sen2.N.lp;
end

%High pass filtering
if filt_HP == 1;
  sen1.N.hp(1) = sen1.N(1);
sen2.N.hp(1) = sen2.N(1);
  for i = 2 : end_point
    sen1.N.hp(i) = sen1.N(i) - sen1.N(i-1) + ...
                   a.hp*sen1.N.hp(i-1);
    sen2.N.hp(i) = sen2.N(i) - sen2.N(i-1) + ...
                   a.hp*sen2.N.hp(i-1);
  end
  sen1.N.hp(1:600) = 0;
sen2.N.hp(1:600) = 0;
  sen1.N = sen1.N.hp;
sen2.N = sen2.N.hp;
end
%% Trigger
\texttt{time = t;}
\texttt{N = length(time);}
\texttt{time, c, plottrigger);}
\texttt{xlim([4.7 5.3])}
\texttt{sen1 = sen1.N;}
\texttt{sen2 = sen2.N;}

%% SISE
\texttt{\% Define params from SYSID}
\texttt{K1 = 0.8441/R;}
\texttt{wn1 = 485.81245; zeta1 = 0.0989;}
\texttt{K2 = 0.8441/R;}
\texttt{wn2 = 509.7232; zeta2 = 0.12615;}
\texttt{b1 = [1 2*zeta1*wn1 wn1^2];}
\texttt{b2 = [1 2*zeta2*wn2 wn2^2];}
\texttt{[A1, B1, C1, D1] = tf2ss(K1*wn1^2, b1);}
\texttt{[A2, B2, C2, D2] = tf2ss(K2*wn2^2, b2);}
\texttt{A = 1*[flipud(fliplr(A1)) zeros(2,2)}
\texttt{zeros(2,2) flipud(fliplr(A2));]
\texttt{B = 1*[flipud(B1) zeros(2,1)}
\texttt{zeros(2,1) flipud(B2)];
\texttt{C = 1*[fliplr(C1) -fliplr(C2);}
\texttt{fliplr(C1) fliplr(C2)];}
\texttt{D = 0;}
\texttt{system.SISE = ss(A,B,C,D);}
\texttt{TF.SISE = tf(system.SISE);}

\% Discretize Known System
\texttt{Ts = 1/fs;}
\texttt{systemD = c2d(system.SISE,Ts);}
\texttt{Ad =systemD.a;}
\texttt{Bd =systemD.b;}
\texttt{Cd =systemD.c;}
\texttt{Dd =systemD.d;}
\texttt{x0 = [0 0 0 0]'}
\texttt{Rw = ((sigma.w*R)^2)*[0 0 0 0; 0 1 0 0; 0 0 0 0; 0 0 0 1];}
\texttt{Rv = (sigma.v^2)*[1 0; 0 1];}
\texttt{y(l,:) = sen1(l:end);}
\[ y(2,:) = \text{sen}2(1:end); \]

\[% Input Reconstruction according to DeMoor's algorithm \%
\]
\[
x_{\text{est}}(:,1) = x0; \]
\[
P_{kml,kml} = 1e6*\text{eye}(4,4); \]
\]
for \( k = 1 : N-1 \)
\[
P_k,kml = A_k P_{kml,kml} A_k' + R_w; \]
\[
R_k = C_k P_{kml,kml} C_k' + R_v; \]
\[
F_k = C_k B_d; \]
\[
M_k = \text{inv}(F_k' \text{inv}(R_k) F_k) * F_k' \text{inv}(R_k); \]
\[
K_k = P_{kml,kml} C_k' \text{inv}(R_k); \]
\[
x_{kml} = A_k x_{\text{est}}(:,k); \]
\[
u_{\text{est}}(:,k) = M_k * (y(:,k) - C_k x_{kml}); \]
\[
x_{\text{star},k}(::,k) = x_{kml} + B_d u_{\text{est}}(:,k); \]
\[
x_{\text{est}}(:,k+1) = x_{\text{star},k}(::,k) + K_k (y(:,k) - C_d x_{\text{star},k}(::,k)); \]
\[
P_{kml,kml} = P_{kml,kml} - K_k C_d P_{kml,kml} + (B_d - ... \]
\[
K_k F_k) \text{inv}(F_k' \text{inv}(R_k) F_k) *(B_d-K_k F_k)'; \]
\[
\text{showmax}(k) = \text{max}(\text{eig}(P_{kml,kml})); \]
\[
\text{showmin}(k) = \text{min}(\text{eig}(P_{kml,kml})); \]
\[
\text{Gain1}(::,k) = M_k; \]
\[
\text{Gain2}(::,k) = K_k; \]
end

