University Mohamed Boudiaf - M'sila

FACULTY OF TECHNOLOGY

DEPARTEMENT OF ELECTRONIQUE

Serial Number: ………………..…

Registration Number: …………..……

Thesis

Presented for obtaining the diploma of

LMD DOCTORATE

Sector: ELECTRONIQUE

Speciality: INSTRUMENTATION ELEVTRONIQUE

THEME

Development of a Leak Detection and Localization System Based on Parametric Models

Presented By

MEFTAH Sabir

Supported on: / /

Examining Committee Members:

Last Name & First Name	Rank	Institution	Role
Guermat Noubeil	**Professor**	Univ. **of M'sila**	President
BENTOUMI Miloud	**MCA**	Univ. **of M'sila**	Supervisor
DIRMAN Hanafi Burhanuddin	**Professor**	Univ. **of Tun Hussein Onn Malaysia**	Co- Supervisor
BOUZIT Nacerdine	**Professor**	Univ. **of Setif**	Examiner
BOUROUBA Nacerdine	**Professor**	Univ. **of Setif**	Examiner
Djerioui Mohamed	**MCA**	Univ. **of M'sila**	Examiner
Bakhti Haddi	**MCA**	Univ. **of M'sila**	Invited

Academic year: 2024/2025

Acknowledgement

Alhamdulillah, who gives me everything to live, read, understand, complete this research work, and every work, here and everywhere, and the best prayer and peace be upon the Prophet Muhammad.

I would like to express my sincerest thanks and gratitude to my supervisor, Professor, Miloud BENTOUMI, for his encouragement, advice, and unwavering support in helping me complete my research work.

My deepest thanks to my co-supervisor, Assoc. Assoc. Prof. Ir. Dr. Dirman Hanafi, for his inspiration, assistance, and overcoming the difficulties.

I would like to express my sincere gratitude to the members of the thesis jury for their time, valuable insights, and constructive feedback.

I extend my deepest thanks to Professor, Guermat Noubeil, who kindly accepted to preside over this defense. Your thoughtful remarks and your involvement in my work are deeply appreciated.

I am also very grateful to Professor, BOUZIT Nacerdine and Professor, BOUROUBA Nacerdine, who generously agreed to review this thesis. Your thorough evaluations and pertinent suggestions have contributed greatly to improving the quality of this work.

My sincere appreciation goes to Professor Bakhti Haddi, who participated as an invited jury member. Your presence and contributions brought additional value and perspective to this research.

Finally, I warmly thank all members of the jury for honoring me with their presence and for the enriching discussions during the defense. Your expertise and perspectives have been a great source of encouragement and inspiration.

To my mother, father, My wife, brothers, sisters, friends. and all family.

Abstract

In the core of this thesis, three methodologies were developed to address water leakage in the water distribution networks (WDNs). The first one was conducted on the development and the demonstration of a mathematical model for leak localization. It depends on the laws of fluid mechanics. Two crucial parameters that can't be calculated, we should optimize. For that we use an evolutionary metaheuristic method, which is the biogeography-based optimization (BBO) method that has three main stages (migration, mutation, and an optional one, which is elitism). After obtaining the two unknown parameters by optimization and using the physical characteristics of the transportation pipe (length, diameter, etc.), the flow rate measurements at the two ends of the pipe, we can define the exact position of the leak. With the development of technology and the transition from the analog world to the digital world, as well as the exploitation of signal processing functions, correlators have emerged. The latter rely for their operations on two acoustic sensors placed on fire hydrants at a distance of 500 m to 1 km. The microphones or hydrophones not only transmit the leak signals but also pick up surrounding noises. The received radio frequency signals will be subjected to signal processing functions to confirm the presence of the leak and its location relative to one of the sensors. Their disadvantages lie in false alarms caused by environmental noise, thus causing the destruction of infrastructure. In addition, they require a qualified workforce. The researchers are oriented to exploit the vibration sensors and the analysis of the transient phenomena that occur. Road traffic and daily work share noises that are added to the useful signal, always causing anomalies in the infrastructure. The problem is to think of an effective and inexpensive way to solve the problem of leaks. The second contribution addresses noise and false alarms in a pressure leak detection system. Using a custom-built laboratory prototype, pressure signals were collected and denoised with a Savitzky-Golay filter. Leak localization was achieved through time-difference calculations of signal arrivals at high-precision transmitters, validated against known leak positions in a zigzag-shaped HDPE pipe network. The third contribution enhances the detection process using a larger experimental prototype. Pressure signals from leaks of varying sizes were processed using discrete wavelet transform (DWT) and Donoho thresholding for noise removal. Reconstructed signals were analyzed for quality metrics such as SNR, NCC, and MSE. Time differences in signal arrivals, combined with pressure wave velocity, allowed accurate leak localization, validated across diverse leak scenarios. This research advances the precision and robustness of leak detection methodologies, providing practical, cost-effective solutions for WDN maintenance and management.

Keywords: WDNs, Leak Detection, Localization, BBO, Signal Processing, DWT, Pressure signals.

