Application of software and hardware-based technologies in leaks and burst detection in water pipe networks: a literature review

water

Review

Application of Software and Hardware-Based Technologies in Leaks and Burst Detection in Water Pipe Networks: A Literature Review

Kiran Joseph [1,2], Ashok K. Sharma [1,*], Rudi van Staden [1], P.L.P. Wasantha [1], Jason Cotton [2] and Sharna Small [2]

[1] Institute for Sustainable Industries and Liveable Cities, Victoria University, Melbourne, VIC 3011, Australia; kiran.joseph2@live.vu.edu.au (K.J.); rudi.vanstaden@vu.edu.au (R.v.S.); wasantha.pallewelaliyanage@vu.edu.au (P.L.P.W.)
[2] Greater Western Water, Melbourne, VIC 3429, Australia; jason.cotton@iwn.org.au (J.C.); misharna.small@gww.com.au (S.S.)
* Correspondence: ashok.sharma@vu.edu.au

Abstract: With the rise of smart water cities, water resource management has become increasingly important. The increase in the use of intelligent leak detection technologies in the water, gas, oil, and chemical industries has led to a significant improvement in safety, customer, and environmental results, and management costs. The aim of this review article is to provide a comprehensive overview of the application of software and hardware-based technologies in leak detection and bursts in water pipeline networks. This review aims to investigate the existing literature on the subject and to analyse the key leak detection systems in the water industry. The novelty of this review is the comprehensive analysis of the literature on software and hardware-based technologies for leak and burst detection in water pipe networks. Overall, this review article contributes to understanding the latest developments and challenges in the application of software- and hardware-based technologies for leak and burst detection in water pipe networks, and serves as a valuable resource for researchers, engineers, and practitioners working in the field of water distribution systems.

Keywords: leak detection; water pipe networks; burst detection; software-based technologies; hardware-based technologies; water infrastructure; Internet of Things (IoT); machine learning; artificial intelligence; sensing technologies

check for updates

Citation: Joseph, K.; Sharma, A.K.; van Staden, R.; Wasantha, P.L.P.; Cotton, J.; Small, S. Application of Software and Hardware-Based Technologies in Leaks and Burst Detection in Water Pipe Networks: A Literature Review. *Water* **2023**, *15*, 2046. https://doi.org/10.3390/w15112046

Academic Editors: Giuseppe Pezzinga and Marco Ferrante

Received: 24 March 2023
Revised: 15 May 2023
Accepted: 24 May 2023
Published: 28 May 2023

1. Introduction

Pipeline networks are crucial for moving water from one place to another to serve larger rural and urban communities [1–4]. Pipelines have also been used since World War II to transport gas and oil [5]. The study explained how a supervisory control and data acquisition (SCADA) system was used to collect production and operational data from an oil field in Western China [6]. It also describes the current development trend and direction towards the creation of an intelligent oilfield transportation pipeline network with big data analysis, complete situation awareness, automatic control, and management capabilities [6]. Kraidi et al. [7] reviewed oil and gas pipelines (OGPs) in Iraq and many other countries with comparable conditions and discussed the risk associated with pipeline failures and mitigation approaches, which can also be suitable for water supply pipes.

Water supply pipeline network systems have existed for hundreds of years. Increased pipeline failures cause property damage, environmental impacts, and deaths [8,9]. Recent cases of pipeline leakage have shown increased environmental awareness and public concern, including increased costs for water service providers in terms of staff vacation time and associated cleaning costs. Affordable and reliable leak detection systems are in demand, as strict legal requirements are increasingly being implemented in industrialised countries against any public loss. This study examines several pipeline leak detection technologies implemented in pipeline network systems.

The significance of research on leak detection in pipelines and related causes include early detection of the following:

- Water leaks and bursts.
- Water theft.
- Low pressure/high flow.
- Potential overflow/blockage.
- Water quality contamination.

It shows the importance of developing an intelligent water network (IWN) for the detection of leaks and bursts based on socioeconomic benefits.

Some of the socioeconomic benefits are as follows:

- Reduction in non-revenue water, and reduction in the operational cost, ultimately leads to an increase in water revenue.
- Minimising price impacts on customers arising from rapid growth in the region.
- Operations to make decisions based on real-time data.

Figure 1 represents the structure of this review article which discusses the importance and economic advantages of implementing an intelligent water network. This article covers several topics, including intelligent water network systems, hardware- and software-based leak detection techniques, and application technologies used to develop intelligent water networks. The figure shows how these topics are interconnected and organized within the article, providing readers with a clear overview of the content.

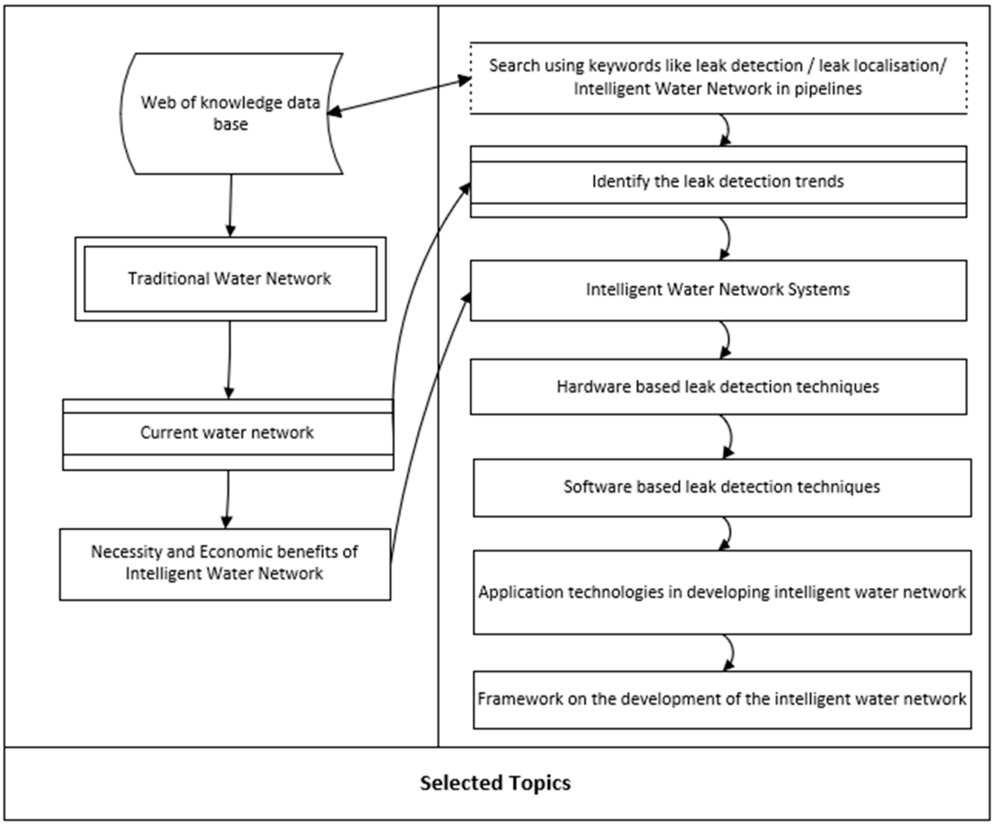

Figure 1. Overall structure of the review article topics.

These include hardware- and software-based approaches. Each approach has its benefits and disadvantages. Seven essential attributes are defined to compare the performance of different approaches, namely leak sensitivity, location estimation capacity, operational change, availability, false alarm rate, maintenance requirement, and cost [10]. The methods currently used do not provide sufficient performance for all the above characteristics. High false alarm rates, when the pipeline is in regular operation, are common problems with most leak detection technologies [10]. Incorrect alarms are undesirable because they increase the workload of operational personnel, reduce the confidence of operators in a system, and increase the risk that a real leak will not be noticed [10]. It is crucial to develop a leak detection system that is both affordable and effective. Joseph, Sharma, and van Staden [11] proposed a leak detection methodology to support the development of an intelligent water network system after an in-depth study of the case studies described in the literature. Figure 2 shows the evolution of the water management and leak detection systems in chronological order according to their historical appearance [11,12].

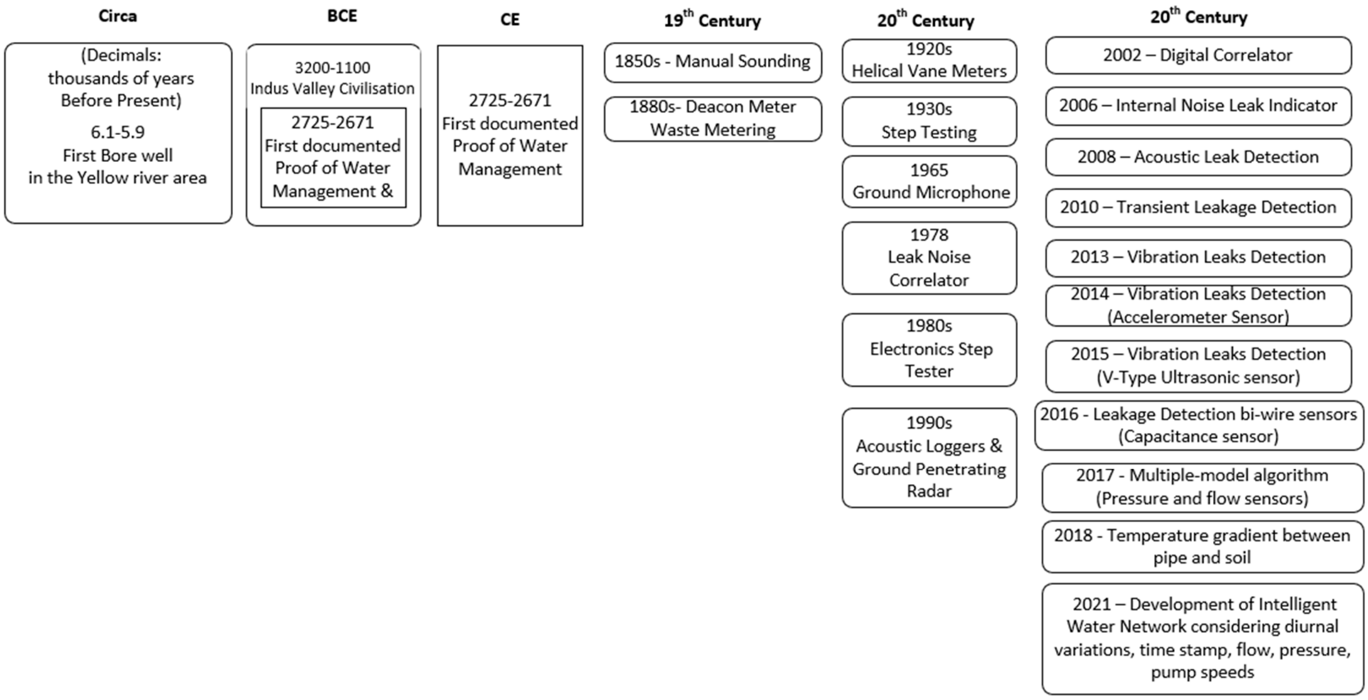

Figure 2. Evolution of water management and leak detection systems charted in chronological order.

