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Review of leakage detection in water distribution networks

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Abstract. The conservation of water is, justifiably, a huge concern to water companies, regulatory bodies, environmentalist and more but, unfortunately, water loss through leakage can remain undetected for long periods of time without effective leakage detection. Leakage detection in water distribution networks has taken many forms through investigating varying properties of leakage. Understanding the characteristic leakage types and properties introduces the different emerging technologies. Even though some methodologies have gained popularity in the past decade, the need to establish a complete, economical leakage detection solution that effectively identifies background leakage as well as burst events persists. The benefits and limitations of the aforementioned technologies has often confused water utilities on adapting the most suitable method. Therefore, there is an arising need to classify and benchmark leakage detection practices. This paper reviews technologies in leakage detection contrasting hardware & software, intrusive & non-intrusive, steady state & transient, single & hybrid methods. A particular focus will be placed on scoping the projected direction of leakage detection and localisation. As anticipated, the various techniques refined over the last two decades introduce different capabilities, conditions, and constraints[1]. Assessing and comparing those methods will provide a deeper novel understanding of the research area thus paving the way for novel solutions.

1. Introduction

The search for a robust leakage detection and localisation method has been the interest of the water industry for the past two decades making it a well-developed research area. This is mainly due to the economic loss that water utilities incur through leakage and the resulting non-revenue water. On average, water networks leak 20% to 30% of the water distributed through them totalling around £7 billion of revenue loss through direct and indirect damage [2]. Additionally, the abusive arm of leakage extends to the environment through increased greenhouse gas emissions from pumping the water across the network. Contaminations from leakage often causes the water quality to decrease beyond acceptable levels thereby risking the health of the public. The occurrence of leakages in WDNs relies heavily on pipe infrastructure such as age-induced corrosion, inadequate fittings, and other sorts of pipe deterioration failures [3]. Operational factors that cause disturbances in the flow within the pipes increase the probability of leakage and burst events. These hydraulic shortcomings can arise from cyclic pressure loading or transient surges [4].

Despite the availability of various hardware and software-based detection equipment, the varying limitations and technical challenges exposes a gap in this field.

2. Leakage Overview

Unreported leakage can be broadly identified into two types: Burst and Background leakage [5]. Burst leakages are often detected through their clear properties such as acoustic emissions (AE) and significant pressure reduction [6],[7]. In contrast, background leaks are often small water loss through fittings, creeping joints or small cracks which do not have inherent detectable qualities. As a result, background leakage often run for longer causing adverse losses to the network [5]. Across the literature, the terms burst events and burst leakage are interchangeable whilst background leakage is referred to as leakage [7]. The detection of leakage can be summarised to three phases that dictate important objectives: Identify, Localise and Pinpoint (ILP) [2,8]. The identification phase is concerned with successfully differentiating leak signals from other network signals, such as fire hydrants, to determine the presence of a leak in the network with little or no false alarms [2]. The second phase of the ILP approach is the localisation stage. This focuses on finding the general section of the network such as a DMA [9]. Pinpointing attempts to site the exact location of the leak down to a radius of 20cm. Formerly, the pinpoint phase were two separate phases (locating and pinpointing, ILLP) where locating signifies estimating the leak location to a 30cm radius. The 10 cm difference makes merging the two phases logical [2].

The detection of leaks requires a meaningful understanding of its hydraulic anatomy and detectable properties. Habitually, a leak induces a sudden pressure decline at its location that spreads through the pipes in a set of waves which could be detected through negative pressure wave (NPW) strategies [10]. This pressure anomaly is difficult to detect for background leakage events and could be an indication of unaccounted demand (e.g., fire hydrants) nevertheless pressure fluctuations have been the basis of several leakage detection techniques. The inversely proportional relationship between pressure and flow rate dictates that this decrease in upstream pressure will trigger a decrease in downstream flow rates. Pressure and flow changes are the most exploited characteristics of burst events [11]. Another measurable leak quality is the resulting acoustic emissions released by the loss of water. These vibrations display several wave properties such as reflection, refraction, absorption, and diffraction that can be exploited to identify and locate burst events [12]. These waves can be collected through a variety of sensors such as dynamic transducers, accelerometers, or microphones [13]. Temperature anomalies in the vicinity of a leak arise making it another identifier that could aid in its detection [7].

