vibration

Article

Detection of Water Leaks in Suburban Distribution Mains with Lift and Shift Vibro-Acoustic Sensors

Lili Bykerk * and Jaime Valls Miro

Robotics Institute (UTS:RI), University of Technology Sydney, Ultimo, NSW 2007, Australia; jaime.vallsmiro@uts.edu.au
* Correspondence: lili.bykerk@uts.edu.au

Abstract: Leaks in Water Distribution Networks (WDNs) account for a large proportion of Non-Revenue Water (NRW) for utilities worldwide. Typically, a leak is only confirmed once water surfaces, allowing the leak to be traced; however, a high percentage of leaks may never surface, incurring large water losses and costs for utilities. Active Leak Detection (ALD) methods can be used to detect hidden leaks; however, the success of such methods is highly dependent on the available detection instrumentation and the experience of the operator. To aid in the detection of both hidden and surfacing leaks, deployment of vibro-acoustic sensors is being increasingly explored by water utilities for temporary structural health monitoring. In this paper, data were collected and curated from a range of temporary Lift and Shift (L&S) vibro-acoustic sensor deployments across suburban Sydney. Time-frequency and frequency-domain features were generated to assess the performance and suitability of two state-of-the-art binary classification models for water leak detection. The results drawn from the extensive field data sets are shown to provide reliable leak detection outcomes, with accuracies of at least 97% and low false positive rates. Through the use of such a reliable leak detection system, utilities can streamline their leak detection and repair processes, effectively mitigating NRW and reducing customer disruptions.

Keywords: water distribution network; structural health monitoring; lift and shift; vibro-acoustic sensors; leak detection; signal processing; machine learning; binary classification; data-driven; neural network

check for updates

Citation: Bykerk, L.; Valls Miro, J. Detection of Water Leaks in Suburban Distribution Mains with Lift and Shift Vibro-Acoustic Sensors. *Vibration* **2022**, *5*, 370–382. https://doi.org/10.3390/vibration5020021

Academic Editors: Hamed Kalhori and Aleksandar Pavic

Received: 10 May 2022
Accepted: 13 June 2022
Published: 16 June 2022

Publisher's Note: MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Copyright: © 2022 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

1. Introduction

The management, monitoring and maintenance of the structural health of potable Water Distribution Networks (WDNs) is critical for continuous and uninterrupted water supply to customers. Depending on their age, frequency of use and environmental surroundings, pipes and fittings are susceptible to failures, resulting in leaks in the WDN. A large percentage of leaks are hidden and will never surface, resulting in unknown water losses that are often categorised as Non-Revenue Water (NRW).

Several technologies and methods exist for water leak detection and pinpointing, including ground penetrating radar, gas injection, hydrophones, vibro-acoustic noise loggers and correlators, infrared thermography and in-line devices, amongst others [1,2]. Many of these methods are either invasive to the WDN, labour-intensive and expensive to deploy or not suitable for remote monitoring. Hydraulic modelling methods that leverage data from continuous monitoring devices such as flow sensors can be used to provide an indication of typical usage and possible leakage in a WDN, although it is not possible to pinpoint a leak location using this method. Similarly, pressure sensors are predominantly used to analyse and identify network issues that can cause large pressure transients and leaks in a WDN. By monitoring the pressure in a WDN, action can be taken to calm the network, which can indirectly reduce leakages; however, there are many practical difficulties and limitations in directly using pressure sensors for leak detection and pinpointing [3].

Traditional methods of hidden leak detection rely on human operators locally inspecting the pipe assets using acoustic detection techniques and equipment, such as listening sticks or ground microphones. These acoustic methods are based on the principle that water discharging from a leak will induce and propagate vibrations along the wall of the pipe, which can be heard by operators tapping and listening on appurtenances in the WDN. The same principle also applies for leakages in gas pipelines [4]. Leak detection personnel must be trained to operate such equipment and discern between expected network noise and leak noise, with experience being a key factor in the success of reliable leak detection [5]. More recent advances in leak detection technologies (real-time correlators) *can* rely less on the experience of the operator, and can be used to accurately pinpoint leaks if the pipe properties and the approximate leak location (e.g., between two fittings) are known [6].

To find hidden leaks, water utilities will commonly schedule Active Leak Detection (ALD) teams to periodically survey sections of a WDN using manual acoustic leak detection equipment (listening sticks, ground microphones or real-time correlators) [7]. Due to the training and equipment requirements, it can be difficult and impractical to schedule ALD teams to continuously monitor WDNs using these manual methods. Furthermore, the success of such methods can be hindered by the prevalence of environmental and water usage noises during the day, when the surveys are often conducted. To increase the likelihood of hidden leak detection, vibro-acoustic sensing for remote leak detection is being increasingly adopted by water utilities, particularly for higher density areas where leaks are more prevalent. The relative low cost, ease of implementation, flexibility, and the passive nature of the sensing system—whereby no permanent changes to the WDN are required for the technology to be installed and function—all constitute attractive features for asset management.

Raw data obtained from vibro-acoustic noise loggers and correlators requires processing and analysis to confidently determine the presence and location of a leak. Semi-permanent vibro-acoustic loggers that send their data to cloud-based servers have built-in algorithms that raise leak alarms based on the intensity and consistency of the recorded noise [8]. Relying on these simple noise level limits alone often results in false positive leak alarms being raised by the system, if the alarm threshold is set too low. On the other hand, if the threshold is set too high, quieter leaks are missed by the monitoring system (false negative leak alarms). These limitations in the interpretation and analysis available from commercially available loggers has driven researchers to explore alternative leak detection approaches to minimise false alarms. Loggers that provide leak alarms through means of correlations between two loggers *can* be more reliable, but are still susceptible to false positive alarms caused by water usage. Lift and Shift (L&S) loggers are intended to be used for short deployments, to capture a snapshot of the WDN on a given night. Loggers are generally deployed on one day, record audio in the early hours of the next morning and are collected later that day to download the data. The loggers can then be re-deployed as required, to cover an entire area of interest. Correlating noise loggers (typically L&S) have not been extensively studied in the literature other than as standalone noise logging devices.