Technologies such as smart water grids enable water utilities to solve these problems effectively. Parida and Thyagarajan [13] proposed a wireless sensor network system based on thermal (infrared) images that can be deployed with distribution pipes to achieve the objective of early leak detection, leading to a significant amount in water savings. For the water distribution system, these technologies allow sensors to detect leaks and bursts and provide important data to support network maintenance. It is possible to use this infrared method in drone applications using a tracking algorithm to develop an automatic system [14]. In water supply systems, it is difficult to identify the source of the leak since junctions, nodes, and curves affect the reflection waves if acoustic methods are used for leak detection technology [15]. Systems that do not consider the pipeline inventory always result in significant leakage location errors. The fact that the reflected wave approach can only be applied to series pipelines is another disadvantage. Another disadvantage is the number of false alerts [15]. Data quality, adaptive thresholds, and accurate alarm reduction are the three key areas that are applied to improve the reliability and accuracy of leak detection techniques [16].

Smart environments are the basic elements of smart cities. Much of the term "smart environment" focuses on the management of air, water, and energy pollution [1–4,17,18]. Large amounts of water are generally transferred from reservoirs to consumers by pumping, which means that water losses caused by pipeline leaks and bursting can cause significant financial losses due to the environmental costs associated with the energy loss of pumping and the potential risk to public health. Old and corroded pipes, including the development of water hammer pressures due to operational errors due to a quick valve closure or opening, can further increase pipe leakage. Numerous methods have been developed for various applications to detect the frequency and scale of leaks in water pipeline systems to reduce future water losses and public concerns [4,12]. The classification of the main methods of finding leakage is shown in Figure 3 as based on the literature [12,19].

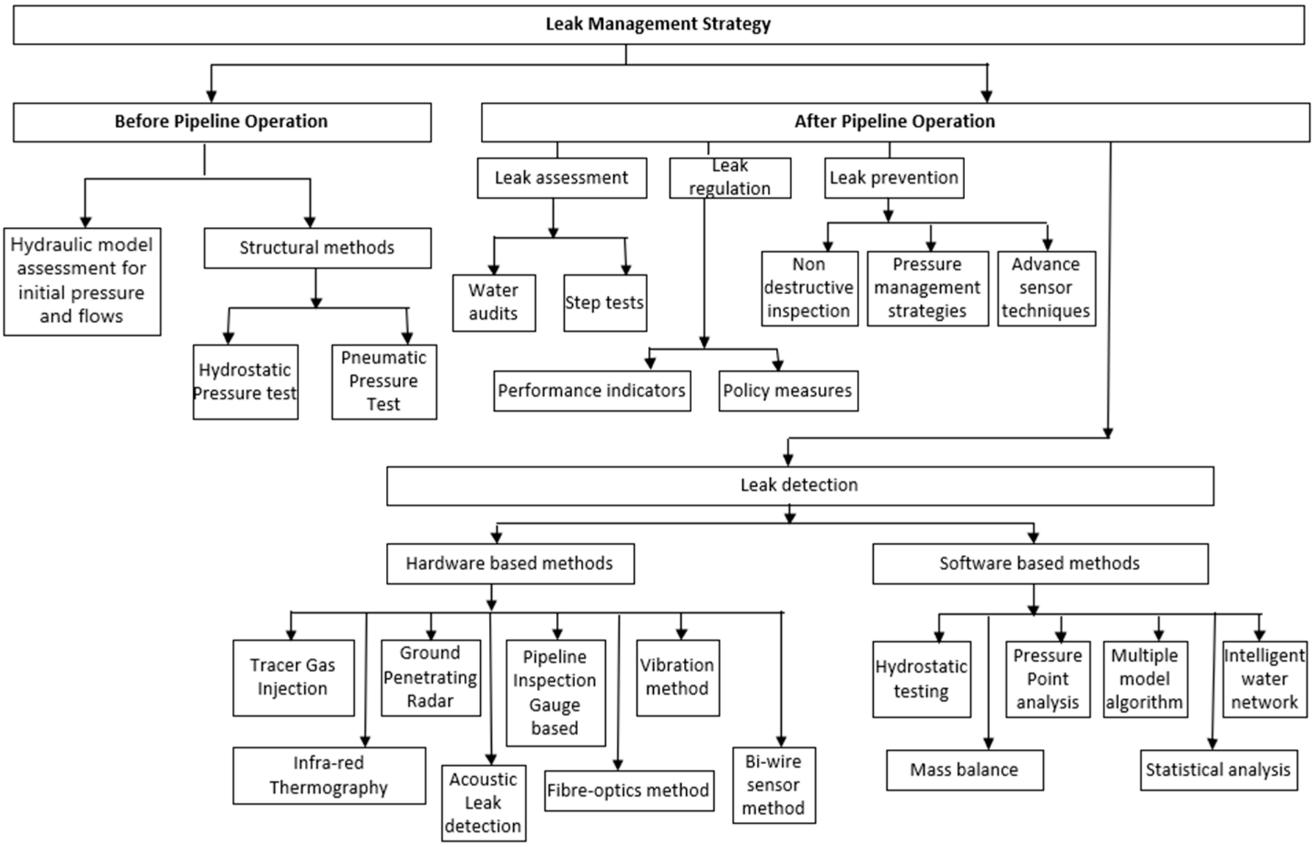

Figure 3. Leak management strategy categorization.

Yussof and Ho [20] indicated that increasing pressures on fast-expanding water supply pipe networks require the establishment of improved leak detection technologies and suggested future research on leak detection techniques. The current state-of-the-art technology for leak detection demonstrates several strategies, including hardware and software solutions. A challenging method used in the industry is hardware techniques, which entail the purchase of industrial hardware instruments and devices, particularly for leak detection. However, software-based approaches incorporate both conventional and cutting-edge methodologies such as image processing and machine learning algorithms and are used for hydraulic data analysis. There are still several unresolved aspects associated with reliability, efficiency, sensitivity, and location accuracy that researchers and developers must address [21]. Sixty-eight countries are experiencing extremely high to medium–high risk water stress, which is a global concern [22]. Globally, there are substantial leaks in water distribution networks (WDN) at a time when water conservation is necessary due to the crisis. These leaks significantly worsen the situation of water shortages because they result in unacceptable environmental risks and significant financial losses. The adoption of cutting-edge technology and leak detection in the WDNs is required to reduce such damage [22].

Finding leaks in water distribution networks (WDN) has proven to be a challenging task over the years. Leak detection in a short period helps to reduce the negative economic and environmental impacts. However, increasing leak detection speed can increase the chances of inaccurate leak detection, which could result in additional costs [23]. Fereidooni et al. (2021) presented an efficient hybrid technique for locating leaks, which involves calculating the volume of material lost and detecting leaks utilising hydraulic relations and AI algorithms. Fereidooni and Tahayori [23] demonstrated that hydraulic equations such as the Hazen-William equation, the Darcy-Weisbach equation, and other pressure drop formulae can be used to generate features that are important for leak identification [23].

Hu and Chen [24] reviewed model-based, and data-driven approaches for WDS leak detection at various locations. They then classified the techniques that fall under these approaches according to their respective leak detection methods. Although these approaches are promising, they have not been well developed. Model-based approaches include sensitivity matrix-based approaches, mixed model-based/data-driven approaches, optimisation calibration approaches, and error domain model falsification. In contrast, data-driven approaches include feature set classification methods, prediction classification methods, statistical methods, and unsupervised clustering methods. They also indicated that neither of the approaches can handle variations due to unexpected water demand [24]. Attaining a comprehensive set of historical data from a real network will enable a data-driven strategy to become more applicable. However, model-based solutions are recommended when there is a lack of data and a simple way to generate the hydraulic model is required. Both model-based and data-driven methodologies have advantages and disadvantages. Hybrid leak detection strategies are the result of researchers trying to combine two or more of these approaches to improve leak detection performance [19]. The performance of several AI-based leak detection methods has also advanced knowledge [25–28].

2. An Overview of Software- and Hardware-Based Leakage Detection Techniques

There are numerous technologies available for locating pipeline leaks [9,10,29]. These technologies can be grouped into two classes: Class 1 Hardware-Based Leakage Detection Techniques; and Class 2 Software-Based Leakage Detection Techniques. These techniques are further discussed below.