Considerable research has been taken to investigate detection strategies in water networks making it a diverse field. Therefore, it is necessary to divide these approaches into appropriate categories. A novel classification tree was formulated to help navigate new readers to the research area (figure 1). The easiest discrimination of leakage detection methodologies in literature can be between hardware-based and software-based. Hardware leakage detection highlights the different sensing methods to identify and locate leakage in a network that exploit the characteristics (acoustic, pressure, flow, temperature, etc). These can be further refined into intrusive, robotic, in-pipe systems or non-intrusive, out-of-pipe systems. However, software-based detection is more concerned with the computational and data analysis of network parameters to extract leakage information. It exceeds hardware methods in its ability to assess leakage for steady state and transient flows.

3. Hardware detection methods

In this section we uncover the varying hardware technology developed for leakage recognition and localisation in literature. This is defined as any form of device that can be used to sense or collect data that can identify leakage anomalies described in Section 2. Some of these hardware detection methods are often paired with data processing software method to provide a more accurate leakage detection strategy.

3.1. In-pipe inspection devices

Intrusive devices are an underdeveloped subsection of hardware detection methods that revolve around inspection devices that enter the pipe networks to explore leaks. Robotic inspection devices vary greatly depending on their system characteristics which include their driving method, sensing technology and level of autonomy [14].

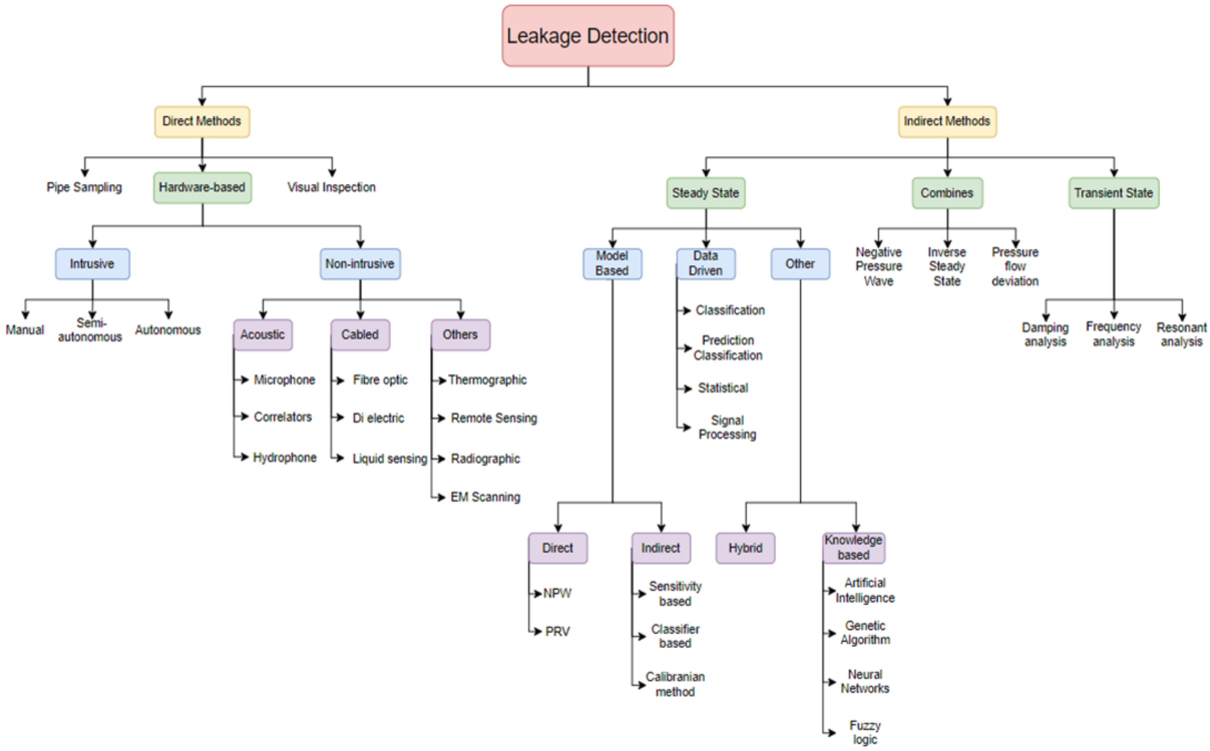

Figure 1. Leakage detection classification tree.

