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Leak Detection Using Flow-Induced Vibrations in Pressurized Wall-Mounted Water Pipelines

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ABSTRACT Wireless sensor networks (WSN) provide a powerful solution to the task of monitoring the operational conditions of buried and non-buried pipes of different lengths and materials. Due to the limited energy stored in the sensor nodes, the use of low-power vibration sensors becomes the preferred choice. However, the monitoring of vibrations for leak detection in wall-mounted pipelines, and the associated complexities are not adequately dealt with in the literature. This article offers to fill this gap by presenting a feasibility study of leak detection in wall-mounted water pipelines through vibrations measurements using low-power accelerometers. The work is divided into two steps: Firstly, a careful analysis is performed to understand the effect of various fittings such as clamps, bends, and leaks of various sizes, on the vibrations produced. Then this knowledge is used to find the best locations for placement of nodes in order to efficiently detect leaks of various sizes. This analysis revealed two important facts: (a) difficulty in detecting medium-size leaks as their vibrations and those from the no-leak condition are very indistinguishable, (b) vibrations measured away from the leak are of a small benefit to the leak detection process. Consequently, 3 different learning models are applied, all fed with information from multiple nodes, in order to reliably detect leaks and classify their size. Comparing the performances of these models shows that the Support Vector Machine (SVM)-based model gives the best results, in that for the worst case of medium-size leaks and with the use of one sensor, the worst accuracies for leak detection and leak size classification have remarkably been improved from being respectively 51% and 36% with one sensor, to being 88% and 93%, respectively, with only a moderate increase in the number of sensors to four.

INDEX TERMS Accelerometers, leak detection, machine learning, vibration measurement, wall-mounted water pipelines, sensor networks.

I. INTRODUCTION

Pipelines play a vital role in transporting various types of fluids in industries, as well as in carrying water and gas for usage in residential and commercial buildings. Due to aging of pipelines and external damages, leaks and ruptures occur, resulting in loss of precious water [1], possibly severe damages and disasters that carry a heavy maintenance and cleaning cost, and even risks to human lives depending on the severity of the damages incurred by the occurrence of these leaks. To mitigate the nefarious effects of the damage caused by leaks and to inform the maintenance authorities in the shortest possible time, various automated Pipeline Monitoring Systems (PMS) have been developed for use in industry. These monitoring solutions differ from each other in various respects such as pipeline characteristics that include the material the pipeline is made of [2], the surroundings of the pipeline itself, the size and geometry of the monitoring network [3], the nature of the application being monitored and various types of leak detection instruments, including sensors, and monitoring methodologies used.

Among various pipe materials, plastic pipes are most commonly used because of their better strength, flexibility [4], light weight that facilitate their deployment over large areas, protection from corrosion and resistance to bursts that may occur due to hydraulic variations and seismic waves.

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Most water distribution companies use plastic pipeline for transporting water instead of cast iron and asbestos or cement pipelines [5]. The monitoring system used depends on several factors such as the pipe material, length, diameter, type of mounting, presence of bends and loops in the pipe, overground or underground pipe locations, etc. [6]. The sensing mechanism most commonly used is a network of pressure and flow sensors. However, vibration sensors consume less power and hence provide a much-needed extension to the operational life of the sensor nodes [7].

After scouring through the available literature for various measurement approaches in different pipeline and leak detection setups, the study carried out here on clamped wall-mounted plastic pipelines for leakage detection and localization purposes is the first of its kind. The novel contribution of this article is to measure flow-induced vibrations in pressurized wall-mounted water pipelines using accelerometers, and to develop a cost-effective and energy-efficient scheme to detect a leak, and classify its size as either small, medium, or large, by optimally placing the sensor nodes at carefully-selected locations.

Our lab setup has a great practical relevance in that it represents typical setups used in residential and commercial buildings. In such environments, and particularly for internal pipelines in high-rise buildings, it is reported that accessibility to pipes is poor, thus rendering the visual detection and localization of leaks quite challenging, difficult and, in some cases, downright impossible [8]. Even for other non-high-rise buildings, the accessibility of pipes in many cases is quite poor due to their location within walls, under slabs and in other tight and difficult-to-access areas [9]. Due to the difficulties in accessing such ''hidden'' pipes, any leaks and/or defects that may develop in them will remain undetected for long periods of time, while slowly and dangerously increasing in severity and gravity, constantly eating away at the very structure of the building that houses the pipes, until these leaks start to have their damaging effects finally manifest themselves and becoming visually noticeable on external surfaces, but at a much later time when the building, or part of it, has already been irretrievably damaged. Such scenarios represent real cases where not only the detection of leaks is difficult to achieve but their localization becomes even worse.

The main objectives and contributions of this study are firstly to examine the variations in the vibrations acquired throughout the pipeline, from clamp to clamp, as well as register the effect on vibration changes, of the presence of valves, flow meters, and both angled-and u-bends. This is achieved by deploying accelerometers at various key locations on the pipeline so as to both compare and analyze the differences in readings. Secondly, these recorded differences are then used to quickly identify the most plausible leaky section of the pipe and help guide the pipeline engineer in the deployment of the sensor nodes at a few key locations in order to localize the leak and classify its size, in two different ways: Firstly, by using sensor readings directly from the identified leaky section of the pipeline, and secondly by using the sensor readings from other adjoining sections of the pipe.

Following the introduction, the rest of the paper is organized as follows: In section II, the related work is discussed. Section III covers the methodology for the acquisition of vibration measurements and their analysis, and discusses the selection of key sensor locations, and its impact on detecting the leak. Section IV presents the experimental results and a thorough analysis and discussion of the performance of the proposed leak detection scheme. Finally, Section V gives the conclusion and briefly outlines some future work.

II. RELATED WORK

The most commonly-used PMSs are based on pressure and flow sensors, that use transient-based analysis for abnormality detection [10]–[17]. This type of monitoring system is easy to install and gives a better sensitivity in leakage detection as compared to other techniques such as using acoustic emission measurements [18]–[22], ground-penetrating radars [23]–[27] and infra-red thermography [28], [29]. All these solutions provide their own unique and intrinsic advantages, but a common disadvantage they all share is their high material, maintenance and deployment costs, specifically their need for sensor deployment at multiple locations in order to cover the entire network, which causes further logistical difficulties. In addition, the power consumption of the above-mentioned techniques is also high. A more detailed comparison of these techniques can be found in [7], [25]. Vibration-based pipeline monitoring systems (V-PMS), however, require less power and are less costly. V-PMS and are equipped with various sensing mechanisms such as geophones, hydrophones and accelerometers [7]. Several studies compare the leak detection performances of these sensing mechanisms with different pipeline materials. It is found that accelerometers are the best sensors to use for measuring vibrations in plastic pipelines [30], [31]. Although such V-PMS cover relatively short distances compared to other sensors, their lower cost allows for the deployment of multiple sensors to cover large areas, thus making them far better candidates for use in WSN-based monitoring schemes, than other sensors.