Résumé

Au cœur de cette thèse, trois méthodologies ont été développées pour aborder les fuites d'eau dans les réseaux de distribution d'eau (WDNs). La première repose sur le développement et la démonstration d'un modèle mathématique pour la localisation des fuites. Ce modèle s'appuie sur les lois de la mécanique des fluides. Deux paramètres cruciaux, impossibles à calculer directement, doivent être optimisés. Pour cela, une méthode métaheuristique évolutive, l'optimisation basée sur la biogéographie (BBO), a été utilisée, comprenant trois étapes principales (migration, mutation, et, éventuellement, élitisme). Après avoir obtenu les deux paramètres inconnus grâce à l'optimisation, et en utilisant les caractéristiques physiques de la conduite de transport (longueur, diamètre, etc.) ainsi que les mesures de débit aux deux extrémités de la conduite, il est possible de définir la position exacte de la fuite. Avec le développement de la technologie et le passage du monde analogique au monde numérique, ainsi que l'exploitation des fonctions de traitement du signal, les corrélateurs ont émergé. Ces derniers fonctionnent grâce à deux capteurs acoustiques placés sur des bouches d'incendie à une distance de 500 m à 1 km. Les microphones ou hydrophones transmettent non seulement les signaux de fuite mais captent également les bruits environnants. Les signaux radiofréquences reçus sont soumis à des fonctions de traitement du signal pour confirmer la présence et la localisation de la fuite par rapport à l'un des capteurs. Leurs inconvénients résident dans les fausses alertes causées par le bruit environnemental, entraînant ainsi des destructions d'infrastructures. De plus, ils nécessitent une main-d'œuvre qualifiée. Les chercheurs se tournent vers l'exploitation des capteurs de vibration et l'analyse des phénomènes transitoires qui se produisent. Le trafic routier et les travaux quotidiens partagent des bruits qui s'ajoutent au signal utile, provoquant toujours des anomalies dans les infrastructures. Le défi consiste à trouver une solution efficace et économique pour résoudre le problème des fuites. La deuxième contribution aborde le problème du bruit et des fausses alertes dans un système de détection de fuites par pression. À l'aide d'un prototype de laboratoire conçu sur mesure, des signaux de pression ont été collectés et débruités avec un filtre Savitzky-Golay. La localisation des fuites a été réalisée grâce au calcul des différences temporelles d'arrivée des signaux à des émetteurs de haute précision, validée par rapport à des positions de fuite connues dans un réseau de tuyaux HDPE en forme de zigzag. La troisième contribution améliore le processus de détection grâce à un prototype expérimental plus grand. Les signaux de pression provenant de fuites de tailles variées ont été traités à l'aide de la transformée en ondelettes discrètes (DWT) et du seuillage de Donoho pour éliminer le bruit. Les signaux reconstruits ont été analysés selon des métriques de qualité telles que le SNR, le NCC et le MSE. Les différences temporelles d'arrivée des signaux, combinées à la vitesse des ondes de pression, ont permis une localisation précise des fuites, validée dans divers scénarios de fuite. Cette recherche améliore la précision et la robustesse des méthodologies de détection des fuites, offrant des solutions pratiques et économiques pour l'entretien et la gestion des WDNs.

Mots-clés : WDNs, Détection de fuites, Localisation, BBO, Traitement du signal, DWT, signaux de pression.

الملخص

في صلب هذه الأطروحة، تم تطوير ثلاث منهجيات لمعالجة تسربات المياه في شبكات توزيع المياه .(WDNs) الأولى تعتمد على تطوير وعرض نموذج رياضي لتحديد مواقع التسرب. يستند هذا النموذج إلى قوانين ميكانيكا الموائع. هناك معلمان أساسيان لا يمكن حسابهما مباشرة، لذا يجب تحسينهما باستخدام طريقة ميتاهيورستية تطورية، وهي طريقة تحسين تعتمد على الجغرافيا الحيوية (BBO) التي تتضمن ثلاث مراحل رئيسية (الهجرة، الطفرة، والمرحلة الاختيارية وهي النخبة). بعد الحصول على القيم المجهولة للمعلمين عبر التحسين، وباستخدام الخصائص الفيزيائية لأنبوب النقل (الطول، القطر، إلخ) وقياسات التدفق عند طرفي الأنبوب، يمكن تحديد الموقع الدقيق للتسرب .مع تطور التكنولوجيا والانتقال من العالم التناظري إلى العالم الرقمي، واستغلال وظائف معالجة الإشارات، ظهرت أجهزة الربط .(Corrélateurs) تعتمد هذه الأجهزة على مستشعرين صوتيين يوضعان على صنابير الحريق على مسافة تتراوح بين 500 م و1 كم. تقوم الميكروفونات أو الهيدروفونات بنقل إشارات التسرب بالإضافة إلى التقاط الضوضاء المحيطة. يتم معالجة الإشارات المستلمة بواسطة وظائف معالجة الإشارة لتأكيد وجود التسرب وتحديد موقعه بالنسبة لأحد المستشعرين. العيوب تكمن في الإنذارات الكاذبة الناتجة عن الضوضاء البيئية، مما يؤدي إلى تدمير البنية التحتية. بالإضافة إلى ذلك، تتطلب هذه الأجهزة عمالة مؤهلة. يتوجه الباحثون إلى استغلال مستشعرات الاهتزاز وتحليل الظواهر العابرة. تتسبب ضوضاء حركة المرور والعمل اليومي في إحداث ضوضاء تضاف إلى الإشارة المفيدة، مما يسبب دائمًا تشوهات في البنية التحتية. التحدي هو التفكير في طريقة فعالة واقتصادية لحل مشكلة التسربات .المساهمة الثانية تتناول مشكلة الضوضاء والإنذارات الكاذبة في نظام كشف التسربات يعتمد على الضغط. باستخدام نموذج مختبري تم تصميمه خصيصًا، تم جمع إشارات الضغط وتنقيتها باستخدام مرشح Savitzky-Golay.تم تحقيق تحديد موقع التسرب عبر حساب اختلافات الزمن لوصول الإشارات إلى أجهزة إرسال عالية الدقة، وتمت مقارنة النتائج بمواقع تسرب معروفة في شبكة أنابيب HDPE على شكل متعرج .المساهمة الثالثة تحسن عملية الكشف باستخدام نموذج تجريبي أكبر. تمت معالجة إشارات الضغط الناتجة عن تسربات بأحجام مختلفة باستخدام تحويل الموجات المتقطعة (DWT) وتطبيق تقنية Donoho للحد من الضوضاء. تم تحليل الإشارات المعاد بناؤها باستخدام معايير جودة مثل SNR و NCCو .MSEمكنت اختلافات الزمن في وصول الإشارات، إلى جانب سرعة موجة الضغط، من تحديد دقيق لموقع التسرب، وتم التحقق من ذلك عبر سيناريوهات تسرب مختلفة. تسهم هذه الدراسة في تحسين دقة ومنهجيات الكشف عن التسرب، مما يوفر حلولًا عملية واقتصادية لصيانة وإدارة شبكات توزيع المياه.