3.2. Driving methods

Generally, moving mechanisms can be defined as passive or active where passive approaches rely on the flow of water to inspect the pipe and active approaches are equipped with their one or more actuators to achieve the desired motion. Passively propelled inspection robots are often named PIGs (pipeline inspection gauge) [15]. PIGs are highly effective, safe and economical devices due to their simple nature and navigation system [14,15]. They have proven useful in clearing deposits gathering on the interior of the pipes in addition to their main role to assess the pipe status and detect leakages. PIG inspection systems utilise one or more sensors such as ultrasonic and eddy current sensors [16]. The navigation is usually achieved through odometers, visual sensors and inertial measurement units [15]. PIGs' motion can be problematic at higher flows where it is hard to halt their motion and when passing through corners in pipe infrastructure however intelligent PIGs might present better speed control capabilities. Commercially available PIGs include the 'smart PIG' by NORSEN GROUP; 'Smartball' by Pure Technology [17] and 'Remoted PIG' by Jiutai Technology [18,19].

Active driving methods are categorised into wheel, track, inchworm, walking and snake mechanisms. Wheel propulsion is generally coupled with a spring mechanism to press against the pipe walls to smoothly adapt to the in-pipe topology. Wheel-based prototypes are available in the following literature [20,21]. Wheeled robots can also be screw-driven which usually entails a stationary and rotational section. For soft or cracked ground motion, wheeled robots are often outperformed by track-driven systems. However, this drive is rarely used due to its higher complexity and energy requirements [22]. An example of legged inspection robots can be found in Bradbeer et al.'s work [23]. Worm-like movements are produced by the cooperation of a clamper and extensor modules to push the robot through the pipe. This motion is often used in foreign environments where caution is a priority. Further work on inchworm movements has been conducted by [24,25], [26], [27]. Like the inchworm, snake robots have proven more adaptable in abnormal environments. They are comprised of several connected modules capable of planar movement [28]. Reptile movement for inspection robots is not widely due to the complexity of increasing degrees of freedom with every adjoining module

3.3. Level of autonomy

Intrusive hardware inspection techniques belong to one of three classes of autonomy: No autonomy, semi-autonomous, or fully autonomous. Most robotic inspection devices lie in the first category of non-autonomous hardware however the introduction of autonomy provides freedom from user interference [14,29].

Fully operated robots are usually controlled through a tether cable by trained users or through a wireless link. The operator examines the inside of the pipe in real time using the incoming sensor data as the robot moves along the network [14]. The tether cable is preferred because it enables a smoother recovery as shown in the study [30]. This is a popular method because, as of now, there are no cost effective solutions that can navigate the varying scenarios inside water networks [30].

Semi-autonomous inspection is achieved through implementing automatic control modules that can remove some of the user’s duties such as navigation or pipe condition assessment. This shifts some of the users’ responsibilities and introduces higher accuracy. Prototypes that belong in this category include the PIRAT [31] and Karo [32] robots.

Fully automated robots are those voids of any user interaction. They are able to navigate, assess and communicate pipe condition through their sensor payload in real-time without being lost in the system. The challenges faced by autonomous inspection devices are numerous but the most prominent is energy and communication in long-time and long-range applications [14]. Kirchner and Hertzberg developed the Kurt robot that uses a map of the pipe network to collect video graphic, ultrasound and gradient data through automatic operation [33].

In this review, we have already specified some smart PIGs and robotic detection prototypes that highlight the range of in-pipe inspection including Makro [21,34], Karo [32], PIRAT [31], Kurt [33] and Smartball [17]. Finding a complete intrusive inspection robot is difficult due to the design challenges they must overcome. Despite that, pipe inspection gauges can be an appealing solution to some network with successful case studies shown [35].

