Smart Water Network Management with In-pipe Leak Detection Robots

by

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Abstract

In this thesis, I created methods and designs to implement smarter, more autonomous water distribution networks (WDNs) and also improved the robots which will travel within the WDN’s pipes to better differentiate pipe leaks from bumps in the pipes. Starting from the unit of the in-pipe leak detection robot, I investigated ways to make its soft leak sensors able to differentiate between pulling (due to leaks) and bending (due to bumps), and showed how a new design of adding fabric to the soft sensor allows the sensors to differentiate bending from pulling. Zooming out to the larger picture I looked at feasible ways these robots could be used throughout a cities’ WDN, and created cost analyzes to compare futuristic methods of WDN management with current methods of district metered areas (DMAs). However, going from our current state of minimally instrumented pipes, to pipes with many valves to direct in-pipe inspection robots is a big leap, and thus I also created a method to help evaluate the cost trade-off of valve placement and the optimal spots for adding valves in the case where it was ideal to place valves on only some of the intersections of the WDN.

Thesis Supervisor: Kamal Youcef-Toumi
Title: Professor
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Chapter 1

Introduction

1.1 The Problem of Water Leakage

Access to clean, fresh water is a basic human need. In addition, global populations continue to grow and are projected to reach 9.8 billion in 2050 and 11.2 billion in 2100. [1] With more people, especially more people per city, water distribution networks will have to reliably distribute more clean, drinkable, water. This increase in demand places a focus on how the water is distributed - is the distribution clean, efficient and reliable? If not, what needs to be fixed?

When one looks into water network distribution problems, one key focus is leakage. Water which leaks out of pipes will not reach the customers in a usable fashion. Water which escapes through leaks was likely perfectly good water lost. This percentage of water lost, otherwise known as non-revenue water, is estimated to average 15% in developed countries and 35% in developing countries.[3]

In addition to water leakage causing issues due to water lost that could have otherwise been used, water leaks can often result in pipe bursts which lead to safety hazards and property damage. A study on water main pipe breaks found that "between 2012 and this 2018 report, overall water main break rates increased by 27% from 11.0 to 14.0 breaks/ (100 miles)/year." [20] This rising percentage of breaks per hundred miles per year, becomes even more concerning as each pipe burst in an urban area may cost $200,000 of property damages and repair expenses. [24]
Overall, water leaks may prevent or lower access to fresh water, cause damage to surrounding environments and property, and are sometimes a safety hazard. By developing methods to reduce leaks and better control water distribution networks, we can allow more people to access clean, fresh water at a lower cost.

1.2 Current Leak Detection and Network Monitoring Methods

Researchers have applied system analysis to water distribution networks since the late 19th century. [16] With the 20th century came greater computing power which fueled further analysis and methods, many focusing on pump operation, water quality management, and valve control. [11] Expanding on the water quality and leak detection section, many papers have examined ideal divisions of district metered areas (DMAs) [2] [17] and ideal placement of valves (to create DMAs) or pressure sensors [13] [19].

Currently, most monitored water distribution networks use District Metered areas to monitor flow and report potential leaks. This is done by creating sections within a water distribution network which each contain many consumers and pipes, where each section, or district, can have a minimal number of input and output pipes where the flow can be measured. Then at night when there is minimal intentional water flow, the difference between the incoming and outgoing water flow is taken. If this difference falls above a threshold, or shows unusual increases from past readings it indicates there is likely a leak. This triggers the investigation to locate the leak(s).

Two commonly used methods to locate leaks are acoustic sounding and signal correlation. To implement acoustic sounding, a technician walks along the path of a water pipe with an instrument to listen for leaks. This method is non-invasive, however due to other noise from traffic or anything else in the ground, this method cannot detect small leaks, and has less than ideal location accuracy. In addition, it requires a technician to walk along each pipe they wish to inspect, which could be a very time consuming task for large networks. To implement signal correlation, two
technicians can listen to signals at different points on a pipe. Then by correlating their signals they can detect noise in common which may have come from a leak. This method has similar drawbacks to the acoustic method of mostly finding larger leaks, and imprecise localization of the leaks. Additionally, both of these methods work better with metallic pipes as acoustic signals travel better in metallic pipes than plastic pipes.

In order to detect smaller leaks and to pinpoint leak location more accurately, in-pipe robots appear to be a candidate solution. Many in-pipe robots travel with the water flow, making them able to be used in active water mains. These in-pipe leak detection robots may use cameras to watch for leaks like pipe crawling inspection robots.[5] Or in-pipe robots may monitor acoustics, like Smartball. [4] These in-pipe robots may successfully detect smaller leaks more precisely than above ground monitoring methods, however they still have room for improvement. Cameras on in-pipe robots are expensive, sometimes bulky, and produce harder to analyze data. Acoustic sensing on in-pipe robots is cheaper, however it still functions better in metal pipes, and a different method might be desirable for plastic pipes.

1.3 Prior Work In Development of Leak Detection Robot

Previously, our In-Pipe Leak Detection team in the Mechatronics lab at the Massachusetts Institute of Technology developed the basis for a pressure gradient based in pipe leak detection robot [25], [24]. This in-pipe leak detection robot has a "skirt" of strain gauge sensors which allow it to detect pressure differentials caused by pipe leaks. Additionally, the simplicity of this design allowed for the robot to be produced in a low cost and small size manner, allowing it to traverse 2 inch diameter water pipes, while many other in-pipe robots cannot.

From this basis of a pressure gradient based in-pipe leak detection robot, it was noticed that the robot could improve if it’s sensors could differentiate between bumps
in the pipes and leaks. Additionally, we were interested in investigating how the robot could be used on an entire water distribution network scale, and how it would compare to alternative technologies.

1.4 Proposed Contributions to Leak Detection and Network Optimization

My goal of this thesis is to improve upon the in-pipe pressure gradient based robot leak sensors design to allow the robot to better sense the features of the pipe, while also investigating how these robots could be used on a larger scale to automate detection and localization of leaks.

Proposed Research Contributions Are:

1. Development and testing of a soft bending and pulling sensor. This sensor allows the robot to differentiate bumps in the pipe from leaks in the pipe as it can differentiate the pull from the leak and the bend from the bump. The capabilities of this sensor to sense direction and magnitude of bending are also shown in a fish tail motion tracking application.

2. Development and modeling of a method to compare the total costs of smarter water distribution networks, versus current optimal district meter area methods. This method models the cost of a smarter network which is either fully instrumented with flow sensors, or fully instrumented with valves and in-pipe robots, or both. This model takes inputs of the cost of smart valves, smart flow meters, in-pipe robots, and in-pipe robot stations to produce optimal method analysis for a variety of water prices.

3. Development and simulation of a method to retrofit a pipe network by adding smart, remotely controlled valves, to allow it to control robot movement through the network. This method takes in a pipe network model and flow conditions, along with a cost model to weigh the pros of increased robot controllability versus the cons of increased price. It evaluates the optimal number of smart valves, robot start stations,
and robot end stations to place and their optimal the placement within the network.

1.5 Thesis Outline

This thesis will cover my proposed research contributions as outlined above. The introduction gave information regarding the problem, state-of-the-art methods, and prior work. The second section on soft bending sensors covers the design of the bending and pull sensors along with their applications on a leak detection robot or a soft robotic fish tail. The third section covers an overall cost analysis of different smart networks for water distribution. The fourth section looks at retrofitting networks to optimally place added valves to control robot movement within the water network. Finally, the conclusion recaps the work presented and gives additional recommendations for future work.
Chapter 2

Soft Bending Sensors

Soft robots provide solutions where traditional robots may not. They are flexible, adaptable, and produce complex motions from simple actuations. In addition, soft robots have many features rigid robots do not. They can bend, conform to irregular restrictions, and incorporate many features into their soft body.

Many robotic tasks are best accomplished by soft robots. For example, when researchers in Singapore wanted to measure the underwater environment without disturbing the plants or animals, they found soft robotic fish and soft robotic stingray to be an ideal fit. These soft robotic animals could swim alongside the real animals undetected, as their soft body movements closely matched the movements of real fish and stingrays.[12] Another example of a soft robot achieving what may have been impossible for a traditional rigid robot, comes in the form of an in-pipe leak detection robot. This robot must contain all the necessary electronics for measuring strain gauge and IMU sensors, recording sensor readings, holding charge in a battery, and recharging the battery all while fitting inside a 2 inch (50 mm) diameter pipe. In addition, this robot must be able to travel smoothly around bends in the pipe without getting its electronics wet. To accomplish this small size and flexibility, a soft body is key. [25]

However with soft robots many traditional sensors can no longer be used. Thus new, soft, sensors need to be designed. These soft sensors have important abilities like bending to different geometries, responding to pressure, and stretching in all types of
robots.

To create these sensors, one can combine textiles, soft composites, rubber, threads, and more. These materials can be molded into a wide variety of different shapes and structures, allowing the soft sensor to take on nearly any form. Both the materials and the scalable fabrication process can also be low cost.

Applications of such low-cost soft sensors are numerous. Here we design such a soft sensor to sense bending and pulls, and we also demonstrate use cases for this sensor. In this chapter we show it’s ability to track motion in a fish tail and enable differentiation between leaks and bumps in an in pipe leak detection robot.

Figure 2-1: Three state-of-the-art manufacturing techniques for soft, thin bending angle sensors: (a) Photolithography, (b) hybrid surface 3D printing, (c) hybrid depth 3D printing, in comparison to (d) an example of the proposed sensor introduced in this chapter.

The state-of-the-art techniques, shown in Fig. 2-1-a,b,c to produce soft sensors require high precision, high cost manufacturing equipment and processes. Most of the techniques in the literature originated from microelectromechanical systems (MEMS) applications, and researchers at Harvard University are pioneering in that field [7, 23, 9]. The popular practice is to print thin layers of a conductive sensing element on the surface of the device via photo-lithography [7], or hybrid 3D printing [23]. The device can also be 3D printed with materials of different properties at different depths [9]. It allows fine control over the local properties such as stiffness within the three-dimensional space of the device, and produces high performance sensors. However, while these manufacturing processes have high precision, they require expensive
machines. 3D printing devices layer by layer is slow and not scalable, especially when making large surface area devices.

In this project, our goal is to design and build low cost, scalable, and practical soft sensors. An example for bending angle and pull sensing is shown in 2-1-d. The state-of-art fabrication technique does not meet our low-cost and scalability requirements.

In the next section, we will look at the overall properties of soft materials and how they can be combined. Then we will dive into the design of a soft sensor for detecting bending angle and pulling. The fabrication process for this device will be explained. Finally, the principle of this sensor will first be demonstrated through a simplified fish tail motion tracking application. Then the leak detection application will be used to demonstrate this design’s high tolerance to errors in the manufacturing process.

2.1 Soft Materials for Sensing

A variety of materials can be used in soft sensors, including many types of rubbers and fabrics. The materials we look at here consist of a soft rubber with a Shore A hardness of 30, which is flexible in stretching and bending in all directions. This rubber can be molded into any shape, and is the blue rubber pictured in Fig. 2-2, Fig. 2-4 and the rest of the chapter. A close cousin of the blue rubber is the black, conductive rubber. It has a Shore A hardness estimated to be 30-35, and comes in sheets of 1.5mm thickness. Like the blue rubber, it is flexible in stretching and bending in all directions. However it possesses an additional property the blue rubber does not - it is conductive. Its electrical resistance increases while experiencing elongation, and it decreases electrical resistance in compression. Its sensitivity in the two directions may differ. A final potential material is fabric. Fabric comes in many types - the two which are investigated here are woven and knit. The fabric can be a thin woven cloth which cannot be stretched at all but can be bent easily. In Fig. 2-2, diagrams of rubber bending and stretching along with woven fabric bending and stretching are shown. Alternatively, fabric could be a knit cloth which is softer, stretchable and equally easy to bend. Those two types of fabrics can be made with the same threads,
but the structure of threads inside these fabrics determines the overall stiffness of the fabrics as seen in Fig. 2-3.