As pipelines are characterized by many parameters that affect flow and leaks, it is therefore very difficult to capture accurately this multi-parameter dependence of the pipeline behavior in a dynamical model. Therefore, in the face of this complex pipeline dynamical behavior, a data-based solution, rather than a model-based one, is preferred to achieve reliable monitoring and accurate leak detection. To this effect, and thanks to their detection and classification power, machine learning models are usually developed, fed with measurements from multiple sensing nodes in order to detect various conditions relevant to the problem at hand. As examples of use of such models, [1] presents a stochastic model for failure forecasting of water mains using the collected data, and [2] provides various intelligent approaches for the prediction. Also, [32] presents a WSN-based monitoring scheme based on a leak identification method for water pipelines that relies on the combined use of Principal Components Analysis (PCA) and SVM. The highest identification accuracy achieved by this model was around 98%. In [6], a deep learning (DL) algorithm is discussed, using accelerometer data from the pipeline for automatic leak detection in PVC pipelines. It is reported by the authors that 95% accuracy is obtained from the CNN (Convolutional Neural Network) model that is based on general locations data for leakage detection. However, the accuracy further improves to 98% when the model is based on carefully selected locations data, thus emphasizing the importance of the effect of sensor location on leak detection accuracy. In [3], an unsupervised classification technique is presented to collect vibration data from PVC pipes using accelerometer data and categorize them into leaky and non-leaky classes.

Various types and models of accelerometers are available, with their own intrinsic merits and demerits, to be selected from, and used in research. These include Hitachi-Metals H34C [52], Beanair-AX3D [39], PCB Piezotronics 393B12 [42], MMA 7361 [44], [53] and MPU6050 [43], [53]. Among these, some are accurate and precise, but consume high power. The obtained accelerations data has three values, each one representing vibration on a single axis. In order to compare vibrations at different locations, a suitable measure/metric is required. Some papers, such as [46], [52], [53], use only single-axis accelerometers, but this requires a good a-priori knowledge about the axis of maximum vibration. In [43], a tri-axis accelerometer was used and the resultant magnitude of the three-axes was used as the final measurement, which is also adopted in this article, as it is a more accurate metric than the single-axis one. The work of [4] compares the leak detection performance in water pipelines, of a three 3-axis accelerometers, ADXL335 MPU6050 and MMA7361, classifies their performances for 3 leak sizes, namely no-leak (hence 0 mm), 1mm and 3mm leak sizes, and concludes that ADXL335 outperforms MPU6050 and MMA7361 in this respect.

The Standard Deviation (SD) of the collected vibration data is used as a further measure to distinguish between vibrations under different pipeline conditions, as in done in [49], [50], [54]. Other Measures, like Inter Quartile Range (IQR) and Monitoring Index efficiency (MIX), were also used in some studies for condition-based vibration discernibility purposes.

Research groups worldwide investigated the feasibility of PMSs using both lab-based as well as real setups. Table 1 summarizes and compares various types of pipeline testbeds along with measurement systems used for leak detection and localization. These schemes considered buried and unburied pipelines of various material types, dimensions and flow-specifications, and different leak detection techniques using hydrophones and accelerometer measurements. However, the monitoring of vibrations for leak detection in wall-mounted pipelines requires a different treatment, such as considering the effect of clamps, and the close proximity of pipe and other components to the wall, thus causing a non-negligible loss of flow- and leak-induced vibrations that will end up being attenuated, if not altogether absorbed, by the nearby walls. To the best of our knowledge, these important factors are not dealt with at all in the literature since these are unique to wall-mounted pressurized pipeline setups.

III. METHODOLOGY

The methodology used here hinges on the use of accelerometers to measure flow-induced vibrations in pressurized wall-mounted water pipelines to detect a leak, and classify its size (i.e. small, medium, large) by optimally placing the sensor nodes at suitable locations. Vibrations depend mainly on the flow rate. However, even with a constant flow rate, steady-state vibrations are different throughout the pipe because of the presence of clamps placed at every few meters along the pipe, the distance of the pipe from the wall it is mounted on, and the various types of bends and junctions in the pipe, as well as the presence of other various instruments connected to the pipe. In order to better monitor the pipe for the presence of a leak, the vibration sensors should be placed at locations where the vibrations are significant enough to distinguish between the flow-induced ones and those due to leaks. This objective is fulfilled in two steps: Firstly, the analysis of the difference in vibrations throughout the pipe, that are due to the effect of bends, clamps, flow meters, leaks, etc., is carried out in order to determine the best possible locations to position the sensor nodes. The best possible location is determined experimentally after carrying out a series of extensive and repeated trials to select, for every sensor, the specific location that reveals the most significant difference in vibration levels for different leak sizes. Secondly, to localize a leak, and estimate its size, first through a single sensor using the direct (non-learning-based) approach, and then using 3 different Machine learning based classifiers i.e. Support Vector Machine (SVM), Fine KNN (k-nearest neighbors) and Medium Decision Tree (DT) using data from 4 sensing locations, for a more accurate and reliable leak localization.

A. APPROACH TO VIBRATION MEASUREMENT AND ANALYSIS

An experimental setup of a wall-mounted pipeline network is developed as shown in Fig. 1, which includes clamps, flow meters, various types of bends, and control valves to simulate the leak. The effect of these components on the generated vibrations is first investigated by first selecting a few candidate pipeline sections, mounting the accelerometer sensors on the pipe surface, and then comparing the measurements collected from these sensors.

Firstly, the variations in vibrations across straight sections (from clamp-to-clamp) are investigated by selecting a few sections from the pipeline, which have different lengths, and which also include some components such as control valves and flow meters. It is intuitively understood that the vibration magnitudes are higher in the middle of the section

TABLE 1. Comparative review of pipeline testbeds and setups along with the major contributions proposed in previous studies for leak detection and localization.

Ref.	Details of pipeline setup	Application	Sensor technology	Main Contribution in the field of pipeline monitoring
[5]	Length: various lengths Diameter: 102mm, 100mm, 120mm Material: Cast Iron, Asbestos Cement and Polyethylene pipe Structure: Real world water distribution systems	Water Distribution pipes buried and backfilled with soil	Accelerometer	Studied the impact of pipe material by investigating vibro acoustic emission signals in a real water distribution system.
[33]	Length:16m Diameter:76mm Material: PVC Structure: Single closed loop with one 45° and two 90° bends	Buried Water Mains at 0.6m depth with underneath Sand Cushion	Bruel and Kjaer 4507-B-006 (accelerometers)	A non-invasive index for leak detection is proposed based on cross-spectral density of pipe surface accelerations
[3], [6], [34]–[36]	Length: 9.76m (main loop) Diameter: 76mm and 102mm Material: PVC Structure: Two Looped having Various bends and T-joints	Buried (Solid Filled) at 0.5m depth and Unburied Water mains with sand cushion	Bruel and Kjaer 4507-B-006 (accelerometer)	In four different studies on same setup they investigated 1. Effect of soil back fills on leak detection index. 2. Leak detection index is evaluated in a complex, multiple looped pipeline setup. 3. CNN model to predict the leakage sizes. 4. Pipeline system dynamics using CNN.
[37]–[39]	Length: 6.33m Diameter: 59mm And 25.4mm Material: Ductile iron and PVC Structure: Straight pipe	Distribution pipes supported on bricks	Beanair AX3D (accelerometer)	A model is proposed for leakage detection and severity. In other study, data was analyzed by SVM, Decision Tree and Naïve Bayes.
[30]	Length: 110m Diameter: 150mm Material: Plastic Structure: Straight pipe	Buried Water Distribution pipes at 0.8m depth	Bruel and Kjaer, 8103 (Hydrophones), Ion, SM-24 (Geophones), Bruel and Kjaer, 4383 and 4384 (Accelerometer)	Previously proposed acoustic model of pipe and sensor is verified by using all three sensors and their accuracy is compared.
[40]–[42]	Length: 25m Diameter: 63mm Material: Medium Density Polyethylene (MDPE) Structure: Oval recirculating pipe with multiple loops.	Buried Water Distribution pipes at 0.5m depth and backfilled with water, geotextile fabric and gravel	PCB Piezotronics 393B12, (Accelerometer), Bruel and Kjaer, 8103 (Hydrophone)	Using Vibro-acoustic emission signals, in three different studies, they evaluated the effect of different backfills, Different leak flow rates and different leak shapes.
[43]–[47]	Length: 10m Diameter: 25.4mm Material: Acrylonitrile Butadiene Styrene Structure: Straight pipe experimental test bed	Distribution Water Pipes	MMA7361, MPU6050 and ADXL335 (Accelerometers)	Different leak detection sensor units are designed and are used against different pipe material in different studies.
[48]–[50]	Length: - Diameter: Various Diameters Material: Plastic Structure: Real world pipelines	Real world Buried pipelines of water mains	IEPE (accelerometer), PCB (piezoelectric)	Vibration-based leakage detection tools and techniques are developed, and cross checked experimentally.
[31], [51]	Length: 28m Diameter: 32mm and 90mm Material: Polyethene Pipe Structure: Straight	Buried and Unburied water pipes of various diameters that mimics customers connections of water mains	Mistras WSα (Acoustic Emission sensor), Wilcoxon Research H571LD-1A (piezoelectric hydrophone) And PCB 333B55 Piezotronics (IEPE monoaxial accelerometers)	Small-diameter pipelines are considerably studied in first study. In next research they cross examined the usage of hydrophones and accelerometers for such pipelines.