2.1. Leakage Detection: Hardware-Based Tools and Methods

Hardware-based leakage detection methods rely on field sensor outputs to operate on the non-algorithmic principle of physical detection of an escaping commodity. The primary externally-based techniques and tools are discussed as follows:

Fibre Optics: Distributed temperature sensing (DTS) technology is the foundation of fibre optic leak detection systems, which use local temperature fluctuations to detect and locate leaks. An optical fibre line installed throughout the whole pipeline might locate the leak by taking temperature readings using 198 different fibre optics techniques, as pipeline leaks typically result in local temperature anomalies [30]. Temperature readings are frequently recorded at every 0.5 m distance along the pipeline [31]. Fibre optic sensors are also used in sewer systems for leak detection [32].

The analysis of scattered light is based on the Raman or Brillouin scattering process to determine the temperature [31].

Acoustic sensor: Since every leak produces a sound, acoustic sensors can be attached to and possibly tapped into pipelines, placed nearby, used to assist in routine external surveys by humans, or even housed inside "intelligent pigs" or "smart balls" for internal inspections [9,10,29]. Dawood et al. (2020) [33] have proposed and validated various acoustic and various non-acoustic-based techniques [34–39]. For example, an acoustic emission approach combined with ANN has been proven to be an effective pattern recognition classifier for the identification of leaks in water supply systems that are prone to socket joint failure [34]. Similar to acoustic methods, non-acoustic methods in conjunction with support vector machines (SVM) have also shown promising results after simulating water pressure and flow data collected from numerous places in the network [35,36]. Acoustic sensors have been installed along the pipeline's length to monitor the noise levels [40]. As a starting point, the allowable noise levels for the pipeline are established [41]. If there are fluctuations outside of a predetermined range, an alert mechanism is triggered. Since the acoustic signal will be the strongest near the leak, it will be possible to locate it. The detection duration, which is limited by the sound speed, the space between sensors, the amount of time needed for data collection, and the amount of computing time needed, is normally between 15 and 1 min [31]. The approximate location of the leak can be determined within 30 metres [31].

Leak location detection with Ground Penetration Radar (GPR): A near-surface geophysical (NSG) method used to analyse various wave and induction properties in materials is the ground penetration radar (GPR) technique [20]. It uses electromagnetic radiation with a microwave frequency as a non-destructive testing (NDT) method [42]. This method transmits and receives echoes using high-frequency electromagnetic pulses [43]. It locates leaks in underground water pipes by detecting holes in the ground created by water leaks as it circles the pipe. GPR is routinely used to find underground infrastructures [44] and assess their condition [45,46]. GPR has also been widely used in several fields such as earth sciences, archaeology, the military, vehicle location, pavement study, and the excavation of structures [42]. Its main use is to locate faults in items that are beneath the ground, such as voids and cracks [47,48]. GPR has been shown in numerous tests to be the most effective method for finding leaks in subsurface pipelines. For example, a researcher in South Korea investigated the mechanisms that cause cavities to form due to sewage pipe degradation in sandy soils using laboratory model studies with poorly graded sand [20,49]. The relationship between the surroundings and the integrity of the sewer pipe has been studied [50]. Test procedures that are responsive to changes in soil strength, porosity, and density, such as GPR, are preferred [42]. A new method of detecting pipeline leaks using pressure or velocity measurements has been successfully field tested. The method, based on "point analysis" technology, operates on a small number of measurements with only typical industry instrumentation [51].

RFID Sensor: A radio frequency identification (RFID) tag sensor detects environmental changes and vents, and wirelessly transfers the information to an RFID reader. Barcodes and RFID tags are frequently used together since the latter can store more data. These markers frequently resemble little plastic objects [52]. They can be preprogrammed with little information and then "read" using a specific location which triggers the tag to respond at the predetermined frequency. The locator reports the pertinent asset, such as an electronic marking system (EMS), after detecting the frequency. These RFID marker systems have the advantage of being detectable in damp conditions where ground penetration radar (GPR) would struggle to acquire significant signal penetration due to the lower frequency at which they operate [20].

The design and simulation of a leakage monitoring system of water pipelines that implements wireless sensor networks and RFID is based on installing a collection of portable wireless sensor nodes that cooperate according to a predetermined timetable [53]. The remaining nodes that are triggered depend on three other types of events: location-based, time-based, and interrupt-based. Each node tracks pressures and its location based on exposure to signals from active RFID tags placed outside of the pipeline surface. Each node is equipped with a pressure sensor, a microprocessor, and an RFID reader. The mobile sensor nodes are carried along by the water current from the pipeline source to the sink, where they are collected, and their memory contents are uploaded to a computer for numerical analysis. Numerical models are tested in the context of household water distribution systems to identify when an event (tap open, high/low water usage, seepage) takes place [54]. This also includes the detection of leaks [55].

2.2. Leakage Detection: Software-Based Methods

2.2.1. Volume Balancing

This involves the measurement of the difference between the volume entering and leaving the system in various time intervals. This difference can be compared to an alarm threshold, with or without inventory compensation. The changes in pressure and flow are compared to values obtained under typical operating conditions to deduce the possibility of a commodity release [9,10,29].

2.2.2. Real-Time Transient Model

A real-time transient model is a pipeline-specific hydraulic model that is configured and runs online based on boundary conditions provided by field instruments at supply, delivery points, and pump and compressor stations. Typical field inputs include flow rate, pressure, temperature, liquid density, or gas composition. Leak alarms are generated by comparing the measured values with model-calculated values [9,10,29,53].

2.2.3. Statistical Analysis—Approaches to Efficiency

Applying statistical analysis to different signals from a pipeline, commodity release is inferred. Typical field data used include flow, pressure, and temperature [9,10,29].

2.2.4. Negative Pressure Waves (NPW)

The pressure wave generated by a leak upstream and downstream results in a commodity release that is inferred by analysing the pressure data sampled at an increased flow rate. Analysis of pressure signals on a pipeline model forms the foundation of the negative pressure wave (NPW) technique. A leak results in an NPW that travels upstream and downstream of the leak source in both directions. The energy conservation legislation serves as the foundation of the system. A leak first manifests as the passage of liquid or gas into the environment which then releases pressure inside the pipeline and creates an NPW. The use of negative pressure waves in oil and gas networks and water distribution systems is common [20]. Some advantages include low equipment investment and practical construction and maintenance costs, while some drawbacks include poor detection accuracy and inapplicability for small or intermittent leaks [20]. The amplitude of negative pressure waves, which may be used to learn more about the extent of damage, is useful in determining the least detectable leakage flow rate using the negative pressure wave technique (for example, leak flow rate and leak area). The propagation time difference can be used to pinpoint the location of the leak. The reflected wave method uses momentary pressure changes caused by modifications in the flow conditions [53]. As a result, pressure waves propagate throughout the system and are symbolised by changes in the geometric or hydraulic characteristics. When a pipeline leak occurs, a reflected wave is created at the location of the leak. These locations can be identified using pressure time series data, and the magnitude of the reflected wave will be a perfect match for the leak size. A disadvantage of this method includes the source of identification of the reflected waves. It is challenging to identify the source of the leaks because junctions, nodes, and bends have an impact on the reflected waves. Systems that do not account for pipeline inventory inevitably result in significant leak location errors.

The location of the leak point can be inferred by using a cross-correlation method with the time difference at which both pressure sensors receive the negative wave signal. Since pressure waves in gas pipelines are quickly attenuated, the negative pressure wave approach is most effective in liquid pipelines [53,56]. Furthermore, several NPW methods [29] are commercially accessible and can be used to determine the magnitude of the leak. However, putting long-distance pipelines into practise is a significant task. Another significant drawback is the increased number of false alarms generated. A significant pressure decrease is typically seen when pipelines operate transiently, such as when valves are opening and closing. As a result, an NPW technique classifies this as a leak event and issues a false alarm. The NPW approach was further studied by [16,53].

2.2.5. Artificial Intelligence and Machine Learning Techniques

Artificial intelligence (AI) has evolved over sixty years, and the maturity of AI technology now leads to widespread applications and industrialisation [57]. Figure 4 shows the architectural layers of artificial intelligence in the detection of leaks and bursts in the water pipeline which is modified from the general architectural layout of artificial intelligence [57].

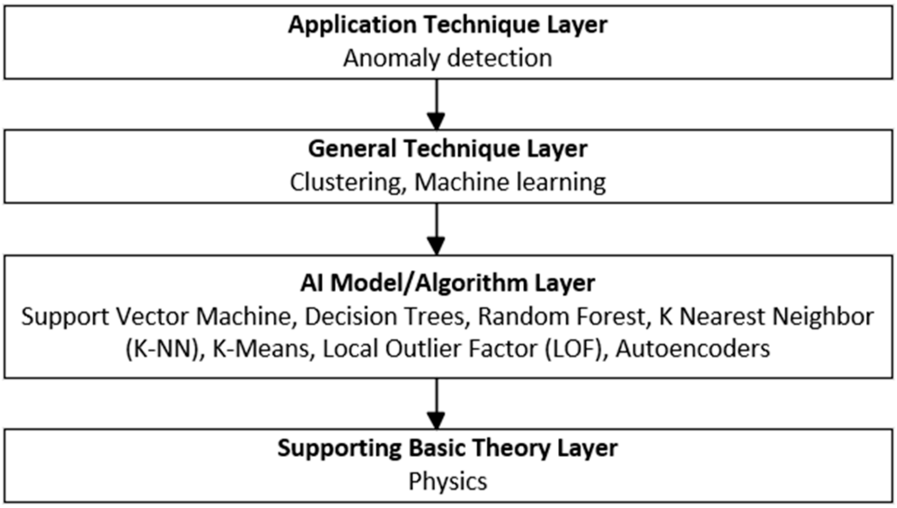

Figure 4. The framework of AI techniques for the detection of leaks and bursts in the water pipeline.

