IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.53
Volume 4, Issue 7, March 2024

The Role of Smart Sensors in Enhancing Leak Detection in Water Systems

Arabinda Nanda[1] and Dr. Sunil Damodar Rathod[2]
Research Scholar, Department of Computer Science and Engineering[1]
Research Guide, Department of Computer Science and Engineering[2]
Sunrise University, Alwar, Rajasthan, India

Abstract: *Water firms, regulatory bodies, environmentalists, and others worry about water conservation, yet leakage may go undetected. Studying leakage characteristics has led to numerous water distribution network leak detection methods. Learning about leakage types and properties reveals new tech. Although numerous technologies have become developed in the previous decade, a complete, affordable leakage detection system that identifies background leaking and burst events is still required. Due to benefits and downsides, water utilities struggle to pick the optimal technology. We must classify and benchmark leakage detection methods. This research analyzes hardware, software, invasive, non-invasive, steady state, transient, single, and hybrid leakage detection methods. Focus will be on detection and location of projected leaks. As predicted, methods developed over the last two decades have different capabilities, conditions, and constraints [1]. Comparing and comparing such ways can improve your study knowledge and provide fresh answers*.

Keywords: Leakage Detection, Water Distribution Networks, Pipeline Monitoring

I. INTRODUCTION

Water companies have spent 20 years detecting and localizing leaks. Mainly because leakage and non-revenue water cost water corporations. Water networks lose 20%–30%, spending £7 billion in direct and indirect damage [2]. Leakage increases greenhouse gas emissions from pumping water across the network. Leaks degrade water quality, jeopardizing public health. WDN leaks may result from age-induced corrosion, faulty fittings, and other pipe deterioration [3]. Operating difficulties that impede pipe flow increase leakage and rupture risk. Cyclic pressure loads or sudden surges may damage hydraulics [4].

Hardware and software-based detection technology exists, however technical constraints create a gap.

Leakage Overview

Unreported leaks are burst or background [5]. Pressure loss and AE are symptoms of burst leaks [6], [7]. Background leaks are negligible water losses from fittings, creeping joints, or cracks. Network losses sometimes result from extended background leaking [5]. Background leakage is termed leakage, although burst events are used interchangeably [7]. The three leak detection processes have important goals: Find, localize, point [2,8]. Finding a network leak without false alarms requires separating leak signals from other network signals like fire hydrants [2]. The second ILP phase is localization. This discovers the network's general section like DMA [9]. Pinpointing locates leaks within 20cm. The pinpoint phase used to have two processes (finding and pinpointing, ILLP), with locating estimating the leak location to 30cm. The 10-centimeter difference justifies merging stages [2].

Leak detection requires hydraulic anatomy and observations. Negative pressure wave (NPW) techniques may detect leaks' rapid pressure drops via pipelines [10]. Various leakage detection techniques involve pressure anomalies, which are difficult to detect for background leakage occurrences and may suggest unaccounted demand (e.g., fire hydrants). Since pressure and flow rate are inversely connected, this upstream pressure drop lowers downstream flow rates. Bursts mainly cause pressure and flow alterations [11]. Sonic emissions from water loss are another leak quality. These vibrations' reflection, refraction, absorption, and diffraction may locate bursts [12]. These waves may be detected by accelerometers, microphones, and dynamic transducers [13]. Temperature anomalies surrounding leaks may help spot them [7].

Water network detection is a vast issue with substantial research. Various methods must be classified. A classification tree was built to introduce new readers to the subject topic (figure 1). Literature makes hardware- and software-based leakage detection solutions easy to identify. Network leaks may be found using auditory, pressure, flow, and temperature monitoring with hardware leakage detection. Invasive, robotic, in-pipe or non-invasive, out-of-pipe technologies are possible. Software-based leak detection analyzes network properties computationally and statistically. It measures steady-state and transient leakage better than hardware.

Hardware detection methods

The literature describes many hardware technologies for leakage recognition and localization. This includes any equipment that may detect leakage abnormalities stated in Section 2. Some hardware detection techniques are combined with data processing software to identify leaks more accurately.

In-pipe inspection devices

Underdeveloped hardware detection approaches include intrusive devices that infiltrate pipe networks to find leaks. The driving mechanism, sensor technology, and autonomy of robotic inspection devices differ substantially. [14].