as compared to those close to clamps, since the latter ones, due to their rigidity, can be viewed as acting like vibrations attenuators to stabilize the wall-mounted pipeline networks. Secondly, the effect of angle bends, U-bends and flow meters on the measured vibration is investigated by taking measurements at various locations for sections that include U-bend, angle bends and flow meters. In addition to analyzing only the magnitude of the collected vibrations, other important

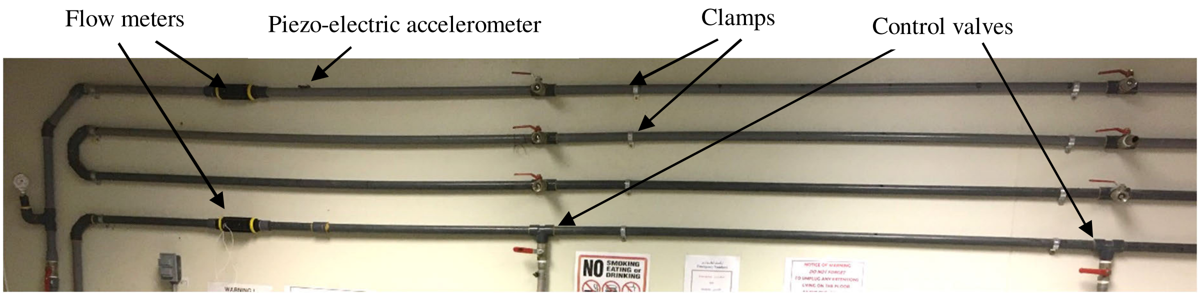


FIGURE 1. Actual wall mounted setup.

characteristics of these vibrations, such as their frequency (or spectral) content and their dominant spectral components need also to be analyzed as these are crucial for selecting the correct sampling rate to use. This is achieved by carrying out a frequency analysis in MATLAB, by taking the Fast Fourier Transform (FFT) of the vibration signals acquired at the various selected locations on the pipeline.

The accelerometer ADXL-345 is selected to measure vibrations because of its better sensitivity, power consumption and inactivity detection capability. ADXL-345 is a tri-axis accelerometer that can sense acceleration due to gravity as well as dynamic acceleration due to motion and velocity has a selectable measurement range (from $\pm$2g to $\pm$16g) and a resolution which increases with the measurement range up to 13bits at $\pm$16g having 4mg/LSB. It gives a digital output in 16-bit 2's-complement format that can be accessed through either an SPI or I2C digital interface. Another important factor to notice is that mounting the accelerometer at different angles gives different vibration sensing and collection performances. To nullify this undesirable effect of the angle-caused unsteady mounting, a small mounting setup is used that firmly attaches the accelerometer with the pipe and keeps it facing upward a mounting position henceforth referred to as face-up mounting. A complete sensor board and the face-up mounting setup with the accelerometer is shown in Fig. 2. Accelerometer measurements are collected at various locations, close to and away from clamps, right angles and U-bends, flow meters and under various leak conditions. To avoid taking vibration measurements during the system's transient phase caused by changing the state of the pump or that of the control valve, enough time is allowed for the system to settle into its steady-state mode so that reliable readings are acquired.

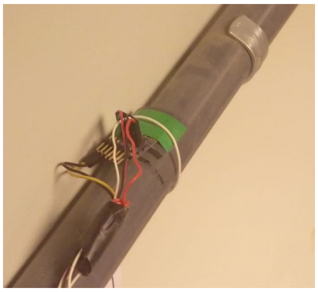


FIGURE 2. Accelerometer ADXL-345 used on pipeline with its mounting setup facing upwards.

B. LEAK DETECTION

The purpose of the vibration analysis is to determine those locations on the pipe with high vibration levels so that the sensors can be deployed at these locations in order to detect the leak and estimate its location and size. The presence of a leak in the pipe introduces additional vibrations in it, with their magnitude depending on the size of the leak, as well as on the distance from the leak, at which the measurements are collected. Furthermore, the vibrations tend to naturally die out as they travel through multiple clamps and bends, and after crossing a certain distance, as shown in our past work [54].

In this work, the control valves serve as leak simulators throughout the analysis. Four different leak conditions are considered when carrying out the vibration analysis and these are termed as no-leak, small-leak, medium-leak and large-leak. A small leak is the smallest opening that is possible for the ball-type control valve and it mimics the closest possible to a real small leak, sometime termed as an incipient (or nascent) leak that first quietly manifests itself in a real pipeline. However, medium and large leaks are simulated by respectively a half (around 50%) or full (100%) opening of the control valve. These bigger leak sizes can be assumed as representing bursts or ruptures that also occur in pipelines, sometimes due to some accidents, deliberate vandalism acts or perhaps some violent atmospheric activity such as earthquakes or thunder-storms.

In determining the leak, first a direct approach is used, where the leak is detected when a significant change in the SD of the vibration level from the no-leak condition is observed at one of the selected sensor locations. However, this method has been found in our experimental work, not to be reliable in most tried cases, where vibrations signals differ remarkably for different locations and for various leak sizes. By way of example, it was observed that the small-size leaks generally increased the level of SD of vibrations close to the leak points, whereas large-size leaks reduced it near the leaks where there would result a reduction in water flow.

Moreover, it was also noticed that the vibration produced by medium-sized leaks are very similar to those in a no-leak state and, hence, are very hard to detect using mere observations from a single location. Therefore, a more discerning Machine learning-based classifier called Medium Gaussian Support Vector Machine (SVM), is applied, which is fed with measurements from one or more locations under various leak conditions, and uses these measurements for both training and validation purposes for its 2 learning models, each with its own designated task as explained next. The first model is dedicated to detecting the leaks, whereas the second one is for classifying the detected leaks according to their sizes. The designed model uses Gaussian kernel function with kernel scale and a box constraint level of 1. The multiclass method used is one-versus-one. To exploit further the power of the Medium Gaussian Support Vector Machine, we used two variants of its classifiers i.e. Fine KNN (k-nearest neighbors) and Medium Decision Tree (DT) and compared their respective results using different algorithmic parameter settings as explained next. For Fine KNN, the number of neighbors was selected as 1, the metric distance as the Euclidean one, and an equal distance weight was selected. For the Decision tree, the maximum numbers of splits is selected as 20 and for the split criterion, the Gini's diversity index was selected.