As an enabling technology, AI can reconstruct the modes of production, distribution, exchange, and consumption in the real economy, particularly in the engineering sector. Artificial intelligence (AI) and machine learning (ML) are software-based techniques. These software-based techniques are used for leak detection in water pipelines. This highlights the increasing importance in the water industry and provides an overview of how AI and ML can be leveraged to improve leak detection accuracy and efficiency. This section discusses several leak detection methods and how AI and ML can help overcome traditional water industry challenges in leak detection. The AI/ML case study conducted in Yarra Valley Water, Australia for the detection of a leak in the water pipeline system proved that it has helped utilities achieve real savings and savings in non-profit water [58]. The implemented AI/ML system promotes the idea that the earlier you detect leakage, the more likely you are to identify bursts before they happen, and that abnormal pressure behaviour in a zone can lead to bursts [59]. The study [60] used an ML technique named clustering-then-localization semi-supervised learning (CtL-SSL), which uses the topological relationship of WDN and its leakage properties for WDN partitioning and sensor placement, and then uses monitoring data for leakage detection and leakage localization. The CtL-SSL framework is applied to two test bed WDNs and achieves 95% leak detection accuracy and around 83% final leak location accuracy using unbalanced data with less than 10% leak data. The developed CtL-SSL framework advances the leak detection strategy by reducing data requirements, guiding the optimal sensor placement, and positioning leakage through the WDN leakage zone partition [60]. To improve the precision and intelligence of leakage detection, [61] proposed a leakage detection method that uses internal mode function, approximation entropy, and main component analysis to build a signal feature set and uses a support vector machine (SVM) as a classification to conduct leakage detection. Simulation analysis and experimental results indicate that the proposed leakage identification method can effectively identify the leakage of water pipelines and has less energy consumption than network methods used in conventional wireless sensor networks [61].

2.2.6. Fuzzy Methods

Using the principles and ideas of fuzzy logic, fuzzy-based approaches find and identify possible leaks. Moubayed and Injadat [62] studied that fuzzy logic is based on the idea that individuals frequently make decisions based on faulty and non-numerical information. Inconsistent and ambiguous facts and information can be recognised, represented, controlled, understood, and used by these models [63].

Artificial intelligence and control theory are two areas where fuzzy logic has been used. A brand-new technique has been proposed to identify and repair breaches in water distribution system faults. A fuzzy-based technique is used. Roughness, nodal needs, and water reservoir levels are only a few of the aspects that have been considered for the water distribution system. The degree of membership and the severity of leakage have been calculated using monitoring pressure at various nodes and flow in various pipes in terms of the index of leakage propensity (ILP) [64]. To locate the nearest leaky node or pipe, degrees of leaking memberships and the ILPs have been employed [64]. A leak detection and locating system based on the given methodology has been created using MATLAB [64]. The investigation demonstrates that the created model can find and identify the leakage. Both hardware and software for leak detection technologies have made considerable advances in the past. Software models are still far more cost-effective to utilise, even though hardware-based techniques offer much higher detection accuracy.

2.2.7. Kalman Filtering

Another machine learning technique used in leak detection systems is Kalman filtering, also known as linear quadratic estimation (LQE). To provide estimates of unknown variables that are typically more accurate than those based on a single measurement alone, the algorithm employed in statistics and control theory uses a sequence of measurements that are observed over time, including statistical noise and other imperfections. A combined probability distribution over the variables for each era is estimated to do this. In addition, Kalman filtering is a time series analysis technique that is commonly used in fields such as signal processing and econometrics [20].

One of the crucial components of robotic motion planning and control is the use of Kalman filtering for trajectory optimisation. To simulate how the central nervous system regulates movement, Kalman filtering can also be used. The application of Kalman filters offers a realistic model to determine the present state of a motor system and issue updated commands due to the latency between sending motor commands and receiving sensory data. A Gaussian white noise perturbation of a linear dynamical system can be estimated using a Kalman filter [41]. In a linear stochastic system, the filter is employed to minimise covariance error. The benefit of a Kalman filter is that it can handle data with significant unpredictability and frequent noise.

Water management and conservation are greatly aided by the frequent detection of bursts and leaks in water distribution systems. Using adaptive Kalman filtering on hydraulic data of flow and pressure at the district metre area (DMA) level, this research creates a novel burst detection approach. The amount of abnormal water usage associated with bursts (or recently discovered leaks) in the downstream network is represented by the residual of the filter, which is the difference between the predicted flow and the measured flow. Adaptive Kalman filtering is used to model normal water usage (or alternatively, water pressure). The size of the bursts and leaks is significantly correlated with the residual of the filter, according to the findings of a series of engineered tests that simulated flushing. Lastly, the approach was used to analyse data from three actual DMAs in the northern region of England. The findings indicate that the discovered bursts closely match known historical operational data, including customer complaint records and task management (repair) data. The findings imply that pressure measurement data are less sensitive to a burst or leak than flow measurement data [65]. An algorithm to automatically identify bursts of flow and pressure data has been developed using the Kalman filtering technique. To identify unusual patterns in water use, the residual was defined as the difference between the measurement of the filter outputs [65]. Kang and Lansey (2009) compared the detection state estimator and the Kalman filter. They suggested that the results of the detection state estimator's results were more accurate [66]. A fracture detection approach was developed using the indicators of residual flow/pressure known as the normal residual, the moving average of the residual, and the normalised moving average of the residual. Okeya et al. (2014) claimed that flow-based indexes were more effective in locating leaks than pressure-based indexes in the case of Kalman filtering methods [67].

2.2.8. K-Nearest Neighbours (KNN)

K-nearest neighbours (KNN) is a supervised learning classifier that uses proximity to predict or categorise a group of one data point. This algorithm implies that related neighbouring objects or connected objects are found near each other. It is simple to comprehend and put into action. Since KNN skips the learning process that other AI algorithms perform, it is sometimes referred to as a lazy learner [20,41]. This method has been used to locate leaks and estimate their magnitude using data from the measured pressure wave method (NPW).

The two classification techniques used were a binary classification with leak and non-leak classes, which had an accuracy of 78.50%, and a five-class strategy for estimating sizes, which had an accuracy of 90.1% [68]. Alternately, to identify and locate leaks in real-time, pressure data have been analysed, and the KNN approach has also related to the binary relevance methodology. This variation in KNN produced independent predictions for each label by conducting a single search of the Ks nearest neighbours [39]. This method outperforms and accelerates the response time when compared to a single KNN algorithm. Next, using flow data gathered from a pipeline network, the effectiveness of KNN, random forest, and Bayesian network techniques for leak identification has been evaluated.

Numerous test situations revealed that the naïve Bayesian and random forest models produced the greatest outcomes [23]. It was interesting to see that the number of leaks in the training data had a direct effect on KNN performance. For lazy learners, the KNN approach is ideal because it does not require training and is simple to use. Even so, it is incredibly sensitive to noisy data.

2.2.9. Convolutional Neural Networks (CNN)

Another leak detection technique based on machine learning is convolutional neural networks (CNNs). A CNN is a particular kind of deep neural network that is used in deep learning to assess visual pictures since it is made up of synthetic neurones with biases, weights, and activation functions [69]. Convolutional neural networks are a type of translation-invariant neural network (CNNs).

Most CNN designs are made up of convolutional layers to extract image features and fully connected layers (dense layers), which use the results of the convolution process and classify images using the characteristics acquired in the earlier stages [41]. CNNs are used for leak detection using sensory input from a water distribution network [70].

As a physics-guided neural network (PGNN), CNN is also used to identify satellite images and locate leaks in canal sections. Environmental variables including soil moisture, fractional vegetation cover (FVC), and land surface temperature (LST) were used to evaluate the condition of canals [71]. These parameters were calculated and used as CNN input characteristics to divide canal segments into leaky and non-leaking parts.

2.2.10. Artificial Neural Network (ANN)

A machine learning technique is based on a neuron model that is a neural network [41]. The fundamental challenge with ANNs is that their performance is dependent on several variables, including the number of parameter tunings, the number of training data sets required, and the difficulty of the computation [41]. The foundation of the ANN forecast is statistical analysis. The effectiveness of these methods typically relies heavily on the number of training samples. A subset of machine learning called "deep learning" teaches computers to learn by imitating human behaviour. These neural networks mimic the functioning of the human brain and learn from vast volumes of data. It is possible to guide all or a portion of the learning. A massive collection of labelled data and multilayered neural network architectures are used to train the models.

In this study, a smart water management system is suggested [72]. The technology uses water flow rates in pipelines to identify leaks and uses machine learning (ML) techniques to predict where the leaks will occur. Different machine learning (ML) algorithms have been developed and tested to predict the location of pipeline leakages. To find the most effective model for location prediction, various models are compared. Changes in flow caused by leaks in the system are the foundation of the machine learning-based leak detection and localisation algorithm. The monitoring of pipes can be accomplished by examining the structural integrity of the pipe for damage to identify leaks. Shravani et al. (2019) suggested a smart water management approach using machine learning to detect leaks in pipelines and identify the locations of leaks [72].

Lei and Sun [26] used a method for reconstructing the signal to achieve noise reduction in the urban water supply pipeline pressure data. Based on pressure sensor measurements, this study forecasted leak locations for two water distribution networks of various sizes. The location of the leak, the size of the leak, and the base node demand uncertainty are three randomly selected factors on which the prediction model is trained. As leaks can occur anywhere along a pipe segment, additional spatial discretisation of the suspicious pipe was suggested in this investigation. Investigation of leak size uncertainty and base demand volatility revealed that several different scenarios can result in identical sensor recordings, making it challenging to accurately pinpoint the leak location using the prediction model. Therefore, new strategies to combine predictive modelling with optimisation techniques were suggested [26].