الكلمات المفتاحية :WDNs، كشف التسربات، تحديد الموقع، BBO، معالجة الإشارة،DWT ، إشارات الضغط.

List of figures

Chapter02

Chapter03

Chapter04

Chapter05

List of Tables

Chapter04

Chapter05

List of abbreviations

WDNs	Water distribution networks.
DSP	digital signal processing.
FFT	Fast Fourier Transform.
IFFT	inverse fast Fourier transform.
STFT	Short-Time Fourier Transform.
CWT	Continuous Wavelet Transform.
DWT	Discrete Wavelet Transform.
IDWT	inverse discreet wavelet transforms.
BBO	Biogeography-based optimization.
MEMS	Microelectromechanical Systems.
S.G	Savitzky-Golay.
SNR	signal-to-noise ratio.
NCC	normalized cross-correlation.
MSE	mean square error.
DWTD	discrete wavelet transform detector.
ITA	Inverse Transient Analysis
DMA	District Metered Area
CEM	Central Event Management
AI	Artificial Intelligence
RTUs	Remote Terminal Units
SCADA	Supervisory Control and Data Acquisition
PSO	Particle swarm optimization
GIS	Geographic Information Systems
CRM	Customer Relationship Management

Contents

Chapter03

Chapter04

Chapter05

Conclusion And Recommendations

GENERAL

INTRODUCTION

INTRODUCTION

1.1 Background of the study

Detecting and localizing water leaks has become more important in recent years, due to the consequences for water conservation, infrastructure maintenance, and economic efficiency. According to data undertaken by the International Water Association and the World Bank, about 45 million cubic meters of water are lost annually due to leaks, which have a significant economic impact, especially in developing nations [1]. As cities expand and water needs increase, effective and efficient leak detection systems become more crucial. Modern innovations, such as smart sensors and remote monitoring solutions, have enhanced proactive leak management. However, challenges remain, including environmental noise interference, false alarms, and the need for skilled operators.

Water distribution networks (WDNs) are an important component of water infrastructure, intended to carry treated water from sources to end consumers in a reliable and efficient manner. These networks are made up of linked pipes, valves, reservoirs, and pumps that work together to provide proper water distribution in a variety of situations. However, the complexity of WDNs renders them vulnerable to problems like as leaks, which may result in significant water losses, operational inefficiencies, and increased expenses. Understanding the structural and operational complexities of WDNs is therefore critical for identifying vulnerabilities and devising effective leak detection and mitigation measures.

Historically, manual methods such as listening rods were labor-intensive and time-consuming. The advent of signal processing techniques brought innovations like acoustic correlators, which use microphones or hydrophones to detect leaks. Despite their effectiveness, these methods face limitations in environments with high noise levels. More recent advancements have introduced vibration sensors and transient analysis for leak detection. Building on these innovations, this study focuses on the use of pressure sensors combined with advanced digital signal processing (DSP) techniques specifically Discrete Wavelet Transform (DWT) followed by the DONOHO threshold to denoise signals and analyze them for leak detection. These methods aim to minimize external noise interference and improve leak localization accuracy using auto-correlation techniques.

Parametric models are statistical models characterized by a finite set of parameters that define the model's structure and behavior. These models are widely utilized across various fields, including statistics, machine learning, and engineering, due to their ability to provide a clear framework for inference and prediction. The choice of parameters allows for the simplification of complex phenomena into manageable mathematical representations, facilitating analysis and interpretation.

The fundamental advantage of parametric models lies in their ability to make strong assumptions about the underlying data distribution. For instance, in the context of point processes, parametric models often rely on specific distributions to characterize the intensity function, which is crucial for understanding the generating processes. Moreover, parametric models can be particularly advantageous when the data is well-understood and adheres to the assumptions of the model, as they can yield precise estimates and predictions [2],[3].

However, the application of parametric models is not without limitations. When the underlying assumptions about the data distribution are violated, the model's performance can degrade significantly. In such cases, non-parametric approaches may be more suitable, as they do not rely on strict assumptions about the data distribution and can adapt to a wider variety of data patterns. This flexibility is particularly useful in exploratory contexts where the data characteristics are not fully known. Additionally, the complexity of real-world phenomena often necessitates the use of hybrid approaches that combine both parametric and non-parametric methods to leverage the strengths of each [2],[4].

Developing a mathematical model for water leak detection based on fluid mechanics principles, along with the optimization of two unknown parameters using a Biogeography-based optimization (BBO) method, indeed falls within the realm of parametric modeling. In this context, the mathematical model serves as a parametric representation of the physical processes governing fluid flow and leak dynamics, where the parameters to be optimized are essential for accurately predicting the behavior of the system under various conditions. The optimization of these parameters is crucial, as it directly influences the model's ability for the leak localisation.

In the literature, various studies emphasize the importance of parameter optimization in enhancing leak detection methodologies. For instance, Ben-Mansour and Suara highlight the significance of understanding flow characteristics for effective leak detection in water pipelines, indicating that precise parameterization can lead to improved management of water distribution systems [5]. Furthermore, Ishido and Takahashi propose a real-time leak detection algorithm that relies on pressure measurements, showcasing how parameter optimization can refine detection algorithms and enhance their responsiveness to leak events [6]. By employing a BBO method, our approach aligns with contemporary practices in the field, where optimization techniques are increasingly integrated into parametric models to achieve better performance in leak detection applications [7],[8]. Thus, our work not only contributes to the existing body of knowledge but also exemplifies the practical application of parametric modeling in addressing critical challenges in water management.