![Figure 2-2: Diagrams of how soft materials can be pulled and torqued. (a) rubber: flexible in all directions. (b) fabric: flexible in bending, but harder to stretch](image)

![Figure 2-3: Two Basic Types of Fabrics [21]: Woven fabrics are difficult to stretch and knit fabrics are easy to stretch](image)

![Figure 2-4: Prototype of the new leak sensor](image)

These soft materials can be combined in a wide variety of ways, and can be used for a variety of functions. Soft materials can help a device reshape to fit unusual spaces, or allow a device to sense its surroundings. As it would be impossible to cover the variety and depth of all soft material sensors in a single chapter, this chapter will focus on soft sensors to sense pure bending in a fish tail application, and a combination of bending and pulling in a leak sensor application. An example of the leak soft sensor design can be seen in Fig. 2-4.
2.2 Engineering the Neutral Axis

Within the class of soft sensors an example is a bending and pulling sensor, and the design of such a sensor requires a carefully chosen placement of the sensing element with respect to the device's neutral axis. The neutral axis of a cantilever beam lies where there is no elongation or compression when the cantilever beam is bent. The membrane sensor in a soft robot can be treated as such a cantilever beam. As illustrated in Fig. 2-5-a, one end of the membrane sensor is fixed in the yellow bracket, and the other end is free to bend, stretch, and more. When the membrane sensor is bent downward, the part of it above the neutral axis will be stretched and the part below the neutral axis will be compressed. As the membrane sensor is made with uniform rubber material, the neutral axis is then right at the center height of the entire device, and the strain distribution is symmetric in magnitude about the neutral axis but opposite in direction (see arrows in Fig. 2-5). The placement of the sensing element determines what its output indicates. The sensing element can be an electrically conductive rubber. When this sensing element is placed on the neutral axis such as in Fig 2-5-b, it will experience equal amounts of elongation and compression during a bending motion. It cannot reliably tell which direction the sensor is bending in. In contrast, if the sensing element is placed above the neutral axis such as in Fig. 2-5-c, it will experience elongation and increase its resistance when the device is bending downward, and it will experience compression and thus decrease in resistance when bending upward. The reserved relationship (bending down leads to decreased resistance and bending up leads to increased resistance) applies to the case when the sensing element is placed on the opposite side of the neutral axis. With this kind of input/ output relationship (Fig. 2-6), one can simply measure the direction of resistance change to estimate the bending direction and the input. Bending down the device in Fig. 2-5-c leads to elongation on the sensing element and thus an increase in resistance. Bending up the same device leads to compression on the sensing element and thus decrease in resistance. There could even be two sensing elements, one on each side of the neutral axis of the device as illustrated in Fig. 2-5-d. In this case,
Figure 2-5: An typical soft bending angle sensor construction: Placement of sensing element with respect to the neutral axis matters. The neutral axis is the dotted line. The horizontal arrows indicate the direction and magnitude of shear stress and strain.

Figure 2-6: Ideal output from a soft bending angle sensor.

the output would be the difference in resistance between the top sensing element and the bottom one. When the change in this difference is positive, the device is bending down. When the change in this difference is negative, the device is bending up.

The solution proposed in Fig. 2-5 of using very thin conductive rubber works in theory, however real world limitations of purchasable conductive rubber show thin enough conductive rubber is not available. The challenge is the size constraint given commercially available electrically conductive rubber. The thickness of the sensing element, h, must be less than a half of the thickness of the entire device, H, because for this sensor to work the sensing element must be on one side of the neutral axis. In the in pipe robot with leak sensors case, which will be discussed in more detail later, H=2mm and thus h must be less than 1mm. At the time of this work in late 2017, the thinnest sheet of this type of material commercially available is 1.5mm, and it is less than 15 US dollars per square foot (equivalently 160 US dollars per square meter). If this conductive rubber is to be used in this 2mm-thick membrane sensor directly as shown in Fig. 2-8, it will experience compression and elongation when the
entire device is bent and therefore will be ineffective. The original membrane sensors for the leak detection robot were built this way, and each individual membrane sensor cannot produce distinctively different signals for leaks (which bend the sensor in one direction) and obtrusions (which bend the sensor in the opposite direction) as shown in Fig. 2-7.

To solve the problem of needing very thin conductive rubber, we present a method of shifting the neutral axis by adding a stiffer material (fabric) to one side of the device. In the typical construction of the soft bending angle sensor, the neutral axis is fixed by the geometry and material first and then the sensing element is placed on one side of it. Instead, we can engineer the neutral axis of the device to be on one side of the sensing element, by simply adding a layer of material of higher stretch stiffness on one side of the sensing element, spanning from one end of the device to the other. This new material can be a stiffer rubber, but it then requires a multi-step molding process to produce this membrane sensor. There is another low cost, commonly available, ordinary material we can simply bond to the inside of the rubber membrane sensor.
Fabric is a great choice for engineering the neutral axis in a soft membrane sensor as it allows the sensor to differentiate bending directions and can isolate bending from horizontal stretch loads. Woven fabric can appear to be almost unstretchable while being extremely soft and easy to bend. The hierarchical structure of the fabrics also makes them very easy to bond to soft rubber material during the molding process. Given the high contrast in the stretching stiffness of the fabric and the other soft material filler, this bending angle sensor’s neutral axis is no longer in the center of the device but instead in the proximity of the interface between fabric and the soft material, as illustrated in Fig. 2-9. When the device is bending down, the sensing element is stretched and produces an elongation signal. When the device is bending up, the sensing element is compressed and produces a compression signal. If the fabric is non-isotropic and very stiff in the stretch direction, such design will isolate the sensing element from any horizontal stretch load.

### 2.3 Fabrication

All soft bending angle sensors presented in this chapter were fabricated through a simple manual process, consisting of cutting the conductive rubber, pouring the blue rubber, adding the fabric, and adding the conductive rubber. In order to make a complete sensor as shown in Fig. 2-10-a, three components are prepared first.

Step 1: The U-shape sensing elements are cut out from the commercially available electrically conductive rubber. They are 1.5mm thick, cut with ordinary scissors into the dimensions detailed in Fig. 2-13 or 2-20 depending on the application. The tolerance in its dimensions is
± 0.5mm; increasing the width or thickness of the sensing element will lead to an increase in its nominal electrical resistance, which is expected to be around 70 kΩ.

Step 2: Liquid rubber is prepared and poured into the mold. The blue non-conductive rubber is produced with Smooth-on Mold Star 30. It comes in two liquid-form compartments. After it is mixed in a 1 to 1 ratio and stirred until reaching a uniform consistency, the liquid rubber is poured into the mold.

Step 3: The fabric is wet with the liquid rubber before pushing it into the bottom of the mold.

Step 4: Once the fabric is in place, the sensing element is pressed into the liquid rubber at the location indicated in Fig. 2-10-a.

The first part of the process, as described above, must be completed before the rubber sets, and then once the rubber sets the sensor can be wired. The process described above must be done within 20 minutes of the mixing of the liquid rubber, or the liquid rubber will become too viscous to work with. In practice, it took less than 2 minutes to wet each fabric and place the items into the liquid rubber. After leaving the mold still for 6 hours at room temperature, the liquid rubber solidifies completely, and this soft bending angle sensor is ready for wiring. In the wiring process, thin 30 AWG stranded wires are stitched with the help of a needle through the two ends of each U-shape sensing element. After the needle is removed, the wires are tied with a knot and fastened to the sensing element.
This soft angle sensor is already low-cost and could be even cheaper if manufactured in an industrial setting. With all off-the-shelf, commonly available materials, each sensor costs 0.15 USD in material. In our manual process, it took about 15 minutes to do the preparation and post-processing of four pieces of sensors, and 6 hours of waiting for the molding to be complete.

The time and cost to make each sensor can be further reduced if thousands of sensors can be manufactured at once using machines and bulk manufacturing. The sensing elements can be stamped or machine cut instead of manually cut with scissors. The fabric can be wet with liquid rubber with a paint roller rather than the manual wetting process. Instead of individual molds or four per batch, a large sheet that consists of 1000s of the sensors can be made at once, and then cut into the individual pieces. Instead of making a few sensors and waiting 6 hours for the liquid rubber to dry, one can make thousands of the sensors with a bigger mold in the same 6 hours.

Table 2.1: Cost Breakdown for Bending and Pull Sensor

<table>
<thead>
<tr>
<th>Item</th>
<th>Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.5mm thickness U Shape Conductive Rubber (0.8 cm²)</td>
<td>0.12 USD</td>
</tr>
<tr>
<td>Mold Star 30 Silicone Rubber (2 gram)</td>
<td>0.02 USD</td>
</tr>
<tr>
<td>0.5mm knit fabric (11 cm²)</td>
<td>0.01 USD</td>
</tr>
<tr>
<td>Total</td>
<td>0.15 USD</td>
</tr>
</tbody>
</table>

2.4 Applications

2.4.1 Demonstration of Principles of The Soft Bending Angle Sensor in A Fish Tail Motion Sensing Application

Motivation: Effective Minimum Sensing For Under-actuated Soft Robot Fish

Soft material has enabled the design of many bio-inspired robots in unconventional ways. For example, the soft robot fish [12, 14] can swim like a real fish, and do so in an under-actuated manner. The robot fish are about 10cm long, and they have
only one servo motor inside to control the swing frequency and magnitude of the fish tail. Through controlling the change in the swing motion, this single-actuator robot fish achieves two degrees of freedom in motion: it can swim forward and backward, and can turn left or right, in a controlled manner. A single actuator is needed for the robot fish due to a design methodology that results in material properties, actuator size, and location. This allows the use of one actuator that makes the whole body behave like the simulation. The under-actuated control makes it feasible. It leads researchers to wonder if it is also possible to instrument a small soft robot fish with a minimum number of sensors in order to perform feedback control. In literature, the minimum requirement of the number of sensors reported is two [10].

With our soft bending angle sensor, we believe we can instrument the smallest robot fish with only one sensor and enable feedback control, and do so with minimum cost. A single bending angle sensor attached to the side of the robot fish will be able to tell both the direction and magnitude of the fish body swing motion. Then the fish robot can know if it is subject to external turbulence and adjust its actuator output accordingly. That will be a single actuator, single sensor robot fish for controlled swimming in changing flow conditions.

**Setup Experiments to Validate Two Hypotheses**

To demonstrate the effectiveness of the proposed low-cost sensor in a simplistic manner, two versions of instrumented fish tails (one with fabric and one without) are fabricated and compared in performance. Both fish tails are 2mm in thickness and 5cm in length. One fish tail is made with only the non-conductive rubber and the 1.5mm-thick conductive rubber as the sensing elements, as shown in Fig. 2-11. The non-conductive rubber used here was Smooth-on Mold Star 30 which has a Shore A hardness of 30. When compared to standard hardness silicone rubber from Smooth-on, it is estimated that the Shore A hardness of the purchased conductive rubber is around 30-35, similar to that of the non-conductive rubber. In all fish tails, the conductive rubber was cut into U-shape sensing elements with dimensions shown in Fig. 2-13. Two braided electrical wires are stitched to the sensing element at the
Figure 2-11: Soft fish tail with soft bending angle sensors embedded.

two tips of the U shape to form a circuit. In the other fish tail, a layer of very thin woven fabric is embedded and molded into the back of the non-conductive rubber. As shown in the cross-section view of the fish tails in Fig. 2-12, the rubber-only fish tail has its neutral axis along the center line of the entire device with the sensing element placed off center. In the rubber-fabric fish tail, the neutral axis is near the interface between the fabric and the non-conductive rubber which is above the top of the sensing elements. The sensing elements' resistances are measured and recorded.

Figure 2-12: Cross-section view along the longitudinal direction of the two soft fish tails. (a) rubber only version (b) rubber-fabric version.

The first hypothesis this experiment will test is that the inclusion of a fabric effectively enables building thin soft bending angle sensors without significantly thinner sensing elements. For this hypothesis to be true, the rubber-fabric fish tail should clearly show more differentiable sensor outputs for bending up and bending down while the rubber only tail may show little or none.

The second hypothesis this experiment will test is that this directional sensing
Figure 2-13: Geometry of the sensing element inside the fish tail. Dimensions were selected so that the U shape maintained a constant width and was large enough to attach wires to, while small enough to not hit the other sensor. It is cut out from 1.5mm thick conductive rubber.

capability is not affected by other external interactions such as how the fish tail is mounted. In the experiment setups as shown in Fig. 2-14, the left end of the fish tail is mounted in between two plates. When the fish tail bends, it may press against the corner of one of the plates and thus cause changes in the sensor outputs. To ensure the differentiable sensor outputs are affected mainly by the neutral axis rather than the mounting device, two independent sensing elements are placed in each fish tail. Sensor A is at the left end of the fish body where the fish tail will be mounted, and sensor B in the middle of the fish tail, unaffected by any normal pressure. Sensor B serves as the benchmark.