Lucin et al. (2013) [73] examined the machine learning method for leak localisation in water distribution networks using huge data derived from computer simulations. In earlier studies, it was simplified to say that leaks only happened on network nodes. In this study, the approach is improved by allowing leaks to occur anywhere on any network pipe.

Kang and Park [74] demonstrated the benefit of an artificial intelligence system for the detection of leaks and bursts in a district metre area. An artificial neural network model for a mixture density network was trained using a continuously updated historical database. The system was found to be an efficient and practical tool for online burst detection in water distribution systems and has the potential to reduce water use and enhance customer service [75]. Shah and Sabu [76] proposed a cost-effective way to detect leaks and manage pressure, which in turn resulted in significant water savings and reduced pipe breakage frequencies. This technique was specially designed for older infrastructure systems and aimed to solve the demand issues for well-equipped and maintained dwellings. EPANET software was used to model and simulate a water distribution system. Using the SuSi framework, python package for unsupervised, supervised, a classification model has been developed based on supervised self-organization maps (SOMs). This shows that the performance of the complex SOM-based model is comparable to that of the less complex MLP-based model. Thus, the suggested approach can be used to stop losses in a pipeline system in intelligent water management systems, guaranteeing the preservation of the natural resource [76].

2.2.11. Support Vector Machine (SVM)

SVM is based on statistical learning theory, which addresses high-dimensional processing problems. As a result, it served as the common denominator in several studies [37–39] relating to leakage zone identification and detection of the leakage zone using quasi-real-time analysis of the hydraulic system. Big sensor-based time series data are a feature of hydraulic analysis that needs to be investigated [75,77]. A high amount of computation and manipulation is typically required for diagnostic and recognition models that rely on sensor indicators [74]. To achieve high-performance metrics, it is useful to combine numerous AI algorithms into a single adaptable design. To accomplish this, a leak detection method based on accelerometers with a 98.25% accuracy is grounded in SVM, decision tree, and Nave Bayes [78]. SVM still produced fewer performance indicators than the other two algorithms, with a higher deviation rate and worse precision. In contrast, [79] noted in their research on leak size detection and estimation that SVM demonstrated lower sensitivity values and higher stability to noise escalation than ANNs. The authors also noted that despite the results, as previously described, the ANN still performed better when the dimensionality issue was addressed. Another method [80] used support vector classifiers and spectral clustering to identify water leaks in water distribution networks. The study used the EPANET programme, whose main purpose was to perform hydraulic what-if scenarios, which model probabilistic pressure-dependent leak situations. In addition to the various ways that fuzzy classifiers [64,81] were developed to manage uncertainties and extract time-domain features from sensor inputs. Integrating leak management and prioritising could lead to the sustainability of urban water infrastructure. Six key effective criteria that improved the accuracy of the evaluation were considered when developing a leakage ratio estimator using principal component analysis and ANNs for the sustainable management of water distribution networks [82]. Along with ANN, a pressure management model based on the optimisation principles of the genetic algorithm (GA) was also suggested, which resulted in a reduction in pipeline leakages by roughly 30% annually [33,83]. For problems involving classification and regression, the supervised machine learning algorithm and SVM can be used. Unsupervised learning methods, such as one-class SVM (OCSVM), have been used to find outliers in acoustic data gathered from a test bed in a laboratory. The technology correctly identified 97% of leakages [73]. Six groups of water leaks were formed dividing into normal, abnormal, broken or burst, large leak, moderate leak, and minor leak using a multiclass SVM (M-SVM) as a supervised technique [84].

Additionally, SVM was evaluated in neural networks, decision trees, and random forest leak detection techniques [85]. These systems use wireless sensor networks and the Internet of Things (IoT) to collect flow data to analyse it. According to the Random Forest available data, the machine learning technique had the highest accuracy, at around 75%, whereas SVM performed the worst across nearly all tests, with the best accuracy of 57% [85]. These findings differ from those of a different study, which used SVM to evaluate the collected water flow data using a similar methodology and attained 92% accuracy [86]. The difference between the parameters used to design the system and the settings of the test environment may be the root of this substantial variation. Compared to an ANN system, the SVM approach produces alerts more quickly. The main advantages include not requiring an explicit statistical model, offering the best classification solution by maximising the decision border margin and solving the dimensionality problem [41]. SVM learning is used with relevance vector machine (RVM) pattern recognition techniques to build hyperplanes and detect leakage using binary and multi-class classification [87]. In an experiment, a steel pipe of 2 m in length, 254 mm in internal diameter, and 5 mm in thickness was used. The study findings showed that by combining the AE characteristics enabled by SVM and RVM, pipeline leaks may be successfully discovered and identified [87]. The novelty detection from WDS time series data can be accomplished by using the SVM-based method. Events similar to sensor failure, hydrant flushing, and pipe breaks are commonly understood as novelty events. The support vector regression (SVR) approach shows an application's ability to perform a complete online operation with an appropriate plan for data quality management, training data selection and scheduling retraining [37]. More efficient leak detection technologies must be developed, especially for use in smart development applications, due to the increasing demand for rapidly increasing water supply networks [20].

3. Discussion on the Application of Various Hardware- and Software-Based Leak Detection Technologies in Pipe Networks

Mounce and Mounce [37] reviewed novelty identification using support vector machines for time series data analysis in WDS. Such data are best handled using a "bottom-up" data-driven method because there is a frequent lack of knowledge of the system and hands-on control at the DMA logger level. The analysis of flow and pressure has been the main emphasis [37]. The ability of any pipe network to identify leaks effectively is essential to minimise loss. Mounce and Mounce [37] provide a thorough analysis of leakage detection and localisation techniques currently in use, as well as the state of research in the leak detection area. It is evident from the analysis that there are differences in accuracy, deployment costs, and environments in the leakage detection techniques currently used. However, it is common practise and advised to combine various leak detection strategies into a hybrid system [56,88].

Background leakage is frequently undetectable in large-scale piping networks, such as water distribution networks (WDN), in contrast to unexpected pipe breaks, which have been the subject of numerous studies. Since background leakage in a WDN cannot be detected using current leakage detection techniques, which rely on signal processing and analysis of rapid changes in pressure and flow inside a pipeline, these techniques cannot detect leaks in large-scale water distribution networks. This form of leakage accounts for a higher percentage of water loss; therefore, more research should be conducted in this area [56].

The idea behind the leak detection system is that a leak causes a sudden change in flow and pressure at the pipeline's intake and output. Typically, when there is a leak in a pipeline, the pressure decreases. This leakage detection technique can be divided into two categories: pressure point analysis and wave alarm (also known as a negative pressure wave or NPW). According to the NPW method, once a leak occurs and the fluid pressure inside a pipe decreases, a pressure wave signal—also referred to as a negative pressure wave—propagates outward from the leak point towards both of its sides (upstream and downstream). Due to a leak, the pressure wave signals in the pipeline section are moving toward the ends [56].

Finding and diagnosing leaks in water distribution systems (WDSs), which are essential for reducing water loss, is very difficult for water utilities. Academics have proposed a variety of methods to discover these breaches in WDS for this purpose. Model-based and data-driven approaches are commonly applied in this discipline. Model-based approaches require well-calibrated hydraulic models and modelling, and measurement uncertainties can affect the quality of these models. Comparatively, data-driven approaches do not demand in-depth familiarity with the WDS. However, they frequently result in high false positive rates [24].

Future leak detection methods may perform significantly better and develop new promising ways on account of "hybridising" several strategies to overcome their unique flaws. The term "economic level of leakage" (ELL) refers to the point at which further reduction of leakage through asset management/renewals is more expensive than obtaining water from a different source [89]. ELL will justify the level and extend leak detection techniques that are practically possible to use.

Using pressure sensors and flow rate metres, researchers concentrated on quasi-static analysis in this work to find the location and determine its size. By substituting gauge pressure sensors with differential pressure sensors that have the necessary accuracy, [79] extended the work of Mashford and De Silva [35].

SVM is based on statistical learning theory, which addresses high-dimensional processing problems. As a result, it served as the common denominator in several studies [37–39] relating to leakage zone identification and detection of the leakage zone using quasi-real-time analysis of the hydraulic system. Large sensor-based time series data are a feature of hydraulic analysis that needs to be investigated [77]. A high amount of computation and manipulation is typically required for diagnostic and recognition models that rely on sensor indicators [74]. To achieve high-performance metrics, it is useful to combine numerous AI algorithms into a single adaptable design. To do this, Dawood and Elwakil [33] suggested and validated an accelerometer-based leak detection method with a precision of 98.25% based on SVM, decision tree, and Nave Bayes [78]. SVM still produced fewer performance indicators than the other two algorithms [76], with a higher deviation rate and poorer precision. In contrast, Nasir and Mysorewala [79] noted in their research on leak size detection and estimation that SVM demonstrated lower sensitivity values and higher stability to noise escalation than ANNs. Another method, by Candelieri and Soldi [80], used support vector classifiers and spectral clustering to identify water leaks in water distribution networks. The study used the US EPANET software, whose main purpose is to perform hydraulic what-if scenarios, which model the probabilistic pressure-dependent leak situations. In addition to the various ways that fuzzy classifiers [67,81] were developed to manage uncertainties and extract time-domain features from sensor inputs. Integrating leak management and prioritising could lead to the sustainability of urban water infrastructure. Six key effective criteria that improved the accuracy of the evaluation were considered when developing a leakage ratio estimator using principal component analysis and ANNs for the sustainable management of water distribution networks [82]. Along with ANNs, a pressure management model based on the optimisation principles of the genetic algorithm (GA) was also suggested. According to the validation results, pipeline leakages have decreased by roughly 30% annually [33,83]. Whittle et al. [90] highlighted the importance of water demand patterns (prediction), which are essential for the successful detection of leaks in dynamic urban water distribution networks. They have described WaterWiSe as an integrated hardware and software platform that combines a real-time wireless sensor network with sophisticated analytics and modelling tools for leak detection. With the integration of the demand prediction tool, water consumption can be predicted in advance for a 24 h rolling window.