3.4. Non-intrusive methods

Leakage detection systems can also be labelled as dynamic or static methods. Whilst intrusive methods are referred to as dynamic due to their motion throughout the network to investigate inner pipe conditions, non-intrusive methods depend on mounted sensors that collect data used to infer leakage making it a static method [2]. Static methods carry the advantage of identifying a leak immediately whereas dynamic detection is often deployed after a leak is expected/identified to pinpoint the leak area [36,37]. The research scene has been marginally focused on the static strategies of leakage detection for the last two decades due to their more tangible benefits and their ability of real-time management [2]. The most prominent technologies exploit acoustic or pressure properties accounting to more than 50% of the literature [2]. Other technologies rely on flow sensors, ground penetrating radars (GPR), tracer gas detection, infrared thermography which will be mentioned in this section.

3.4.1. Acoustic technique. Acoustic based leakage detection and localisation can be traced back to the early 1990s in water and oil networks [38]. The localisation of leak events through acoustic methods can be classified into time-of-flight-based or attenuation-based. Attenuation based relies on the decrease of signal amplitude as the acoustic signals travel across the pipeline while time based monitors the increase of signal transit time [39]. Acoustic emissions result from turbulent pressure fluctuations at the leak, vapor bubbles forming at high velocities and imploding as shock waves on pipe walls. The frequency of those acoustic emissions (AE) varies depending on the source where turbulent flows produce low frequency signals and cavitation bursts cause high them in plastic pipes requires a denser distribution of the sensors [40]. These instruments could be geophones (electrical or mechanical), hydrophones, listening sticks, accelerometers, or correlators.

3.4.2. Fibre optics. These systems measure temperature anomalies inherent in leaks throughout the pipe. In comparison to oil and gas pipelines, the leak induced temperature change in water pipelines is smaller and harder to detect [41]. Daily and seasonal temperature fluctuations increase the difficulty of fibre optics leakage detection [41]. Optical fibres could alternatively monitor the strain in the pipe wall due to leaks [42,43]. Developments to increase the use of fibre optics for pipeline monitoring of leak-induced temperature or strain include the use of Raman Distributed Temperature Sensor (RDTS), Fibre Bragg Gratting (FBG) [41] and Brilloun Optical Time Domain Reflectometry (BOTDR) [6]. The use of fibre optics exceeds other methods in its immunity to electrical noise, corrosion resistance and stability [7] however their high initial and operating costs make them less desirable to water utilities.

3.4.3. Infrared thermography. Like fibre optics, infrared thermography exploits the thermal effects of leakage in pipelines to identify and locate the event. IR cameras have been applied to asses pipe conditions [44,45] as well as leakage detection in water networks [46,47]. Despite it being a scarce research topic, thermography could provide a cost-effective, efficient, non-destructive way to monitor large areas of water networks. Capturing the thermal anomalies translated to the surface above the leakage is affected by several factors [48]. IR should be measured during times where the ambient temperatures is closer to equilibrium, hence increasing thermal visibility. Pre-sunrise and post-sunset hours have been suggested as the most suitable periods for thermography [48,49]. Soil moisture tends to hinder the investigation which can be problematic in rainy countries such as the UK despite the moist soil's superior heat transfer ability [49].

3.4.4. Ground Penetrating. Radars Ground penetrating radars have gained some interest in the leakage research community [50,51]. Their ability to utilise the electromagnetic irregularity of water leakage in infrastructure to identify and locate the failure. This imaging method excels in its applicability to both metal and plastic pipes regardless of the material and size [2]. GPRs are easy to use and transport making it possible to survey large areas with less manpower [52]. Despite that, the disadvantages of deploying GPRs outweigh the possible benefits. Its inability to discriminate between leak-induced irregularities and soil inhomogeneity increases the false alarm rate [38]. This strategy is limited to pipes buried less than 5m deep and highly influenced by soil types. The reliability of this method can be improved through the aid of decision support systems [53] and evolutionary search algorithms to obtain accurate leakage detection.