In recent decades, DSP techniques have revolutionized leak detection. Methods such as Fast Fourier Transform (FFT), Short-Time Fourier Transform (STFT), Continuous Wavelet Transform (CWT), and DWT have significantly enhanced the analysis and interpretation of signals. These techniques enable the detection of leaks even in noisy environments by providing time-frequency analysis and multi-resolution capabilities. According to studies, methods like FFT and STFT can identify leaks amidst background noise, while CWT and DWT excel in capturing transient and steady-state signals, offering superior resolution for detecting fleeting leak events. By combining DSP methods with correlation techniques, it is possible to compare sensor data and accurately localize leaks, improving responsiveness to leak events [9], [10],[11],[12].

This thesis contributes to the existing body of knowledge by integrating DSP techniques, parametric modeling and optimization to enhance leak detection systems. It emphasizes the use of advanced signal processing and mathematical modeling to improve the precision and reliability of water leak detection, thereby addressing critical challenges in water resource management and infrastructure maintenance.

1.2 Problem statement

In the event of a leak, rapid intervention is crucial to minimize the damage and reduce the associated costs. Innovative technologies, such as smart sensors and remote monitoring solutions, can also play a key role in the proactive management of leaks. Several means and techniques have been deployed to confront this problem. The basic element for detecting and locating a leak is rods of listening. By examining the suspicious area, we can find out the place of the leak. Its disadvantage lies in the fact that the method is very time-consuming and requires a large number of personnel. With the development of technology and the transition from the analog world to the digital world as well as the exploitation of signal processing functions, correlators have emerged. The latter rely for their operations on two acoustic sensors placed on fire hydrants at a distance of 500 m to 1 km. We transmit not only the leak signals but also the surrounding noises that have been picked up by microphones or hydrophones. The received radio frequency signals will be subjected to signal processing functions to confirm the presence of the leak and its location relative to one of the sensors. Their disadvantages lie in false alarms caused by environmental noise thus causing the destruction of infrastructure. In addition, they require a qualified workforce. The researchers are oriented to exploit the vibration sensors and the analysis of the transient phenomena that occur. Road traffic and daily work share noises that are added to the useful signal always cause anomalies on the infrastructure. The fundamental problem is to provide a cost-effective, dependable, and efficient technique for leak detection and localization. Such a system should reduce dependence on costly equipment and trained personnel while mitigating the effects of external noise. Using modern signal processing methods and precise measurements, such as pressure and flow rate, provides a viable approach to addressing the ongoing problem of water leakage in distribution networks.

1.3 Research objectives

Th research objectives are intended to address key challenges in water leak detection and localization by integrating theoretical, computational, and experimental methodologies. These objectives aim to increase the accuracy, reliability, and usefulness of leak detection systems by developing advanced models, using innovative optimization methodologies, and evaluating results with experimental prototypes. The particular research objectives are as follows:

i. To examine the architecture and structure of WDNs water to identify weaknesses and implement effective leak detection techniques.

ii. To review existing water leak detection technologies, their limitations, and the specific challenges they address in different water distribution systems.

iii. To summarize the evolution and applicability of DSP techniques, including FFT, STFT, CWT, and DWT, for detecting water leaks under various noise and signal conditions.

iv. To optimize correlation method for improving the accuracy and efficiency of leak localization by analyzing data from two transmitters by enhancing signal quality in leak detection systems by employing advanced denoising techniques such as the Savitzky-Golay (S.G) filter and DWT.

v. To demonstrate and analyze an existing mathematical model for water leak detection based on fluid mechanics laws, identifying two unknown variables critical to leak detection: the friction factor and discharge flow through a leak, and to solve these using the BBO method.

vi. To develop and utilize experimental prototypes equipped with precise instrumentation to collect pressure data, validate mathematical equations for leak localization, and confirm findings through experimental measurements under various simulated scenarios.

vii. To utilize advanced signal processing tools, such as the DSpace microlab box unit connected to MATLAB Simulink and ControlDesk software, for high-frequency (1 kHz) and high-precision data acquisition and analysis.

1.4 Outline of the thesis

In this thesis:

Chapter 2 presents a thorough study of water leak detection systems, examining the technologies and approaches used in the field. It starts with an overview of WDNs and divides leak detection methods into four main categories: acoustic, non-acoustic, transient-based, and alternative approaches. We thoroughly examine each category's concepts, types, benefits, and restrictions, providing critical basic information. The chapter goes on to explore classic measures like acoustic and vibration monitoring, as well as newer ones that use machine learning and complex signal processing techniques. This review not only outlines the current state of the art but also points out important gaps in the literature. It underlines the need of developing more robust algorithms to increase the accuracy and reliability of leak detection systems, especially in complicated metropolitan situations.

In Chapter 3, the focus shifts to the application of DSP techniques in the realm of water leak detection and localization. This chapter examines a variety of DSP approaches, including the FFT, STFT, CWT, DWT, and cross-correlation techniques. Each of these technologies is assessed for its efficacy in processing data from leak detecting devices. The chapter stresses the benefits of wavelet transformations, notably DWT, in managing non-stationary data seen in water leak situations. Wavelet transformations are very useful for identifying transient signals because of their ability to give both temporal and frequency information.