4. Proposed Methodology for Software- and Hardware-Based Leak and Burst Detection System

Figure 5 shows a redesigned framework of smart leak detection framework based on the wide literature review. According to Campos and Jiménez-Bello [91], an IoT framework can have several layers. In Figure 5, four layers are suggested to develop an IWN framework consisting of (i) the sensor layer; (ii) the communication layer; (iii) the water system and operation layer; and (iv) the application and prediction layer. Supervisory control and data acquisition (SCADA) will receive data from sensors and flow metres about flow, pressure, and water quality characteristics. The best distribution of pressure sensors and flow metres will depend on the topography of the area, the size of the water delivery system, historical data on water quantity changes (water demand patterns), and other local factors. The SCADA system in a water network connects flow metres, pressure sensors, and other monitoring devices to the data analysis centre. Data from the flow and pressure sensors will be used to calibrate the hydraulic model and make comparisons with the real-time simulation of the water networks.

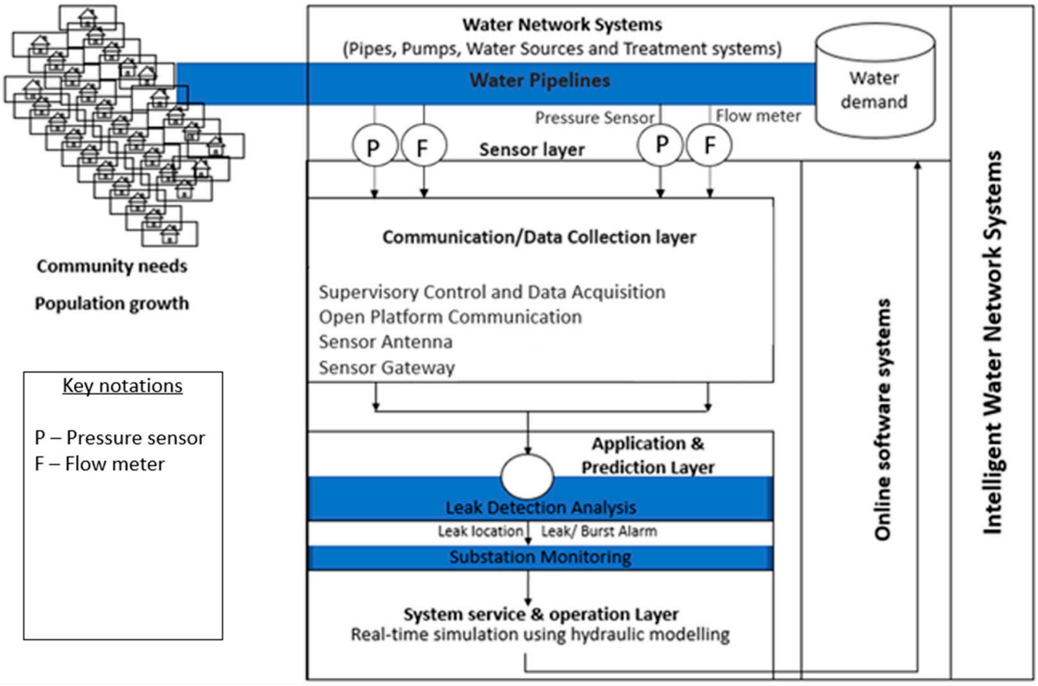

Figure 5. Smart leak detection.

The warnings from the prediction models on the state of the network will be utilised for general asset planning, scheduling maintenance, and general operation. Artificial intelligence (AI) models will be used for this study of flow and pressure data in the system. The literature demonstrates that there is still a gap between what is available and what is needed by industry. Therefore, further development and analysis are necessary for leak detection technologies to meet the needs of the pipeline industry. For that reason, this review of the literature discussed the development of an intelligent water network. The development of an intelligent water network should be studied, and work must be executed in terms of research and development to continue closing the gap between the ideal system and what is currently possible. Figure 5 shows the pipeline (Water Network Systems) connected to the pressure sensors denoted by P and the flowmeter represented as F; these are connected to the data logger (Network Layer).

The following are some possible research questions for further investigation based on the literature review:

1. In a long-distance water transport system, the distance between pressure sensors used for burst detection should be evenly distributed and not exceed 5000 m. It is not required to increase the sensor density because the results would not improve but the management costs would increase.
2. The sampling return period should not last more than five minutes. The backflow of water in the pipe after the point of burst will alter the sensor readings if the sample period is too long, which will result in significant errors in the calculations. More power will be needed to process the findings of more frequent sampling, but precision will not improve significantly. For the monitoring system to be feasible and successful, a reasonable sampling frequency is required.
3. The long-distance water pipeline data fluctuations are compatible with the behaviour of a water distribution system. By considering the statistical properties of the monitored data during the normal operation of the system, the accuracy of instrumental monitoring can be increased in practice.
4. The economic level of leakage estimation can guide the level and extent of leak detection methods application in a water distribution network. Leak detection methods

and water pipe asset management/operation should be combined for the overall water network management strategy.

5. Conclusions

In conclusion, the use of software- and hardware-based technologies for the detection of leaks and bursts in water pipe networks has gained significant attention in recent years due to the urgent need to reduce water losses and increase efficiency in water supply systems. This review of the literature highlights that both software- and hardware-based technologies have been widely studied and implemented worldwide, offering benefits such as improved accuracy, speed, and cost-effectiveness in detecting and locating leaks and bursts. Various leak detection methods were compared on multiple factors, including leak detection principle, sensitivity, accuracy, reliability, and ease of use. Software-based technologies, such as hydraulic models, artificial intelligence, and machine learning algorithms, provide accurate predictions and early detection of water loss, while hardware-based technologies, such as acoustic sensors, pressure sensors, and flow metres, are effective in the real-time detection and location of leaks and bursts. A proposed software- and hardware-based methodology for the identification of leaks and bursts, documented in this study, offers a comprehensive framework for a smart leak detection system, focusing on real-time monitoring and proactive maintenance for reliability and effectiveness. By adopting advanced technologies and best practises, pipeline operators can mitigate the risks associated with leaks or bursts and ensure the long-term sustainability of their operations. This review article serves as a valuable resource for pipeline operators and managers seeking to implement an effective leak detection system and underscores the importance of an intelligent approach to pipeline management.

Author Contributions: All authors have worked on this manuscript. All authors provided substantial contributions to the conceptual future design of the intelligent water network; the drafting of this work included critical revision for important intellectual content. All authors have read and agreed to the published version of the manuscript.

Funding: This research is funded by Victoria University, Melbourne, Australia, and Greater Western Water, Melbourne, Australia.

Data Availability Statement: No new data were created.

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

References

1. Ullah, R.; Faheem, Y.; Kim, B.-S. Energy and congestion-aware routing metric for smart grid AMI networks in smart city. *J. IEEE Access* **2017**, *5*, 13799–13810. [CrossRef]
2. Chen, L.J.; Ho, Y.H.; Lee, H.C.; Wu, H.C.; Liu, H.M.; Hsieh, H.H.; Huang, Y.T.; Lung, S.C.C. An open framework for participatory PM2. 5 monitoring in smart cities. *J. IEEE Access* **2017**, *5*, 14441–14454. [CrossRef]
3. Bacco, M.; Delmastro, F.; Ferro, E.; Gotta, A. Environmental monitoring for smart cities. *IEEE Sens. J.* **2017**, *17*, 7767–7774. [CrossRef]
4. Hunaidi, O.; Chu, W.; Wang, A.; Guan, W. Detecting leaks in plastic pipes. *J. Am. Water Work. Assoc.* **2000**, *92*, 82–94. [CrossRef]
5. Liu, H. Pipeline. Pipeline Technology 11 August 2021. Available online: https://www.britannica.com/technology/pipeline-technology (accessed on 10 February 2023).
6. Wang, H.; Xu, Y.; Shi, B.; Zhu, C.; Wang, Z. Optimization and intelligent control for operation parameters of multiphase mixture transportation pipeline in oilfield: A case study. *J. Pipeline Sci. Eng.* **2021**, *1*, 367–378. [CrossRef]
7. Kraidi, L.; Shah, R.; Matipa, W.; Borthwick, F. An investigation of mitigating the safety and security risks allied with oil and gas pipeline projects. *J. Pipeline Sci. Eng.* **2021**, *1*, 349–359. [CrossRef]
8. Shaw, D.; Phillips, M.; Baker, R.; Munoz, E.; Rehman, H.; Gibson, C.; Mayernik, C. *Leak Detection Study–DTPH56-11-D-000001*; U.S. Department of Transportation Pipeline and Hazardous Materials Safety Administration: Washington, DC, USA, 2012.
9. Zhang, J.; Hoffman, A.; Murphy, K.; Lewis, J.; Twomey, M. Review of Pipeline Leak Detection Technologies. In Proceedings of the PSIG Annual Meeting, Prague, Czech Republic, 16–19 April 2013; OnePetro: Richardson, TX, USA. Available online: https://onepetro.org/PSIGAM/proceedings-abstract/PSIG13/All-PSIG13/2399 (accessed on 12 October 2022).
10. Zhang, J. Designing a cost-effective and reliable pipeline leak-detection system. *J. Pipes Pipelines Int.* **1997**, *42*, 20–26.