3.4.5. Tracer gas. Gas injection utilises inert, non-toxic, insoluble, traceable gases such as halogens, ammonia, and helium to pinpoint leakage sites. As these gases seep through faulty infrastructure, operators detect their location by surveying the suspected area [54].This requires a proficient knowledge of the network's flows to limit the gas flow to the suspected area by blocking other routes to exit the system. Tracer gas is able to detect both background leakage and burst events with low false alarm rate [7,46]. The fast and accurate response of this technique is crippled by its expense especially in large, low-pressure networks that require higher volumes of gas and the implementation cost of in-built sensors for monitoring and possible filtering stages makes this method unrealistic [7,55].

3.4.6. Magnetic induction. Magnetic induction is an accurate detection technique that establishes a communication link between two sets of sensors. One of the sets captures the flow, pressure and acoustic properties of the suspected leak from within the pipe whilst the other assesses the external factors such as humidity, temperature and soil properties outside the pipeline [56]. Through a current-modulated signal, the coils of the magnetic transmitter induces the current to the receiver [57]. This communication link enables real time control of leakage detection hence increasing the response rate of utilities in harsh underground conditions. However, this strategy incurs high implementation costs making it undesirable.

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4. Software detection Methods

Background leakage poses a large threat to water networks as they often go undetected by the conventional hardware methods accumulating more losses over time. Therefore, the application of software methods is essential to counter this prevailing issue. The long-time savings that accompany software techniques are usually offset with the initial costs of installing sensors throughout the network making it a less popular option to utilities *[58]*. Water distribution systems often operate their leakage detection techniques under the premise of steady-state flow *[59]*. This method compares the behaviour of the actual network in comparison to the expected performance to detect anomalies that are often caused by leakage or blockage. An abundance of real data (historic and live) from the network suggests a data-driven approach to leakage detection however, in networks where data is scarce, a model-based approach takes precedence given that the hydraulic model is available.

4.1. Model based

As the name suggests, model-based detection relies heavily on the model's resemblance to the actual network, the data analysed and the arithmetic techniques employed [1]. Therefore, building a realistic accurate model is crucial to the success of this technique, often having a separate calibration stage to compare the model and the network. Zaman et al. [1] display a useful general framework for the model-based leakage detection method. a used Developing a reliable replica on hydraulic simulation machines (e.g., EPANET, LOOP) should include input information of a leak-free system through different streams of information such as Supervisory Control and Acquisition (SCADA), Geographic Information Systems (GIS) and more. Some model platforms have an inherent leakage detection module such as WaterGEMS that exercises a genetic algorithm (GA) to signify potential leak nodes.

As soon as the model is complete, it is necessary to validify the model through several techniques to ensure that the model tracks the real-life example. In some cases, model pre-processing is performed before calibration to decrease the potential candidates [59]. The calibration techniques used are steady-state and extended period simulation (EPS) and contrast them to the field data.

Once the model has been calibrated successfully, several leakage detection strategies can be applied to the model to predict and inform of possible leak locations and their corresponding sizes.

Several detection strategies have been developed for the model-based approached. They exploit the simulated parameters and field data to locate possible leak areas However, these leakage detection models often suffer with the unaccounted ageing properties of the pipe causing the pipe diameters to decrease [6]. A simple method for investigating leakage is applying the conservation of mass calculation. Balancing the mass in and out of nodes can uncover unaccounted for loss hinting at a possible leak. Whilst this approach, works well for steady-state, they are prone to disturbances and pipeline dynamics resulting in false alarms [60]. A different method called pressure residual vector (PRV) exploits the leak-induced pressure changes in the real system and compares it to the leak-free model from their subsequent locations on the network [61]. When the disparity between the modelled and actual pressure exceeds a pre-determined threshold, set through uncertainty analysis and statistical considerations, the area is flagged as a potential leak location and investigated [62,63].