The experiments were conducted on the fishtails sandwiched between two acrylic sheets and then bent to a given angle, released, and recorded. The fishtails were held in-between two clear acrylic sheets, as shown in Fig. 2-14. Two binder clips were used to hold the acrylic sheets and the sensing element tight. The total force exerted by the binder clips was measured with a Vernier dynamo-meter, and it was 50N total over a 5mm by 30mm area on the fish tail. The fish tail was then bent to a 15 degree angle into the page in Fig. 2-14 slowly within 2 seconds and then released. We denoted this test as bending up 15 degrees. Similar tests were performed for bending up 30, 45 degrees, as well as 15, 30, 45 degrees in the opposite direction (bending down). The resistance value outputs were recorded by a micro-controller (Arduino Mini Pro 328) at a sampling rate of 50Hz.
Experimental Results

The experimental results clearly validated the first hypothesis as the fabric fish tail was able to sense direction while the non-fabric fish tail was not. We compared the output of Sensor B in the rubber only fish tail (Fig. 2-15) and the same sensor in the rubber-fabric fish tail (Fig. 2-16). We found the device with fabric in it clearly indicated distinctive and different measurements in the up and down bending modes. In the rubber only fish tail, the sensor B showed a small change during the bending phases, but the difference between the output of bending up and that of bending down was minimal. This is as expected since the sensing element overlapped the neutral axis of the fish tail (Fig. 2-12, a). It does not work as a bending angle sensor if the commercially available thick conductive rubber is simply embedded in the thin, rubber-only fish tail. In contrast, the same sensor at the same position in the rubber-fabric fish tail displayed clearly different outputs for bending up and bending down modes. As shown in Fig. 2-12, the fabric was embedded in the top side of the sensor (into the page in Fig. 2-14). Thus when the fish tail was bent downward (out of the page in Fig. 2-14), the sensing element was predicted to be compressed and its resistance reduced. When the fish tail was bent upward (into the page in Fig. 2-14 and towards the fabric), the sensing element was predicted to be stretched and its resistance increased. The measurement indicated in Fig. 2-16 agreed with the prediction. In comparison to the same conductive rubber sensor in the fish tail of the same thickness but no embedded fabric, the fabric version could tell not only the
direction of the bending motion, but also the magnitude of the bending, as indicated in Fig. 2-16. Through embedding an ordinary fabric, we successfully relocated the neutral axis of the entire device. We used a single piece of commercially available, low cost but thick conductive rubber in this thin fish tail to enable bending angle and direction measurement.

Figure 2-15: Rubber only fish tail, Sensor B output. Difficult to see bending direction.

Figure 2-16: Rubber-fabric fish tail, Sensor B output. Easy to see bending direction.

The experimental results showed the additive effect from the device’s interaction with the mounting tool on the sensor outputs. Because the fish tails are soft, local deformation is higher at the mounting location (sensor A) and gradually reduces toward the tip of the fish tail. Thus, in comparison to sensor B, sensor A was expected
Figure 2-17: Rubber only fish tail, Sensor A output. Affected by normal pressure of the clamp.

to be compressed more and produce a larger magnitude resistance drop when the fish tails were bent down. When the fish tails were bent up, Sensor A was expected to be stretched more and produce a larger magnitude resistance increase. When the sensor A output in the rubber-only fish tail (Fig. 2-17) is compared to that of sensor B (Fig. 2-15), it was visible that sensor A was able to tell the bending direction much better than sensor B. Similar trends were also observed in the rubber-fabric fish tail when comparing Fig. 2-18 with Fig. 2-16. However, there is a noticeable difference in Sensor A’s output and Sensor B’s output when the fish tails were bent up. Sensor A, during the bend-up tests, demonstrated a two-phase effect. As Fig. 2-17 indicates, after an initial phase of increasing resistance as sensor A was stretched, the resistance dropped gradually. The resistance drop while the fish tail was bent further up indicated that compression was more significant than elongation at Sensor A. The resistance drop kicked in earlier when the input bending angle was larger.

This additive effect which was produced by normal force from the corner of the mounting tool, explains the differences between signals seen from sensor A and sensor B. The corner of the mounting tool would press against the fish tail and the sensing element in it in the same way regardless of which direction the fish tail bent. In the case of the rubber-only fish tail, sensor A was compressed by the corner of the mounting tool on the top (as indicated in Fig. 2-12) when the fish tail was bent up.
This compression was concentrated and it was in the normal direction rather than the longitudinal direction of the fish tail. This increase of normal pressure on the conductive rubber sensor would cause a reduction in the sensor's resistance output. Before a threshold, sensor A was mainly stretched and its resistance increased. After the threshold, the normal pressure increased faster than the stretch on sensor A, and thus the resistance of sensor A reduced. This explains the two phase effect in the bend up phase on the rubber-only fish tail (Fig. 2-17). In the case of the rubber-fabric fish tail, the resistance drop phase was less significant because the fish tail was stiffer. The concentrated normal compression on top did not effectively reach the sensing element on the bottom side of the neutral axis. The same normal compression was also expected to occur when the fish tails were bending down; the corner of the mounting tool in the bottom would compress Sensor A and reduce its resistance. However, Sensor A was already compressed due to the downward bending moment on the fish tail. These two compression effects added to each other, and Sensor A outputted a larger, single-phase resistance reduction in response to the downward bending moment on the fish tail.
Summary: Effective Low-Cost Way to Break The Thickness Limit For Soft Bending Angle Sensors

The design of the low cost soft bending angle sensor was demonstrated in a simple fish tail motion tracking application. To instrument a 2mm thin fish tail, conventional design requires a sub 1mm thin conductive rubber which is not commercially available and is hard to fabricate precisely. However, it is not the thickness of the sensing element and the device that determines the effectiveness of the bending angle sensor. What really matters is the placement of the sensing element with respect to the device’s neutral axis. Through the inclusion of more stiff material in the fish tail, such as ordinary fabric, the location of the neutral axis in the device can be designed in a low-cost way. Because the materials are all ordinary and widely available, bending angle sensors made this way cost less than $1 each. A single rubber-fabric bending angle sensor allowed us to track both the direction and the magnitude of the fish tail displacement due to external forces. It is an effective approach to instrument robot fish as it only needs one of these sort of bending angle sensors.

2.4.2 Demonstrate High Manufacturing Tolerance of The Soft Bending Angle Sensor In The Application Of Leak Detection

Use Soft Bending Angle Sensor In Leak and Obtrusion Detection

In prior work, [25], an in pipe leak detection robot with 4 strain gauge sensors has been designed and tested. This in pipe leak detection robot is pictured in Fig. 2-19. As shown in Fig. 2-20, the new leak sensor is 2mm thick, with 1.5mm thick electrically conductive rubber embedded inside as the sensing element. Underneath the conductive rubber is a layer of fabric, indicated by the green region. The rest of the leak sensor is made with soft silicone rubber; more specifically, Smooth-on Mold Star 30. This silicone rubber and the sensing element shared similar stiffness. A layer of fabric was embedded inside the soft silicone rubber, right underneath the sensing
Figure 2-19: Prior Leak Detection Robot

Figure 2-20: Illustration of the design of the new leak sensor in comparison to the previous leak sensor. [25] Dimensions of the conductive rubber were chosen to fit within the yellow bracket, which is 10mm long.

When viewed from the top, this fabric layer has to be the exact same shape and size as the entire sensor. The end of the leak sensor where the sensing element resided was placed inside a yellow loose bracket. As shown in Fig. 2-20, the left end of the sensing element was bonded with super glue to the vertical wall of the bracket. With this configuration, any kind of deformation on the right hand side of the leak sensor would be transferred to the sensing element and measured. The sensing element must be fully enclosed inside the bracket. As described in the Fish Tail section, it is undesirable to have any part of the sensing element come into contact with the corner of the bracket while the leak sensor is bent. It results in an additional normal pressure on the sensing element and noise to the measurement.

Several versions of the new leak sensors were compared in experiments with varying choice of fabric, length of sensing element in comparison to the length of the
bracket, and the length of the fabric. The first thing to highlight is the choice of fabric. There were many choices of fabrics; the only selection criteria on the fabrics was that they should be stiffer in the elongation direction than the soft rubber. It could be a thin woven cloth which cannot be stretched at all but can be bent easily. It could also be a knit cloth which is softer, stretchable and equally easy to bend. Fabrics of different stiffness affect the leak sensor's performance differently. This will be shown first in the experiment. Afterwards we will define the manufacturing requirements.

**Experimental Setup**

A set of experiments were designed to evaluate the new leak sensors' capability to tell leaks and obtrusions apart. The membrane leak sensors were placed inside the black rigid brackets as shown in Fig. 2-4. The test vehicle had two brackets to hold two membrane leak sensors. This design allowed the test vehicle to slide on flat surfaces in a stable manner, and ensures the quality of the measurement. It also improved the data collection rate; two sets of data could be collected in one experiment. In the experiment, the test vehicle was placed on top of a flat surface in a large water tank filled with water. On the flat surface there were artificial obtrusions and leaks. In the experiments, the water was not moving but the test vehicle was. The test vehicle was pushed at a speed about 100mm per second in a straight line and slid over the obstruction. As illustrated in the sketch at Fig. 2-21, the obtrusions were long triangular prisms, with a cross-sectional profile of 4mm high and 5mm wide. It was 45mm in length, and that was longer than the width of the membrane leak sensor (37mm). In other experiments, the test vehicle was pushed at the same speed of 100mm per second and slid over a leak. The leak was a 8mm long crack aligned with the direction of the vehicle's motion. It simulated a longitudinal crack leak in a water pipe. The bottom side of the crack is connected to a 1/4 inch (6.35mm) inner diameter hose. The other end of the hose connects to a vacuum chamber that was pressurized. When the leaks were left open, the pressure drop at the leak was estimated to be 11 Psi (0.8 Bar) and the water was leaking at a rate of 0.8 gallon (3 Liters) per minute. The actual experiment setup is shown in Fig.2-22. The 4mm
high obtrusions were in the back row, and the 8mm crack leak is in the middle of the central row where the hose is connected.

Figure 2-21: Illustration of the experiment setup for testing the new leak sensors’ ability to tell leaks and obstacles apart

Baseline: leaks and obtrusions are the same to rubber only sensor: The rubber-only membrane leak sensor developed in [25] was first experimented with to establish a benchmark and it could not tell leaks apart from obtrusions. The rubber-only leak sensor, as illustrated in Fig. 2-20, was expected to produce similar resistance changes in response to obtrusions and leaks. When the obstruction bends the rubber-only leak sensor, the sensing element that crosses the neutral axis may experience elongation on the bottom side and compression on the top side, as one side of the neutral axis compresses while the other stretches. This mixed effect makes it difficult to observe the direction of motion from the resistance change alone. It depends on the different directional sensitivities of the sensing element to elongation and compression, and this
particular sensing element is more sensitive to elongation than compression. As the experimental results in Fig. 2-23 and Fig. 2-24 show, in all three repeated tests on the obstruction and the leak, the leak sensor outputs a positive peak for each obstruction or leak in its resistance measurement. When comparing the response to obstructions in Fig. 2-23 to the response to leaks in Fig. 2-24, they were not significantly different. The obstructions caused reactions of large magnitude, but so could a bigger leak with a larger pressure drop. The rubber-only leak sensor is not an effective directional bending angle sensor and it cannot tell leaks apart from obstructions.

Fabric-rubber sensor can measure leaks and obstructions separately: In contrast, the new leak sensor, is an effective bending angle sensor, and can clearly tell leaks (upward spikes) apart from obstructions (downward spikes). The new leak sensor has
Figure 2-26: Lab experimental result, stretch fabric-rubber sensor, measurement on three leaks (8mm cracks, 0.8 gal/min flow rate, 0.8 Bar pressure drop)

a stiff fabric layer in the bottom as shown in Fig. 2-20. Based on the neutral axis analysis, its sensing element should experience 100% compression and decrease in resistance when the leak sensor is bent upward by obtrusions. In contrast, the sensing element should experience 100% elongation and increase in resistance when the leak sensor is bent downward and pulled by the leak. This predicted difference was clearly visible in the experimental results. As shown in Fig. 2-25, three obtrusions caused three drops in the resistance measurement. In comparison, three leaks caused three peaks in the resistance measurement as shown in Fig. 2-26. The soft bending angle sensor is an ideal implementation for differentiating leaks from obtrusions in pipes. Moreover, it can even be used to measure leaks and obtrusions at the same time.