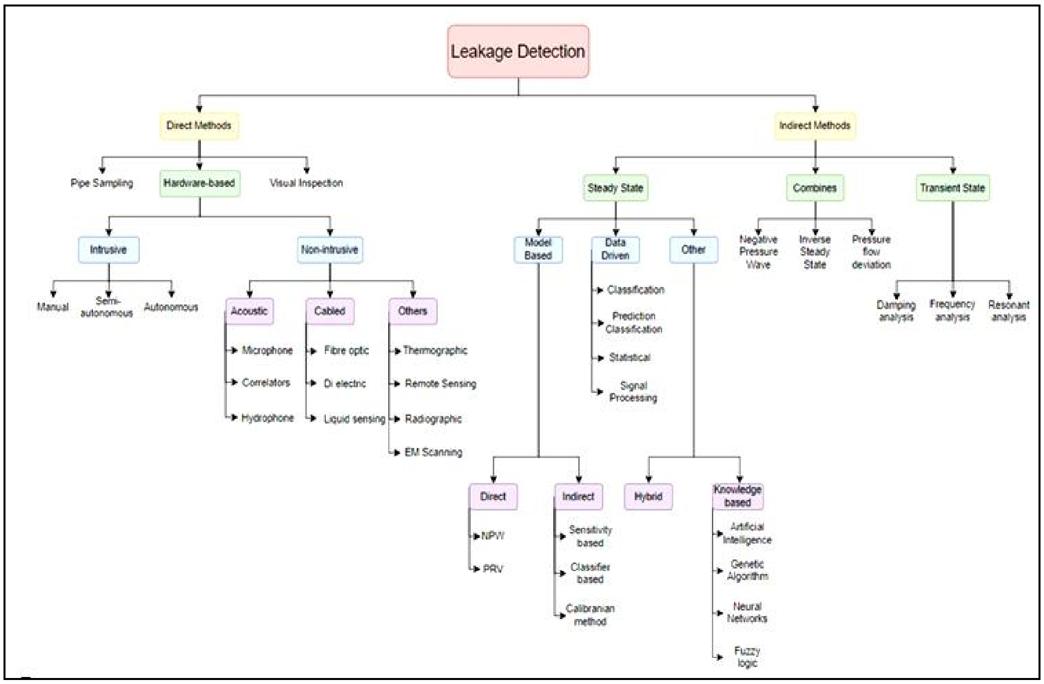

Figure 1. Leakage detection classification tree.

Driving methods

Mechanisms may move passively or actively. Active techniques verify the pipe using actuators, whereas passive methods utilize water. PIGs are passively propelled inspection robots [15]. Its simplicity and navigation make PIGs safe, effective, and cost-effective [14,15]. They have assessed pipe condition, detected leaks, and removed deposits. PIG inspection uses ultrasonic and eddy current sensors [16]. Navigation uses vision, inertial measurement, and odometers [15]. PIGs are hard to stop and pass around pipe bends at higher flows, although intelligent PIGs may have better speed control. 'smart PIG' by NORSEN GROUP, 'Smartball' by Pure Technology [17], and 'Remoted PIG' by Jiutai Technology [18,19] are commercial PIGs.

Active driving systems include wheel, track, inchworm, walking, and snake. Wheel propulsion and a spring mechanism press against pipe walls for smooth in-pipe topological adaption. Literature has wheel-based prototypes [20,21]. Stationary and rotating parts make up screw-driven wheeled robots. Wheeled robots seldom outperform track-driven devices on soft or broken terrain. Complex and energy-intensive, this drive is seldom used [22]. Bradbeer et al. [23] display legged inspection robots. Clamper and extensor modules worm-like drive the robot down the pipe. Prudent foreigners use this gesture. Recently published inchworm movement study [24,25,26,27]. Snake robots, like inchworms, handle abnormalities well. Multiple connected modules may move planarly [28]. Complexity of increased degrees of freedom with every surrounding module makes inspection robot reptile movement unusual.

Level of autonomy

No autonomy, semi-autonomous, or completely autonomous intrusive hardware inspection methods exist. Most robotic inspection systems are non-autonomous, however autonomy eliminates operator intervention [14,29].

Fully operated robots are controlled by skilled operators by tether or wireless connection. As the robot goes across the network, the operator uses sensor data to inspect the pipe [14]. In the research [30], the tether cable was selected for smoother recovery. There are no cost-effective ways to traverse water network problems, hence this strategy is popular [30].

Semi-autonomous inspection uses automated control modules to eliminate human tasks like navigation and pipe condition evaluation. This transfers user responsibility and improves accuracy. These prototypes include the PIRAT [31] and Karo [32] robots.

Fully autonomous robots don't communicate with humans. They can navigate, analyze, and transmit pipe status in real time using their sensor payload without getting lost. Long-term and long-range autonomous inspection devices confront several problems, but energy and communication are the biggest [14]. Kirchner and Hertzberg created the Kurt robot, which automatically collects video, ultrasound, and gradient data using a pipe network map [33].

We've previously mentioned Makro [21,34], Karo [32], PIRAT [31], Kurt [33], and Smartball [17] as smart PIGs and robotic detecting prototypes for in-pipe inspection. Due to design problems, comprehensive invasive inspection robots are hard to find. However, successful case studies suggest pipe inspection gauges may appeal to certain networks [35].

Non-intrusive methods

Leak detection systems may be dynamic or static. Dynamic intrusive approaches move across the network to explore inner pipe conditions, whereas static non-intrusive methods employ mounted sensors to infer leakage [2]. Static approaches identify leaks instantly, whereas dynamic detection is used after a leak is expected/identified to localize the leak spot [36,37]. For the previous two decades, static leakage detection techniques have been marginally researched owing to their practical advantages and real-time management [2]. The most popular methods use acoustic or pressure features in over 50% of the literature [2]. Other technologies use flow sensors, GPR, tracer gas detection, and infrared thermography.