Cross validation (CrV) is used for training and testing the obtained model. In CrV, the full input data set is randomly divided into k folds (or subsets) of almost equal size, and in each run, one of the k folds is used as the test/validation set while the remaining (k-1) folds are lumped together to form a training set so as to improve the data fitting performance of the learning algorithm [55]. In effect, each data point gets to be in the validation test exactly once, while being in the training set exactly (k-1) times. This results in significantly reducing the bias, as the estimation error is averaged over all of the k folds, thus improving the total effectiveness of the learning model, since most of the data is used for fitting purposes. In addition, CrV also enjoys a smaller variance as most of the data is also used for validation purposes, again resulting in a significant performance improvement of the learning model. This is clearly far better than using the simple train-and-test split (corresponding to a single fold or to $k = 1$). In all of our classification, five folds ($k = 5$) have been chosen.

In order to improve both the learning and classification performances of the learning models used for leak detection and classification, there is therefore a need to acquire a rich set of vibration measurements from various sensor locations and under different leak conditions. The detailed steps adopted in the running of the pipeline setup and for the collection of the needed training data are detailed in Table 2. As the flow rate is unchanged, the flow-induced vibrations will therefore not change much. Hence, to enrich the required vibration data set, we resort to running the leak through its full range, doing so in small steps and in both directions, and for various such cycles. This involves changing the state of the leak-simulating valve from being fully-open to being fully-closed, and vice-versa, and doing so in small steps in each cycle, so as to acquire a data set that would capture as much of the leak dynamics and as much of any significant hysteresis and stiction effects as possible. This would therefore provide the learning models used with an informationally-rich vibration data set that will vastly enhance their respective performances and accuracies.

TABLE 2. Detailed steps for running the pipeline system and collecting the training data.

Step Number	Actions Taken
1	- Close Leak-simulating valve to simulate no-leak condition (0% leak) - Wait for t seconds for the transient to die away - Collect accelerometer data for T seconds with a sampling frequency f for each of the n sensors - Calculate standard deviation of accelerometer data every m samples, leading to a total of (T x f / m) training data per sensor for the no leak condition
2	- Open leak-simulating valve a bit to introduce a small-size leak - Wait for t seconds for the transient to die away - Collect accelerometer data for T seconds with a sampling frequency f for each of the n sensors - Calculate standard deviation of accelerometer data every m samples, leading to a total of (T x f / m) training data per sensor for the small leak condition
3	- Open Leak-simulating -valve halfway through to introduce a medium-size (50%) leak - Wait for t seconds for the transient to die away - Collect accelerometer data for T seconds with a sampling frequency f for each of the n sensors - Calculate standard deviation of accelerometer data every m samples, leading to a total of (T x f / m) training data per sensor for the medium-size leak condition
4	- Open Leak-simulating -valve fully to introduce a large-size (100% or maximum) leak - Wait for t seconds for the transient to die away - Collect accelerometer data for T seconds with a sampling frequency f for each of the n sensors - Calculate standard deviation of accelerometer data every m samples, leading to a total of (T x f / m) training data per sensor for the large-leak condition
5	Repeat step 4 in the reverse order (i.e. from a 100% to a 50% leak)
6	Repeat step 3 in the reverse order (i.e. from a 50% leak to a small-size leak)
7	Repeat step 2 in the reverse order (i.e. from a small-size leak to no-leak (to fully-closed valve)
8	Repeat step 1

It is important to note here that in this study, the training data used for vibrations have been acquired under steady-state conditions, as they have been collected for long enough periods of time (several seconds) after the transients due to leak or any other conditions have died out. For each valve condition, the data is collected for $T = 40$ seconds, and a delay of $t = 90$ seconds is considered. These time values have been chosen based on a repeated experimentation with the leak simulation exercise. As shown in the experimental results, the dominant frequency in the vibration signal produced in this pipeline is around 40 Hz, therefore a sampling rate of f = 100 samples/sec is used as it safely satisfies the Nyquist sampling criterion.

C. EXPERIMENTAL SETUP AND ASSUMPTIONS

A lab-based pipeline setup is developed to mimic the scenarios expected to take place in real-life wall-mounted water pipelines and to thoroughly analyze the behavior of vibrations in their various sections. Fig. 1 and Fig. 3 respectively show the actual wall-mounted setup and layout used in acquiring the experimental results. The experimental setup is made of a 1-inch (25.4mm)-diameter PVC pipeline with two 45° bends and three U-bends. Multiple 1-inch stainless steel single-hole conduit straps support the wall-mounted pipeline and keep it stable during the experiments. Eight ball-type control valves are installed at different locations to mimic leaks of different sizes. To control pressure in the pipeline, another output control valve is used at the end of the pipeline. A pressure gauge from WIKA is used, that can show pressure in both psi and bar units, up-to 160 psi (equivalent to 11 bars). To circulate water in the setup, a jet pump motor with 1/2 HP and 3450 rpm from GE Motors is used. The jet pump motor can generate a pressure in the pipeline of around 30 psi with the output valve closed and around 18psi with it fully-open. For most measurements, a slightly-higher minimal flow pressure of 20 psi was maintained as this is more realistic and more representative of the setting used in actual real-life water distribution networks [52] subjected to ambient noises, rather than using a fully-opened output control valve which will give a steady flow at 18 psi. However, for the leak analysis, different leak sizes give rise to different pressure drops down to 18 psi.

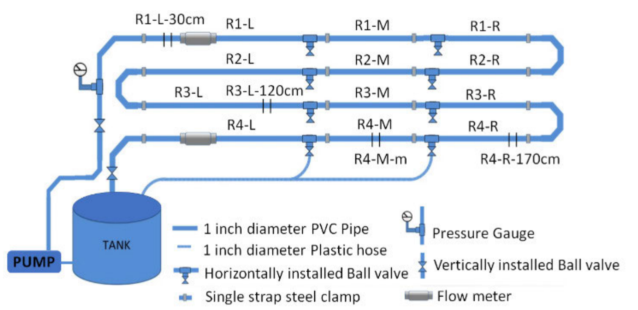


FIGURE 3. Layout showing labels of pipeline sections, and examples of some locations in which distance is measured with respect to the clamp on the left-hand side (diagram not drawn with scale).

The sensors used to carry out the experiments are accelerometers. For data logging from these sensors, My-RIO controller from National instruments is used which is programmed in a LabVIEW environment. The MATLAB package is used for frequency analysis and other software-based analysis. The sampling rate used to acquire the measurements from both accelerometers is selected to be (1/10ms =) 100 Hz with an inter-clock timing source of the controller as 1kHz. Since the pipeline has various portions, therefore an easy nomenclature, developed here to represent these different parts, is presented below in Table 3.

TABLE 3. Terminologies used for referring to different pipeline parts.

No.	Term	Referring to
1	Pipeline	Complete pipeline from pump to control valve at the end.
2	Pipeline row	One Complete Horizontal Row of pipeline
3	Pipeline section	Section of pipe between two clamps
4	Portion of Pipeline	Further divisions or subparts of the Pipeline section
5	Leak Section	The pipeline section that has leak, which is R4-R for this analysis.