Comparing leak sensors made with stretch cloth to those made with non-stretch cloth we see that the stretch cloth sensors are more effective as they react to both the pull and the slight angular change due to the leak. The results above were produced by the leak sensor made with stretch, knit cloth rather than a non-stretch, woven cloth. Its response to leaks was much stronger than that with non-stretch fabric because it can also measure pulling force. The pulling effect of a leak is much stronger than bending, since the maximum angular displacement is constrained by the the 1mm gap between the leak sensor and the leak surface as shown in Fig. 2-21. Moreover, the bending angle sensor made with non-stretch fabrics such as the woven cloth can measure bending angle well, but it cannot measure pulling force. Given the high contrast in stiffness between the non-stretch fabric and the soft rubber, the sensing element will feel minimal input from the pulling effect of the leak. A leak sensor made with non-stretch fabric is not effectively measuring leaks; it is measuring the minor effect of bending while neglecting the major effect of pulling. This was
observed in experimental results with the non-stretch fabric-rubber leak sensor, as no significant peaks could be seen. In comparison to the sensor made with non-stretch fabric, the one made with stretch fabric produced a stronger response to the same leaks as shown in Fig. 2-26. With a lower contrast in stiffness between the fabric layer and the rubber layer, the sensing element shares a part of the pulling input with the fabric layer. Since the fabric is placed in the bottom layer, both the pulling and downward bending input from the leaks elongate the sensing element and increase its resistance. The upward bending input from obtrusions compresses the sensing element and reduces its resistance. Leak sensors made with stretch fabric are well suited for both measuring leaks and obtrusions with high differentiability and high sensitivity.

**Summary: A Low Cost Leak Sensor That Can Measure and Distinguish Leaks and Obtrusions**

The soft bending angle sensor was successfully implemented in leak detection, in a low cost and robust way. It was capable of differentiating leaks and obtrusions. The principle of this sensor is based on engineering the neutral axis of the device. This can be done by embedding in the soft device a piece of simple, ordinary fabric. Fabric is thin and extremely stiff in the elongation direction, allowing us to use thick but commercially available conductive rubber to build previously impossibly thin soft bending angle sensors. This design allows us to build high performance sensors with low cost ordinary material. This design also has high tolerance to manufacturing errors. Thus the sensor can be produced by hand rather than needing high precision machines. It is a low cost but effective solution to a complex problem.

### 2.5 High Manufacturing Tolerance

The manufacturing of these soft bending angle sensors, as described in the Fabrication section, has a high tolerance to errors. For example, the liquid rubber can be mixed at 0.95 to 1 ratio and the outcome is still a solid sensor. Within this range of mixture
ratio, no significant changes in the material or the effect on the sensor are observed. Neither the sensing element nor the soft rubber have to be of uniform thickness. The high contrast in stiffness between the soft rubber and the fabric ensures the soft bending angle sensor is effective regardless of millimeter thickness errors. The fabric does not even need to be flat in the sensor. In the multiple prototypes we made, the fabric inside the soft bending angle sensor was sometimes curved as indicated in Fig. 2-27. There were sometimes air bubbles trapped underneath the fabric during the molding process and they produced enough buoyancy to push the fabric upward. However, the prototypes still worked. They measured bending directions and pulling forces equally well when compared to the perfect sensors.

![Diagram of Soft Rubber and Fabric Layers](Soft Rubber above Fabric+Rubber Layer)

Figure 2-27: Manufacturing tolerance: the fabric (green) does not need to be flat

However, there are two manufacturing errors (one in the fabric layer length, and the other in the sensing element length) that lead to failures. The first one is when the fabric layer falls short of covering the entire sensor. This disables the sensor’s ability to differentiate bending directions. The other failure mode is when the sensing element is excessively long and comes into contact with the edge of the bracket. This interaction adds significant noise to the sensor’s measurement. These two failures are discussed in more depth in [24].

These two failure modes can easily be avoided by making the device longer and then trimming to length. To avoid having a short fabric in the device, we can first make a longer device with longer fabric and then trim it to the right length. During the trimming process, any excessive length of the sensing element can be reduced as well. In addition, there is enough tolerance built into the sensor design for the trimmed sensor to function in a nominal manner. The sensing element is intended to be 8mm long. If it is made 9mm long, it is still shorter than the 10mm long bracket and it would not touch the edge of the bracket. Those precautions are easy to implement, making the manufacturing process of this soft bending angle sensors
even more tolerant to errors. It is a robust way to produce effective soft bending angle sensors.

2.6 Conclusion

This chapter investigated soft sensors and their design and fabrication using soft materials. It demonstrates novel and tangible functions and applications of soft sensors in robots to enable data collection for feedback, monitoring, and prognostics. These soft sensors can have different sensing features such as different physical quantities, different sensitivities in desired directions, different sizes and different materials. Then the chapter looked specially at one example of a soft sensor - the bending and pull sensor. This sensor was demonstrated by designing, manufacturing, and testing it in two applications: measuring bending angle of a fish tail, and measuring leaks and obstructions in pipes. It is a low cost sensor made of silicone rubber and ordinary fabrics. It is designed for low-cost manufacturing and each sensor costs less than 1 USD. Even with this low cost, it shows ability to distinguish between different bending angles in the fish tail application, and ability to distinguish between bending up and bending down plus pulling in the leak sensor application. This application of leak detection is important as an average city looses 20% of its water to leaks, and this sensor can help identify smaller leaks and minimize water losses.[8] There are definitely more applications worth exploring with this soft bending angle sensor, and an even greater variety of applications for soft sensors as a whole.
Chapter 3

Cost Analysis of Network Management Methods

3.1 Introduction

3.1.1 Prior Work with DMA Configurations

Managing fresh water delivery and quality is key to urban areas and rural areas as well as homes and businesses. Thus, it is not surprising that researchers have applied system analysis to water distribution networks since the late 19th century. [16]

With the 20th century came greater computing power which fueled further analysis and methods, many focusing on pump operation, water quality management, and valve control. [11] Expanding on the water quality and leak detection section, many papers have examined ideal divisions of district metered areas (DMAs) [2] [17] and ideal placement of valves or pressure sensors [13] [19]. These methods focused on getting a maximal amount of data from a minimal number of additional smart devices. However, with the 21st century we have begun to see smaller, cheaper sensors enabling sensing within pipes themselves [18] and further communication between sensors as many look toward a future of an internet of things. As sensors become cheaper and easier to integrate, and water distribution network (WDN) research recognizes the importance of flexible systems [16], we may reach a point where more sensors,
actuation within pipe networks, and robotic monitoring/repair becomes a logical option.

This chapter sets out to analyze a few smarter, more sensor and robot heavy methods of WDN management, and compare them with the current front runner in leak detection and monitoring, DMAs. Through an explanation of the three methods and cost models, the methods can be compared to each other and also to cost analysis previously conducted on different DMA control methods. [6]

3.1.2 Proposed Smart Network Management Methods

To explore alternatives to the prior DMA control methods, we look at three methods to further instrument a pipe network to allow for faster and more autonomous detection and localization of water leaks. These three methods are:

Case (A): Flow Sensors to Fully Monitor

To speed up localization of leaks, flow sensors could be placed at each pipe branch, as shown by the purple circles in Fig. 3-2. Each purple flowmeter circle represents a cluster of flowmeters as each incoming/outgoing pipe has a flowmeter on it. These sensors, along with household/business water meters would allow for easy identification of the area of a leak. They would greatly reduce the pipe length which needed to be surveyed in the case of an identified water loss and would allow for improved error checking in water flow measurement.

This method of leak sensing and localization would operate in a manner where all flow sensors can continuously send data to a main processor, which could automatically analyze the data for anomalies or leaks. When a leak occurs a team with acoustic leak detection tools would be dispatched, and they would scan the small region containing the leak to locate it well enough for the repair team to take action.
Case (B): Smart Valves and In-pipe Robots

To automate the localization of leaks, instead of having flowmeters paired with humans that run above ground acoustic surveys, in-pipe leak detection robots can be used to detect and localize leaks. For these in-pipe robots to function they need a start station at the source reservoir and end stations at each possible end point (shown as green and yellow circles in Fig. 3-1), along with valves at pipe joints to direct the robots (shown as blue circles in Fig. 3-2).

This method of leak sensing and localization would operate in a manner where periodically a batch of robots large enough to survey the entire network is sent out. The valves would be automated to direct the robots such that each pipe is inspected by at least one robot. Once the robots reach their end station, their data on the localized leaks would be sent to the leak repair crews. Periodically, each of the robot end stations would be emptied of robots, and the robots would be driven back to their starting station.

Case (C): Flow Sensors, Smart Valves, and In-pipe Robots

To both speed up and automate the localization of leaks, both of the prior methods can be used together. To use both of these methods at once, one would need in-pipe leak detection robots, robot start stations and end stations (see yellow and green circles in Fig. 3-1), along with flow meters and valves (see blue and purple circles in Fig. 3-2).

This method of leak sensing and localization would operate in a manner where when the flow meters detected an irregularity in a pipe, a leak detection robot would be automatically sent to that pipe to localize it. When the robot reached the end station it could then transmit the exact location of the leak to the repair team. Periodically, each of the robot end stations would be emptied of robots, and the robots would be transported back to their starting station.
Figure 3-1: Example scenario of start and end stations for in-pipe leak detection robots. The robots would start at the reservoir and move with the flow to one of the most downstream locations.

Figure 3-2: Example placement of smart valves and smart flowmeters in a zoomed in portion of the network in Fig. 3-1. Valves can be used to direct robots, and flowmeters can be used to sense and measure leakage. Each valve cluster or flowmeter cluster contains the same number of valves/flowmeters as the number of pipes entering/exiting. This means the upper left cluster contains four valves and four flowmeters, while the upper right cluster contains three of each.
3.2 Analytical Derivation of Smart Network Management Methods

Next we will examine the derivation of costs associated with each of the three proposed methods of smarter control. In accounting for the total cost, all needed components up to leak repair are taken into account. These components fall under the main categories of money lost due to lost water, money spent on purchase and maintenance of leak detection equipment, and money spent on staff to operate and monitor the system. All of the variables used in the following equations can be seen in table 3.1.

Within the category of money lost due to water loss we take into account the average time to detect each leak as well as the average time to pinpoint it’s flow. With systems that are periodically checking flow at less frequent intervals, there is also a chance that the leak will be reported, or “called in", before the system’s periodic inspection is conducted. This is accounted for.

Within the category of money spent on purchase and maintenance of leak detection equipment, the costs of flowmeters, smart valves, in-pipe leak detection robots, and in-pipe leak detection robot stations are accounted for as needed in each of the three examined cases. In case (A), without in-pipe leak detection robots, money is also used to purchase acoustic leak detection technology for teams to use to pinpoint the leaks.