11. Joseph, K.; Sharma, A.; van Staden, R. Development of an Intelligent Urban Water Network System. *Water* **2022**, *14*, 1320. [CrossRef]
12. 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. *J. IEEE Access* **2019**, *7*, 51965–51981. [CrossRef]
13. Parida, R.K.; Thyagarajan, V.; Menon, S. A thermal imaging based wireless sensor network for automatic water leakage detection in distribution pipes. In Proceedings of the 2013 IEEE International Conference on Electronics, Computing and Communication Technologies, Bangalore, India, 17–19 January 2013.
14. Penteado, C.; Olivatti, Y.; Lopes, G.; Rodrigues, P.; Filev, R.; Aquino, P.T. Water leaks detection based on thermal images. In Proceedings of the 2018 IEEE International Smart Cities Conference (ISC2), Kansas City, MI, USA, 16–19 September 2018.
15. Moubayed, A.; Sharif, M.; Luccini, M.; Primak, S.; Shami, A. Water leak detection survey: Challenges & research opportunities using data fusion & federated learning. *J. IEEE Access* **2021**, *9*, 40595–40611.
16. Tian, C.H.; Yan, J.C.; Huang, J.; Wang, Y.; Kim, D.-S.; Yi, T. Negative pressure wave based pipeline leak detection: Challenges and algorithms. In Proceedings of the 2012 IEEE International Conference on Service Operations and Logistics, and Informatics, Suzhou, China, 8–10 July 2012.
17. Kulkarni, P.; Farnham, T. Smart city wireless connectivity considerations and cost analysis: Lessons learnt from smart water case studies. *J. IEEE Access* **2016**, *4*, 660–672. [CrossRef]
18. Rostirolla, G.; Rosa Righi, R.; Barbosa, J.L.V.; da Costa, C.A. ElCity: An elastic multilevel energy saving model for smart cities. *J. IEEE Trans. Sustain. Comput.* **2017**, *3*, 30–43. [CrossRef]
19. Zaman, D.; Tiwari, M.K.; Gupta, A.K.; Sen, D. A review of leakage detection strategies for pressurised pipeline in steady-state. *J. Eng. Fail. Anal.* **2020**, *109*, 104264. [CrossRef]
20. Mohd Yussof, N.A.; Ho, H.W. Review of Water Leak Detection Methods in Smart Building Applications. *Buildings* **2022**, *12*, 1535. [CrossRef]
21. El-Zahab, S.; Zayed, T. Leak detection in water distribution networks: An introductory overview. *Smart Water* **2019**, *4*, 5. [CrossRef]
22. Tariq, S.; Bakhtawar, B.; Zayed, T. Data-driven application of MEMS-based accelerometers for leak detection in water distribution networks. *J. Sci. Total Environ.* **2022**, *809*, 151110. [CrossRef]
23. Fereidooni, Z.; Tahayori, H.; Bahadori-Jahromi, A. A hybrid model-based method for leak detection in large scale water distribution networks. *J. Ambient Intell. Humaniz. Comput.* **2021**, *12*, 1613–1629. [CrossRef]
24. Hu, Z.; Chen, B.; Chen, W.; Tan, D.; Shen, D. Review of model-based and data-driven approaches for leak detection and location in water distribution systems. *J. Water Supply* **2021**, *21*, 3282–3306. [CrossRef]
25. Zhou, X.; Tang, Z.; Xu, W.; Meng, F.; Chu, X.; Xin, K.; Fu, G. Deep learning identifies accurate burst locations in water distribution networks. *Water Res.* **2019**, *166*, 115058. [CrossRef]
26. Lei, J.; Sun, M.; Liu, H. Burst Detection for District Metering Areas Based on Soft-Voting Ensemble Model in Water Distribution System. In Proceedings of the 2020 IEEE International Conference on Progress in Informatics and Computing (PIC), Shanghai, China, 18–20 December 2020.
27. Wang, X.; Guo, G.; Liu, S.; Wu, Y.; Xu, X.; Smith, K. Burst detection in district metering areas using deep learning method. *J. Water Resour. Plan. Manag.* **2020**, *146*, 04020031. [CrossRef]
28. Xu, W.; Zhou, X.; Xin, K.; Boxall, J.; Yan, H.; Tao, T. Disturbance extraction for burst detection in water distribution networks using pressure measurements. *Water Resour. Res.* **2020**, *56*, e2019WR025526. [CrossRef]
29. de Joode, A.S.; Hoffman, A. Pipeline leak detection and theft detection using rarefaction waves. In Proceedings of the 6th Pipeline Technology Conference, Hannover, Germany, 4–5 April 2011.
30. Ren, L.; Jiang, T.; Li, D.-S.; Zhang, P.; Li, H.-N.; Song, G.-B. A method of pipeline corrosion detection based on hoop-strain monitoring technology. *Struct. Control Health Monit.* **2017**, *24*, e1931. [CrossRef]
31. Mohd Yussof, N.A.; Ho, H.W. *Economic Comparison of a Simulator-Based GLR Method for Pipeline Leak Detection with Other Methods*; University of Oklahoma: Norman, OK, USA, 2009.
32. Bremer, K.; Meinhardt-Wollweber, M.; Thiel, T.; Werner, G.; Sun, T.; Grattan, K.T.V.; Roth, B. Sewerage tunnel leakage detection using a fibre optic moisture-detecting sensor system. *Sens. Actuators A Phys.* **2014**, *220*, 62–68. [CrossRef]
33. Zaman, D.; Tiwari, M.K.; Gupta, A.K.; Sen, D. Artificial intelligence for the modeling of water pipes deterioration mechanisms. *Autom. Constr.* **2020**, *120*, 103398.
34. Li, S.; Song, Y.; Zhou, G. Leak detection of water distribution pipeline subject to failure of socket joint based on acoustic emission and pattern recognition. *Measurement* **2018**, *115*, 39–44. [CrossRef]
35. Mashford, J.; De Silva, D.; Marney, D.; Burn, S. An approach to leak detection in pipe networks using analysis of monitored pressure values by support vector machine. In Proceedings of the 2009 Third International Conference on Network and System Security, Gold Coast, QLD, Australia, 19–21 October 2009.
36. Mashford, J.; De Silva, D.; Burn, S.; Marney, D. Leak detection in simulated water pipe networks using SVM. *Appl. Artif. Intell.* **2012**, *26*, 429–444. [CrossRef]
37. Mounce, S.R.; Mounce, R.; Boxall, J. Novelty detection for time series data analysis in water distribution systems using support vector machines. *J. Hydroinformatics* **2011**, *13*, 672–686. [CrossRef]