Some providers of vibro-acoustic sensors provide access to the raw audio files recorded by the sensors, allowing for signal processing and data-driven methods to be explored as options for reliable leak detection. There are several challenges and uncertainties in analysing the acoustic sensor data for leak detection: (1) A leak noise can be attenuated due to fittings, joints, junctions and service connections, which are often undocumented in Geographic Information System (GIS) data; (2) the presence of environmental noises and water usage in the network; (3) the signal recorded by the acoustic sensor is directly related to the pipe material and diameter, proximity to the leak noise and the quality of the sensor's mounting point on the asset [9,10].

Acoustic signal-based leak detection approaches in the literature extract features from audio recordings, which are either directly used to interpret signals for leakage [10–13] or used to train machine learning (mostly binary) classifiers. Time-frequency features generated using discrete Short-time Fourier Transforms (STFTs), such as spectrograms, reveal the temporal nature of a signal that is not captured by analysing frequency-domain features alone [14]. Mel-frequency spectrograms, which closely align with the human perception of sound, are commonly used as features in machine learning applications, including leak classification problems [15,16]; however, the majority of data-driven machine learning studies leverage frequency-domain features of acoustic signals for training such as the Power Spectrum Density (PSD) [17,18] or Intrinsic Mode Functions (IMFs) [19]. Frequency-domain features may prove effective for classification in controlled environments, but they are easily influenced by a temporary ambient noise, which can mask a persistent leak noise in the PSD, leading to decreased classification performance. This limitation is critical for sensor deployments on functioning WDNs, where persistent or transient non-leak noises are prevalent, leak noises are not controlled, and the WDN can be complex.

Many of these studies are conducted in controlled laboratory environments [20–23], with few examples of data sets obtained from real WDNs. Studies on functioning WDNs have predominantly contained unbalanced data sets, with small sets of leak samples [24–26] or data collected in WDNs with minimal interference noises, where Gaussian White Noise (GWN) is added to augment the data sets with different Signal-to-Noise Ratios (SNRs) [27]. Other studies rely on having collected signals before and after a leak has been repaired [17,28,29], to establish leak detection thresholds. Moreover, studies with data recorded from real WDNs do not specifically delineate between the use of semi-permanent or L&S vibro-acoustic loggers, or provide any acoustic performance analysis of different commercially available sensors. One study analysed the performance of permanent Von Roll and L&S Primayer Enigma acoustic sensors, under controlled field leak tests in a functioning WDN, where a small sample of acoustic signals were directly compared using STFTs [30]. Another study provided a cost and performance report of three different types of commercially available leak detection systems (acoustic sensors/real-time correlators) [31] evaluated on a controlled test-bed; however, no technical analysis or comparison of the collected raw audio signals was conducted.

This paper evaluates state-of-the-art data-driven methods for leak classification using data collected from vibro-acoustic L&S logger deployments in small reticulation mains across suburban Sydney. Data from two commercially available types of L&S sensors in different deployment areas were used to evaluate the efficacy of the proposed data-driven methods. Real field-collected data sets are necessarily unbalanced. This remains a limitation in evaluating the success of any leak detection classifier, particularly for real-world sensor deployments in WDNs where pipe materials, diameters, soil properties, service lines or offtakes—amongst other geospatial features—can vary significantly and heavily influence the signals recorded by the vibro-acoustic sensors. The two data sets collected and analysed in this paper are both also unbalanced, given their real field deployment nature. Despite these challenges, the results are indicative of reliable leak detection using vibro-acoustic L&S loggers.

The paper is organised as follows. The vibro-acoustic sensors and data loggers are described in Section 2. The process to deploy loggers, collect and process the acoustic data; the binary classification analysis is presented in Section 3. Section 4 presents the results and discussion. Finally, the conclusions are presented in Section 5.

2. Vibro-Acoustic Sensors and Data Loggers

Water leaks create vibrations in a WDN due to the pressure differential between the inside and the outside of a pipe. These vibration waves can travel thorough both pipe material and water, thus vibro-acoustic sensors (accelerometers) can measure the vibration inflicted on the pipe material. Due to rapid signal attenuation in plastic materials, accelerometer-based sensors are most effective when deployed on metallic pipes. Manufacturer specifications indicate that vibro-acoustic sensors are effective in recording leakage noises on reticulation mains with diameters smaller than 375 mm, and can correlate over distances of up to 150 m between adjacent loggers.

The sensing hardware used in this study consists of single integrated vibro-acoustic sensor and data logger units (Primayer Enigma and HWM PCorr+ correlating noise loggers shown in Figure 1). The Primayer loggers are provided in kits of 8 per box, with each logger from the same box being time-synchronised prior to deployment and therefore capable of correlating with its neighbour in the pipeline. HWM loggers are standalone units, which are also time-synchronised such that any adjacent sensor can correlate with its neighbour. Analysis of the recordings made with L&S loggers provide an understanding of the network activity at a snapshot in time.

Figure 1. Primayer Enigma (**top**) and HWM PCorr+. (**bottom**) L&S correlating vibro-acoustic sensors.

As summarised in Table 1, six discrete pressure zones in suburban Sydney were targeted for the L&S sensor trials over the course of a 1 year trial period (August 2020 to July 2021). For each of the five Primayer Enigma deployments, five boxes of eight loggers were deployed in staggered approaches to completely cover each of the pressure zones. In total, 70 HWM PCorr+ sensors were available, which were deployed in two stages to completely cover the desired area. The loggers were mostly installed on appurtenances (typically valves and hydrants) attached to iron or steel pipelines, ranging in diameter from 100 mm to 450 mm and up to more than 100 years old. Depending on the available space in a hydrant or valve chamber and the condition of the assets, the sensors were often mounted in different orientations and with differing mounting points, examples of which are shown in Figure 1.

Table 1. Lift and Shift Vibro-Acoustic Logger Deployment Details.