Within the category of staff, overhead and necessary vehicles are also accounted for. In case (A), staff acoustically pinpoint the leaks, while in cases (B) and (C), staff return the robots from their ending (downstream) locations to their starting locations. If the case is one where leak detection through the system may take longer than a day, then additional staff is funded to respond to user reports of observed leaks.
Table 3.1: Variable names look up table.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>c</td>
<td>cost of water (as purchased by utility company)</td>
<td>$/m³</td>
</tr>
<tr>
<td>cₐ</td>
<td>equipment cost for one acoustic survey team</td>
<td>$/yr</td>
</tr>
<tr>
<td>cₑ</td>
<td>total equipment cost for all acoustic surveying teams</td>
<td>$/yr</td>
</tr>
<tr>
<td>cₑₐ</td>
<td>equipment cost for robots and robot stations</td>
<td>$/yr</td>
</tr>
<tr>
<td>cᶠ</td>
<td>cost of a smart flowmeter/yr</td>
<td>$/yr</td>
</tr>
<tr>
<td>cₙ</td>
<td>human salary to pinpoint leaks</td>
<td>$/yr</td>
</tr>
<tr>
<td>cₒ</td>
<td>labor and tools cost to transport all robots</td>
<td>$/yr</td>
</tr>
<tr>
<td>cₜ</td>
<td>human labor cost to survey entire system</td>
<td>$</td>
</tr>
<tr>
<td>cₚ</td>
<td>human labor cost to respond to reported leaks</td>
<td>$/yr</td>
</tr>
<tr>
<td>cᵣ</td>
<td>labor and tools cost to move robots per team</td>
<td>$/yr</td>
</tr>
<tr>
<td>cᵥ</td>
<td>cost of a smart valve/yr</td>
<td>$/yr</td>
</tr>
<tr>
<td>cₑₜₐ</td>
<td>cost of unreported water lost per year</td>
<td>$/yr</td>
</tr>
<tr>
<td>cₑₜᵣ</td>
<td>cost of reported water lost per year</td>
<td>$/yr</td>
</tr>
<tr>
<td>fₑ</td>
<td>cost of a smart flowmeter</td>
<td>$</td>
</tr>
<tr>
<td>fᵣ</td>
<td>lifetime of a smart flowmeter</td>
<td>yr</td>
</tr>
<tr>
<td>fₑₘₑ</td>
<td>cost to maintain a smart flowmeter</td>
<td>$/yr</td>
</tr>
<tr>
<td>fₑₘᵣ</td>
<td>freq. unreported leaks in mains/km pipe (leaks/(km*yr))</td>
<td></td>
</tr>
<tr>
<td>fₑₘₛ</td>
<td>fraction of leaks unreported in mains</td>
<td></td>
</tr>
<tr>
<td>fₑₘᵤ</td>
<td>freq. unreported leaks in services/km pipe (leaks/(km*yr))</td>
<td></td>
</tr>
<tr>
<td>lₐ</td>
<td>length of pipe an acoustic team can survey</td>
<td>km/yr</td>
</tr>
<tr>
<td>lₜ</td>
<td>total length of system</td>
<td>km</td>
</tr>
<tr>
<td>lₚ</td>
<td>average length of uninterrupted pipe</td>
<td>km</td>
</tr>
<tr>
<td>nₑ</td>
<td>number of robot batches to drive per year</td>
<td>1/yr</td>
</tr>
<tr>
<td>nᵣ</td>
<td>number of robot endpoint stations</td>
<td></td>
</tr>
<tr>
<td>nₐ</td>
<td>number of flowmeters</td>
<td></td>
</tr>
<tr>
<td>nₑᵣ</td>
<td>number of robot trips to fully survey network once</td>
<td></td>
</tr>
<tr>
<td>nₑᵣₑₑ</td>
<td>number of robot trips to localize a leak in given pipe (1/leak)</td>
<td></td>
</tr>
<tr>
<td>nₛ</td>
<td>number of robot startpoint stations</td>
<td></td>
</tr>
<tr>
<td>nₛₑ</td>
<td>number of robot batches moveable by team per year (1/yr)</td>
<td></td>
</tr>
<tr>
<td>nₛᵣ</td>
<td>number of smart valves in system</td>
<td></td>
</tr>
<tr>
<td>rₑ</td>
<td>max # of robots which can be moved back to start at once</td>
<td></td>
</tr>
<tr>
<td>rₑₑ</td>
<td>cost of a leak detection robot</td>
<td>$</td>
</tr>
<tr>
<td>rₑᵣ</td>
<td>lifetime of a leak detection robot</td>
<td>yr</td>
</tr>
<tr>
<td>rₑₘₑ</td>
<td>flow rate of leaks in mains</td>
<td>m³/(yr*leaks)</td>
</tr>
<tr>
<td>rₑᵣᵣ</td>
<td>cost to maintain a leak detection robot</td>
<td>$/yr</td>
</tr>
<tr>
<td>rₑᵣₛ</td>
<td>flow rate of leaks in services</td>
<td>m³/(yr*leaks)</td>
</tr>
<tr>
<td>sₑ</td>
<td>cost of a robot start or end station</td>
<td>$</td>
</tr>
<tr>
<td>sₑᵣ</td>
<td>lifetime of a robot station</td>
<td>yr</td>
</tr>
<tr>
<td>sₑₘₑ</td>
<td>cost to maintain a robot station</td>
<td>$/yr</td>
</tr>
<tr>
<td>tₑ</td>
<td>time to acoustically locate leak</td>
<td>yr</td>
</tr>
<tr>
<td>tₑᵣ</td>
<td>time to locate a reported leak</td>
<td>yr</td>
</tr>
<tr>
<td>tₑᵣᵣ</td>
<td>time for robot to visit a leak</td>
<td>yr</td>
</tr>
<tr>
<td>tₑᵣᵣₑₜᵣ</td>
<td>time between entire system robot surveys</td>
<td>yr</td>
</tr>
<tr>
<td>vₑ</td>
<td>cost of a smart valve</td>
<td>$</td>
</tr>
<tr>
<td>vₑᵣ</td>
<td>lifetime of a smart valve</td>
<td>yr</td>
</tr>
<tr>
<td>vₑₘₑ</td>
<td>cost to maintain a smart valve</td>
<td>$/yr</td>
</tr>
</tbody>
</table>
3.2.1 Case (A): Flow Sensors to Fully Monitor Cost of Unreported Water Loss

To find the cost of water loss which was unreported by people calling in leaks, we multiply $f_m \ [\text{leaks}/(\text{km*yr})]$, which is the frequency of unreported leaks in the mains per km of total pipe, with $r_m \ [\text{m}^3/(\text{yr*leaks})]$, which is the average flow rate of these leaks, with $l_t \ [\text{km}]$, which is the total length of pipes, with the average time to acoustically survey and find the leak. This average time is $l_p \ [\text{km}]$, the length of an average pipe, divided by the two times $l_a \ [\text{km/yr}]$, which is the average pipe length an acoustic surveying team can cover in a year. We do the same for the leaks in the service pipes, using $f_s \ [\text{leaks}/(\text{km*year})]$ and $r_s \ [\text{m}^3/(\text{yr*leaks})]$ respectively. This sum is the total water lost in unreported leaks per year, and hence we then multiply it by $c \ [\$/\text{m}^3]$, the cost of water$/\text{m}^3$. Thus, the cost of unreported water loss per year is given by:

$$C_{wlu} = c \cdot l_t \cdot \frac{l_p}{2 \cdot l_a} \cdot (r_m \cdot f_m + r_s \cdot f_s). \quad (3.1)$$

Cost of Reported Water Loss

The cost of reported water loss is calculated in a similar manner to the unreported water loss. The frequency of reported leaks for the mains can be found by dividing the frequency of unreported leaks by $f_{mu} \ [\text{leaks}/(\text{km*yr})]$, the fraction of leaks which are unreported, and then multiplying by $1 - f_{mu} \ [\text{leaks}/(\text{km*yr})]$. The only other notable difference for the reported leaks is that they will take a different average time before repair, which is notated $t_r \ [\text{yr}]$. Thus, the cost of reported water loss per year is given by:

$$C_{wlr} = c \cdot l_t \cdot t_r \cdot \left( \frac{r_m \cdot f_m \cdot (1 - f_{mu})}{f_{mu}} + \frac{r_s \cdot f_s \cdot (1 - f_{su})}{f_{su}} \right). \quad (3.2)$$

Cost of Human Salary to Pinpoint Leaks

To calculate the cost of human labor to pinpoint detected leaks, we first calculate the average number of leaks per year to be the sum of $f_m \ [\text{leaks}/(\text{km*yr})]$, the frequency of
leaks in the mains/km, with \( f_s \) [leaks/(km*yr)], the frequency of leaks in the service pipes/km, multiplied by \( l_t \) [km], the total length of pipes in the system. This is then multiplied by \( l_p \) [km/leak], the average length of an uninterrupted pipe per leak, divided by \( l_t \) [km], the total length of pipes in the system, and multiplied by \( c_t \) [$], the cost to survey the entire system. Thus, the cost of human salary to pinpoint leaks per year is given by:

\[
ch = \frac{l_p}{l_t} \cdot l_t \cdot (f_m + f_s) \cdot c_t = l_p \cdot (f_m + f_s) \cdot c_t. \tag{3.3}
\]

**Cost of Equipment for Humans to Pinpoint Leaks**

To calculate the cost of equipment to pinpoint detected leaks, we take \((f_s + f_m) \cdot l_t\) [leak/yr], the average number of leaks per year, and multiply it by \( l_p \) [km/leak], the average length that must be surveyed to find a leak. This is then divided by \( l_a \) [km/yr], which is the length of pipe each sounding team can survey each year, and multiplied by \( c_a \) [$/yr], which is the equipment cost for a sounding team for a year. Thus, the cost of equipment for humans to pinpoint leaks per year is given by:

\[
c_e = (f_s + f_m) \cdot \frac{l_t \cdot l_p}{l_a} \cdot c_a. \tag{3.4}
\]

**Cost of a Smart Flowmeter Per Year**

The total cost of a smart flowmeter is the sum of \( f_c \) [$], the initial flowmeter purchase cost, and \( f_{mc} \) [$/yr], the maintenance cost per year, times \( f_l \) [yr], the expected lifespan of the flowmeter. To calculate the flow meter cost per year the total flowmeter cost is divided by \( f_l \) [yr], the flowmeter’s expected lifespan. Thus, the cost of a smart flowmeter per year is given by:

\[
c_f = \frac{f_c + f_l \cdot f_{mc}}{f_l}. \tag{3.5}
\]
Overall Cost of Management System and Water Lost Per Year

The overall cost of the management systems and water lost per year for the smart flowmeter method is $c_{wlu}$ [$$/yr$], the cost of water loss in unreported leaks, plus $c_{wlr}$ [$$/yr$], the cost of water lost in reported leaks, plus $c_h$ [$$/yr$], which is salary to pay humans to pinpoint the leaks, and $c_e$ [$$/yr$], which is the cost of equipment for use in pinpointing leaks. In addition $n_f$, which is the number of flowmeters, times $c_f$ [$$/yr$], which is the cost of flowmeter/year and $c_p$ [$$/yr$], the cost of staff to respond to user reported leaks, are added on. Thus, the overall cost of management system and water lost per year for case (A) is given by:

$$c_o = c_{wlu} + c_{wlr} + c_h + c_e + n_f \cdot c_f + c_p.$$  (3.6)

3.2.2 Case (B): Smart Valves and In-pipe Robots

Cost of Unreported Water Loss

Unreported water loss in case B is similar to that of Equ. (3.1), however the time to locate is now based on the frequency of robotic inspection and thus $t_{rr}$ [yr] is used rather than $t_l$ [yr]. Thus, the cost of unreported water loss per year is given by:

$$c_{wlu} = c \cdot l_t \cdot t_{rr} \cdot (r_m \cdot f_m + r_s \cdot f_s).$$  (3.7)

Number of Batches of Robots Needed to Move Per Year

After all the robots have traveled from a start point to an end point they will need to be transported back to a start point in order to detect further leaks. The total number of individual robot runs needed per year is the quotient of $n_r$, the number of robot trips to fully survey the system once, and $t_{rr}$ [yr], the time between each robot survey. Thus the number of times all robots need to be cycled through the system per year is that number divided by $n_{robot}$ [], which is the total number of robots. Since the scenario used has multiple endpoints and one start point, each time all robots are used, there will be at least one carload of robots returning from each endpoint, and
thus we multiply by $n_e [\text{\#}]$, the number of endpoints. Thus, the number of batches of robots needed to move per year is given by:

$$n_b = \frac{n_r}{t_{rr}} \cdot \frac{n_e}{n_{\text{robot}}}. \tag{3.8}$$

**Cost of Robot Movement Staff and Tools Per Year**

To find the average number of trips needed to move a batch of robots, we take $n_r/t_{rr} \text{[1/yr]}$, the total number of robot runs each year, and divide it by the product of $n_b \text{[1/yr]}$, the number of robot batches, and $r_c [\text{\#}]$, the maximum number of robots that can be moved back to the start at once, and finally take the ceiling of that result (using the ceil() function which rounds to the next integer which is greater than or equal to the current number). From this number we next want to calculate the number of teams needed to manage this many carloads of robots. To do this we multiply by $n_b \text{[1/yr]}$, the number of robot batches per year, and then divide by $n_t \text{[1/yr]}$, the number of carloads of robots each team can handle in a year. Then the ceiling of this result is taken. Lastly, the number of teams needed is multiplied by $c_r \text{[$/yr$]}$, which is the cost of each team per year (which includes salary, overhead, and vehicle costs). Thus, the cost of robot movement staff and tools per year is given by:

$$c_{\text{move}} = c_r \cdot \text{ceil}(\text{ceil}(\frac{n_r}{n_b \cdot t_{rr} \cdot r_c} \cdot \frac{n_b}{n_t})). \tag{3.9}$$