Acoustical method. Acoustic leakage detection and localization in water and oil networks began in the early 1990s [38]. Acoustic leak localization might be time-of-flight or attenuation-based. As acoustic signals move through the pipeline, attenuation decreases signal amplitude, while time increases signal transit time [39]. Turbulent pressure fluctuations near the breach cause vapor bubbles to develop at high speeds and implode as shock waves on pipe walls, causing acoustic Acoustic emissions (AE) vary by source, with turbulent flows producing low-frequency signals and cavitation bursts causing high-frequency signals in plastic pipes, requiring denser sensor coverage [40]. Electrical or mechanical geophones, hydrophones, listening sticks, accelerometers, and correlators are examples.

Fiber optics. These technologies detect pipe leak temperature anomalies. The leak-induced temperature change in water pipelines is less and harder to detect than in oil and gas pipelines [41]. Fiber optic leakage detection is harder due to daily and seasonal temperature changes [41]. Alternatives include optical fibers to monitor pipe wall strain from leaks [42,43]. Raman Distributed Temperature Sensor (RDTS), Fibre Bragg Gratting (FBG) [41], and Brilloun Optical Time Domain Reflectometry (BOTDR) [6] have increased the usage of fibre optics for pipeline leak-induced temperature or strain monitoring. Fiber optics outperforms other techniques in electrical noise immunity, corrosion resistance, and stability [7], but water utilities dislike their high startup and running expenses.

IR thermography. Infrared thermography, like fibre optics, uses pipeline leakage's thermal effects to localize the occurrence. Pipe conditions and water network leaks have been assessed using IR cameras [44,45,46,47]. Thermography might monitor vast water networks cost-effectively, efficiently, and non-destructively despite its low research status. Several variables impact thermal anomalies transferred to the surface above leaking [48]. IR should be recorded when ambient temperatures are closer to equilibrium to increase thermal visibility. Thermography is best done before and after dawn and sunset [48,49]. Soil moisture hinders study, especially in wet regions like the UK, despite its improved heat transmission [49].

Ground-penetration. Radars Leakage researchers are interested in ground penetrating radars [50,51]. They use electromagnetic irregularities of infrastructure water leaking to find the collapse. This imaging approach works well on metal and plastic pipes of any size [2]. GPRs are portable and simple to operate, allowing large-scale surveying with little labor [52]. Despite that, GPRs have more drawbacks than benefits. Its inability to distinguish leak-induced anomalies from soil inhomogeneity raises false alarms [38]. It works only for pipelines buried less than 5m deep and depends on soil type. To identify leaks accurately, decision support systems [53] and evolutionary search algorithms may enhance this strategy.

Tracer gas. Gas injection locates leaks using inert, non-toxic, insoluble, traceable gases such halogens, ammonia, and helium. Operators inspect the suspected region to find these gasses leaking via damaged infrastructure [54].To restrict alternative pathways out of the system and limit gas flow to the suspicious location, network flows must be understood. Tracer gas detects background leakage and bursts with minimal false alarms [7,46]. This technology is quick and precise, but it is expensive, particularly in big, low-pressure networks that demand greater gas volumes, and the cost of in-built sensors for monitoring and probable filtering stages makes it impractical [7,55].

Induction magnetic. Magnetic induction accurately detects and connects two sensor sets. One set measures the suspected leak's flow, pressure, and acoustic qualities from within the pipe, while the other measures humidity, temperature, and soil properties outside the pipeline [56]. The magnetic transmitter coils generate current to the receiver via a current-modulated signal [57]. This communication connection allows real-time leakage detection, improving utility response times in severe subterranean circumstances. Due to significant implementation costs, this technique is unfavorable.

Software detection Methods

Background leakage threatens water networks because standard hardware approaches typically miss it, compounding losses. Therefore, software approaches are needed to solve this problem. The upfront expenses of putting sensors across the network negate the long-term benefits of software solutions, making it less popular among utilities [58]. Leakage detection in water distribution systems frequently assumes steady-state flow [59]. This approach compares network behavior to predicted performance to find leakage or blockage-related abnormalities. A data-driven method to leakage detection is recommended when the network has a lot of historical and current data, but when data is sparse, a model-based approach is preferred since the hydraulic model is accessible.

Model based

Model-based detection depends on the model's likeness to the network, the data analyzed, and the mathematical methods used [1]. This approach relies on a realistic, precise model and a calibration step to compare the model and network. Zaman et al. [1] provide an effective model-based leakage detection approach. A used A trustworthy replica on hydraulic simulation machines (e.g., EPANET, LOOP) should incorporate leak-free system input information from SCADA, GIS, and other sources. Model platforms like WaterGEMS use a genetic algorithm (GA) to find leak nodes.

After the model is finished, it must be validated using multiple methods to match the real-life example. Pre-processing the model before calibration may reduce the number of candidates [59]. In contrast to field data, steady-state and extended period simulation (EPS) calibration methods are utilized.

After calibration, different leakage detection algorithms may be used to forecast and notify on leak sites and sizes.