Zone #	Sensors Deployed	Quantity of Loggers Deployed	Number of Connections	Pipe Length (km)	Average MNF (L/C/H)	Leaks Detected	Types of Leaks Detected
1	HWM PCorr+	70 loggers (133 locations)	1481	19.89	16.83	9	1 main tap leak, 3 hydrant leaks, 1 main leak, 1 main break, 1 m coupling leak, 2 mains to meter leaks
2	Primayer Enigma	144 (18 boxes)	438	9.7	15.0	6	3 m tap/ coupling leaks, 2 stop valve leaks, 1 DV breach/fault
3	Primayer Enigma	72 (9 boxes)	1163	12.9	19.0	6	4 hydrant leaks, 1 main break, 1 mains to meter leak
4	Primayer Enigma	80 (10 boxes)	650	14.4	20.5	2	1 DV breach/fault, 1 hydrant leak
5	Primayer Enigma	88 (11 boxes)	1064	16.8	27.2	5	2 main tap leaks, 1 hydrant leak, 2 m tap/ coupling leaks
6	Primayer Enigma	240 (30 boxes)	1179	38.4	30.7	21	3 main leaks, 3 main breaks, 9 hydrant leaks, 1 main tap leak, 2 stop valve leaks, 1 m tap leak, 2 fire service leaks

3. Methodology

The process to deploy the data loggers, data collection, processing and classification analysis is presented in this section.

3.1. Data Collection

For the five zone deployments using Primayer Enigma loggers, a total of 550 loggers were deployed overnight, collecting three 60-s duration audio recordings at 2, 3 and 4 am. These times were selected for audio recordings as there is generally low water usage and theoretically low environmental noise during these hours. The deployment of HWM PCorr+ loggers in zone 1 used 133 HWM PCorr+ loggers, configured to record one 10-s duration audio recording only if the sensor node itself had first determined that there was likely a leak present (based on a noise level and spread calculation). This pre-set configuration limited the amount of data that was retrieved from these loggers, resulting in a smaller data set for analysis. The Primayer L&S loggers need to be physically retrieved from their installation locations for the data to be downloaded directly. A patroller unit is used to download the data from each HWM PCorr+ logger during a drive-by data collection period.

The collected data consists of 'leak' and 'no-leak' audio recordings originating from a range of leak sources such as hydrants, valves, service lines, water main failures, main taps, meter couplings and meter taps. The approximate locations of these sources are shown in Figure 2, where valves and hydrants (not shown) vertically branch off the water main, either directly or via risers. The collected signals are from single locations in the WDN for a given deployment night, and therefore, the data set does not contain both 'leak' and 'no-leak' data for a single location, as the deployment zones were not re-scanned following leak repairs.

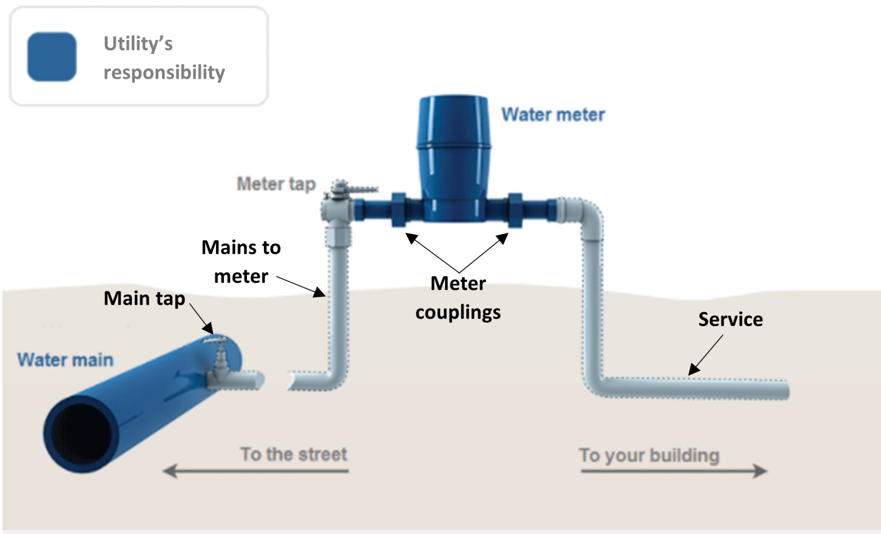


Figure 2. Utility's mains to meter diagram.

Leaks were confirmed on-site by the utility network technicians using listening sticks and/or real-time correlators, prior to excavation for leak repairs. Some examples of validated leaks detected by the L&S vibro-acoustic sensors are shown in Figure 3.

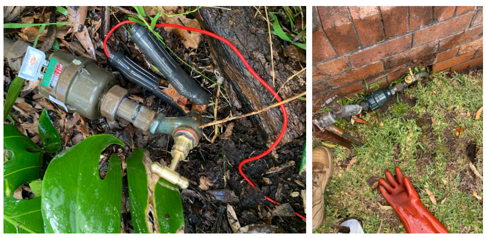
(**a**) Hydrant leak

(**b**) Main leak (left) and repair (right)

(**c**) Main tap leak (left) and repair (right)

(**d**) Valve leak

(**e**) Meter coupling leak (repaired)



(**f**) Meter tap leaks (repaired)

Figure 3. Examples of validated leaks from L&S logger deployments.

3.2. Data Analysis—Signal Processing

Through the application of STFT signal processing techniques to generate spectrograms, acoustic signals can be visualised and temporal changes to the frequency content can be observed. Since leaks in a WDN will be continuous, any leak noises and their corresponding higher power frequencies will be persistent in the audio spectrum, with any other non-leak (typically, environmental or usage) noises showing as transient or intermittent frequency components. Some environmental noises, such as those from mechanical or electrical sources will also show in a spectrogram as persistent noise, although usually with very low frequencies and in a narrow band with higher power (unlike most leak noises). Figure 4 shows some examples of various noise sources. Depending on a logger's proximity to a given leak source, the noise from a leak will typically be dominant in the spectrum, even in the presence of other transient noises.