**Cost of a Smart Valve Per Year**

The total cost of a smart valve is the sum of $v_c [\text{$\}$], the initial valve purchase cost, and $v_m [\text{$/yr$}]$, the maintenance cost per year, times $v_l \text{[yr]}$, the expected lifespan of the valve. To calculate the valve cost per year the total valve cost is divided by $v_l \text{[yr]}$, the valve’s expected lifespan. Thus, the cost of a smart valve per year is given by:

$$c_v = \frac{v_c + v_l \cdot v_m}{v_l}. \tag{3.10}$$
Cost of Robots, Robot Stations, and Maintenance Per Year

The total cost of the in-pipe leak detection robots is \( r_{\text{cost}} \) [\$, the initial robot cost, plus \( r_{\text{maintain}} \) [\$/yr], the maintenance cost, times \( r_t \), the robot lifespan, all divided by the robot lifespan. Multiplying by \( n_{\text{robot}} \), the total number of robots, gets the total cost of all robots. The same math is done for the robot stations which have an initial cost \( s_c \) [\$, a maintenance cost \( s_m \) [\$/yr], and a lifespan \( s_t \) [yr]. There are \( n_s \) [] robot starting stations and \( n_e \) [] robot ending stations. Thus, the cost of robots, robot stations, and maintenance per year is given by:

\[
c_{\text{er}} = \frac{n_{\text{robot}} \cdot (r_{\text{cost}} + r_{\text{maintain}} \cdot r_t)}{r_t} + \frac{(n_e + n_s) \cdot (s_c + s_m \cdot s_t)}{s_t}.
\]  
(3.11)

Cost of Reported Water Loss

The cost of water lost in reported leaks is calculated in the same method used in method A, which can be seen in Equ. (3.2).

Overall Cost of Management System and Water Lost Per Year

The overall cost of the management systems and water lost per year for the robots and valves method is \( c_{\text{wlu}} \) [\$/yr], the cost of water loss in unreported leaks, plus \( c_{\text{wlr}} \) [\$/yr], the cost of water lost in reported leaks, plus \( c_{\text{move}} \) [\$/yr], the costs to transport the robots from the end points to the start point, and \( c_{\text{er}} \) [\$/yr], the cost of robots and robots stations. In addition \( n_v \) [], the number of valves, times \( c_v \) [\$/yr], the cost of valve/year, and \( c_p \) [\$/yr], the cost of staff to respond to user reported leaks, are added on. Thus, the overall cost of the management system and water lost per year for case (B) is given by:

\[
c_o = c_{\text{wlu}} + c_{\text{wlr}} + c_{\text{move}} + c_{\text{er}} + n_v \cdot c_v + c_p.
\]  
(3.12)
3.2.3 Case (C): Flow Sensors + Smart Valves + In-pipe Robots

Cost of Unreported Water Loss

Unreported water loss in case C is similar to that of Equ. (3.1), however the time to locate is now based on the speed of the system processing a flow difference and sending a robot to pinpoint the leak and thus \( t_{\text{robot}} \) [yr] is used rather than \( t_t \) [yr]. In this case, all water loss is unreported as it is detected instantly and localized very quickly after - eliminating the need to pinpoint leaks from reports. Thus, the cost of unreported water loss per year is given by:

\[
C_{wu} = C \cdot l_t \cdot t_{\text{robot}} \cdot (r_m \cdot f_{\text{in}} + r_s \cdot f_s).
\]  

(3.13)

Number of Batches of Robots Needed to Move Per Year

After all the robots have traveled from a start point to an end point they will need to be transported back to a start point in order to localize further leaks. The total number of individual robot runs needed per year is \( (f_m + f_s) \cdot l_t \) [1/yr], which is the number of leaks per year, times \( n_{\text{runs}} \) [1/leak], which is the number of runs to localize a leak in a given pipe. Since the scenario used has multiple endpoints and one start point, each time all robots are used, there will be at least one carload of robots returning from each endpoint, and thus we divide by \( n_{\text{robot}} \), the number of robots, and multiply by \( n_e \), the number of endpoints. Thus, the number of batches of robots needed to move per year is given by:

\[
n_b = \frac{(f_m + f_s) \cdot l_t \cdot n_{\text{runs}} \cdot n_e}{n_{\text{robot}}}.
\]  

(3.14)

Cost of Robot Movement Staff and Tools Per Year

To find the average number of carloads needed to move a batch of robots, we take \( (f_m + f_s) \cdot l_t \cdot n_{\text{runs}} \) [1/yr], which is the total number of robot runs each year, and divide it by the product of \( n_b \) [1/yr], the number of robot batches, and \( r_c \), the maximum number of robots that can fit in a car, and finally take the ceiling of that result (by
rounding up to an integer). From this number we next want to calculate the number of teams needed to manage this many carloads of robots. To do this we multiply by the number of robot batches per year, and then divide by $n_t \, [1/\text{yr}]$, the number of carloads of robots each team can handle in a year. Then the ceiling of this result is taken. Lastly, the number of teams needed is multiplied by $c_r \, [\$/\text{yr}]$, the cost of a team per year (which includes salary, overhead, and vehicle costs). Thus, the cost of robot movement staff and tools per year is given by:

$$
c_{\text{move}} = c_r \cdot \left\lceil \left( \frac{(f_m + f_s) \cdot l_t \cdot n_{\text{runs}}}{(n_b \cdot r_c)} \right) \cdot \frac{n_b}{n_t} \right\rceil. \tag{3.15}
$$

**Cost of a Smart Flowmeter Per Year**

The cost of a smart flowmeter per year is calculated in the same method as used in method A, which can be seen in Equ. (3.5).

**Cost of a Smart Valve Per Year**

The cost of a smart valve per year is calculated in the same method as used in method B, which can be seen in Equ. (3.10).

**Cost of Robots, Robot Stations, and Maintenance Per Year**

The cost of robots, robot stations, and maintenance per year is calculated in the same method as used in method B, which can be seen in Equ. (3.11).

**Overall Cost of Management System and Water Lost Per Year**

The overall cost of the management systems and water lost per year for the robots and valves method is $c_{\text{wlu}} \, [\$/\text{yr}]$, the cost of water loss in unreported leaks, plus $c_{\text{move}} \, [\$/\text{yr}]$, the costs to transport the robots from the end points to the start point, and $c_{\text{er}} \, [\$/\text{yr}]$, the cost of robots and robots stations per year. In addition $n_v \, [\text{]}$, the number of valves, times $c_v \, [\$/\text{yr}]$, the cost of each valve/year, and $n_f \, [\text{]}$, the number of flowmeters, times $c_f \, [\$/\text{yr}]$, the cost of each flowmeter/year, are added on. Thus,
the overall cost of management system and water lost per year is given by:

\[ c_0 = c_{wl} + c_{move} + c_{ev} + n_v \cdot c_v + n_f \cdot c_f. \]  

(3.16)

### 3.3 Numerical Example of Smart Network Management Methods

These models were applied to a large distribution system to allow for a comparison between the three models described and past DMA work. To allow for this overarching comparison the distribution system used was the one described in [6]. This distribution system is comprised of 2,391 km of distribution pipes, and has 168,704 service connections to service 765,000 people. The values used for the numerical example are presented in table 3.2 below.

This numerical model, along with the equations presented earlier, allowed a clear total cost versus cost of water to be plotted in Fig. 3-5 for case (A).

However the other two cases were slightly more complex as they contained more free variables which needed to be optimized. For cases (B) and (C) which both contain in-pipe leak detection robots, there was no past data or standard case for how many robots should be in the system and how often the robots should be transported from the end stations (downstream) back to the starting stations.

For case (B), where robots inspect the entire system periodically, the number of robots and frequency of periodic inspection were both varied and optimized within the code. Fig. 3-3 shows that with too few robots, or too frequent of inspections the total cost dramatically increases due to increased robot transport costs. However with too many robots or too infrequent of inspections, total cost more gradually increases due to upfront robot cost and water loss cost, respectively. The figure shown is for a sample case with \( v_c = \$75, \ r_{cost} = \$100, \ s_c = \$1,000, \) and \( c = \$0.046/m^3, \) where the optimal frequency of inspection is found to be every 0.12 years with 19,020 robots total.

For case (C), where robots only inspect a certain pipe section after flow meters
Table 3.2: Variable values look up table.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$c$</td>
<td>varied in code between $0.046/m^3$ - $2.00/m^3$</td>
</tr>
<tr>
<td>$c_a$</td>
<td>$9700/yr$</td>
</tr>
<tr>
<td>$c_t$</td>
<td>$485,154$</td>
</tr>
<tr>
<td>$c_p$</td>
<td>$120,000/year$</td>
</tr>
<tr>
<td>$c_r$</td>
<td>$143,150/year$</td>
</tr>
<tr>
<td>$f_c$</td>
<td>input to code</td>
</tr>
<tr>
<td>$f_l$</td>
<td>20 yr</td>
</tr>
<tr>
<td>$f_{mc}$</td>
<td>$0.2*f_c/f_l$</td>
</tr>
<tr>
<td>$f_m$</td>
<td>0.1169 leaks/(km*yr)</td>
</tr>
<tr>
<td>$f_{mu}$</td>
<td>0.5</td>
</tr>
<tr>
<td>$f_s$</td>
<td>0.5 leaks/(km*yr)</td>
</tr>
<tr>
<td>$l_a$</td>
<td>253.6 km/yr</td>
</tr>
<tr>
<td>$l_t$</td>
<td>2391 km</td>
</tr>
<tr>
<td>$l_p$</td>
<td>0.015 km</td>
</tr>
<tr>
<td>$n_e$</td>
<td>7,592</td>
</tr>
<tr>
<td>$n_f$</td>
<td>318,800</td>
</tr>
<tr>
<td>$n_{robot}$</td>
<td>varied and optimized in code</td>
</tr>
<tr>
<td>$n_r$</td>
<td>411</td>
</tr>
<tr>
<td>$n_{runs}$</td>
<td>1 (1/leak)</td>
</tr>
<tr>
<td>$n_s$</td>
<td>1</td>
</tr>
<tr>
<td>$n_l$</td>
<td>1,300 (1/yr)</td>
</tr>
<tr>
<td>$n_v$</td>
<td>318,800</td>
</tr>
<tr>
<td>$r_c$</td>
<td>100</td>
</tr>
<tr>
<td>$r_{cost}$</td>
<td>input to code</td>
</tr>
<tr>
<td>$r_l$</td>
<td>20 yr</td>
</tr>
<tr>
<td>$r_m$</td>
<td>65,700 (m$^3$/yr*leaks)</td>
</tr>
<tr>
<td>$r_{maintain}$</td>
<td>$.2*r_{cost}/r_l$ ($/yr$)</td>
</tr>
<tr>
<td>$r_s$</td>
<td>11,800 (m$^3$/yr*leaks)</td>
</tr>
<tr>
<td>$s_c$</td>
<td>input to code ($)</td>
</tr>
<tr>
<td>$s_l$</td>
<td>20 yr</td>
</tr>
<tr>
<td>$s_m$</td>
<td>$.2*s_c/s_l$ ($/yr$)</td>
</tr>
<tr>
<td>$t_r$</td>
<td>1/365 yr</td>
</tr>
<tr>
<td>$t_{robot}$</td>
<td>1/365 yr</td>
</tr>
<tr>
<td>$t_{rr}$</td>
<td>varied and optimized in code</td>
</tr>
<tr>
<td>$v_c$</td>
<td>input to code ($)</td>
</tr>
<tr>
<td>$v_l$</td>
<td>20 yr</td>
</tr>
<tr>
<td>$v_m$</td>
<td>$.2*v_c/v_l$</td>
</tr>
</tbody>
</table>

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have detected an anomaly, the total number of robots in the system needs similar optimization as for case (B). Thus, in the code the number of robots is varied and the number of robots resulting in the minimum total price is found. Figure 3-4 shows for a sample case with $v_c = $75, $r_{cost} = $100, $v_c = $1,000, and $c = $0.046/m$^3$, the optimal number of robots is found to be 8,620 robots total.