Fig. 3 shows the layout and labeling of the experimental pipeline setup shown in Fig. 1. Four rows of the pipeline are given the names of R1, R2, R3 and R4, starting from top to bottom, respectively. In each row, three sections are named as Right (R), Middle (M) and Left (L), having clamp-to-clamp dimensions of 200cm, 150cm and 225cm, respectively. To indicate a specific location in the pipe section, either a variable 'm' is used or the distance from the left clamp of the same section is explicitly mentioned. Mentioning the letter 'm' shows that the location lies exactly in between two adjacent clamps. By using this nomenclature, the name of each location will have four parts with the first one representing the row-number on which the location lies (i.e. R1, R2, R3 and R4), while the second one representing the pipeline section (R, M or L) and finally, the last one showing the distance, in centimeters, from the closest support at the left of the location in the same pipe section. An example of such a name is R1-L-30cm (as is shown in Fig. 3) which lies in the first row, in the left section and at 30cm from the nearest left clamp. Another example is R4-M-m that shows a location that is in the fourth row, in its middle section and which lies at the middle of two adjacent clamps. Some other locations are also shown (in Fig. 3) on the pipeline in different sections to give more examples of the adopted nomenclature shown in Table 3.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

In the first phase of our experiments, measurements are collected in different sections of the pipeline, to first analyze the amplitude and frequency of vibrations, and then investigate the changes in these vibrations that are due to clamps, U-bends, and leaks which are simulated using a control valve. Note here that, out of the eight control valves used, only the one that is on the right-hand pipe section of the last pipe row is used as a leak simulator in this study. This analysis is needed in order to select the best locations at which to deploy the sensors for leak detection purposes. In the second phase, the sensors are deployed at the experimentally-selected best locations and the data collected under various leak conditions, is used as the training data set for the two developed learning models and for both tasks of leak detection and size classification.

A. ANALYSIS OF VIBRATIONS IN VARIOUS PIPE SECTIONS

The vibration measurement analysis is performed in two parts. In the first part, vibrations across straight pipe sections are observed. In the second part, those pipe sections that have angled bends, U-bends and flow meters are examined next.

1) STRAIGHT SECTIONS

Three sample pipe sections are selected for this analysis, namely R1-M, R4-R and R2-L, of lengths 150cm, 180cm and 225cm, respectively, and two of these sections have control valves (CV) in them on different sides. Fig. 4 shows the locations on these 3 pipe sections where data is collected, along with vibration amplitudes. The results show that, on average vibration amplitudes are higher at locations that are farther from the clamps, and show more variability for longer pipe sections, such as R2-L, which has more vibrations in the middle of the section, compared to R1-M and R4-R. It can also be noted that sections R2-L and R4-R include Control Valves (CV), respectively on the right-hand and left-hand sides, as shown in the graphs of Fig. 4(b) and Fig. 4(c). A gradual decrease in vibrations close to CVs is due to the contact between CVs and the nearby wall, which tends to have a dampening effect on these vibrations. In fact, this dampening effect on vibrations is due to the fact that CVs act like a mechanical load on the pipe sections, hence absorbing some of the generated vibrations and hence reducing the measured vibration levels near these CVs. However, it was also noticed that the maximum vibrations also shift toward the CV instead of being maximum in the middle of the section. This effect can be clearly viewed by comparing the R4-R-40cm and R2-L-150cm in Fig. 4(b) and Fig. 4(c). Both locations show that the maximum vibration location is shifted towards right and left respectively because of the CVs.

The frequency response analysis of the acquired vibration signals is carried out using the FFT of the data sampled from the left-hand side clamps of each of section R2-L 15cm, 90cm, and 180cm, section R1-M 60cm, and section R4-R 120 cm. The graphs of Fig. 5 show that the energy is distributed over a range of frequencies. However, at some locations, peaks appear more visible showing that the signal energy is concentrated at those frequencies. The locations that are very close to clamps show no clear peaks (such as the case for R2-L-180cm). However, moving towards the center of the section, the dominant frequency becomes more visible (such as the case for R1-M-60cm). Among the three sections considered in this analysis, for R2-L, two prominent frequencies are noticeable, 41 Hz due to left-hand side clamp and 8 Hz due to CV on the right-hand side of the sampled locations. Similarly, for R4-R, the 41 Hz- vibration frequency is due to the clamp and that of 15 Hz-one is due to the CV on the right-hand side of the sampled locations. For R1-M, since there are only clamps at both ends of this section,

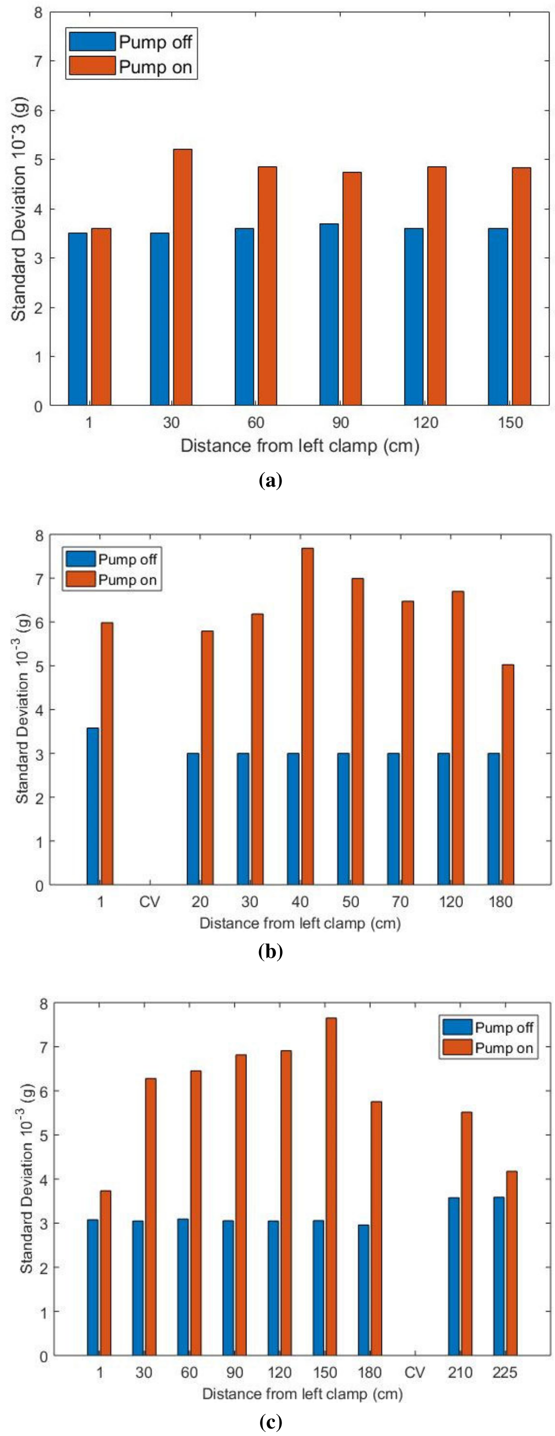
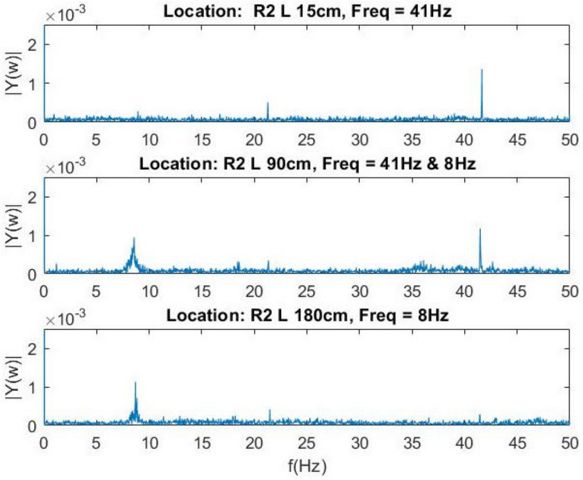


FIGURE 4. Standard deviations of vibrations at (a) five locations in section R1-M, (b) seven locations in section R4-R, and (c) eight locations in section R2-L.