The model-based method has many detection mechanisms. They use simulated parameters and field data to find leaks. These leakage detection algorithms generally suffer from unexplained pipe aging, which decreases pipe diameters [6]. Using conservation of mass to investigate leaks is easy. Balancing mass in and out of nodes might reveal unexplained loss, suggesting a leak. This method works well in steady-state, but pipeline dynamics and disturbances might cause false alarms [60]. Another approach, pressure residual vector (PRV), compares leak-induced pressure fluctuations in the actual system to the leak-free model from their network locations [61]. When the difference between predicted and real pressure reaches a threshold specified by uncertainty analysis and statistical considerations, the region is inspected for leaks [62,63].

Figure 1 shows three indirect model leakage detection approaches. Calibration-based approaches improve model calibration by adding leakage information. Modeling leakage as pressure demand yields this data. Genetic algorithms (GA) may be used to calibrate evolutionary search algorithms (EAs) to find leaks [64]. The complete literature study [65] shows that EA is frequently utilized in single- and multi-objective water distribution system design optimization. Sensitivity-based methodology uses network models to study node pressure sensitivity under leak and non-leak scenarios [61,66]. Combining the sensitivity matrix and pressure residual vector helps better detect leaks. This is shown in [67] using the angle-based technique. To create that, [68] provides classifier-based leakage detection. Using statistical classifiers enhances fault localization over the angle technique in [67], particularly for demand uncertainties. Classifiers are frequently data-driven, although model-based detection has been successful.

Data-driven

By avoiding hydraulic modeling, leak detection can traverse complicated, heterogeneous, huge water distribution networks with plentiful data. Due to its use of actual data, it is more trustworthy and accurate yet more sensitive to sensor failure. These approaches detect abnormal signals/patterns in monitoring data that may indicate a leak.

Data pre-processing

Data-based detection commonly manipulates flow, pressure, and demand. Consumer demand is the least likely data source because to its ambiguity in localization [68] and insensitivity to minor leak flow rates [69]. Different data sources, sample sources (1-15 minutes), and time series lengths are important [67]. Sensor readings are typically raw and need pre-processing before being used in leakage detection algorithms. It's arduous to sort, filter, and alter incoming data during data pre-processing. Using actual data requires consideration of uncertainty and variability, whereas using data from models avoids this. Data-driven leakage detection requires pre-processing to filter erroneous data, fill time-series gaps, and organize findings for evaluation [1].

Detection methods

By technical procedure, our classification tree (figure 1) divided data-driven techniques into four categories. Data source and type may arrange these techniques. This overview covers signal processing, classification, prediction, and statistics. Transient leakage detection employs these methods.

Flow/pressure monitoring. The simplest data-driven approaches are NPW and PPA pressure monitoring. Transducers measure pressure fluctuation on both sides of the leak in NPW [70]. Correlating sensor readings' timing differences locates leaks. NPW is hard to implement for long-range pipelines [6]. NPW generates many false alarms due to its network transient flux sensitivity. Study [71] offers several false alarm reduction changes to increase process reliability. NPW hybrid leakage detection should provide alarms like [57]. Pair pressure transducers to compare leak results and avoid false alarms [71]. The last idea uses pattern recognition to distinguish leakage-induced pressure variations from valve-induced ones [71]. NPW may improve with a configurable threshold, background noise filtering, and data processing. EFA technologies ltd.'s PPA statistically examines pipe mean pressure [55]. Like other pressure-based leakage detection technologies, PPA warns after a mean pressure reduction beyond a threshold. This method is inexpensive and easy, but it cannot find leaks and is unreliable in temporary conditions [6].

Statistical. Leakage detection statistical analysis uses statistical theory without classification or prediction [69]. Control charts track measurement changes in statistical process control (SPC). Used to preprocess data [69]. Jung et al. [72] compare univariate and multivariate SPC. WEC rules, CUMSUM, and EWM are univariate methods. WEC only examines the latest eight readings, whereas EWMA has the maximum memory [72]. Hotelling T2 control chart with elliptical control, CUMSUM, and EWMA multivariate methods were used. Statistics like PCA and ICA reduce data state space without diminishing value. PCA gains higher-order statistics from ICA [73]. Clustering, SVM, ANN, and multivariate algorithms are new statistical methodologies.

Classification. Models classify normal and outlier data. Simple classification algorithms calculate the absolute mean hydraulic value difference between anticipated and observed [1]. Tagging normal and abnormal hydraulic data trains

IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.53
Volume 4, Issue 7, March 2024

most burst detection algorithms. Mounce and Machell used flow reading analysis to evaluate static and time-delay ANNs for burst detection [76]. Alternative designs improved detection due to dynamic input interactions. Quality of inputs and quantity of normal and outlier data used to train the classification model determine its performance. The classification model may produce 0-1 node leak probability using a leak function and SOM ANN [77]. Without supervision or labeled training data, our method detects leak data better [77]. Its main limitation is that it needs labeled and balanced training data for normal and outlier circumstances, hence unsupervised learning is better. Incorrectly trained classification models may have large false positive rates (FPR), hindering leakage detection.