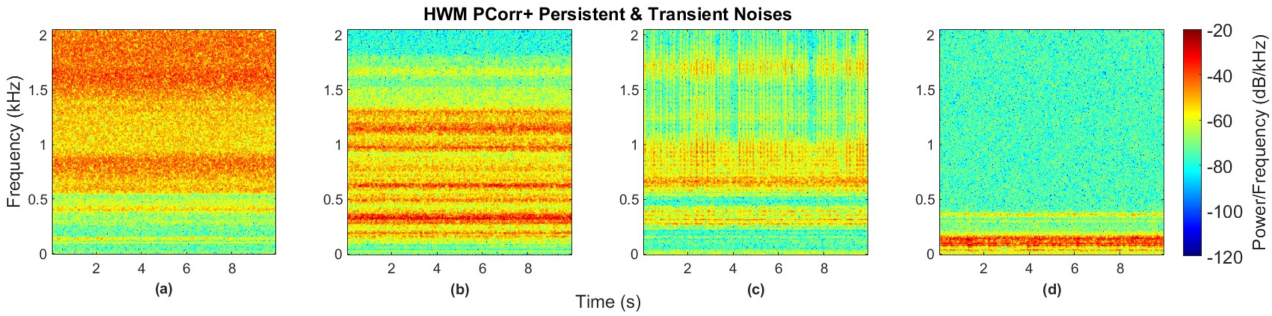


Figure 4. Spectrograms for HWM PCorr+ recordings with persistent leak noises—(**a**) hydrant leak, (**b**) service leak; transient and persistent non-leak noises—(**c**) water usage noise with meter ticking, (**d**) environmental noises likely from electrical and mechanical sources.

Across the six deployment zones, some audio files were omitted from the data sets, as they were indicative of leaks, but no field validation was conducted. Furthermore, some logger locations were in close proximity to noises from WDN appurtenances (breached Dividing Valves (DVs)), facilities (pumping stations) and equipment (Pressure Reducing Valves (PRVs)), which could be easily confused by a classifier as leak noise (see Figure 5 for examples).

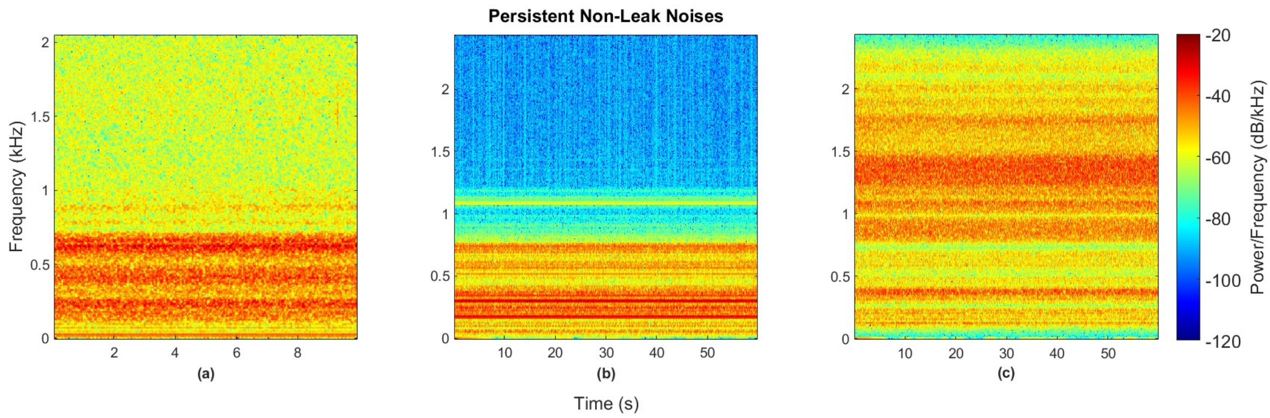


Figure 5. Spectrograms of audio files removed from the data sets, due to loggers in close proximity to water induced noises similar to leak noises. Persistent non-leak noises are from a: (**a**) DV breach; (**b**) pumping station; (**c**) PRV.

Due to clustering of the loggers in the WDN to permit correlations between loggers, for each of the leaks detected, often more than one logger was able to record noise from a single leak source. In general, the further away the logger is to the leak location, the higher frequency components of the spectrum are attenuated and the lower frequency noises are more prevalent. With increased distance between the logger and the noise source, the intensity (power) of the noise also decays, the further away from the leak source the logger is. An example of this can be observed in Figure 6, where three individual HWM PCorr+ loggers recorded noise from the leaking service line shown.