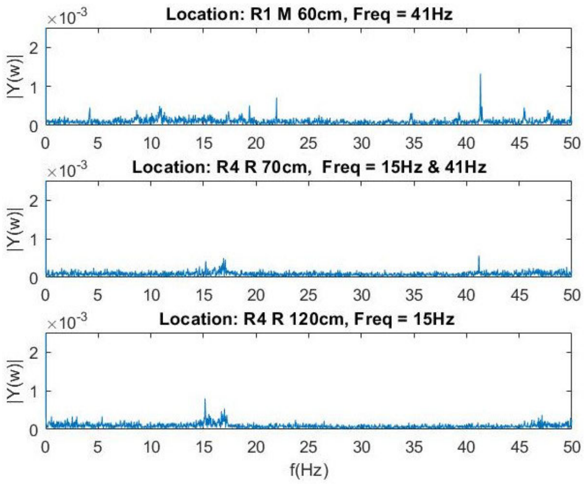
the location R1-M-60cm only shows therefore the dominant frequency of 41 Hz.

2) EFFECT OF ANGLE BENDS, U-BENDS AND FLOW METERS

Here, the effects of three types of fittings (angled and U bends and flowmeters), commonly used in wall-mounted pipelines,

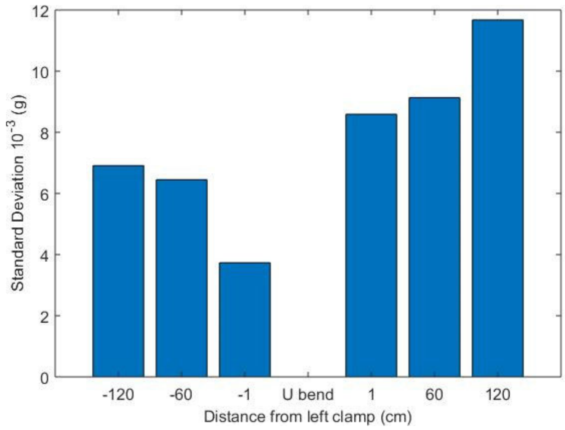


(a)

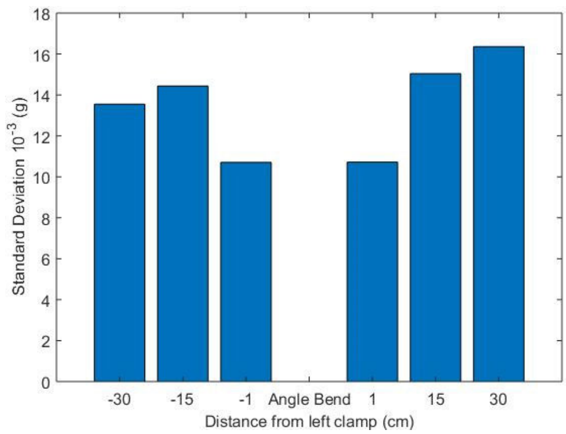


(b)

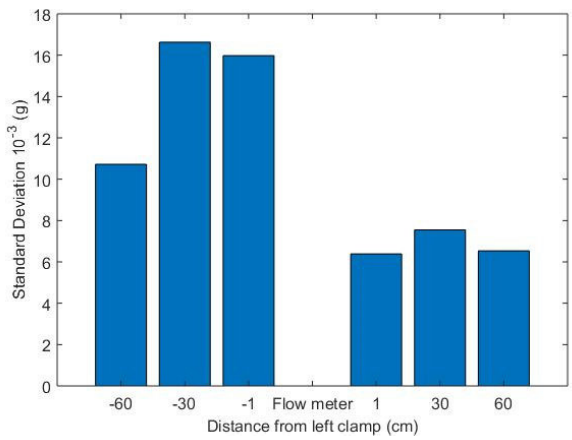
FIGURE 5. Vibration frequency analysis. (a) three locations in sections R2-L. (b) Three locations in sections R1-M and R4-R.



(a)



(b)



(c)

FIGURE 6. Standard deviations of vibrations signals with respect to distance, (a) before and after U-bend between sections R2-L and R3-L, (b) *before and after the angled bend in sections R1-L and R4-L, and* (c) *before and after the flowmeter in section R1-L. Negative and positive distances on the x-axis respectively show distances on left and right sides from angle bend / flow meter.*

on vibrations are examined. First, the effect of U-bends is analyzed by comparing the magnitude of vibrations taken from locations ahead of, and following, the U-bends between sections R2-L and R3-L. The results of Fig. 6(a) show vibrations measured at 3 locations i.e. 1 cm, 60cm and 120 cm with respect to the left-hand side clamp in sections R2-L and R3-L. It can be concluded that there is a significant increase in the amount of vibration after the U-bend. This may be explained by the fact that a U-bend tends to add to the turbulence of the flow due to the perturbation (sharp change in flow direction) it causes it, and hence an increase in the sensed vibration level.

A second analysis is carried out to examine the effect on vibration levels, of angled bends. Angled bends are usually used for connecting horizontal and vertically-mounted pipelines. In this experiment, two angled bends are considered. One is placed ahead of section R1-L and the other is after R4-L. Three locations (at distances of 1cm, 15cm and 30cm) are selected on both sides of the clamps that are used for holding the angled bends.

The results in Fig. 6 (b) show a small increase in the vibration magnitude after the angled bend. However, after completing the analysis on all pipe sections, it is found that the vibrations are highest at locations that are close to angled bends in pipe sections R1-L and R4-L, compared to rest of the pipeline.

These higher vibrations at the vertical angled locations of the pipe may be due to combined effect of the change of flow direction and the gravitational effect since, as the water passes through the vertical angled sections on its way down to the tank, it undergoes first a change in direction at the top corner of the pipe angle which causes it to bump into the inner wall of the pipe with a greater force and then be subjected to the additional gravitational force which makes it bump into the inner wall at the bottom angle of the pipe with an even greater force, than would be the case in any horizontal section of the pipe. These 2 effects are therefore believed to be the primary cause for the highest vibration levels being recorded at the angled sections of the pipe.

The third and final analysis is carried out to investigate the effect of the presence of flowmeters, on vibration levels. Three locations in R1-L are selected which are before and after the flowmeter, at distances of 1cm, 30cm and 60cm. The results Fig. 6 (c) show that vibrations decrease at location following the flowmeter. This decrease in vibration level may be due to a decrease in pressure due to the fact that the flowmeter also acts like a mechanical load, and hence as a vibration damper, for this pipe section, partly through the presence of its built-in rotary mechanism.

3) SUMMARY OF THE ANALYSIS OF THE EXPERIMENTS

The results obtained from the vibration recordings during the experiments carried out on the pipeline across various sections and at different locations of the pipelines are summarized below and conclusions drawn from these experiments:

The locations with highest vibration levels in horizontal sections lie away from the clamps, and at the middle of the sections. Also, if a CV is present in any of these sections, then additional vibrations of different frequencies are produced due to the presence of the CV.

1) Sections that are after U-bends and at angled bends show more vibrations than in other sections.
2) The dominant vibration frequency of about 41 Hz, can be clearly seen to occur at the middle of the horizontal pipe sections and away from CVs. Lower frequency components such as 8 Hz or 15 Hz are seen to occur close to CVs.