Indirect methods for model leakage detection can be classified into three types as shown in figure 1. Calibration-based methods rely on optimising the model calibration stage by infusing it with leakage information. This information is obtained by modelling leakage as a pressure demand. Genetic algorithms (GA) have proved as a useful evolutionary search algorithm (EAs) to investigate possible leak location through calibration [64]. EA has been widely used in the optimisation of water distribution system design for both single objective and multi-objective as highlighted by the comprehensive literature review [65]. Sensitivity-based analysis is another method that exploits network models [61,66] through investigating the pressure sensitivity of nodes in the model under leak and non-leak conditions. Combining the sensitivity matrix with the corresponding pressure residual vector can more accurately indicate potential leakage. This is represented in the study [67] with the aid of the angle based method. To develop that further, [68] introduces a classifier-based method to detect leakage. Exploiting statistical classifiers, greatly improves fault localisation with comparison to the angle method demonstrated in [67] especially regarding demand uncertainties. Classifiers are often used as a data-driven approach however, their used in model-based detection has proved rewarding.

5. Data-driven

Using abundant data, leak detection can navigate complex, heterogenous, large water distribution networks by bypassing the complications of hydraulic modelling. This makes it a more reliable and accurate technique due to its reliance on real data at the cost of increased sensitivity to faulty sensors. These methods rely on their ability to reveal aberrant signals/patterns in the monitoring data received that could suggest the existence of a leak.

5.1. Data pre-processing

Data-based detection often engineers one or a combination of flow, pressure, and demand readings. Consumer demand being the least probable data source can be rationalised by their uncertainty in the localisation stage [68] and its relative insensitivity to smaller leak flow rates [69]. The data used might differ in source, sample source (1-15 minutes) and length of time series which are crucial aspects to consider [67]. These sensor readings are often raw and require pre-processing before they can be implemented to any leakage detection algorithm. Data pre-processing often involves sorting, filtering, and transforming the incoming data making it a tedious task. Other issues such as uncertainty and variability must be considered when employing real data, yet this could be avoided in the instances data is extracted from models. Pre-processing is essential to filter erroneous data, filling gaps in the time-series and arranging the results for assessment making a critical step in data-driven leakage detection [1].

5.2. Detection methods

In our classification tree (figure 1), data-driven techniques were divided into four types depending on their technical procedure. A different way to organise these techniques is to match their data source and data types. The technical procedures highlighted in this review include statistical, classification, prediction, signal processing. These methods are also used for transient leakage detection.

5.2.1. Pressure/flow monitoring. The simplest data-driven techniques utilise pressure monitoring such as negative pressure wave (NPW) and pressure point analysis (PPA). The NPW method detects the propagating pressure fluctuation at both sides of the leak through the use of transducers [70]. Localising the leak is established by contrasting the time difference between the reading on both sensors through cross-correlation. Applying the NPW approach practically is challenging particularly for long-range pipes [6]. Another limitation of NPW is its high false alarm rate resulting from its sensitivity to transient flows in networks. In order to increase the method’s reliability, study [71] proposes several improvements regarding false alarm reduction. NPW hybrid leakage detection techniques are encourage to justify the alarms such as represented in [57]. Pairing pressure transducers to compare their leak results is an alternative method to reduce false alarms [71]. The last recommendation uses the aid of pattern recognition to distinguish leakage-induced pressure fluctuations from valve-induced variations [71]. Other ways to improve NPW, include implementing an adaptive threshold and improving data quality which could be achieved through filtering background noise and advanced data processing. Pressure point analysis (PPA) developed by EFA technologies ltd. is commercially available technique that statistically analyses the mean pressure measurements along a pipe [55]. Similar to the other pressure-based leakage detection strategies, PPA issues an alarm when the mean pressure value drops beyond an established threshold. This method is straightforward and economic but lack credibility under transient conditions and cannot localise the leaks [6].