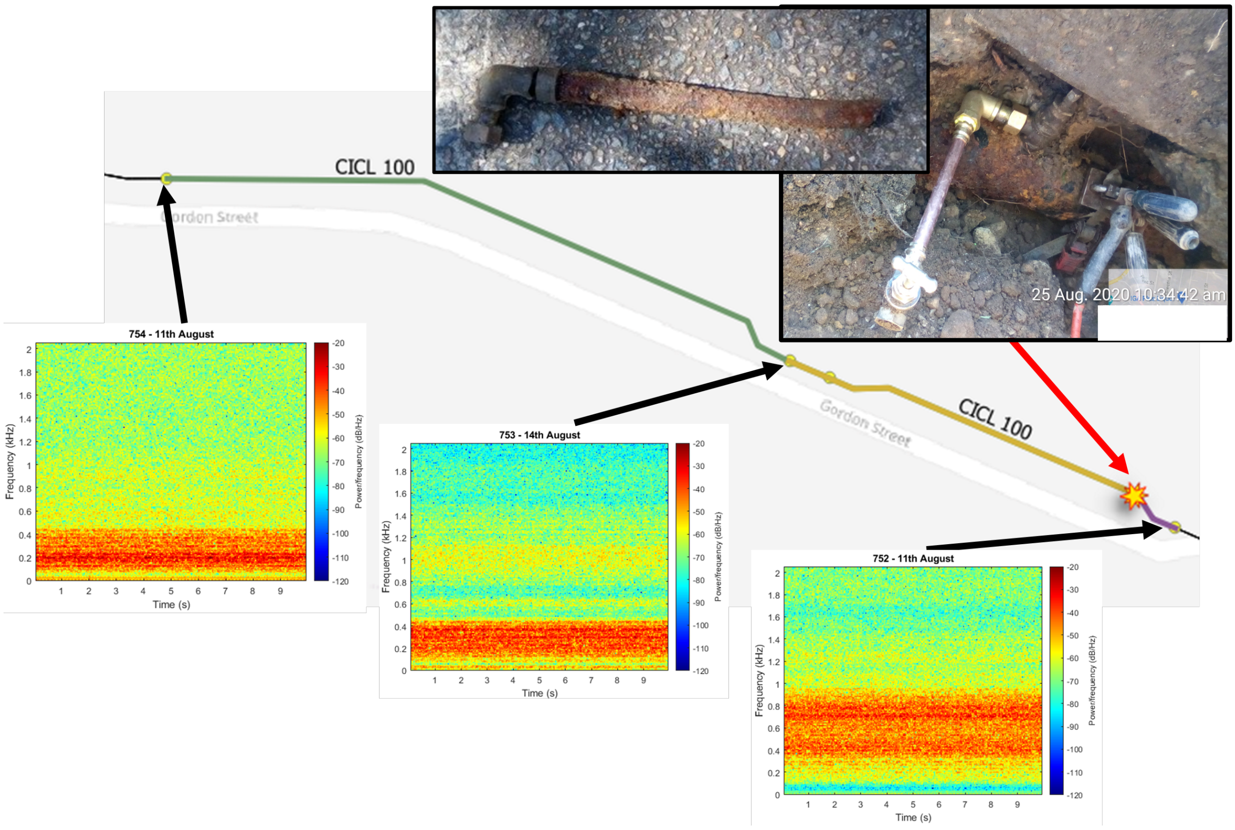


Figure 6. Leaking service line, detected by three individual HWM PCorr+ loggers at distances of 11 m (purple), 75 m (yellow) and 210 m (green) from the leak source.

3.3. Binary Classification

Following an extensive review of literature for data-driven leak detection methods using acoustic data collected from real WDNs, it was found that a Time-Frequency Convolutional Neural Network (TFCNN) model [27] reported the best performance, when compared with a Frequency Convolutional Neural Network (FCNN) model, as well as a range of other common binary classification models such as decision trees and support vector machines, amongst others. The classifiers were trained with data collected from a small number of acoustic sensors deployed in a WDN in China. The collected data sets contained a range of 'leak' and 'no-leak' audio samples from various leak sources, from which time, frequency and time-frequency features were extracted for classifier training and testing. Several performance metrics, including accuracy, sensitivity and specificity were analysed to evaluate which input features and classification models were most effective in accurately and reliably classifying the acoustic signals. The findings of this paper reported that the TFCNN model provides the best classification performance due to the input features (leakage spectrograms) more effectively representing the characteristics of the audio signal and providing more valuable information for classification than time or frequency domain features alone.

In this paper, two of the CNN-based models (FCNN and TFCNN) [27] are trained and evaluated with data collected from the various sensor deployments in Sydney. The two model structures are shown in Figure 7. The models were implemented in Python 3.9 using Keras and Tensorflow version 2.6.0. The input to the FCNN model is simply a Fast Fourier Transform (FFT) of the band-pass filtered (100–2000 Hz) raw audio signal, and the TFCNN model inputs are three different resolutions of spectrograms generated from the same filtered raw audio signal. The three resolutions of spectrograms are intended to improve the leakage detection performance, since with varying resolutions, the changes of the signal in the time and frequency domains can be better represented. This is due to the nature of a 'leak' signal being persistent (stable in the time domain), and 'no-leak' noise sources being transient in nature (unstable in the time domain). Due to different sampling rates of the two sets of loggers, the dimensions of the three spectrograms that are the inputs for the TFCNN model differ slightly, as listed in Table 2.

Table 2. TFCNN model spectrogram matrix sizes for different resolutions.

Logger	Audio Sampling Rate (Hz)	Spectrogram Resolution High Time	Transitional	High Frequency
HWM PCorr+	4096	[114,60]	[226,28]	[451,12]
Primayer Enigma	4864	[96,72]	[190,34]	[380,15]

To evaluate the performance of the TFCNN model on the data sets from the HWM and Primayer L&S loggers, the data were prepared by first augmenting [32] (splitting) each audio file into several 1-s audio chunks. The three 60-s audio recordings obtained from each of the 550 Primayer Enigma deployment locations equates to a total of 1650 60-s audio recordings. These recordings were split into individual 1-s chunks, for a total data set of 99,000 1-s duration samples (consisting of 15,840 'leak', and 83,160 'no-leak' samples). The 21 10-s duration audio recordings from the HWM PCorr+ loggers were also split into 10x1-s chunks, for a total data set of 210 1-s duration samples (consisting of 150 'leak', and 60 'no-leak' samples). Due to the vast array of samples, including various 'no-leak' noise sources, it was not deemed necessary to further augment the data sets by adding GWN with different SNRs into the raw signals. Each of the complete data sets (for each logger type) were split, with 80% used for training and 20% for testing.

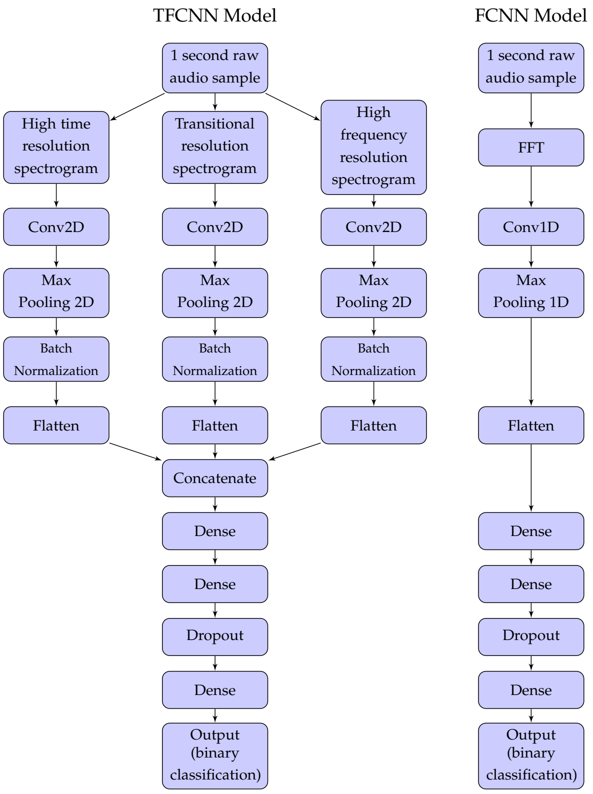


Figure 7. TFCNN and FCNN model structures.