Figure 3-4: Total cost of method 3 as it varies with number of in-pipe leak detection robots.
3.4 Comparison and Analysis of Network Management Methods

A numerical example allows for the four methods (traditional DMA, fully monitoring flow sensors, smart valves with robots, and smart valves with robots and flow sensors) to be analytically compared. The cost evaluation software created allows for inputs of the flowmeter price per unit, the smart valve price per unit, the leak-detection robot price per unit, and the robot station price per unit. For example, one could set costs as shown in table 3.3.

Table 3.3: Sample component costs in Fig 3-5.

<table>
<thead>
<tr>
<th>Component</th>
<th>Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price of flowmeter</td>
<td>$150</td>
</tr>
<tr>
<td>Price of smart valve</td>
<td>$75</td>
</tr>
<tr>
<td>Price of leak-detection robot</td>
<td>$100</td>
</tr>
<tr>
<td>Price of robot station</td>
<td>$1,000</td>
</tr>
</tbody>
</table>

Figure 3-5: Total cost of each of the four methods varying with water price. Inputs of flowmeter cost, valve cost, robot cost, and robot station cost are given in table 3.3.

For the instrumentation costs shown above, it can be seen in Fig. 3-5 that for a water cost under $0.50/m³, the traditional DMA method is optimal, while for a water cost between $0.50/m³ and $1.26/m³, a robots and valves control method is optimal,
and for a water cost above $1.26/m³, a fully monitoring flow meter setup is optimal.

These water price cutoffs, which define the borders of each optimal method, vary significantly with the inputs of the prices of flow meters, smart valves, leak detection robots, and robot stations. To look at the costs of flow meters and smart valves as dependent variables on water costs, we specifically looked at case (A) with just flow meters and case (B) with just robots and valves. In the case of just flow meters, to determine the maximum allowable flow meter cost, the total cost of the optimal DMA method at a given water cost was found, and then the total cost of the fully flow meter monitored system was set equal to that. From the total cost of fully flow meter monitored system, the price of a flow meter could be found. This analysis showed as expected that the acceptable price of a flow meter increased with the cost of water, as can be seen in Fig. 3-6. With water at $0.046/m³, a flow meter would have to cost $54, however if the price of water increased to $0.51/m³, a fully monitored flow meter system would be beneficial as long as the flow meter cost $135 or less.

![Maximum Flow Sensor Price to Break Even with DMA Creation](image.png)

Figure 3-6: Cost of flow meter in fully monitored flow meter method to equate to optimal DMA method at given water cost.

To create an equivalent plot in the case of just robots and valves is slightly more complex as the valves serve minimal use without robots and robot stations. Thus to evaluate the maximum feasible price of valves the robot unit cost was set to $100 and the robot station unit cost was set to $1,000. Then the total cost of the optimal DMA
method at a given water cost was found, and then the total cost of the valve-robot system was set equal to that. From the total cost of valve-robot system the price of a valve could be found. This analysis showed as expected that the acceptable price of a valve increased with the cost of water, as can be seen in Fig. 3-7. With water at $0.046/m³, a flow meter would have to cost $16.50, however if the price of water increased to $0.51/m³, a fully monitored flow meter system would be beneficial as long as the flow meter cost $76 or less.

In addition to evaluating the cost comparison of these four systems for leak detection and localization, other factors could play into the ultimate choice of a system. For example, in the fully flow sensing case (A), flowmeters could enable sensing of water quality or contaminant levels to allow for improvements in water quality sensing that would not be seen in a traditional DMA system. Alternatively, in either the valves and robots case (B) or the valves, robots, and flowmeters case (C), the valves and robots could allow for additional control and speed of repair. Smart valves could be remotely controlled or automated to shut of water supply to small localized regions in the event of a pipe burst or other maintenance that needs water to be shut off. Robots could be augmented so that in addition to detecting and localizing leaks they could temporarily patch and repair leaks, allowing less water to be wasted and low-
ering repair costs. Additionally, leak detection robots have been shown to be able to
detect smaller leaks than can’t be found through traditional, above ground methods. [24] By detecting smaller leaks, the net water lost can be further minimized, and the water system can be better modeled and understood.

3.5 Conclusions

In this chapter we have examined the cost analysis of three new, more instrumented systems for leak detection and localization. A mathematical formulation has been created to evaluate the trade off between these systems and more traditional DMA systems given the cost of water and cost of technology needed (smart valves, smart flow meters, in-pipe leak detection robots, and robot stations). To continue this analysis, one could expand to incorporate costs which were not typically analyzed such as infrastructure damage due to pipe bursts. Another possible future analysis could include analyzing more than just leak detection and localization; one could look into how leak repair costs could be lowered with more potential shutoff valves, or robots that might be able to repair some leaks with minimal human assistance. As research and production of low cost sensors continues to grow, understanding the trade offs in smart WDNs will allow for water to be used more safely and efficiently.
Chapter 4

Adding Valves to Retrofit Pipe Networks

4.1 Overview of Robot Control In Pipes

Currently our lab is developing in-pipe leak detection robots which travel with the flow of water to detect leaks. In order for these robots to operate in more complex systems of pipes with branches, their trajectory needs to be controlled in some manner. To control their trajectory one could:

1. Add actuation to the robots to give them control over turning in water pipes.

2. Manually open and close valves to control robot movement.

3. Add smart valves to some or all of the pipe joints to automate water flow and hence robot movement.

The first option has been used previously in more expensive and complex robots which detect leaks in pipes [22], and has been investigated to minimize the complexity of a swimming robot in [26] and [15]. By adding robot actuation the robots are in control of their own path, however they are also more expensive and larger. The second option requires a lot of human intervention and precise coordination to time the opening and closing of these valves to align with the robot’s movement. These
manual valve turnoffs can often be buried underground, and thus need to be dug up, or if they are more easily accessible need to be secured to ensure they are not tampered with. Overall having humans control the valves might work for a low number of robot inspections, but for sustainable use a more automated system would be beneficial. The third option, which is also discussed in the cost analysis chapter, allows control of smaller, cheaper robots. Hence in this section we will look into this method.

We will look at this method to determine the cost/ benefit tradeoff of how many valves are placed. To do so we will aim to develop an algorithm to answer the questions:

1. At what threshold is it beneficial to put a valve at every pipe joint?

2. If that threshold has not been reached, where valves should be placed to meet the optimal cost versus functionality tradeoff?

### 4.2 Valve Placement Cost Function

The optimal cost versus functionality tradeoff was defined to be the sum of all the costs minus the functionality benefit. The costs were simply the number of smart valves \( n_v \), plus the number of robot end stations \( n_e \), plus the number of robot start stations \( n_s \). The functionality was the sum of the maximum probability (in a given valve on/ off configuration) that a robot would travel through each pipe.

For example, if a system had two valves it would have four configurations \(((v1,v2)\) could be (open, open), (open, closed), (closed, open), or (closed,closed)). If a system had only one valve it would have two configurations (open) or (closed). Looking at this system with one valve, if it had five pipes \( n_p = 5 \) and when the valve was open the probability the robot would flow through each of these five pipes was \((1,.5,.5,.1,.4)\) and when the valve was closed the probabilities would be \((1,0,1,.2,.8)\) then the maxima of those two sets would be \((1,5,1,2,.8)\), and the total benefit of that scenario where just one valve is added would be \(1+.5+1+.2+.8 = 3.5\). This benefit sum is finally multiplied by a tunable weight \( w \), depending on the relative importance.
to the user of the costs versus the benefits. Writing this out as an equation, with

\[ p_{\text{robot}}(i) = \text{probability robot travels in a given pipe } i \] and \( c_v = \text{combination of valves which are closed} \), the cost function looks like:

\[
\text{cost} = n_e + n_s + n_v - w \sum_{i=1}^{n_p} \max(p_{\text{robot}}(i)|c_v)
\] (4.1)

4.3 Valve Placement Algorithm

Next I wrote an algorithm to test possible robot station and valve placements to find an optimal solution for an arbitrary input network. To do this I used EPANET to initially model the system, and also to run flow simulations to find the water flow in different pipes given different configurations. The EPANET simulations were controlled by MATLAB code, which given an input EPANET .inp file, and weight \( w \), can output optimal placement of robot stations and valves. The overall structure of this optimization algorithm is outlined below.

Table 4.1: Algorithm: Identify Optimal Placement and Number of Valves and Robot Stations

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Iterate through possible combinations of closed pipes, keep those that are hydraulically feasible.</td>
</tr>
<tr>
<td>2</td>
<td>Iterate through potential starting points, find robot path probabilities.</td>
</tr>
<tr>
<td>3</td>
<td>Find baseline probabilities that a robot will reach each pipe, for a robot in a pipe system with no valves.</td>
</tr>
<tr>
<td>4</td>
<td>Remove configurations that are worse than or equal to all baseline probabilities.</td>
</tr>
<tr>
<td>5</td>
<td>Search through combinations of valve placements and starting locations to find an optimal combination.</td>
</tr>
</tbody>
</table>

4.3.1 Find Hydraulically Feasible Configurations

As the first step, the program iterates through each combination of potentially closed pipes to find which pipe closure combinations are hydraulically feasible. A pipe closure combination is hydraulically feasible if the demands at each node can be
met in a steady-state manner. This is executed by looping through the $2^i$ possible combinations of pipes which could be open or closed (where $i$ is the total number of pipes). Each combination of pipe closures is simulated in EPANET, and if EPANET throws an error by reporting a large negative pressure, that combination of closed and open pipes is marked as infeasible and will be excluded from the rest of the analysis. Fig 4-1-a shows an example of a hydraulically feasible set of pipe closures, and 4-1-b shows an infeasible set of pipe closures.

Figure 4-1: Part (a) shows a pipe closure which is hydraulically feasible as water flow can still reach each of the nodes. Part (b) shows a hydraulically infeasible set of pipe closures as a node is unable to meet its water demands.

4.3.2 Find Robot Path Probabilities

Each hydraulically feasible configuration is next expanded into $n$ potential robot start points where $n$ is the number of nodes in the graph. For each of these start points the recorded flow rates from step 1 for the given configuration are used to determine the probability a robot starting at that start point would pass through each of the pipes. The robot is modeled to have the same probability distribution as the water that pushes the robot, and hence if $x\%$ of the water flow takes the left branch, $x\%$ of the time the robot will take the left branch.

An example of this can be seen in Figure 4-2 as the flow dictates that if the robot starts at the node circled in green, it will follow the shown path with probability = 100 $\%$ and end at the node circled in red.
Figure 4-2: An example robot path is shown if the robot starts at the node circled in green, it will follow the shown path with probability = 100 % and end at the node circled in red.

4.3.3 Find Baseline Probabilities

Now that we have all the robot flow possibilities that can be generated by opening/closing valves and varying starting points we want to choose one as a baseline to make the data set a more manageable size. To choose this baseline I chose to look at the case where no valves are present. For each of the potential starting points in this case of no-valves, the cost function (4.1) is evaluated. This case is chosen to be the baseline, and the baseline case for the sample network is shown in 4-3.

Figure 4-3: For this network, when no valves are present it is optimal for the robots to start at the tank circled in green.
4.3.4 Remove Sub-par Configurations

To limit the number of configurations that need to be analyzed, in this step all configurations that do not improve on the base configuration are removed. Configurations that do not improve on the base configuration are ones that for each pipe in the network have an equal or lower probability of a robot passing through that pipe on an average run. One example of such a case is shown in 4-4 where the robot has a 100% chance of going through the last pipe, however this is also true in the base case and thus this configuration can be removed from further analysis.

![Diagram](image)

Figure 4-4: In comparison to the baseline case shown in 4-3, this case is sub-par as it adds no improved chances of a robot visiting a given pipe.