if (0)
figure()
plot(showmax,'k')
hold on
plot(showmin,'r')
legend('Max Eigenvalue', 'Min Eigenvalue')
end

x_{\text{est}}_{\text{deg}} = x_{\text{star},k}(::,k)*180/pi;

if(1)
figure()
plot(t(1:end-1),u_{\text{est}}(1,:),'r')
title('Estimated Disturbances vs Time')
ylabel ('Reconstructed Inputs in [Nm]')
xlabel('Time in [s]')
hold on
plot(t(1:end-1),u_{\text{est}}(2,:),'b--')
legend('d-1','d-2')
xlim([4.7 5.3])
end

if (1)
figure()
plot(t,y)
title('Output Measurements (y) vs Time')
legend('y_1','y_2')
ylabel('y in [N]')
xlabel('Time in [s]')
xlim([4.7 5.3])
end

theta_est = zeros(1,N);
Fz_est = zeros(1,N);
for i = 2:N-1 %t1.star : t2.star
    theta_est(i) = atan2(-u_est(1,i),u_est(2,i))*180/pi;
    Fz_est(i) = sqrt(u_est(1,i)^2 + u_est(2,i)^2)/R;
end

%%
THETA_EST = zeros(1,N);
for i = 1:length(tstar)
    THETA_EST(tt.ini(i):tt.end(i)) = (theta_est(tt.ini(i):tt.end(i)));
end
%%
%Accounting for some errors in the backwards movement of the ...
% sensor and problems in the correct negative angle calculation
for i = 1:length(tstar)
    if THETA_EST(tt.ini(i))<0
        for j = tt.ini(i) : tt.end(i)
            if (THETA_EST(j))>0
                THETA_EST(j) = - THETA_EST(j);
            end
        end
    end
    if THETA_EST(tt.ini(i))>0
        for j = tt.ini(i) : tt.end(i)
            if (THETA_EST(j))<0
                THETA_EST(j) = - THETA_EST(j);
            end
        end
    end
end
for i = 1 : length(tstar)
    Theta_Estimate(i) = mean((THETA_EST(tt_ini(i):tt_end(i))));
    Fz_Estimate(i) = mean(Fz_est(tt_ini(i):tt_end(i)));  
    end

d.Est(i) = sqrt(Fz_Estimate(i)*4 / (pi*mu*Dp)) * 1000;
end

for i = 1 : length(tstar)
    display(['Theta Est', num2str(Theta_Estimate(i)) ' FzEst ' num2str(Fz_Estimate(i)) ' d-Est [in mm]'])
end