Chapter 4, outlines the methodologies developed in this research to address the challenges of water leak detection and localization in WDNs. It describes the key contributions upon which the suggested solutions are founded. The chapter starts by developing a mathematical model based on fluid mechanics concepts. The BBO technique is used to optimize this model by adjusting crucial factors such as the friction factor and discharge flow. The optimization procedure improves the model's accuracy and suitability for different leak circumstances. Next, the chapter describes the experimental setup designed for signal processing and noise reduction. Pressure signals are collected using high-precision transmitters and processed through the S.G filter, optimized for denoising. The time difference in signal arrivals at sensors is calculated and incorporated into a mathematical model for leak localization. The experimental prototype, built using zigzag-shaped HDPE pipes, provides a platform for validating the leak positions based on known distances. The chapter further advances to a larger and more complex experimental setup with circular-shaped HDPE pipes. This setup includes pressure transmitters paired with high-precision data acquisition units. Various leak sizes and distances are tested to validate the approach. The pressure signals are processed using DWT for decomposition, followed by Donoho thresholding to remove noise. The reconstructed signals are analyzed using metrics such as signal-to-noise ratio (SNR), normalized cross-correlation (NCC), and mean square error (MSE). The time difference in signal arrival is then used to pinpoint leaks with high precision.

Chapter 5 summarizes the important discoveries and outcomes from this thesis, concentrating on crucial areas of water leak detection and localization. It starts by describing the process of selecting critical system parameters and assessing optimization behavior across numerous iterations. The chapter then delves into the processing of experimental data acquired in controlled environments, focusing on noise reduction techniques and methods for precisely detecting and pinpointing leaks. Advanced signal processing approaches are presented, with a focus on enhancing data quality and detection accuracy. The latter was assessed by the calculation of some metrices. The chapter also examines the performance of the suggested methodologies using experimental validation and compares them to current methods, demonstrating their efficiency and dependability.

Chapter 6, concludes the thesis by summarizing the key findings of the research and presenting recommendations for future work in water leak detection. This chapter emphasizes the significance of the proposed methods and their potential applications in improving water management systems.

References

[1] "The World Bank, "The World Bank and the International Water Association to establish a partnership to reduce water losses," The World Bank, Sep. 1, 2016. [Online]. Available: https://www.worldbank.org/en/news/press-release/2016/09/01/the-world-bank-and-the-international-water-association-to-establish-a-partnership-to-reduce-water-losses."

[2] M. Chiodi and G. Adelfio, "Forward likelihood-based predictive approach for space-time point processes," *Environmetrics*, vol. 22, no. 6, pp. 749–757, 2011, doi: 10.1002/env.1121.

[3] Nihat Ay. Jürgen Jost. Hông Vân Lê. Lorenz Schwachhöfer. "Parametrized measure models." Bernoulli 24 (3) 1692 - 1725, August 2018. https://doi.org/10.3150/16-BEJ910.

[4] S. Skaperas, L. Mamatas, and A. Chorti, "Real-Time Algorithms for the Detection of Changes in the Variance of Video Content Popularity," *IEEE Access*, vol. 8, pp. 30445–30457, 2020, doi: 10.1109/ACCESS.2020.2972640.

[5] P. F. Mushumbusi, A. Chaudhari, J. Leo, and V. G. Masanja, "CFD Analysis of Flow Characteristics and Diagnostics of Leaks in Water Pipelines," *Engineering, Technology & Applied Science Research.*, vol. 14, no. 5, pp. 16272–16280, 2024, DOI: https://doi.org/10.48084/etasr.8146.

[6] Y. Ishido and S. Takahashi, "A new indicator for real-time leak detection in water distribution networks: Design and simulation validation," in *Procedia Engineering*, 2014, pp. 411–417. doi: 10.1016/j.proeng.2014.11.206.

[7] P. K. Amoatey, A. Bárdossy, and H. Steinmetz, "Inverse optimization based detection of leaks from simulated pressure in water networks, Part 2: Analysis for two leaks," *Journal of Water Management Modeling.*, vol. 2018, pp. 1–10, 2018, DOI: https://doi.org/10.14796/JWMM.C461.

[8] C. Sun, B. Parellada, V. Puig, and G. Cembrano, "Leak localization in water distribution networks using pressure and data-driven classifier approach," *Water (Switzerland)*, vol. 12, no. 1, 2020, https://doi.org/10.3390/w12010054.

[9] A. Lay-Ekuakille, C. Pariset, and A. Trotta, "Leak detection of complex pipelines based on the filter diagonalization method: Robust technique for eigenvalue assessment,"

Meas. Sci. Technol., vol. 21, no. 11, 2010, doi: 10.1088/0957-0233/21/11/115403.

[10] M. F. Siddique, Z. Ahmad, N. Ullah, and J. Kim, "A Hybrid Deep Learning Approach: Integrating Short-Time Fourier Transform and Continuous Wavelet Transform for Improved Pipeline Leak Detection," *Sensors*, vol. 23, no. 19, 2023, https://doi.org/10.3390/s23198079.

[11] S. Ahmad, Z. Ahmad, C. H. Kim, and J. M. Kim, "A Method for Pipeline Leak Detection Based on Acoustic Imaging and Deep Learning," *Sensors*, vol. 22, no. 4, 2022, https://doi.org/10.3390/s22041562.

[12] A. Martini, M. Troncossi, and A. Rivola, "Automatic Leak Detection in Buried Plastic Pipes of Water Supply Networks by Means of Vibration Measurements," *Shock Vib.*, vol. 2015, 2015, http://dx.doi.org/10.1155/2015/165304.

Chapter02

Literature Review

I. Introduction

Potable water is a vital resource for human civilization and is necessary for industry, agriculture, health, and general well-being. However, many obstacles exist in moving potable water from its source to its destination, such as mistakes and inefficiencies that waste energy and resources. Water shortages are becoming a major worldwide concern due to the restricted availability of fresh water supplies and the rising demand for drinkable water. Reducing water loss during distribution is one of the best strategies to address this issue and offers a large window of opportunity for conservation.