5.2.2. Statistical. Statistical analysis techniques for leakage detection are methods that have no classification or prediction stage and depend completely on statistical theory [69]. Statistical Process Control (SPC) is a central method in this category often using control charts to monitor measurement variations. They are also used for data pre-processing [69]. The differences between univariate and multivariate SPC methods can be found in Jung et al. work [72] The univariate methods elicited are Western Electric Company (WEC) rules, Cumulative Sum (CUMSUM) and Exponentially Weighted Moving Average (EWMA). WEC rules can only consider the past eight readings whilst EWMA has largest memory [72]. The multivariate methods described where Hotelling T2 control chart with elliptical control and the multivariate versions of the CUMSUM and EWMA methods. Other statistical strategies include Principle and Independent Component Analysis (PCA, ICA) that are used to reduce the state space of the data without decreasing its value. ICA can be considered an extension to PCA that considers higher order statistics [73]. Newer methods of statistical procedures rely on data clustering [74], support vector machine (SVM), artificial neural networks (ANN) [75] and newer versions of the multivariate methods mentioned earlier.

5.2.3. Classification. Classification based strategies build models that can effectively distinguish (classify) normal and outlier data. The simplest form of a classification technique calculates the absolute mean difference between expected and recorded hydraulic measurements [1]. More commonly used models are trained using sets of labelled normal and abnormal hydraulic data to successfully detect bursts. An example of this is the comparative study conducted by Mounce and Machell on burst detection through flow reading analysis using static and time-delay artificial neural networks (ANN) [76]. The different architectures displayed a different relationship with the inputs causing improved detection due to its more dynamic nature. It is clear that the performance of the classification model relies heavily on the abundance of normal and outlier real data to train the model and the quality of the inputs used. Using a leak function and a self-organising map (SOM) ANN, the classification model can output a value from 0-1 to identify the probability of a leak at a node [77]. This method is more adept in distinguishing leak data without supervision or labelled training data [77]. The need of adequately labelled and balanced training data for both normal and outlier conditions is the main disadvantage of this technique therefore unsupervised learning is a logical step for further research. In addition to that, poorly trained classification models often lead to high false positive rates (FPR) which is another concern for classification-based leakage detection.

5.2.4. Prediction-classification. Unlike classification techniques, prediction-based method introduces a preliminary stage of outlier data prediction hence enabling the classification model to be built effectively with normal hydraulic data alone. An additional stage of data selection is required to achieve this which often utilises some of the statistical methods mentioned earlier [78,79]. A linear Kalman Filter (LKF) could be trained using normal historical data to provide a statistical description of the current system [80]. This is an efficient method that can extract the prediction using live data alone. Expert systems such as Fuzzy Interference Systems (FIS) and Bayesian Interference Systems (BIS) provide reliable detection results however they can be developed further by using historical data, evolutionary algorithm (EA) and expectation maximisation (EM) to optimise their parameters. Mounce et Al. employs a combination of an artificial neural network called mixed density network (MDN) in the prediction stage [78] followed by a FIS in the classification stage to improve burst detection in the form imitate human cognition [81]. Following a prediction stage, support vector regression (SVR) was used to classify deviations in the input data for leakage detection [82]. Changes in historical data used for prediction-classification propagates the data uncertainty decreases the accuracy of leakage detection and requires a data selection stage.

5.2.5. Signal Processing. Digital signal processing (DSP) is a commonly used technique to improve leak detection and localisation using pressure or acoustic signals due to sharper transitions than traditional techniques such as NPW. This benefit is often offset by the bandwidth restrictions that these methods introduce through pipe resonance [36].

The use of time and frequency response analysis of acoustic emissions for leakage feature extractions has been fruitful leading researchers to explore hybrids that can exploit their benefits. This initiated the need for time-frequency analysis to obtain valuable information from both domains. Several types of Fourier transforms have been used to capture leakage characteristics, but short-term Fourier transform (STFT) has been the primary interest of researchers. STFT introduces a time variable to the spectrum by slicing the signal using a time window function. The short time segments (called frames) are then input to a discrete Fourier transform (DFT) to produce a time-frequency analysis. This method has been justified in multiple occasions and compared to fast Fourier transform (FFT) in [83] where it outperforms FFT in the uncertainty analysis. Li et al.'s proposed methodology of wavelet denoising and STFT combination has shown higher accuracy than other signal processing methods such as wavelet decomposition, gaussian mode, recurrence plot, Wigner-Ville distribution (WVD), Wigner-Hough Transform (WHT), and empirical mode decomposition (EMD) [84]. Fast Fourier transform has also been validated in the study [85] through a fault detection and isolation (FDI) system of underground plastic pipes.