%% Plots
if(1)
    figure()
    title('Estimated Quantities for Leak Incidence')
    subplot(2,1,1)
    plot(t, THETA_EST,'-')
    ylabel ('Est. Angle \phi in [deg]')
    xlabel('Time in [s]')
    xlim([4.7 5.3])
    subplot(2,1,2)
    plot(t, Fz_est,'-')
    ylabel ('Estimated Leak Force F_z in [N]')
    xlabel('Time in [s]')
    xlim([4.7 5.3])
end

if(1)
    figure()
    plot(t, Fz_est,'-')
    ylabel ('Estimated F_z in [N]')
    xlabel('Time in [s]')
    title('Estimated Leak Force F_z vs Time')
    transparent'
    xlim([4.7 5.3])
end
function "Triggering"

```matlab
function [J, tstar, tend, tt_ini, tt_end] = triggering(F1, F2, ...
    time, limit, triggerplot);

    dt = time(2)-time(1); % Compute the time interval dt
    J = sqrt(F1.^2 + F2.^2); % Calculate the triggering metric

    % Calculate triggering times
    J = find(J>limit); %Find times that J is above the threshold c
    incid = find(diff(tt)>500); %Find incidents (different incidents should differ by more than 1sec (-300 datapoints)
    incid = [1 incid+1]; %Add one by definition
    num_incid = length(incid); %Calculate number of incidences in current signals

    tt_ini = tt(incid);
    for i = 1 : num_incid
        %Find end time for each incidence
        [maximum(i) tt_end(i)] = max(J(tt_ini(i) : tt_ini(i) + 100));
        tt_end(i) = tt_end(i) + tt_ini(i);
    end

    for i = 1 : num_incid
        tstar(i) = time(tt_ini(i));
        tend(i) = time(tt_end(i));
    end

    %Plot if needed
    if (triggerplot)
        figure()
        plot(time, J,'b')
        xlabel('Time [s]')
        ylabel('Trigerring Metric')
        title('J vs Time')
        hold on
        plot([0 max(time)], [limit limit])
        xlim([4.7 5.3])
    end
```
function "Linear Dynamics"

```matlab
function [A,B,C,D] = linear_dynamics

% This function computes the linear dynamics of the new detector
% (force sensors under 4 springs)

global Ixx Iyy bl b2 D R kapal kapa2 kapa3 kapa4 r alpha beta

kltheta = k*r^2*sind(kapal)^2 + k*r^2*sind(kapa2)^2 + ...
           k*r^2*sind(kapa3)^2 + k*r^2*sind(kapa4)^2;
klpsi = k*r^2*cosd(kapal)^2 + k*r^2*cosd(kapa2)^2 + ...
        k*r^2*cosd(kapa3)^2 + k*r^2*cosd(kapa4)^2;

k2theta = k*r^2*sind(kapal)*cosd(kapal) + ...
          k*r^2*sind(kapa2)*cosd(kapa2) + k*r^2*sind(kapa3)*cosd(kapa3) ...
          + k*r^2*sind(kapa4)*cosd(kapa4);
k2psi = k*r^2*sind(kapal)*cosd(kapal) + ...
        k*r^2*sind(kapa2)*cosd(kapa2) + k*r^2*sind(kapa3)*cosd(kapa3) ...
        + k*r^2*sind(kapa4)*cosd(kapa4);

b1theta = b1*r^2*sind(kapal)^2 + b1*r^2*sind(kapa2)^2 + ...
          b1*r^2*sind(kapa3)^2 + b1*r^2*sind(kapa4)^2;
b2theta = b1*r^2*sind(kapal)*cosd(kapal) + ...
          b1*r^2*sind(kapa2)*cosd(kapa2) + b1*r^2*sind(kapa3)*cosd(kapa3) + b1*r^2*sind(kapa4)*cosd(kapa4);

b1psi = b2*r^2*cosd(kapal)^2 + b2*r^2*cosd(kapa2)^2 + ...
        b2*r^2*cosd(kapa3)^2 + b2*r^2*cosd(kapa4)^2;
b2psi = b2*r^2*sind(kapal)*cosd(kapal) + ...
        b2*r^2*sind(kapa2)*cosd(kapa2) + ...
        b2*r^2*sind(kapa3)*cosd(kapa3) + b2*r^2*sind(kapa4)*cosd(kapa4);

A = [ 0 1 0 0;
     -kltheta/Ixx -b1theta/Ixx k2theta/Ixx b2theta/Ixx;
     0 0 0 1;
     k2psi/Iyy b2psi/Iyy -klpsi/Iyy -b1psi/Iyy];
B = [ 0 0;
     1/Ixx 0;
     0 0;
     0 1/Iyy];
C = [k*r*sind(alpha) 0 -k*r*cosd(alpha) 0;
     k*r*sind(beta) 0 -k*r*cosd(beta) 0];
D = zeros(2,2);
```
Appendix C