The design of a water distribution system plays a critical role in ensuring both a dependable water supply and the development of an efficient, cost-effective network. A thorough understanding of these systems' structure is significant for pinpointing potential vulnerabilities and applying successful leak detection and localization strategies. This chapter offers an in-depth review of current water leak detection technologies, their limitations, and the diverse types of leaks that can arise in various WDN configurations.

We will start by reviewing the many kinds of WDNs frequently utilized in the actual world, emphasizing their special qualities and weaknesses. The various water leak detection and localization methods that are now available will next be examined, along with their advantages and disadvantages. We can better grasp the challenges involved in maintaining a reliable and effective water distribution system if we have a better understanding of the current technology and its limitations.

This chapter, in summary, prepares the reader for a thorough examination of the crucial elements of water leak detection and the structural complexities of WDNs. Understanding these components in-depth will help us emphasize how critical it is to address water losses and how innovative solutions are possible in this crucial resource management area.

The water distribution system is a crucial component of water infrastructure, responsible for conveying treated water from a central source like a pumping station or conduit to various end-users. Customized to meet local conditions, this network includes pipes of varying sizes, valves, meters, pumps, distribution reservoirs, hydrants, and standposts, working together to ensure efficient and reliable water delivery to households, industries, and public areas. Pipes transport water through streets, valves regulate flow, and pumps maintain pressure by directing water to elevated reservoirs or mains. Meters monitor water consumption at individual and municipal levels, supporting effective distribution and management of clean water while preserving water quality. The distribution system distributes water to houses, estates, industries, and public places through a network of pipes, valves, meters, pumps, reservoirs, and hydrants, ensuring adequate pressure and monitoring water usage for efficient delivery [1]. The fundamental design of the WDNs is seen in Figure.2.1.

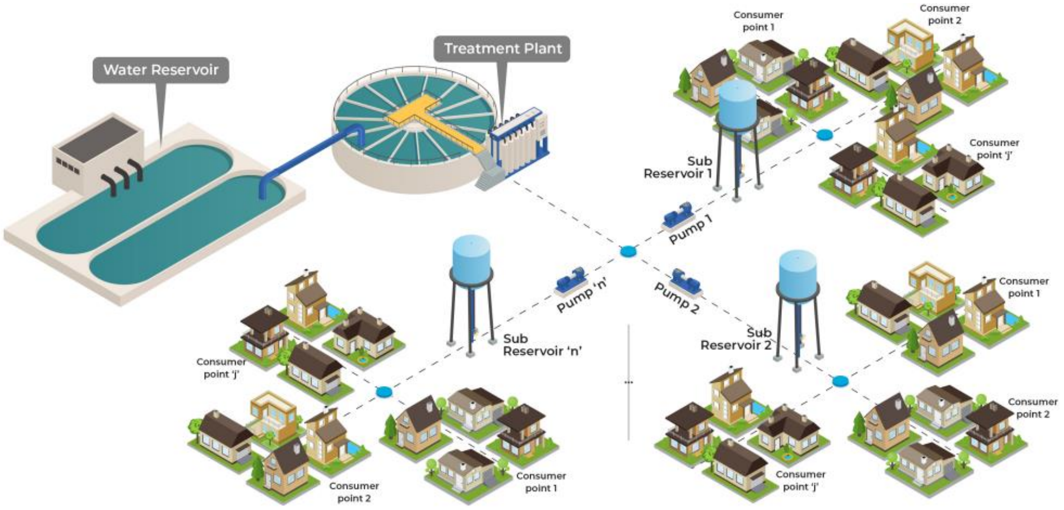

Figure.2.1 Fundamental design of WDNs. [2]

To continuously provide the community with safe and clean drinking water, contemporary water treatment plants are designed with state-of-the-art sensors and cutting-edge technology for water quality monitoring and management. The facility may produce a high-quality product that satisfies or beyond regulatory criteria by utilizing sophisticated wastewater treatment technologies and disinfection techniques to efficiently remove impurities and pollutants. The plant is an environmentally friendly answer to the community's water demands because of its effective design and optimization techniques, which also limit energy usage and lower running costs. This has led to the documentation of several types of WDN designs in the literature on water distribution systems and management. This chapter will begin with an explanation of the basic kinds. In the actual world, there are five common architectural or layouts for water distribution systems. We define each one and discuss the benefits and drawbacks of each.

1- Dead-end (Tree) Network

The tree water distribution system, also known as a dead-end or branching network, resembles a tree with a main trunk and branches extending outward as illustrated in Figure.2.2. This system brings water into an area through a central transmission main, which then branches off into smaller mains that typically end in dead ends. The primary advantages of this design are its simplicity (a smaller number of cut-off valves), ease of construction, and cost-effectiveness

(Economical design) [3][4]. However, it has several significant disadvantages, including susceptibility to water stagnation, pressure drops, and maintenance challenges due to the lack of redundancy. This means there are no backup pathways or alternative routes for water flow in case of system failures or blockages. Dead-end mains can restrict water flow, especially during high-demand situations such as firefighting, as water can only be drawn through a single line. Additionally, the absence of cross-connections between branches and sub-mains can lead to sediment accumulation and water quality issues. Despite these drawbacks, site-specific conditions sometimes necessitate the use of a tree system [3]-[5].