4. Results and Discussion

Tables 3 and 4 summarise the results of the FCNN and TFCNN classification models for the two logger data sets. The metrics used to evaluate the model performance were accuracy, sensitivity, specificity, precision, F-beta and the Area Under the Receiver Operating Characteristic (ROC) curve (AUC). The following abbreviations are used to simplify the presentation of the equations: True Positive (TP); True Negative (TN); False Positive (FP); False Negative (FN).

Table 3. FCNN Results.

Logger Type	Total # Files	# Leak Files	# No Leak Files	Accuracy (%)	Specificity (%)	Sensitivity (%)	Precision (%)	AUC	F-beta
HWM	210	150	60	97.62	90.00	100.00	96.97	1.0	0.98
Primayer	99,000	15,840	83,160	97.67	98.96	90.98	94.38	0.99	0.93

Table 4. TFCNN Results.

Logger Type	Total # Files	# Leak Files	# No Leak Files	Accuracy (%)	Specificity (%)	Sensitivity (%)	Precision (%)	AUC	F-beta
HWM	210	150	60	100	100	100	100	1.0	1.0
Primayer	99,000	15,840	83,160	97.99	99.17	91.89	95.51	0.98	0.94

Accuracy is the measure of the classifier's overall correct classification performance: $TP + TN/(TP + TN + FP + FN)$. Sensitivity is the classifier's ability to label a 'leak' signal as 'leak' (recall of the positive class): $TP/(TP + FN)$. Specificity is the classifier's ability to label a 'no-leak' signal as 'no-leak' (recall of the negative class): $TN/(TN + FP)$. Precision is the classifier's ability to not label a 'no-leak' signal as 'leak': $TP/(TP + FP)$. The F-beta score is a weighted harmonic mean of the precision and sensitivity. The ROC curve plots the TP rate vs. FP rate at different classification thresholds. The AUC provides a measure of performance across all classification thresholds. For both the F-beta and AUC scores, the best value is 1 and the worst value is 0.

Although the classification results of the FCNN model were excellent, it was found that the TFCNN model was able to outperform the FCNN model across each of the performance metrics studied, even if doing so marginally. This indicates that spectrogram-based inputs are more effective than purely frequency-domain-based inputs in representing the characteristics of both 'leak' and 'no-leak' signals for classification. Figure 8 shows the confusion matrices for each of the four different trained models. For a practical leak detection system that utilities can rely on, high accuracy, but also high specificity (true negative) and sensitivity (true positive) rates are key performance metrics. Notably, a reliable leak detection system should minimise false positive leak alarms, thus ensuring that any costly follow-up field investigations are confidently driven by real leak events, maximising the efficiency for utilities.

Despite the limited data set available from HWM PCorr+ loggers, the results indicate that the type of sensor used (different vibro-acoustic sensor with different sampling rate, sensitivity, etc.) does not affect the performance of the classifier. Furthermore, the results demonstrate that a leak detection system using either model (and either logger) can be effectively trained, even without containing data from a single location both before and after a leak repair. By including a large number of 'no-leak' signals from elsewhere in the WDN during a deployment, the classifier appears sufficiently trained to be able to discriminate between 'leak' and 'no-leak' noises in that said environment.

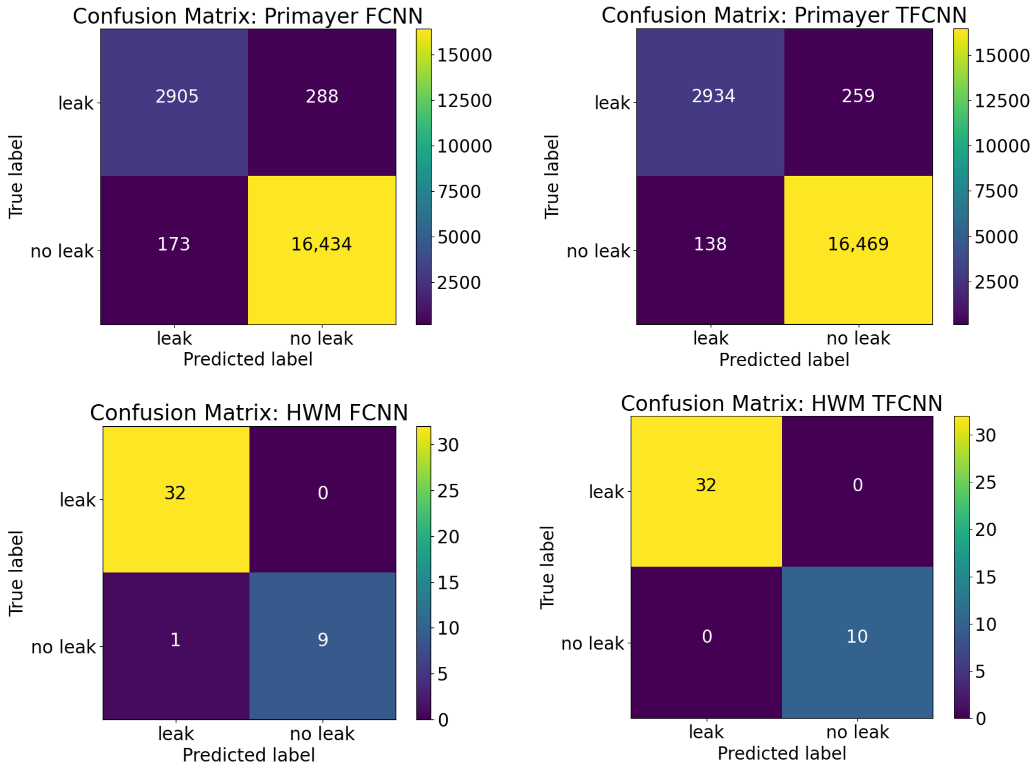


Figure 8. Primayer Enigma (**top**) and HWM PCorr+ (**bottom**) confusion matrices for FCNN (**left**) and TFCNN (**right**) models.