Appendix: MATLAB Code for Monte Carlo Simulations

```matlab
% This mfile is built in order to simulate the complete Leak Detection & Estimation Scheme for the MIT Leak Detector - ... MONTE CARLO SIMULATION.

% Initialize
clc;
clear all;
close all;

global Ixx Iyy b1 b2 k D R kapal kapa2 kapa3 kapa4 r alpha beta

% User Inputs
filename = 'MonteCarlo_3KIters_LPfilter200Hz.sysID.linDynamics';

SIGMA_V = [0.01 0.03 0.05 0.10 0.25 0.50 1]*1/100;   ...
%different values for sensor noise
SIGMA_W = [0.01 0.05 0.10 0.50 1.00 3.00 5.00 10]*1/100; %different values for process noise
iterationsMC = 3000;  %number of iterations for monte carlo

Fz = 2;    %leak force (force on detector) [N]
mu = 3.1;  %effective friction coefficient
Dp = 10*6894.757;  %pressure in pipe [psi*conversion = Pa]
dnom = sqrt(Fz*4/(pi*mu*Dp)) * 1000; %Nominal size of leak in mm
R = 50e-3;  %radial distance of drum [m]
leff = 12e-3; %effective length of membrane [m]
vrob = 0.38;  %robot speed for leak detection [m/s]
fs = 3000;   %sampling rate [hz]
```

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wlp = 2*pi*200; %Low pass cutoff freq
whp = 2*pi*10; %High pass freq
filt_LP = 1; %True for LP filter on
filt_HP = 0; %True for HP filter on
c = .8; %Triggering threshold
plottrigger = 0; %True in order to plot incidence line on ...
...trigger
counter = 1;

% Define Mechanical Parameters of Detector
Ixx = 0.9882e-5;
Iyy = 0.9794e-5;
b1 = 1.5;
b2 = 2;
k = 2738.98;

% Angles and Positions of Supports (Springs -- Dashpots)
kapa1 = 45; % + (5)*rand(1) - 5/2;
kapa2 = 45+90; % + (5)*rand(1) - 5/2;
kapa3 = 45+90+90; % + (5)*rand(1) - 5/2;
kapa4 = 45+90+90+90; % + (5)*rand(1) - 5/2;

% Angles and Positions of Force Sensors
sor = 40/2*1e-3;
alpha = kapa1;
beta = kapa2;

% Define params from SYSID
[A.det,B.det,C.det,D.det] = linear.dynamics;
detector = ss(A.det,B.det,C.det,D.det);
s = tf('s');

K1 = 0.8441/R;
wn1 = 485.81245; zetal = 0.0989;
K2 = 0.8441/R;
wn2 = 509.7232; zeta2 = 0.12615;
b_1 = [1 2*zetal*wn1 wn1^2];
b_2 = [1 2*zeta2*wn2 wn2^2];
[A1, B1, C1, D1] = tf2ss(K1*wn1^2, b_1);
[A2, B2, C2, D2] = tf2ss(K2*wn2^2, b_2);