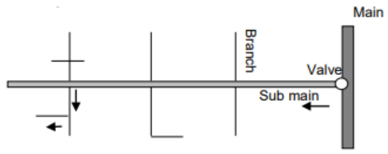

Figure.2.2 Architecture of a tree water network. [6]

2- Radial Network

A radial WDN is a system where water is distributed from a central point, such as a reservoir or pumping station, outward in a radial pattern as shown in Figure.2.3. This design simplifies control and management, as each radial line can be independently controlled. However, it can suffer from pressure drops and a lack of redundancy, similar to tree networks. The central point serves as the main source, and the radial lines extend outward to deliver water to various areas, making it easier to isolate and manage individual sections of the network. The area is divided into different zones, with water pumped into distribution reservoirs in the middle of each zone, and supply pipes laid radially towards the periphery. A branched network, or a tree network, lacks loops and is commonly used for rural water supply. In hilly areas, radial water distribution systems are implemented based on local development and water source locations. The radial system consists of gravity-sustained water distribution mains, designed by treating each branch as a distribution main following a specific methodology [6][7].

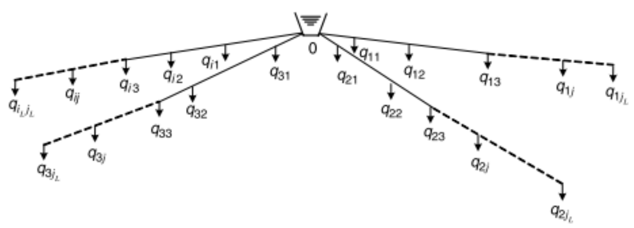

Figure.2.3 Radial network in gravity distribution system. [7]

3- Loop (Ring) Network

The Loop (or Ring) water distribution system is a circular or ring-shaped network that surrounds a central area, with branches extending inward or outward. This unique configuration provides several benefits, including redundancy and consistent water pressure throughout the system. While it may be more complex and costly to implement compared to linear systems, the Loop design ensures reliable water distribution and mitigates the impact of localized disruptions. The system is comprised of a main pipeline that encircles the area in a radial or rectangular shape, with smaller areas enclosed by sub-main pipelines (Refer to Figure.2.4, which shows the Loop water distribution system architecture). In the event of a failure, the impact is contained to a small area, and other areas ahead can still receive water from alternative points. The Loop system requires a higher number of valves, allowing water to be supplied to any point from two directions [6]. This added security and flexibility make the Loop design a valuable choice for critical infrastructure projects.

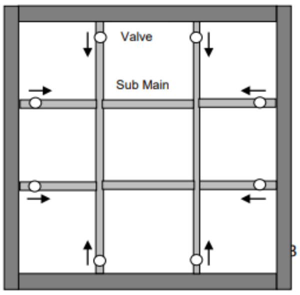

Figure.2.4 Ring architecture. [6]

4- Grid (Looped) Network

A Grid (Looped) WDN is a sophisticated system characterized by its interconnected loops, forming a grid-like pattern that creates multiple pathways for water flow (see Figure.2.5). This design offers several significant advantages, including enhanced reliability and consistent water pressure throughout the network. The grid pattern facilitates easier maintenance due to the redundant paths, ensuring that a blockage in one area does not disrupt the water supply in other areas. This redundancy also helps to avoid water stagnation, as water can flow in more than one direction, reducing the likelihood of long-lasting stagnation. Additionally, during system maintenance, the affected area can still receive water from other directions, maintaining supply continuity [6]. Figure.2.5 illustrates the Grid water distribution architecture, showcasing the interconnected loops and nodes that make up this complex system.

In such a system, main, sub-main, and branch pipes are interconnected, forming a comprehensive grid. Although this design requires a higher total length of pipeline and a greater number of valves, it ensures equitable water pressure across the network. The interconnected loops also mitigate the impact of water demand fluctuations on pressure, providing a more stable supply. However, the complexity of the grid system makes it more expensive to design, construct, and operate compared to simpler branched systems. The hydraulic behavior of a grid system is far more intricate, as the flow pattern is influenced not only by the layout but also by the system's operational conditions. This complexity is further heightened in networks with multiple source nodes, where the analysis of critical pressures becomes more challenging. Despite these challenges, the Grid (Looped) WDN is a reliable option for large-scale water distribution, particularly in urban and industrial areas that require a high-capacity and redundant water supply [6],[8],[9]. The looped structure of the network eliminates many disadvantages of branched systems, such as susceptibility to pressure fluctuations and supply interruptions. In a single-source network, there is one source node, while a multiple-source network features several source nodes, adding to the system's robustness. The grid system's ability to maintain water supply during maintenance and its resistance to pressure variations make it an ideal choice for areas with high-reliability demands. In summary, while the Grid (Looped) WDN is more expensive and complex, its benefits in terms of reliability, pressure consistency, and maintenance ease make it a preferred solution for high-demand areas. The interconnected loops ensure that water flows in multiple directions, reducing stagnation and maintaining supply even during maintenance activities [3],[4],[7]. This makes the grid system a vital infrastructure component in urban and industrial water distribution.

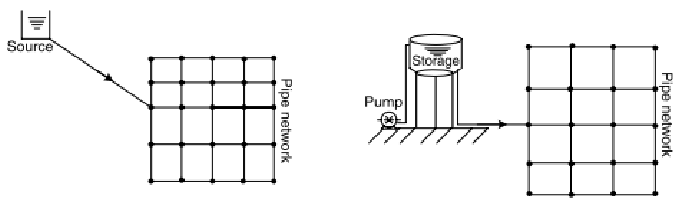

Figure.2.5 Looped architecture. [7]

5- Combined (Mixed) Network

A combined WDN combines elements of both grid and tree network configurations as shown in Figure.2.6. This hybrid approach optimizes costs, provides redundancy, and is easy to maintain. However, it requires careful planning and design to ensure efficiency and reliability. Typically, the network consists of both looped and branched sections. The central parts of large urban areas are served by the looped structure, while peripheral areas are served by extended mains. This design allows efficient distribution of water to both high- and low-density population areas. The looped structure provides a backup system to ensure a continuous supply of water. The branched sections, with their multiple paths, also promote efficient distribution. Overall, the combined network is the most common type of network in large urban areas [4],[9]. Its design offers a balance between the benefits of grid and tree networks, making it a reliable and efficient solution. Careful planning and design are essential to ensure that the network operates efficiently and reliably.