5. Conclusions

This work studied the performance of two state-of-the-art data-driven classification models (FCNN and TFCNN) for leak detection with true field-collected signals. Data for training and evaluating the two models were collected from two types of L&S vibro-acoustic loggers across six deployment zones in suburban Sydney. The results presented are the first known documented specifically for L&S loggers, demonstrating that these state-of-the-art CNN-based models are transferrable, and not only applicable to permanent acoustic sensors, as has previously been documented in the literature.

The excellent classification results show that the two CNN-based models have been able to learn sufficiently with vibro-acoustic sensor data from (a) a wide range of leak sources, (b) at varying distances from the leak sources, (c) on pipes with varying materials and diameters and (d) from a wide range of deployment zones, each with unique pipe networks and soil conditions. Considering all these factors which affect the recorded signals, the results presented show great promise for water utilities looking to integrate the use of L&S vibro-acoustic sensors into their ALD programs to enhance the outcomes of such manual surveys for structural health monitoring of their WDNs.

Future work to enhance the results of this study would involve obtaining further validated data collected from HWM PCorr+ loggers, and other brands of L&S loggers deployed in new zones and WDNs. A comparison of the classification performance of semi-permanent and L&S vibro-acoustic sensors would also provide further insights into the potential success of implementing such leak detection methods for utilities.

Author Contributions: Conceptualisation, L.B. and J.V.M.; methodology, L.B. and J.V.M.; software, L.B.; validation, L.B. and J.V.M.; formal analysis, L.B.; investigation, L.B.; resources, J.V.M.; data curation, L.B.; writing—original draft preparation, L.B.; writing—review and editing, J.V.M.; visualisation, L.B.; supervision, J.V.M.; project administration, L.B. and J.V.M.; funding acquisition, J.V.M. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The data presented in this study cannot be made publicly available due to confidentiality; readers should contact the corresponding author for details.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

ALD	Active Leak Detection
AUC	Area Under the Receiver Operating Characteristic curve
CNN	Convolutional Neural Network
DV	Dividing Valve
FCNN	Frequency Convolutional Neural Network
FFT	Fast Fourier Transform
FN	False Negative
FP	False Positive
GIS	Geographic Information System
GWN	Gaussian White Noise
L&S	Lift and Shift
MNF	Minimum Night Flow
NRW	Non-Revenue Water
PRV	Pressure Reducing Valve
PSD	Power Spectrum Density
ROC	Receiver Operating Characteristic
RP	Recurrence Plot
SNR	Signal-to-noise Ratio
STFT	Short-time Fourier Transform
TFCNN	Time-frequency Convolutional Neural Network
TN	True Negative
TP	True Positive
WDN	Water Distribution Network

References

1. Puust, R.; Kapelan, Z.; Savic, D.A.; Koppel, T. A review of methods for leakage management in pipe networks. *Urban Water J.* **2010**, *7*, 25–45. [CrossRef]
2. El-Zahab, S.; Zayed, T. Leak detection in water distribution networks: an introductory overview. *Smart Water* **2019**, *4*, 5. [CrossRef]
3. Stoianov, I.; Maksimovic, C.; Graham, N.; Dellow, D. Field validation of the application of hydraulic transients for leak detection in transmission pipelines. *Adv. Water Supply Manag.* **2003**, *9*, 86–97.
4. Xiao, R.; Hu, Q.; Li, J. Experimental investigation of vibro-acoustic techniques to detect and locate leakages in gas pipelines. *Meas. Sci. Technol.* **2021**, *32*, 114004. [CrossRef]
5. Hunaidi, O.; Wang, A.; Bracken, M.; Gambino, T.; Fricke, C. Acoustic methods for locating leaks in municipal water pipe networks. In Proceedings of the International Conference on Water Demand Management, Dead Sea, Jordan, 30 May–3 June 2004.
6. Hamilton, S.; Charalambous, B. *Leak Detection: Technology and Implementation*, 1st ed.; IWA Publishing: London, UK, 2013; pp. 13–14.
7. Kumar, S.S.; Abraham, D.M.; Behbahani, S.S.; Matthews, J.C.; Iseley, T. Comparison of Technologies for Condition Assessment of Small-Diameter Ductile Iron Water Pipes. *J. Pipeline Syst. Eng. Pract.* **2020**, *11*, 04020039. [CrossRef]
8. Pilcher, R.; Hamilton, S.; Chapman, H.; Field, D.; Ristovski, B.; Stapely, S. *Leak Location and Repair: Guidance Notes*; Version 1; International Water Association: London, UK, 2007; p. 16.
9. Fuchs, H.V.; Riehle, R. Ten Years of Experience with Leak Detection by Acoustic Signal Analysis. *Appl. Acoust.* **1991**, *33*, 1–19. [CrossRef]
10. Gong, J.; Lambert, M.F.; Stephens, M.L.; Cazzolato, B.S.; Zhang, C. Detection of Emerging through-Wall Cracks for Pipe Break Early Warning in Water Distribution Systems Using Permanent Acoustic Monitoring and Acoustic Wave Analysis. *Water Resour. Manag.* **2020**, *34*, 2419–2432. [CrossRef]
11. Stephens, M.; Gong, J.; Zhang, C.; Marchi, A.; Dix, L.; Lambert, M.F. Leak-Before-Break Main Failure Prevention for Water Distribution Pipes Using Acoustic Smart Water Technologies: Case Study in Adelaide. *J. Water Resour. Plann. Manag.* **2020**, *146*, 05020020. [CrossRef]