Prediction-classification. Prediction-based approaches detect outliers before developing the classification model using hydraulic data, unlike classification methods. Additional data selection using statistical methods is needed [78,79]. Normal historical data may train a linear Kalman Filter (LKF) to statistically characterize the system [80]. This excellent method predicts from live data. Fuzzy Interference Systems (FIS) and Bayesian Interference Systems (BIS) give reliable detection results, however historical data, evolutionary algorithm (EA), and expectation maximisation may enhance their parameters. Mounce et al. improve burst detection by mimicking human cognition using an MDN in prediction and a FIS in classification [78, 81]. After prediction, SVR identified input data deviations for leakage detection [82]. Historical data changes used for prediction-classification increase data uncertainty, reducing leakage detection accuracy and necessitating data selection.

Signal processing. DSP is used to improve leak identification and localization using pressure or audio inputs due to sharper transitions than NPW. Pipe resonance reduces bandwidth, negating gain [36].

Time and frequency response study of acoustic emissions has helped researchers build hybrids by identifying leakage patterns. Finding meaningful data from both areas required time-frequency analysis. Researchers have studied leakage using short-term Fourier transform (STFT). A time window function adds a time variable to the spectrum of STFT slices. Time-frequency analysis uses frames' discrete Fourier transform (DFT). This method has been justified multiple times and outperforms FFT in uncertainty analysis [83]. Li et al.'s wavelet denoising and STFT combination outperforms wavelet decomposition, gaussian mode, recurrence plot, WVD, WHT, and EMD [84]. Fast Fourier transform was proven using an underground plastic pipe fault detection and isolation (FDI) system [85].

Wavelet transformations (WT) have superseded STFT and other time-frequency analysis methods for leakage detection and localization. The narrow window size of STFT limits its resolution, unlike WT. This method performs better for multi-resolution leakage and burst events [86]. WT is used for signal processing denoising, decomposition, recognition, classification, and feature extraction. WT relies on the mother wavelet moving and scaling over data to produce offspring wavelets. Ahadi and Bakhtiar emphasized this while comparing Haar and db8 mother wavelets [87]. Studies [86,87] show WT's benefits over STFT. Wavelet transformations are limited by parental wavelet length and non-adaptability [12]. Mother wavelets include Meyer, Morlet, Daubechies, and Mallet functions [1]. WT increases sharp transition detection and decreases leak signal noise [1]. Two Dempster-Shafer-fused Multi-Layer Perceptron Neural Networks (MLPNN) excelled wavelet characteristics of pressure signals for feature extraction and leakage categorization in [88]. D-S classifier fusion technique had 95.11% CCR, wavelet 86.94%, and statistical features 64.56% [88]. Neural networks outperformed wavelet.

II. CONCLUSION AND FUTURE WORK

Leakage detection is a sparse, multi-directional area, and academics are seeking to provide water companies a reliable solution. This page should point readers to the various research subjects and prospective discoveries, however evaluating the subject is challenging. Each component breaks down the issue and compares technology to describe key findings and techniques.

The robotic systems explored vary in driving, sensing, and autonomy. The pipe and its surroundings determine the wheeled, screw-driven, track-driven, worm, snake, and legged active driving mechanisms for intrusive inspection equipment. Smart PIGs and autonomous robots sacrifice recoverability for fewer staff. No inexpensive devices can automatically adjust to water network conditions and interact with users.

Several sensors detect leak-induced anomalies to identify non-intrusive hardware events. Acoustic sensors including microphones, geophones, hydrophones, accelerometers, leak noise loggers, and correlators are most common. Other sensors include infrared thermography, fiber optics, GPR, magnetic induction, and tracer gas. These are usually insufficient and need signal processing.

Two ways detect software leakage. The analyst must utilize hydraulic analysis techniques to develop an accurate water distribution network model and compare expected pressures/flows to actual data to find outliers for model-based leakage detection. Data-driven methods collect, pre-process, and analyze data to find leak-induced outliers. Data-driven methods are statistical, classical, predictive, or signal processing. Models and data-driven techniques may enhance hydraulic analysis together, but they need sensor data availability and quality. These leakage detection methods rely on computation and may benefit from data engineering and AI.

To gain from these methods, researchers and industry typically combine them. We should explore this to use our knowledge to fix these methodologies. Discovering background leaking requires novel model leakage prediction venues. Graph neural networks may approximate functions due to their similar data formats. Neural network methods for transfer learning should also be studied to minimize water distribution network modeling training time.

REFERENCES

[1]. Zaman D, Tiwari MK, Gupta AK and Sen D 2020 A review of leakage detection strategies for pressurised pipeline in steady-state Eng. Fail. Anal. 109 104264

[2]. El-Zahab S and Zayed T 2019 Leak detection in water distribution networks: an introductory overview Smart Water 4

[3]. Barton NA, Farewell TS, Hallett SH and Acland TF 2019 Improving pipe failure predictions:

[4]. Factors effecting pipe failure in drinking water networks Water Res. 164

[5]. Rezaei H, Ryan B and Stoianov I 2015 Pipe failure analysis and impact of dynamic hydraulic conditions in water supply networks Procedia Eng. 119 253–62

[6]. Adedeji KB, Hamam Y, Abe B and Abu-Mahfouz AM 2017 Leakage detection algorithm integrating water distribution networks hydraulic model SimHydro 2017 pp 1–9