B. EFFECT OF LEAK ON VIBRATIONS

In order to detect a leak and classify its size in a wall-mounted pipeline using accelerometers, two types of experiments are conducted in order to understand the effect of leaks of different sizes, on vibrations recorded in different pipe sections. In the first experiment, vibrations are recorded from the leaky section, and the effect of the leak on these vibrations is then analyzed. In the second experiment, the effect of leaks of different sizes, on vibrations, is analyzed based on vibrations recorded from other pipe sections that are close to, and far from, the leak, to see the extent of this effect, as far as vibration levels are concerned.

1) EFFECT OF LEAK IN THE SAME LEAK SECTION

In order to observe the effect of the leak on vibration levels, section R4-R is considered, and the CV located in this section, is variably opened to simulate leaks of different sizes. The results on the Fig. 7(a) show various cases of leak sizes: no-leak (CV fully closed), small leak (CV slightly-opened) medium-size leak (CV half-opened), and Large-leak (CV fully-opened). The leak location is 15cm away from the left-hand side clamp, and vibration measurements are collected at distances of 20cm, 50cm, 110cm and 170cm away from the left-hand side clamp. These four locations are selected after observing previous results that, beside of primary objectives, also showed that change in vibration magnitude occur gradually and some locations close to clamps and in between are enough for determining this change. In the results, it can be easily noticed that the vibration magnitudes recorded for the medium- and large-leak cases are significantly less than those obtained for the no-leak condition, and, therefore, these the cases for these two leak sizes can easily be distinguished from the no-leak case using measurements at any of the 4 locations. Contrary to this, the effect of the small-leak is not significantly different from the no-leak unless the difference in the recorded vibration levels are higher such as those recorded at the farther distances of 110 cm and 170 cm. It can therefore be concluded that it is better to place the sensor nodes at locations where significant differences in vibration levels exist for different leak sizes.

The right-hand side of Fig. 7 (b) shows the results of the SDs of vibrations at the location R4-R-150cm for an experiment that runs for almost 14 min, and going through a cycle defined by the pump being first turned off, then it turned on with the CV being first fully closed, then gradually opened to get small leak, then a medium leak and finally a large leak. It can be observed from these results that the vibrations are at their highest level with a small leak, which is due to additional leak vibrations. For medium and full leaks, the vibrations are less because of the significant reduction in flow pressure due to these 2 bigger leaks. From these results, it is concluded that it is difficult to distinguish between no-leak and medium-leak situations compared to other sizes, because of similar magnitude of vibrations.

2) EFFECT OF LEAK IN DIFFERENT PIPE SECTIONS

Leaks of various sizes are introduced from the CV (located at R4-R-15cm) one after another, and their effects are observed at 12 different locations on the pipeline. The sampling frequency for accelerometer measurements is 100 Hz, and a snapshot of 3000 samples of SD values of recorded data is shown in Fig. 8. The locations are shown in the order in which they appear from inlet to the outlet. For clarity, the location of the leak in the pipe (i.e. R4-R-15cm) is also shown on the graph. While collecting readings for various leak sizes, once the CV switches to another state, some sufficient time is given for the transients to die away before the steady-state readings are recorded.

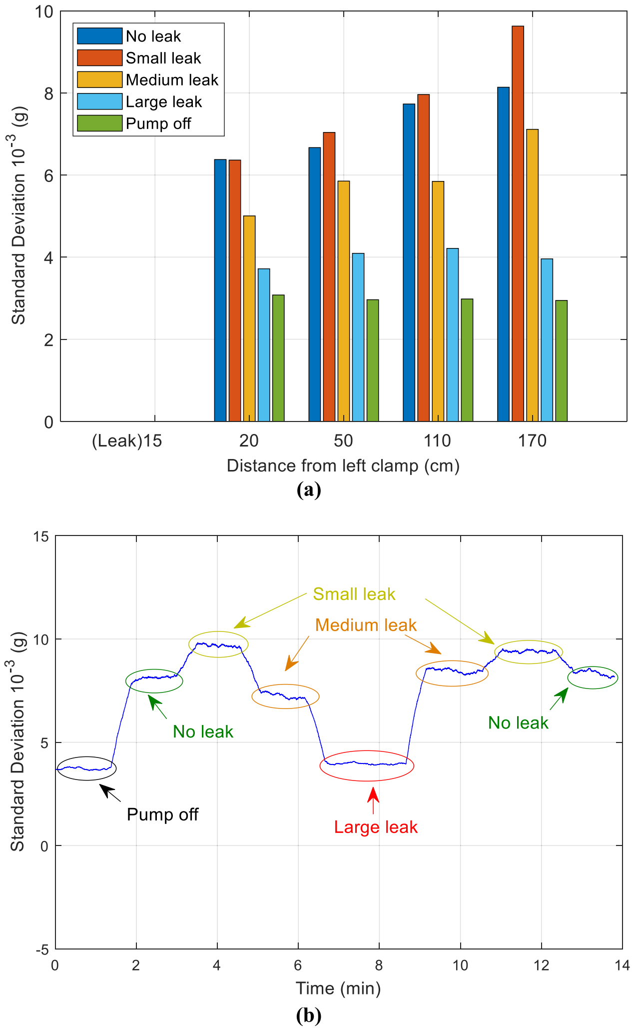


FIGURE 7. Standard deviation (SD) of vibrations at 4 locations on R4-R for various conditions, (b) A full cycle showing SD of vibrations under the 4 leak conditions in section R4-R-150cm.

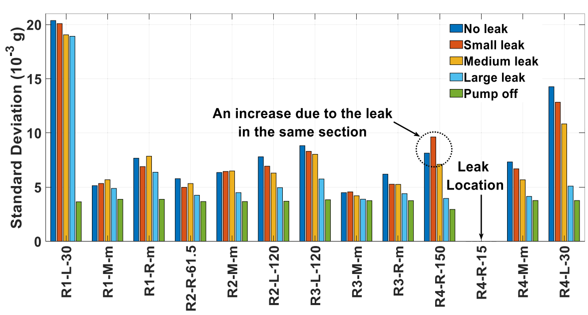


FIGURE 8. Standard deviation at different locations in all pipe sections under different leak conditions and in an order given by the direction of flow.

The results in Fig. 8 show that the leak at R4-R-15cm changes the vibration landscape in the entire pipeline. However, the pattern is not consistent since for example, the vibrations increase at R4-R-150cm due to small size leak but are then reduced at other locations. This is because R4-R-150cm lies in the same section as the leak, where a clear increase in vibration is noticed for a small leak. One possible reason behind the increase in magnitude of vibration for this section is that introducing the small leak adds continuous noise vibrations in that pipe section, but since these additional vibrations die out due to clamps, they do not therefore appear in other sections. On the contrary, the vibrations are reduced because of the decrease in the pressure of the pipeline due to presence of the leak. This explains why a further increase in the size of the leak decreases the flow pressure further and, as a result, the vibration magnitude is also decreased, as can be seen from the vibration magnitudes at other locations.

3) LEAK DETECTION

Leaks of different sizes change the vibration magnitudes in unintuitive ways. Therefore, a single measurement from one of the sensors will not confirm that there is leak, and classify its size except in few cases only, e.g. when the measurement node is in the same section as the leak. For that purpose, machine learning algorithm is applied in which data from 4 locations is used to correctly detect leaks of various sizes. The locations that are selected are R4-R-150cm, R4-L-30cm, R3-L-120cm and R1-L-30cm. The reason for choosing these 4 locations is that these are in different sections, have significant magnitudes of vibrations and show considerable difference in different leak conditions as shown in Fig. 8.