A = 1*[flipud(fliplr(A1)) zeros(2,2)
    zeros(2,2) flipud(fliplr(A2))];
B = 1*[flipud(B1) zeros(2,1);
    zeros(2,1) flipud(B2)];
C = 1*[fliplr(C1) -fliplr(C2);
    fliplr(C1) fliplr(C2)];
```matlab
...  \( \text{phi = rand(1)*360} \)

for \( \text{t = 1:iterations} \):
\nonumber
  for \( \text{t} = 1: \text{length}(t) \): \text{T} \nonumber
\nonumber
end
\nonumber

end
\nonumber

% START MONTE CARLO SIMULATION
\nonumber

% Probability of the high-pass filter is \( \text{prob} = \text{poled} \)
\nonumber

% Probability of the high-pass filter is \( \text{prob} = \text{calculated} \)
\nonumber

% Create filter t constant
\nonumber

% Band-pass filtering
\nonumber

% Calculate pulse lengths
\nonumber

% Create impulse
\nonumber

% Discrete known system
\nonumber

% System S = SS(\text{sysname}, \text{a}, \text{b}, \text{c}, \text{d})
\nonumber

T = 1/60
\nonumber

d = 0;
```

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% incidence angle [deg]

% Run noise levels
if ii==1
    sigma_v = SIGMA_V(iter_W, iter_V);
    sigma_w = SIGMA_W(iter_W, iter_V);
end

% Input disturbance from leak
u = zeros(2, length(t));
u(1,ceil(end/2):ceil(end/2)+pulselength) = -Fz*R*sind(phi);
u(2,ceil(end/2):ceil(end/2)+pulselength) = Fz*R*cosd(phi);

% add process noise
w = random('norm', 0, sigma_w*R, 2, length(t));
u = u + w;

% MIT Leak Detector Dynamics & Simulation
Y = lsim(detector, u, t);
v = random('norm', 0, sigma_v, 2, length(t));

% add sensor noise
sen1.N = Y(:,1) + v(1,:)
sen2.N = Y(:,2) + v(2,:)

start_point = 1;
end_point = length(sen1.N);

% Low pass filtering
if filt(LP) == 1
    sen1.N.lp(1) = sen1.N(1);
    sen2.N.lp(1) = sen2.N(1);
    for i = 2 : end_point
        sen1.N.lp(i) = (sen1.N(i)*dt + Tcon*sen1.N.lp(i-1)) ./ (dt + Tcon);
        sen2.N.lp(i) = (sen2.N(i)*dt + Tcon*sen2.N.lp(i-1)) ./ (dt + Tcon);
    end
    sen1.N = sen1.N.lp;
    sen2.N = sen2.N.lp;
end

% High pass filtering
if filt(HP) == 1;
    sen1.N.hp(1) = sen1.N(1);
    sen2.N.hp(1) = sen2.N(1);
    for i = 2 : end_point
        sen1.N.hp(i) = sen1.N(i) - sen1.N(i-1) + ... 
                        a_hp*sen1.N.hp(i-1);
        sen2.N.hp(i) = sen2.N(i) - sen2.N(i-1) + ...
a_hp*sen2_N_hp(i-1);
end
sen1_N_hp(1:600) = 0;
end
sen2_N_hp(1:600) = 0;

sen1N = sen1_N_hp;

end

%Trigger

[J, tstar, tend, tt.ini, tt.end] = triggering(sen1_N, ...
    sen2_N, time, c, plottrigger);

sen1 = sen1_N;

sen2 = sen2_N;

% SISE

Rw = ((sigma_w*R)^2)*[0 0 0 0; 0 1 0 0; 0 0 0 0; 0 0 0 1];
Rv = (sigma_v^2)*[1 0; 0 1];

y(1,:) = sen1(1:end);
y(2,:) = sen2(1:end);