[7]. Adedeji KB, Hamam Y, Abe BT and Abu-Mahfouz AM 2017 Towards achieving a reliable leakage detection and localization algorithm for application in water piping networks: An overview IEEE Access 5 20272–85

[8]. Chan TK, Chin CS and Zhong X 2018 Review of current technologies and proposed intelligent methodologies for water distributed network leakage detection IEEE Access 6 78846–67

[9]. Hamilton S 2009 ALC in low pressure areas - It can be done 5th IWA Water Loss Reduction Cape Town, South Africa

[10]. El-Abbasy MS, Mosleh F, Senouci A et al 2016 Locating leaks in water mains using noise loggers J. Infrastruct. Syst. 22 04016012

[11]. Abdulshaheed A, Mustapha F and Ghavamian A 2017 A pressure-based method for monitoring leaks in a pipe distribution system: A review Renew. Sustain. Energy Rev. 69 902–11

[12]. Abdulla MB and Herzallah R 2015 Probabilistic multiple model neural network based leak detection system: Experimental study J. Loss Prev. Process Ind. 36 30–8

[13]. Adnan NF, Ghazali MF, Amin MM and Hamat AMA 2015 Leak detection in gas pipeline by acoustic and signal processing - A review IOP Conf. Ser. Mater. Sci. Eng. 100 012013

[14]. Khulief YA, Khalifa A, Mansour RB and Habib MA 2012 Acoustic detection of leaks in water pipelines using measurements inside pipe J. Pipeline Syst. Eng. Pract. 3 47–54

[15]. Tur JMM and Garthwaite W 2010 Robotic devices for water main in-pipe inspection: A survey J. F. Robot. 27 491–508

[16]. Guan L, Gao Y, Liu H et al 2019 A review on small-diameter pipeline inspection gauge localization techniques: Problems, methods and challenges 2019 Int. Conf. Communications, Signal Processing and their Applications (ICCSPA) pp 1–6

[17]. Bickerstaff R, Vaughn M, Stoker G et al 2002 Review of sensor technologies for in-line inspection of natural gas pipelines Sandia Natl. Lab. Albuquerque

[18]. SmartBall 2022 Leak and Gas Pocket Detection https://puretechltd.com/technology/smartball- leak-detection/

[19]. Ismail IN, Anuar AS and Sahari KSM 2012 Developments of in-pipe inspection robot: A review 2012 IEEE Conf. Sustainable Utilization and Development in ENgineering and Technology (STUDENT) pp 310–5

[20]. Roslin NS, Anuar A, Jalal MFA and Sahari KSM 2012 A review: Hybrid locomotion of in-pipe inspection robot Procedia Eng. 41 1456–62

[21]. Roh SG and Choi HR 2005 Differential-drive in-pipe robot for moving inside urban gas pipelines IEEE Trans. Robot. 21 1–17

[22]. Kolesnik M and Streich H 2002 Visual orientation and motion control of Makro Adaptation to the sewer environment https://kolesnik.leute.server.de/papers/pdf/sab2002.pdf

[23]. Roman HT, Pellegrino BA and Sigrist WR 1993 Pipe crawling inspection robots: An overview IEEE Trans. Energy Convers. 8 576–83

[24]. Bradbeer R, Harrold S, Nickols F and Yeung LF 1997 Underwater robot for pipe inspection Proc. Annu. Conf. Mechatronics Mach. Vis. Pract. MViP 152–6

[25]. Bertetto AM and Ruggiu M 2001 In-pipe inch-worm pneumatic flexible robot IEEE/ASME Int. Conf. Adv. Intell. Mechatronics, AIM 2 1226–31

[26]. Lim J, Park H, Moon S and Kim B 2007 Pneumatic robot based on inchworm motion for small diameter pipe inspection 2007 IEEE Int. Conf. Robot. Biomimetics, ROBIO 330–5

[27]. Choi C, Jung S and Kim S 2004 Feeder pipe inspection robot with an inch-worm mechanism using pneumatic actuators Int. J. Control. Autom. Syst. 4 87–95

[28]. Menciassi A, Park JH, Lee S et al 2002 Robotic solutions and mechanisms for a semi-autonomous endoscope IEEE Int. Conf. Intell. Robot. Syst. 2 1379–84

[29]. Liljebck P, Pettersen KY, Stavdahl O and Gravdahl JT 2012 A review on modelling, implementation, and control of snake robots Rob. Auton. Syst. 60 29–40

[30]. Liu Z and Kleiner Y 2013 State of the art review of inspection technologies for condition assessment of water pipes Measurement 46 1–15

[31]. Moraleda J, Ollero A and Orte M 1999 A robotic system for internal inspection of water pipelines IEEE Robot. Autom. Mag. 6 30–41

[32]. Kirkham R, Kearney PD, Rogers KJ and Mashford J 2000 PIRAT A system for quantitative sewer pipe assessment The International Journal of Robotics Research 19(11) 1033-1053 doi:10.1177/02783640022067959

[33]. Kuntze HB and Haffner H 1998 Experiences with the development of a robot for smart multisensoric pipe inspection Proc. IEEE Int. Conf. Robot. Autom. 2 1773–8