38. Zhang, Q.; Wu, Z.Y.; Zhao, M.; Qi, J.; Huang, Y.; Zhao, H. Leakage zone identification in large-scale water distribution systems using multiclass support vector machines. *J. Water Resour. Plan. Manag.* **2016**, *142*, 04016042. [CrossRef]
39. Kayaalp, F.; Zengin, A.; Kara, R.; Zavrak, S. Leakage detection and localization on water transportation pipelines: A multi-label classification approach. *Neural Comput. Appl.* **2017**, *28*, 2905–2914. [CrossRef]
40. Ozevin, D.; Yalcinkaya, H. Reliable monitoring of leak in gas pipelines using acoustic emission method. In Proceedings of the Civil Structural Health Monitoring Workshop (CSHM), Berlin, Germany, 6–8 November 2012.
41. Kammoun, M.; Kammoun, A.; Abid, M. Leak Detection Methods in Water Distribution Networks: A Comparative Survey on Artificial Intelligence Applications. *J. Pipeline Syst. Eng. Pract.* **2022**, *13*, 04022024. [CrossRef]
42. Park, S.; Lim, H.; Tamang, B.; Jin, J.; Lee, S.; Park, S.; Kim, Y. Preliminary Study on Leakage Detection of Deteriorated Underground Sewer Pipes Using Aerial Thermal Imaging. *Int. J. Civ. Eng.* **2020**, *18*, 1167–1178. [CrossRef]
43. Lai, W.W.L.; Chang, R.K.W.; Sham, J.F.C.; Pang, K. Perturbation mapping of water leak in buried water pipes via laboratory validation experiments with high-frequency ground penetrating radar (GPR). *Tunn. Undergr. Space Technol.* **2016**, *52*, 157–167. [CrossRef]
44. Grasmueck, M.; Weger, R.; Horstmeyer, H. Full-resolution 3D GPR imaging. *Geophysics* **2005**, *70*, K12–K19. [CrossRef]
45. Chen, D.H.; Wimsatt, A. Inspection and condition assessment using ground penetrating radar. *J. Geotech. Geoenvironmental Eng.* **2010**, *136*, 207–214. [CrossRef]
46. Evans, R.D.; Frost, M.; Stonecliffe-Jones, M.; Dixon, N. A review of pavement assessment using ground penetrating radar (GPR). In Proceedings of the 12th International Conference on Ground Penetrating Radar, Birmingham, UK, 16–19 June 2008.
47. Daniels, D.J. *Ground Penetrating Radar*; IET: London, UK, 2004; Volume 1.
48. Jol, H.M. *Ground Penetrating Radar Theory and Applications*; Elsevier: Amsterdam, The Netherlands, 2008.
49. Oh, S. Laboratory Model Test for Identification of a Rear Cavity Occurrence Mechanism at Sewage Pipe in Sandy Ground. Master's Thesis, Chonnam National University, Gwangju, Republic of Korea, 2016; pp. 16–22.
50. Kim, J.; Park, S.; Kim, J.; Ahn, S.; Park, S.; Kim, Y. Accuracy evaluation and terrain model automation of reservoir using unmanned aerial vehicle system. *J. Korean Soc. Agric. Eng.* **2017**, *59*, 57–67.
51. Jönsson, L. Interaction of a hydraulic transient with a leak in a pipe flow. In Proceedings of the 14th Australasian Fluid Mechanics Conference, Adelaide, Australia, 10–14 December 2001.
52. Hao, T.; Rogers, C.D.F.; Metje, N.; Chapman, D.N.; Muggleton, J.M.; Foo, K.Y.; Wang, P.; Pennock, S.R.; Atkins, P.R.; Swingler, S.G.; et al. Condition assessment of the buried utility service infrastructure. *Tunn. Undergr. Space Technol.* **2012**, *28*, 331–344. [CrossRef]
53. Adedeji, K.B.; Hamam, Y.; Abe, B.T.; Abu-Mahfouz, A.M. Towards achieving a reliable leakage detection and localization algorithm for application in water piping networks: An overview. *J. IEEE Access* **2017**, *5*, 20272–20285. [CrossRef]
54. Nasir, A.; Hussain, S.I.; Soong, B.-H.; Qaraqe, K. Energy Efficient Cooperation in Underlay RFID Cognitive Networks for a Water Smart Home. *Sensors* **2014**, *14*, 18353–18369. [CrossRef]
55. Martinsanz, G.P. Sensors for Fluid Leak Detection. *Sensors* **2015**, *15*, 3830–3833. [CrossRef]
56. Geiger, I.G. Principles of leak detection. Fundamentals of leak detection. *KROHNE Oil Gas* **2005**, *399*.
57. Li, X.; Jiang, H. Artificial intelligence technology and engineering applications. *J. Appl. Comput. Electromagn. Soc. J.* **2017**, *32*, 381–388.
58. Sorbello, J.; Marck, R. Applications for intelligent water network systems. *J. Water J. Aust. Water Assoc.* **2014**, *41*, 75–80.
59. Thompson, K.; Sorbello, J.; Dang, H.; Snadden, D. *Approaches to Efficiency and Intelligent Water Networks at Yarra Valley Water*; Yarra Valley Water: Mitcham, Australia, 2012.
60. Fan, X.; Yu, X. An innovative machine learning based framework for water distribution network leakage detection and localization. *J. Struct. Health Monit.* **2022**, *21*, 1626–1644. [CrossRef]
61. Liu, Y.; Ma, X.; Li, Y.; Tie, Y.; Zhang, Y.; Gao, J. Water pipeline leakage detection based on machine learning and wireless sensor networks. *J. Sens.* **2019**, *19*, 5086. [CrossRef]
62. Moubayed, A.; Injadat, M.; Nassif, A.B.; Lutfiyya, H.; Shami, A. E-learning: Challenges and research opportunities using machine learning & data analytics. *IEEE Access* **2018**, *6*, 39117–39138.
63. Kruse, R.; Gebhardt, J.; Klowon, F. *Foundations of Fuzzy Systems*; John Wiley & Sons, Inc.: Hoboken, NJ, USA, 1994.
64. Islam, M.S.; Sadiq, R.; Rodriguez, M.J.; Francisque, A.; Najjaran, H.; Hoorfar, M. Leakage detection and location in water distribution systems using a fuzzy-based methodology. *Urban Water J.* **2011**, *8*, 351–365. [CrossRef]
65. Ye, G.; Fenner, R.A. Kalman filtering of hydraulic measurements for burst detection in water distribution systems. *J. Pipeline Syst. Eng. Pract.* **2011**, *2*, 14–22. [CrossRef]
66. Kang, D.; Lansey, K. Real-time demand estimation and confidence limit analysis for water distribution systems. *J. Hydraul. Eng.* **2009**, *135*, 825–837. [CrossRef]
67. Okeya, I.; Kapelan, Z.; Hutton, C.; Naga, D. Online burst detection in a water distribution system using the Kalman filter and hydraulic modelling. *Procedia Eng.* **2014**, *89*, 418–427. [CrossRef]
68. Rashid, S.; Akram, U.; Khan, S. WML: Wireless sensor network based machine learning for leakage detection and size estimation. *Procedia Comput. Sci.* **2015**, *63*, 171–176. [CrossRef]
69. Shukla, H.; Piratla, K. Leakage detection in water pipelines using supervised classification of acceleration signals. *Autom. Constr.* **2020**, *117*, 103256. [CrossRef]

70. Cody, R.; Narasimhan, S.; Tolson, B. One-class SVM–Leak detection in water distribution systems. In Proceedings of the Computing and Control for the Water Industry, CCWI, Sheffield, UK, 5–7 September 2017.
71. Chang, S.; Yang, P.P.J.; Yamagata, Y.; Tobey, M.B. *Modeling and Design of Smart Buildings, in Urban Systems Design*; Elsevier: Amsterdam, The Netherlands, 2020; pp. 59–86.
72. Shravani, D.; Prajwal, Y.R.; Prapulla, S.B.; Salanke, N.S.; Girish, R.; Shobha, G.; Ahmad, S.F. A machine learning approach to water leak localization. In Proceedings of the 2019 4th International Conference on Computational Systems and Information Technology for Sustainable Solution (CSITSS), Bengaluru, India, 20–21 December 2019.
73. Lučin, I.; Čarija, Z.; Družeta, S.; Lučin, B. Data-driven leak localization in urban water distribution networks using big data for random forest classifier and Pipe Segmentation. *J. Math.* **2021**, *9*, 672. [CrossRef]
74. Kang, J.; Park, Y.-J.; Lee, J.; Wang, S.-H.; Eom, D.-S. Novel leakage detection by ensemble CNN-SVM and graph-based localization in water distribution systems. *IEEE Trans. Ind. Electron.* **2017**, *65*, 4279–4289. [CrossRef]
75. Mounce, S.; Boxall, J.; Machell, J. Development and verification of an online artificial intelligence system for detection of bursts and other abnormal flows. *J. Water Resour. Plan. Manag.* **2010**, *136*, 309–318. [CrossRef]
76. Shah, K.; Sabu, S.; Chaphekar, V. Water leakage detection using neural networks. In Proceedings of the Future Technologies Conference, Vancouver, BC, Canada, 5–6 November 2020; Springer: Berlin/Heidelberg, Germany, 2021.
77. Mounce, S.R.; Khan, A.; Wood, A.S.; Day, A.J.; Widdop, P.D.; Machell, J. Sensor-fusion of hydraulic data for burst detection and location in a treated water distribution system. *Inf. Fusion* **2003**, *4*, 217–229. [CrossRef]
78. El-Zahab, S.; Abdelkader, E.; Zayed, T. An accelerometer-based leak detection system. *Mech. Syst. Signal Process.* **2018**, *108*, 276–291. [CrossRef]
79. Nasir, M.T.; Mysorewala, M.; Cheded, L.; Siddiqui, B.; Sabih, M. Measurement error sensitivity analysis for detecting and locating leak in pipeline using ANN and SVM. In Proceedings of the 2014 IEEE 11th International Multi-Conference on Systems, Signals & Devices (SSD14), Barcelona, Spain, 11–14 February 2014.
80. Candelieri, A.; Soldi, D.; Conti, D.; Archetti, F. Analytical leakages localization in water distribution networks through spectral clustering and support vector machines. The ice water approach. *Procedia Eng.* **2014**, *89*, 1080–1088. [CrossRef]
81. Valizadeh, S.; Moshiri, B.; Salahshoor, K. Multiphase pipeline leak detection based on fuzzy classification. *AIP Conf. Proc.* **2009**, *1159*, 72–80.
82. Jang, D.; Park, H.; Choi, G. Estimation of leakage ratio using principal component analysis and artificial neural network in water distribution systems. *Sustainability* **2018**, *10*, 750. [CrossRef]
83. Nazif, S.; Karamouz, M.; Tabesh, M.; Moridi, A. Pressure management model for urban water distribution networks. *Water Resour. Manag.* **2010**, *24*, 437–458. [CrossRef]
84. Mamo, T.G. *Virtual District Metered Area Municipal Water Supply Pipeline Leak Detection and Classification Using Advance Pattern Recognizer Multi-Class Support Vector Machine for Risk-Based Asset Management*; Polytechnic Institute of New York University ProQuest Dissertations Publishing: New York, NY, USA, 2014.
85. Alves Coelho, J.; Glória, A.; Sebastião, P. Precise water leak detection using machine learning and real-time sensor data. *J. IoT* **2020**, *1*, 474–493. [CrossRef]
86. Lin, H.; Lin, H.; Fang, X.; Wang, M.; Huang, L. Intelligent pipeline leak detection and analysis system. In Proceedings of the 2020 15th International Conference on Computer Science & Education (ICCSE), Delft, The Netherlands, 18–22 August 2020.
87. Banjara, N.K.; Sasmal, S.; Voggu, S. Machine learning supported acoustic emission technique for leakage detection in pipelines. *Int. J. Press. Vessel. Pip.* **2020**, *188*, 104243. [CrossRef]
88. Turkowski, M.; Bratek, A.; Słowikowski, M. Methods and systems of leak detection in long range pipelines. *J. Autom. Mob. Robot. Intell. Syst.* **2007**, *1*, 39–46.
89. Lords, H.O. *Water Management*; House of Lords Science and Technology Committee: London, UK, 2006; Volume 1.
90. Whittle, A.J.; Allen, M.; Preis, A.; Iqbal, M. Sensor Networks for Monitoring and Control of Water Distribution Systems. In Proceedings of the 6th International Conference on Structural Health Monitoring of Intelligent Infrastructure (SHMII 2013), Hongkong, 9–11 December 2013.
91. Campos, J.A.; Jiménez-Bello, M.; Alzamora, F. Real-time energy optimization of irrigation scheduling by parallel multi-objective genetic algorithms. *Agric. Water Manag.* **2020**, *227*, 105857. [CrossRef]