4.3.5 Find Optimal Combination of Configurations

Finally in this step we iterate through a variety of combinations of configurations to find the combination with the minimal cost. For the example shown, we chose to look at combinations of three configurations at once, and for each combination of three configurations the total number of unique starting and ending points would be combined with the highest probability the robot passes through each pipe segment to calculate the total cost for that combination. In 4-5 it can be seen that for this case the optimal combination was 3 very controlled and very certain paths.
4.4 Valve Placement Example Results

In this example network, there are two alternating tanks - for the majority of the time the lower left tank supplies the nodes to meet their water demands, and then occasionally the upper tank will be used to refill the lower left tank. For this analysis we looked at the condition where for the majority of the time the water is flowing out of the tank on the bottom left and to the five nodes to its right.

To run an example, one must chose a weight $w$, to weight the relative importance of the costs of the robots and robot stations versus the benefits of having a higher probability of reaching any given pipe. Here the weight was chosen to be $w = 10$ which showed a strong preference to a high probability the robot could reach any section of the pipe.

From this weight and the input pipe map, the algorithm found that the optimal control was to add valves to every branch to maximize control over the robot’s movement. The pipes controlled by valves, along with the starting and ending stations can be seen in 4-6. By placing many valves, the optimal solution allowed the robot to
reach any given pipe with 100 % certainty, as can be seen in 4-7. Finally, the paths combined into this optimal solution can be seen in 4-5.

![Diagram](image)

Figure 4-6: This shows the results optimal control when \( w = 10 \) is to use valve control on the yellow pipes, have one starting station at the green star, and one ending station at the red star.

![Diagram](image)

Figure 4-7: This shows the results optimal robot reaching pipe probability when \( w = 10 \) is that the robot is 100 % certain it can reach any of the pipes which are currently connected to the water flowing from the left tank to the consumers.

To contrast the \( w = 10 \) example, I next present a \( w = 1 \) example. From this weight and the input pipe map, the algorithm found the optimal control was to add valves to two of the branches to balance control over the robot's movement with the importance of lowering installation cost by not placing too many valves. The pipes controlled by valves, along with the starting and ending stations can be seen in 4-8.
By placing valves on two pipes the optimal solution allowed the robot to reach pipes with improved, but less than 100\% certainty, as can be seen in 4-9.

Figure 4-8: This shows the results optimal control when $w = 1$ is to add valve control to the yellow pipes, have one starting station at the green star, and one ending station at the red star.

Figure 4-9: This shows the results optimal robot reaching pipe probability when $w = 1$ is that the robot can reach pipes which are currently connected to the water flowing from the left tank to the consumers with improved, but less than 100\% certainty.

Overall, we can see that as the weighted importance of the probability of a robot reaching a given pipe in the first trial versus the installation cost of valves and robot stations is varied, the optimal solution varies. For this sample network, the correspondence can be seen in 4.2.
Table 4.2: Optimal Network Solutions for Varying the Parameter $w$

<table>
<thead>
<tr>
<th>$w$</th>
<th># of valves</th>
<th># of start stations</th>
<th># of end stations</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>3</td>
<td>4</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>10</td>
<td>4</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

4.5 Conclusions

In this chapter a method for determining where to place smart valves in networks to best direct in-pipe leak detection robots has been developed and demonstrated. This method currently accounts for a weight which signifies the relative importance of low initial material cost versus higher probability of robot reaching a specified location on a given run. The method can easily be modified to give different weights to the individual costs of each valve, each starting station, and each ending station. The method can also be modified to give different weights to each pipe, to say that some pipes are more important to be able to reliably reach with a robot than others.

The more difficult aspect of this method to improve is it’s scalability. Currently a large number of pipe configurations are generated (lets call this $x$) and then some subset of them are selected to find a subset with an optimal cost (lets call this number of solutions in each subset $y$). However, this creates a solution space that is of size $x!/(y!(x-y)!)$, which grows as $x!/(y!(x-y)!))$. Thus this method could be improved by finding a faster way to solve these large combinations, which would allow the algorithm to run on larger and hence more realistically sized pipe networks.
Chapter 5

Conclusions and Recommendations

5.1 Conclusions

This thesis built upon the concept and prior versions of a pressure gradient in-pipe leak detection robot to improve the robot’s leak detection capabilities, and model how leak detection robots could be used in a smarter Water Distribution Network (WDN). To model how leak detection robots could be used in a smarter WDN, this thesis first modeled and compared the costs of a few highly instrumented, smart WDNs against the current leading model of District Metered Areas (DMAs). In addition, this thesis presented an algorithm to convert a network of pipes into a smarter network by optimizing the number and location of smart valves placed to direct in-pipe leak detection robots.

To improve the leak sensing capabilities of the robots, this thesis looked into designing a soft sensor to sense bending direction and magnitude. The design of this sensor consisted of an electrically conductive rubber piece to serve as a strain gauge, a piece of fabric, and some non-conductive rubber. By putting the fabric on one side of the strain gauge, the neutral axis of the device is shifted so that bending the sensor in one direction results in compression in the conductive rubber, while bending the sensor in the other direction results in elongation of the rubber. This soft bending and pull sensor is demonstrated in two applications: as a sensor for the movement of a fish tail, and as a sensor on an in-pipe leak detection robot to sense leaks and...
bumps. The bending angle sensor for the fish tail showed an ability to differentiate the direction of bending and the magnitude (as tested with 15, 30, and 45 degree bends). It significantly outperformed the past sensor, as the past sensor could rarely sense direction of bend and had less sensitivity to magnitude of bend. The bump and leak sensor for the in-pipe leak detection robot demonstrated the sensor's ability to differentiate between a leak pulling on the sensor and a bump bending the sensor inward. This sensor showed significant improvement on the prior no-fabric sensor, which could notice bumps and leaks, but was unable to differentiate between the two.

After improving the leak sensing capability this thesis zooms out to look at the larger picture of comparing current Water Distribution Networks optimized using a District Metered Area approach to proposed, smarter, more instrumented methods. In particular, it compares three more instrumented methods: one with complete coverage of the network using smart flowmeters, one with added smart valves on each joint to direct in pipe leak detection robots, and a final network with both smart flowmeters and smart valves paired with in-pipe robots. These methods were compared by analyzing the total cost to sustainably implement each control method per year. These average costs per year were compared with varying source water costs. As one might predict, it was seen that the total yearly cost of the smarter, more instrumented, methods was less dependent on the price of the sourced water. Thus at higher source water prices the more instrumented methods showed greater benefits in comparison to the traditional DMA method. Additionally a sample case with inputs of price of flowmeter = $150, price of smart valve = $75, price of leak detection robot = $100, and price of robot station = $1,000 was analyzed. This sample case showed that at low water prices the traditional DMA method is optimal, at slightly higher prices the robots and valves method is optimal, and at even higher water prices the flowmeters on each pipe method is optimal. Overall, to complete this comparison a method was developed with inputs of flowmeter price, smart valve price, robot price, and robot station price, which allows for the yearly operating cost to be calculated and analyzed.

After looking at overall smarter network costs, this thesis looks at how to effec-
tively convert a standard network into a smarter network. This section focuses on the control method where robots travel through pipes and are directed by smart valves. In this method, fewer valves require more robots to be sent on average in order to reach a particular pipe. Alternatively, if more valves are placed, there is a greater startup cost to purchase and install valves. Thus this optimal valve placement method is developed to determine the optimal number and placement of valves, start locations, and end locations, given a network and a relative importance of not placing too many valves versus having more control of robot travel in the pipe network. This thesis demonstrates the method on a sample pipe network, and shows how as the relative importance changes the optimal number of valves and placement of valves changes. As is expected, placing a higher weight on the importance of not sending too many robots results in more valves placed. In the sample network analyzed, a weight of 1 results in 2 valves placed, a weight of 2 results in 3 valves placed, and a weight of 3 or higher results in 4 valves placed. Overall this method has been demonstrated to successfully places valves, robot start locations, and robot end locations optimally according to the defined cost function.

5.2 Recommendations

To continue toward a future of automated water distribution and leak detection there are important steps to take on improving the pressure based leak detection robot and improving the management of the smart water distribution network. The overall aim of these future steps is to make the leak detection and network management technologies more reliable and more affordable.

With the in-pipe leak detection robot, in order to use this robot on a larger scale and for a larger period of time, the robot will need to be able to fully manage itself within a large and complex pipe network. This means the robot will need improved localization technology and automation to accurately pinpoint a leak location and report it to the water utilities company. Additionally, the robot could be improved to not only locate leaks, but to also help temporarily patch, or permanently repair
them. By automating a larger section of water pipe network maintenance, the entire process could happen faster, result in less water loss, and require less human labor.

Within the section of choosing an optimal water network control method, the choice is highly dependent on cost of smart valves, flowmeters, in-pipe robots and robot stations. Thus future work could focus on creating lower cost sensors, or minimizing the installation cost of these sensors. In addition to the sensors themselves, there needs to be communication between the sensors to create a smarter pipe network. Some of these communication methods are already in development with the Internet of Things, however sensors on underground water pipes add challenges. For these sensors, their signals must either travel along the pipe or through potentially multiple meters of dirt, while also not consuming too much power. This communication and powering technology is key to improving and potentially implementing a smarter, fully sensing, water distribution network.

Thirdly, within the section of retrofitting a standard water pipe network with sensors, the method could be further improved. Currently the method for optimally placing valves along with start and end robot stations works well for small systems but time to run scales exponentially with network size. To further develop valve placement algorithms, the constraint on optimality could be relaxed, and replaced with an emphasis on finding a good solution for a larger network in a more scalable manner.

Through this further suggested work, improved in-pipe leak detection robots and automated leak detection networks can be created. The automation of the leak detection (and potentially the repair process) too will allow for lower water losses, lower damage due to water pipe bursts, and fewer interruptions in water service. This will allow cities around the world to not only be more environmentally friendly by conserving water, but also provide a higher quality of life in terms of uninterrupted access to clean, fresh water.
Appendix A

Additional Notes for Soft Sensor Experiments

For the general sensor build process it is key to note that when the Smooth Mold Star 30 rubber is mixed, it is important to avoid adding bubbles to the mixture as if those bubbles end up in the final sensor they will change the bending motion of the sensor and make the sensor more likely to rip. Bubbles may be minimized by placing the mixture in pressure controlled container immediately after mixing, and lowering the pressure so bubbles rise out of the mixture. However this is an additional step and takes time, so it may not always be beneficial. Additionally, for some molds it is helpful to spray the mold with mold release before pouring the rubber, as the mold release will make it easier to removed the molded part at the end.

For the soft leak sensor experiment a few additional details about implementation may be helpful. Most of the non-sensor parts of the experiment: the molds, and the test robot frame, were 3d printed. The sensors were then super glued to the 3d printed brackets so that they would not fall out when pulled, but would still be able to stretch. After the sensors were glued into place, hot glue and Silpoxy were used to waterproof all connections. To test the waterproofing one should start the data collection program with the sensors out of the water, and then lower the sensors into the water. Any sensor which sees a significant delta between the out of water and in water state is not fully waterproofed. Not waterproofed sensors will have much
higher noise levels, making data collection and analysis very difficult. Alternatively, a
similar variant of this experiment can be conducted without the sensors in water, and
the water leak can be replaced with an air leak. Additionally, for the data collection
for both the fish tail and leak sensor experiments Labview was used.
Appendix B

Additional Notes for Simulations

Two main simulations were presented in this thesis. The first set of simulation software is related to the "Cost Analysis of Network Management Methods" chapter, and the second set of simulation software is related to the "Adding Valves to Retrofit Pipe Networks" chapter. Both of these simulations were written in MATLAB R2017b, and can be found in the Dropbox>Leak Detection Project>Past Work>emittman folder.

The "Cost Analysis of Network Management Methods" software only needs the appropriate MATLAB installation to run. All the plots included can be generated by running the "overallNewAndOldCostCompare.m" file.

The "Adding Valves to Retrofit Pipe Networks" software requires the appropriate MATLAB installation, along with the MATLAB EPANET library. In my report I have used EPANET 2.0 and the corresponding EPANET to MATLAB library for MATLAB. This simulation can be run by first running "start_toolkit.m" and then running "overallvFinal.m". By adjusting the parameters for number of solution combinations, "n", and the cost weight, "scalarWeight", all presented plots can be produced.
Bibliography