The use of STFT and other time-frequency analysis methods has been overshadowed by the application of wavelet transforms (WT) for leakage detection and localisation. STFT has the disadvantage of a strict resolution limit due to its limited window size which does not exist when using WT. Therefore, using this method better fits the multi-resolution nature of leakage and burst events [86]. WT can be used in multiple areas of signal processing such as denoising [84], decomposition [84] recognition, classification, and feature extraction. The effectiveness of WT relies heavily on the selection of the mother wavelet used is shifted and scaled across the signal to create daughter wavelets. This was emphasised in the work of Ahadi and Bakhtiar and their comparison of Haar and db8 mother wavelets [87]. Studies [86,87] further prove the benefits of WT over STFT. Wavelet transforms, however, are limited by the length of the mother wavelet and its non- adaptive nature [12]. Examples of mother wavelets used also include Meyer, Morlet, Daubechies and Mallet functions [1]. WT has proven to reduce noise and better locate sharp transitions in the leak signals [1]. In study [88], wavelet features pf pressure signals were compared and outperformed by two Multi-Layer Perceptron Neural Networks (MLPNN) for feature extraction and leakage classification that are then fused by the Dempster-Shafer (D-S). The neural networks have outperformed the wavelet feature methodology in correct classification rate (CCR%) where D-S classifier fusion method resulted in 95.11%, wavelet at 86.94% and statistical features trailing behind at 64.56% [88].

6. Conclusion and future work

The leakage detection field spare and multi-directional filled with researchers attempting to equip water companies with a solid method to tackle the heterogenous nature of this issue. Reviewing the field is challenging but this paper should offer guidance to the multiple research areas and possible novelties that can be uncovered in each. Every section offers a further breakdown of the research area and a light comparison between technologies within to collate the most research findings and methodologies.

The robotic platforms reviewed include many platforms that vary in driving methods, sensing capabilities and autonomy. The active driving method sin intrusive inspection devices include wheeled, screw-driven, track-driven, worm, snake and legged showing that they all vary in applicability depending on the nature of the pipe and its environment. The autonomy level of the Smart PIGs and robots introduce an interesting trade-off between recoverability and less manpower. However, there are no economical devices capable of autonomously adjusting to all the scenarios present in all water networks and effectively communicating with the users with no intervention.

Non-intrusive hardware detection consists of a range of sensors that detect leak-induced anomalies to identify and locate events. The most common are acoustic sensors which include microphones, geophones, hydrophones, accelerometers, leak noise loggers and correlators. Other sensors mentioned are magnetic induction, infrared thermography, fibre optics, ground penetrating radar and tracer gas. These are often insufficient alone and will benefit further if paired with signal processing methods.

Software leakage detection draws from two general methodologies. Model-based leakage detection requires the analyst to construct an accurate model of the water distribution network using hydraulic analysis software and compare expected pressures/flows to the actual measurements to find outliers. In comparison, data-driven techniques include varying methods of collecting, pre-processing, and analysing data to directly find leak-induced outliers. Data-driven methods are classified into several categories based on their nature including statistical, classical, prediction and signal processing. Using models or data-driven methods rely solely on the availability of sensor data and their accuracies but can often be used together to provide a better hydraulic analysis of the system. These methods rely heavily on computational efforts to detect leakage and can benefit majorly from the rise of data engineering and artificial intelligence breakthroughs.

It is common for researchers and industry to use a hybrid between the methods reviewed to draw on their advantages and this should be explored further to use our current knowledge to bridge the faults of these methodologies. It is also crucial to explore new venues for model leakage prediction which can help identify background leakage. This can benefit from the emergence of neural networks as function approximators especially graph neural network due to their similar data types. Furthermore, neural networks models should be tested for transfer learning applications hence reducing the training time required for neural networks to model water distribution networks.

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