% Input Reconstruction according to DeMoor's algorithm

if ii==1
    x_est(:,1) = x0;
Pkm1.kml = 1e6*eye(4,4);
end

for k = 1 : N-1
    Pk.kml = Ad*Pkm1.kml*Ad' + Rw;
    Rk = Cd*Pkm.kml*Cd' + Rv;
    Fk = Cd*Bd;
    Mk = inv(Fk'*inv(Rk)*Fk)*Fk'*inv(Rk);
    Kk = Pk.kml*Cd'*inv(Rk);
    x_k.kml = Ad*x_est(:,k);
    u_est(:,k) = Mk * (y(:,k) - Cd*x_k.kml);
    xstar_k.k(:,k) = x_k.kml + Bd*u_est(:,k);
    x_est(:,k+1) = xstar_k.k(:,k) + ...
        Kk*(y(:,k)-Cd*xstar_k.k(:,k));
    Pkm1.kml = Pk.kml - Kk*Cd*Pkm1.kml + (Bd - ...
        Kk*Fk)*inv(Fk'*inv(Rk)*Fk)*(Bd-Kk*Fk)';
end

x_est.deg = xstar_k.k*180/pi;
theta_est = zeros(1,N);
Fz_est = zeros(1,N);
for i = 2:N-1 %t1.star : t2.star
    theta_est(i) = atan2(-u_est(1,i),u_est(2,i))*180/pi;
    Fz_est(i) = sqrt(u_est(1,i)^2 + u_est(2,i)^2)/R;
end

THETA_EST = zeros(1,N);
THETA_EST(tt.ini:tt.end) = (theta_est(tt.ini:tt.end));

% Accounting for some errors in the backwards movement of ... the sensor and
% problems in the correct negative angle calculation
if THETA_EST(tt.ini)<0
    for j = tt.ini:tt.end
        if (THETA_EST(j))>0
            THETA_EST(j) = - THETA_EST(j);
        end
    end
end

if THETA_EST(tt.ini)>0
    for j = tt.ini:tt.end
        if (THETA_EST(j))<0
            THETA_EST(j) = - THETA_EST(j);
        end
    end
end

Theta.Estimate = mean((THETA_EST(tt.ini:tt.end)));
Fz.Estimate = mean(Fz_est(tt.ini:tt.end));
d.Est = sqrt(Fz.Estimate^4 / (pi*mu*Dp)) * 1000; % in mm

incidence(ii) = phi;
estimate.incidence(ii) = Theta.Estimate;
estimate.force(ii) = Fz.Estimate;
estimate.d(ii) = d.Est;
end

display('')
toc

display(['A total of ', num2str((counter/total)*100),'
% is ...completed'])

% MonteCarlo results
for i = 1:length(estimate.incidence)
    if estimate.incidence(i)>360
estimate_incidence(i) = estimate_incidence(i) - 360;
end
if estimate_incidence(i)<0
estimate_incidence(i) = estimate_incidence(i) + 360;
end
tilda_incidence = incidence - estimate_incidence;
tilda_force = Fz - estimate_force;
tilda_diam = dnom - estimate_d;
for i = 1:length(tilda_incidence)
if tilda_incidence(i)>300
tilda_incidence(i) = tilda_incidence(i) - 360;
elseif tilda_incidence(i)>170 & tilda_incidence(i)<300
tilda_incidence(i) = tilda_incidence(i) - 180;
elseif tilda_incidence(i)<-170 & tilda_incidence(i)>-300
tilda_incidence(i) = tilda_incidence(i) + 180;
elseif tilda_incidence(i)<-300
tilda_incidence(i) = tilda_incidence(i) + 360;
end
MEAN_INCIDENCE(iter_W, iter_V) = mean(tilda_incidence);
MEAN_FORCE(iter_W, iter_V) = mean(tilda_force);
MEAN_DIAMETER(iter_W, iter_V) = mean(tilda_diam);
SD_INCIDENCE(iter_W, iter_V) = std(tilda_incidence);
SD_FORCE(iter_W, iter_V) = std(tilda_force);
SD_DIAMETER(iter_W, iter_V) = std(tilda_diam);
end
surf(SIGMA_V, SIGMA_W, SD_DIAMETER)
xlabel('sigma_v')
ylabel('sigma_w')
colormap jet
colorbar
toc
save(filename)
Bibliography