[34]. Kirchner F and Hertzberg J 1997 A prototype study of an autonomous robot platform for sewerage system maintenance Auton. Robot. 1997 44 4 319–31

[35]. Rome E, Hertzberg J, Kirchner F et al 1999 Towards autonomous sewer robots: the MAKRO project Urban Water 1 57–70

[36]. Pure Technologies 2022 Lyon inspects water main for leaks with SmartBall tool (Xylem)

[37]. Cataldo A, Persico R, Leucci G et al 2014 Time domain reflectometry, ground penetrating radar and electrical resistivity tomography: A comparative analysis of alternative approaches for leak detection in underground pipes NDT E Int. 62 14–28

[38]. Lee PJ, Vítkovský JP, Lambert MF et al 2005 Frequency domain analysis for detecting pipeline leaks J. Hydraul. Eng. 131 596–604

[39]. Gupta A and Kulat KD 2018 A selective literature review on leak management techniques for water distribution system Water Resour. Manag. 32 3247–69

[40]. Lee MR and Lee JH 2000 Acoustic emission technique for pipeline leak detection Key Eng. Mater. 183–187 887–92

[41]. De Silva D, Mashford J and Burn S 2011 Computer Aided Leak Location and Sizing in Pipe Networks http://www.urbanwateralliance.org.au/publications/UWSRA-tr17.pdf

[42]. Jacobsz SW and Jahnke SI 2019 Leak detection on water pipelines in unsaturated ground by discrete fibre optic sensing https://doi.org/10.1177/1475921719881979 19 1219–36

[43]. Inaudi D and Glisic B 2008 Long-range pipeline monitoring by distributed fiber optic sensing Proc. Bienn. Int. Pipeline Conf. IPC 3(B) 763–72

[44]. Davila M, Davila Delgado JM, Brilakis I and Middleton C 2016 Distributed monitoring of buried pipelines with Brillouin fiber optic sensors Proc. Int. Conf. Smart Infrastructure and Construction 3338

[45]. Joung OJ and Kim YH 2006 Application of an IR thermographic device for the detection of a simulated defect in a pipe Sensors 6 1199–208

[46]. Gross W, Hierl T, Scheuerpflug H et al 1999 Quality control of heat pipelines and sleeve joints by infrared measurements Thermosense XXI 3700 63–9

[47]. Hunaidi O, Chu W, Wang A and Guan W 2000 Detecting leaks in plastic pipes J. Am. Water Works Assoc. 92 82–94

[48]. Khawandi S, Daya B and Chauvet P Automated monitoring system for fall detection in the Elderly Int. J. Image Process. 476

[49]. Bach PM and Kodikara JK 2017 Reliability of infrared thermography in detecting leaks in buried water reticulation pipes IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 10 4210–24

[50]. Huang Y, Fipps G, Maas SJ and Fletcher RS 2010 Airborne remote sensing for detection of irrigation canal leakage Irrig. Drain. 59 524–34

[51]. Demirci S, Yigit E, Eskidemir IH and Ozdemir C 2012 Ground penetrating radar imaging of water leaks from buried pipes based on back-projection method NDT E Int. 47 35–42

[52]. Wai-Lok Lai W, Dérobert X and Annan P 2018 A review of ground penetrating radar application in civil engineering: A 30-year journey from locating and testing to imaging and diagnosis NDT E Int. 96 58–78

[53]. Hamilton S and Charalambous B 2013 Leak detection: Technology and implementation Water Intell. Online 12

[54]. Kiss G, Konez K and Melinte C 2007 WaterPipe project: An innovative high resolution ground penetration imaging radar for detecting water pipes and for detecting leaks and a decision support system for the rehabilitation management of the water pipeline IWA Water Loss Conference (Bucharest, Romania) pp 622–31

[55]. Geiger G 2006 State-of-the-Art in leak detection and localisation Pipeline Technology (Hannover, Germany) pp 1–25

[56]. Boaz L, Kaijage S and Sinde R 2014 An overview of pipeline leak detection and location systems Proc. 2nd Pan African Int. Conf. Sci. Comput. Telecommun. PACT 2014 133–7

[57]. Sun Z, Wang P, Vuran MC et al 2011 MISE-PIPE: Magnetic induction-based wireless sensor networks for underground pipeline monitoring Ad Hoc Networks 9 218–27

[58]. Farley B, Mounce SR and Boxall JB 2010 Field testing of an optimal sensor placement methodology for event detection in an urban water distribution network Urban Water J. 7 345– 356

[59]. Perez R, Sanz G, Puig V et al 2014 Leak localization in water networks: A model-based methodology using pressure sensors applied to a real network in Barcelona [Applications of Control] IEEE Control Syst. 34(4) 24–36

[60]. Wan J, Yu Y, Wu Y et al 2012 Hierarchical leak detection and localization method in natural gas pipeline monitoring sensor networks Sensors 12 189–214

[61]. Pérez R, Puig V, Pascual J et al 2011 Methodology for leakage isolation using pressure sensitivity analysis in water distribution networks Control Eng. Pract. 19 1157–67