The data set which includes almost 40,000 samples is collected from each of the 4 sensors under different leak conditions. Since the raw vibration data has a lot of variations, and to alleviate the amount of noise in these data values, the SD of every 100 such values is calculated and used instead of the individual data values. This results in a total of 400 samples of SD values of vibrations data for training the model used for leak detection purposes. These results are shown in Fig. 9. It is noticed again that vibration

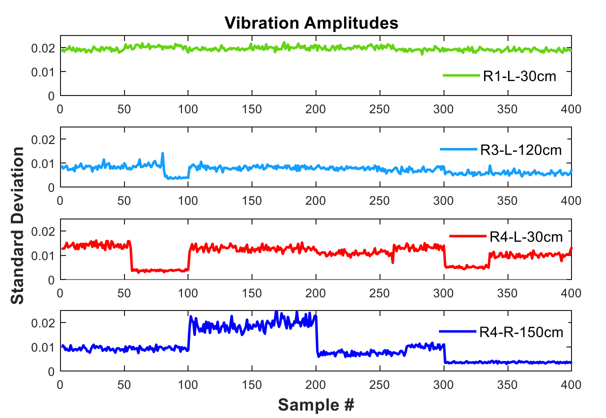


FIGURE 9. Standard deviation of vibration amplitudes versus number of samples, for the locations R1-L-30cm, R3-L-120cm, R4-L-30cm, and R4-R-150cm due to leak at R4-R-15cm. This is used as training data for the two SVM models. For each leak condition 100 Sample values are used. As shown on x-axes, first 100 Sample values are for no leak condition, next 100 for small leak and then for medium leak and large leak conditions, respectively.

signals for no-leak, small-, medium- and large-leak cases are clearly distinguishable at R4-R-150cm, while not so in the other 3 sections due to poor differences in vibration levels recorded by the 3 sensors located in other sections. This data is stored for training the SVM, KNN, and DT classifiers using MATLAB classification toolbox. The same data set is used for the 3 selected classifiers in order to compare their results on a similar playing fields.

Two separate models are trained: First model is for detecting the leak by differentiating the no-leak condition from other conditions due to leaks of different sizes. The results in Table 4 show the best results that are achieved when data from all 4 sensors is used for training purposes. Then, for the case where sensor located in section R4-R-150cm is used individually, whereas the results are worst if other sensors are used individually. It can also be concluded that the best results are for large size leaks, then for small leaks and lastly for medium-sized leaks. Second model is for classifying the correct leak sizes from the 3 sizes that are considered and the results are tabulated in Table 5. Again, the best results are obtained when using 4 sensors, followed by the case where the sensor located in section at R4-R-150cm is used individually The accuracy of the SVM models turned out to be better than, or at worst the same as, that of the other two models obtained from KNN and DT. This indicates that the results obtained from the SVM-based models can be relied upon to support the objectives of this feasibility study and the reasons behind our selection of accelerometers as the best sensors to use for wall-mounted plastic pipelines, from the crucial practical aspects of energy consumption, cost and efficiency.

TABLE 4. Accuracy of results for SVM, KNN and DT models to detect leaks of various sizes using different number of sensors.

Leak Size	Using sensor data from location	% Accuracy of leak detection for various leak sizes		
		SVM	KNN	DT
Small leak	R1-L-30cm	60	50	55
	R3-L-120cm	65	58	54
	R4-L-30cm	80	71	75
	R4-R-150cm	100	100	100
	All 4 sensors	100	100	100
Medium Leak	R1-L-30cm	51	47	52
	R3-L-120cm	68	64	65
	R4-L-30cm	77	74	76
	R4-R-150cm	75	66	66
	All 4 sensors	88	83	84
Large Leak	R1-L-30cm	66	64	66
	R3-L-120cm	93	92	93
	R4-L-30cm	98	98	98
	R4-R-150cm	100	100	100
	All 4 sensors	100	100	100

In conclusion, it can be stated that comparing the results obtained at different and carefully-selected locations, as used in this study, has given us an important and guiding insight into the choice of the optimal number of sensors required to provide a complete pipeline monitoring for both leakage detection and leak size classification purposes. Hence, it can be concluded that great benefits have been accrued from the combined use of both the newly-developed scheme based on (a) an experimentally-based selection of the best locations for sensor placement and (b) the use of the powerful SVM-based machine learning models for both leak detection and leak size classification, achievable at any point on the wall-mounted water pipeline testbed.

TABLE 5. Accuracy of results for SVM, KNN and DT models to classify leaks of various sizes using different number of sensors.

Using sensor data from location	% Accuracy for classifying correct leak size		
	SVM	KNN	DT
R1-L-30cm	36	32	34
R3-L-120cm	57	45	52
R4-L-30cm	61	51	59
R4-R-150cm	89	85	87
All 4 sensors	93	89	92

V. CONCLUSION AND FUTURE WORK

This article presents a feasibility study for detecting a leak and classifying its size in wall-mounted pressurized water pipelines through vibrations measurements using low-power accelerometers. The testbed is chosen to be representative of typical water pipelines used in real life, consisting of angled and U-bend sections, thus adding to the practical importance and usefulness of our findings. As such a study has not been carried out before, it will surely add to the increasing body of applied research into this important practical area. The first set of results (presented in Section IV.A) showed that the feasible locations for the placement of nodes with significant vibrations, are the locations away from the clamps, close to angled-bends, and after u-bends in the pipe.

As per the results provided in section IV-B, it was also observed that small-size leaks generally lead to an increase in vibrations close to the leak points, whereas large-size leaks reduce the amount of vibrations due to a reduction in water pressure as illustrated in figure 7(b). Our study uncovered the interesting facts that medium-size leaks are hardest to detect due to their vibrations being similar to those under no-leak conditions, and that measurements from a single sensor (or from a single location on the pipeline) have proved to be, in most cases, insufficient to achieve an acceptably-accurate leak detection in sections that do not contain the single sensor used. This therefore led to the development and successful use of two powerful learning models, one for leak detection and the other for leak size classification, that are trained with data acquired from 4 sensing nodes placed at different locations on the pipeline. The comparison between the individual performances of the learning models developed in this study, namely SVM, KNN and DT, revealed that the SVM was generally the best-performing of the 3 learning models used.

Our study also showed in Table 4 that, for the SVM model and with the hardest medium-size leak detection case, the worst accuracy achieved was 51% when using a single sensor, and that a much better accuracy of 88% was obtained with only a moderate increase of the number of sensors to 4. Similarly, for the leak size classification model, the accuracy of classification accuracy increased from 36% to 93% as shown in Table 5. Hence, it is concluded that resorting only to a moderate increase in the number of sensors used, produced an informationally-richer training data set and a remarkable improvement in performance underlined by a higher leak detection and leak size classification accuracies. The results obtained give ample encouragement to develop more cost-efficient schemes and seek further improvements in leak detection and leak size classification by investigating the use of piezo-electric energy harvester, instead of accelerometers, in order to make the sensor nodes self-sustaining. With the help of wireless technology supported by a good energy harvesting scheme, the resulting sensor network will enjoy a longer operational lifetime, a wider monitoring range with a concomitant increase in its applicability range. Finally, besides seeking better ways of deploying these energy harvesters at carefully-selected locations where vibrational activity is high so as to harvest the maximum possible energy, some efforts are also underway to explore the use of other powerful machine learning tools with a view to extending the capability of the proposed scheme to successfully handle the simultaneous detection and accurate localization of multiple leaks in the pipeline, as well as classifying their sizes.

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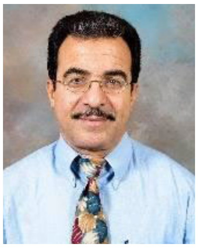

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