12. Marmarokopos, K.; Doukakis, D.; Frantziskonis, G.; Avlonitis, M. Leak Detection in Plastic Water Supply Pipes with a High Signal-to-Noise Ratio Accelerometer. *Meas. Control* **2018**, *51*, 27–37. [CrossRef]
13. Martini, A.; Troncossi, M.; Rivola, A. Automatic Leak Detection in Buried Plastic Pipes of Water Supply Networks by Means of Vibration Measurements. *Shock Vib.* **2015**, *2015*, 165304. [CrossRef]
14. Cody, R.A.; Tolson, B.A.; Orchard, J. Detecting Leaks in Water Distribution Pipes Using a Deep Autoencoder and Hydroacoustic Spectrograms. *J. Comput. Civ. Eng.* **2020**, *34*, 04020001. [CrossRef]
15. Chuang, W.; Tsai, Y.; Wang, L. Leak Detection in Water Distribution Pipes Based on CNN with Mel Frequency Cepstral Coefficients. In Proceedings of the 3rd International Conference on Innovation in Artificial Intelligence, Suzhou, China, 15–18 March 2019.
16. Müller, R.; Illium, S.; Ritz, F.; Schröder, T.; Platschek, C.; Ochs, J.; Linnhoff-Popien, C. Acoustic Leak Detection in Water Networks. In Proceedings of the 13th International Conference on Agents and Artificial Intelligence–Volume 2, Vienna, Austria, 4–6 February 2021.
17. El-Zahab, S.; Asaad, A.; Abdelkader, E.M.; Zayed, T. Collective Thinking Approach for Improving Leak Detection Systems. *Smart Water* **2017**, *2*, 3. [CrossRef]
18. Teruhi, S.; Yamaguchi, Y.; Akahani, J. Water Leakage Detection System for Underground Pipes by Using Wireless Sensors and Machine Learning. *J. Disaster Res.* **2017**, *12*, 557–568. [CrossRef]
19. Butterfield, J.D.; Meyers, G.; Meruane, V.; Collins, R.P.; Beck, S.B.M. Experimental investigation into techniques to predict leak shapes in water distribution systems using vibration measurements. *J. Hydroinf.* **2018**, *20*, 815–828. [CrossRef]
20. El-Zahab, S.; Abdelkader, E.M.; Zayed, T. An accelerometer-based leak detection system. *Mech. Syst. Sig. Process.* **2018**, *108*, 276–291. [CrossRef]
21. Ismail, M.I.M.; Dziyauddin, R.A.; Salleh, N.A.A.; Muhammad-Sukki, F.; Bani, N.A.; Izhar, M.A.M.; Latiff, L.A. A Review of Vibration Detection Methods Using Accelerometer Sensors for Water Pipeline Leakage. *IEEE Access* **2019**, *7*, 51965–51981. [CrossRef]
22. Martini, A.; Rivola, A.; Troncossi, M. Autocorrelation analysis of vibroacoustic signals measured in a test field for water leak detection. *Appl. Sci.* **2018**, *8*, 2450. [CrossRef]
23. Chi, Z.; Li, Y.; Wang, W.; Xu, C.; Yuan, R. Detection of water pipeline leakage based on random forest. *J. Phys. Conf. Ser.* **2021**, *1978*, 012044. [CrossRef]
24. Ravichandran, T.; Gavahi, K.; Ponnambalam, K.; Burtea, V.; Jamshid Mousavi, S. Ensemble-based machine learning approach for improved leak detection in water mains. *J. Hydroinf.* **2021**, *23*, 307–323. [CrossRef]
25. Nam, Y.W.; Arai, Y.; Kunizane, T.; Koizumi, A. Water leak detection based on convolutional neural network using actual leak sounds and the hold-out method. *Water Supply* **2021**, *21*, 3477–3485. [CrossRef]
26. Tijani, I.A.; Abdelmageed, S.; Fares, A.; Fan, K.H.; Hu, Z.Y.; Zayed, T. Improving the leak detection efficiency in water distribution networks using noise loggers. *Sci. Total Environ.* **2022**, *821*, 153530. [CrossRef]
27. Guo, G.; Yu, X.; Liu, S.; Ma, Z. Leakage Detection in Water Distribution Systems Based on Time–Frequency Convolutional Neural Network. *J. Water Resour. Plann. Manag.* **2021**, *147*, 04020101. [CrossRef]
28. Martini, A.; Troncossi, M.; Rivola, A. Leak Detection in Water-Filled Small-Diameter Polyethylene Pipes by Means of Acoustic Emission Measurements. *Appl. Sci.* **2017**, *7*, 2. [CrossRef]
29. Tariq, S.; Bakhtawar, B.; Zayed, T. Data-driven application of MEMS-based accelerometers for leak detection in water distribution networks. *Sci. Total Environ.* **2022**, *809*, 151110. [CrossRef]
30. Stephens, M.; Gong, J.; Marchi, A.; Dix, L.; Lambert, M. Field Testing of Adelaide CBD Smart Network Acoustic Technologies. In Proceedings of the 1st International WDSA/CCWI Joint Conference, Kingston, ON, Canada, 23–25 July 2018.
31. Anguiano, G.; Chiang, E.; Araujo, M.; Strum, S.; Medina, V.; Waisner, S.; Condit, W.; Matthews, J.; Stowe, R. *Innovative Acoustic Sensor Technologies for Leak Detection in Challenging Pipe Types (Cost and Performance Report)*; Naval Facilities Engineering Command Engineering and Expeditionary Welface Centre: Port Hueneme, CA, USA, 2016; pp. 42–44.
32. Kang, J.; Park, Y.; Lee, J.; Wang, S.; Eom, D. Novel Leakage Detection by Ensemble CNN-SVM and Graph-Based Localization in Water Distribution Systems. *IEEE Trans. Ind. Electron.* **2018**, *65*, 4279–4289. [CrossRef]