[62]. Sousa J, Muranho J, Sá Marques A and Gomes R 2014 WaterNetGen helps C-Town Procedia Eng. 89 103–10

[63]. Ishido Y and Takahashi S 2014 A new indicator for real-time leak detection in water distribution networks: Design and simulation validation Procedia Eng. 89 411–7

[64]. Sophocleous S, Savić DA, Kapelan Z and Giustolisi O 2017 A two-stage calibration for detection of leakage hotspots in a real water distribution network Procedia Eng. 186 168–76

[65]. Mala-Jetmarova H, Sultanova N and Savic D 2018 Lost in optimisation of water distribution systems? A literature review of system design Water (Switzerland) 10

[66]. Geng Z, Hu X, Han Y and Zhong Y 2018 A novel leakage-detection method based on sensitivity matrix of pipe flow: Case study of water distribution systems J. Water Resour. Plan. Manag. 145(2)

[67]. Casillas MV, Garza-Castanon LE and Puig V 2013 Extended-horizon analysis of pressure sensitivities for leak detection in water distribution networks: Application to the Barcelona network 2013 Eur. Control Conf. ECC 2013 404–9

[68]. Ferrandez-Gamot L, Busson P, Blesa J et al 2015 Leak localization in water distribution networks using pressure residuals and classifiers IFAC-PapersOnLine 48 220–5

[69]. Wu Y and Liu S 2017 A review of data-driven approaches for burst detection in water distribution systems Urban Water J. 14 972–83

[70]. Silva RA, Buiatti CM, Cruz SL and Pereira JAFR 1996 Pressure wave behaviour and leak detection in pipelines Comput. Chem. Eng. 20 S491–6

[71]. Tian CH, Yan JC, Huang J et al 2012 Negative pressure wave based pipeline Leak Detection: Challenges and algorithms Proc. IEEE Int. Conf. Serv. Oper. Logist. Informatics, SOLI 2012 372–6

[72]. Jung D, Kang D, Liu J and Lansey K 2015 Improving the rapidity of responses to pipe burst in water distribution systems: a comparison of statistical process control methods J. Hydroinformatics 17 307–28

[73]. Westra S, Brown C, Lall U and Sharma A 2007 Modeling multivariable hydrological series: Principal component analysis or independent component analysis? Water Resour. Res. 43 6429

[74]. Wu Y, Liu S, Wu X et al 2016 Burst detection in district metering areas using a data driven clustering algorithm Water Res. 100 28–37

[75]. Zhou X, Tang Z, Xu W et al 2019 Deep learning identifies accurate burst locations in water distribution networks Water Res. 166 115058

[76]. Mounce SR and Machell J 2007 Burst detection using hydraulic data from water distribution systems with artificial neural networks 3 21 http://dx.doi.org/10.1080/15730620600578538

[77]. Aksela K, Aksela M and Vahala R 2009 Leakage detection in a real distribution network using a SOM Urban Water J. 6 279–89

[78]. Mounce SR, Khan A, Wood AS et al 2003 Sensor-fusion of hydraulic data for burst detection and location in a treated water distribution system Inf. Fusion 4 217–29

[79]. Mounce SR, Boxall JB and Machell J 2009 Development and verification of an online artificial intelligence system for detection of bursts and other abnormal flows J. Water Resour. Plan. Manag. 136 309–18

[80]. Ye G and Fenner RA 2010 Kalman filtering of hydraulic measurements for burst detection in water distribution systems J. Pipeline Syst. Eng. Pract. 2 14–22

[81]. Mounce S, Boxall JB and Machell J 2007 An Artificial Neural Network/Fuzzy Logic system for DMA flow meter data analysis providing burst identification and size estimation Proc. Water Management Challenges in Global Change 313320

[82]. Mounce SR, Mounce RB and Boxall JB 2011 Novelty detection for time series data analysis in water distribution systems using support vector machines J. Hydroinformatics 13 672–86

[83]. Lay-Ekuakille A, Vendramin G, Trotta A and Vanderbemden P 2009 STFT-Based spectral analysis of urban waterworks leakage detection Proc. XIX IMEKO World Congress 2172□76.

[84]. Li H, Li H, Pei H and Li Z 2019 Leakage detection of HVAC pipeline network based on pressure signal diagnosis Build. Simul. 12 617–628 https://doi.org/10.1007/s12273-019-0546-0

[85]. Kadri A, Yaacoub E and Mushtaha M 2014 Empirical evaluation of acoustical signals for leakage detection in underground plastic pipes Proc. Mediterr. Electrotech. Conf. - MELECON 54–8

[86]. Wu R, Liao Z, Zhao L and Kong X 2008 Wavelets application on acoustic emission signal detection in pipeline Can. Conf. Electr. Comput. Eng. 1211–4

[87]. Ahadi M and Bakhtiar MS 2010 Leak detection in water-filled plastic pipes through the application of tuned wavelet transforms to Acoustic Emission signals Appl. Acoust. 71 634–9

[88]. Zadkarami M, Shahbazian M and Salahshoor K 2017 Pipeline leak diagnosis based on wavelet and statistical features using Dempster–Shafer classifier fusion technique Process Saf. Environ. Prot. 105 156–63.