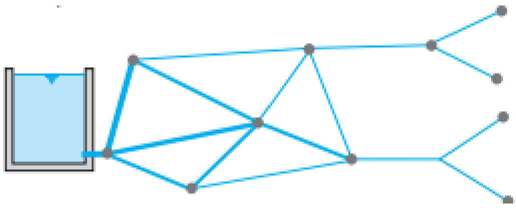

Figure.2.6 Combined network. [9]

II. Methods of water distribution

The type of WDN used has a significant impact on the method of distribution employed. For instance, Dead-end (Tree) Networks often rely on gravity systems in areas with significant elevation changes, whereas Radial Networks typically use pumping systems to maintain adequate pressure. On the other hand, Loop (Ring) Networks and Grid (Looped) Networks benefit from combined systems, utilizing both gravity and pumps to ensure consistent pressure and reliability. Meanwhile, the Combined (Mixed) Network's adaptability allows it to adopt a mix of gravity and pumping systems depending on the specific requirements of different sections of the network. Understanding this relationship between network type and distribution method is crucial for achieving an efficient, reliable, and cost-effective water supply system, as seen in the ancient Roman system, which successfully utilized gravity-fed distribution to supply 40 million gallons of water per day. Modern water distribution systems, composed of various elements like pipes, pumps, and storage tanks, play a vital role in ensuring potable water availability and are crucial to urban planning and infrastructure development, especially in rapidly growing towns [1],[10].

1. Gravity system

The gravity system of water distribution uses only gravity to move water from a source at a higher height to users at a lower level, doing away with the necessity for pumping. With the Romans being among the first to construct vast gravity-based aqueducts as early as 312 B.C., this technology has historical origins, see the Figure.2.7. For the gravity system to function properly, there has to be enough elevation differential between the water source and the distribution region to sustain sufficient pressure at the consumer end even after considering pipe friction and other losses [11],[12].

The affordability of the gravity system is one of its key benefits. There is no energy expenses related to the as there is no need for pumping. This also translates into simpler operation, as the system has fewer mechanical components and does not require a power supply, making it more reliable and easier to manage. In addition, maintenance costs are generally lower compared to systems that rely on pumps. The gravity system also experiences slower pressure changes, which can reduce the risk of pipe bursts and other pressure-related problems. It also provides a buffer capacity for irregular situations, such as sudden increases in water demand or minor interruptions in supply. Gravity storage is particularly effective in smoothing demand and minimising friction head, which can result in significant energy savings for water utilities [1], [3], [6], [9],[10].

However, the gravity system is not without its drawbacks. One significant limitation is the need for suitable topography; the water source must be at a higher elevation than the distribution area. This requirement can limit the applicability of the gravity system in flat or low-lying areas. In addition, the initial construction of such a system can be challenging and costly, as it may require the construction of extensive infrastructure to connect the high-altitude source to the distribution network. The fixed pressure range of gravity systems also makes them less flexible for future expansion, and they require larger pipe diameters to minimize pressure losses. Air entrainment can cause capacity reduction, which is a major operational concern. In addition, these systems often have high levels of unaccounted for water, particularly in mountain communities where water is cheap and pressure is poorly managed. Treating large volumes of water, especially where turbidity is high, can also lead to increased treatment costs [7], [9],[10].

In summary, while the gravity system of water distribution offers several advantages, including cost savings, simplicity, and reliability, it also has limitations related to topography, initial construction costs, and operational challenges. Understanding these factors is critical to determining the feasibility and effectiveness of implementing a gravity-based water distribution system in a given area.

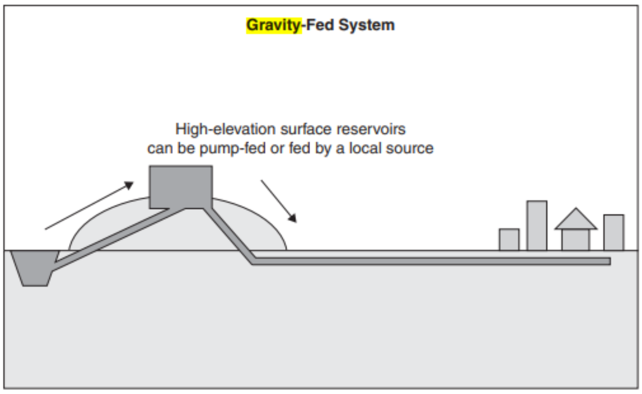

Figure.2.7 Gravity distribution system. [10]

2. Pumping system

When geographic factors prevent water from naturally flowing from a source to consumers at the required pressure and volume, the pumping technique of water distribution is utilized. There are two basic approaches to implementing this method: one with storage and the other without. Water is pumped continuously into raised reservoirs in a storage system, where gravity distributes the water to users. This strategy acts as a buffer in case of pump failure or power outages, while also ensuring a consistent supply and assisting in the management of demand changes. Pumping without storage, on the other hand, does not require any intermediate storage; water is pumped straight into the distribution network. High-lift pumps that can adjust their speed to meet changing demand are needed for this strategy. This method has a lot of disadvantages even if it can supply a lot of water under a lot of pressure during situations like fires. Because there is no storage, this system is less dependable because any interruption to the power supply or pump failure causes the water to stop being distributed right away. Due to the pumps' inconsistent performance, it also necessitates ongoing monitoring and repair, which raises operating expenses and shortens pump life [12].

The main advantage of the pumping method is its ability to deliver water at the required pressure in areas where the topography does not provide a natural elevation. However, this system is more expensive to design and operate due to the costs associated with pumps, energy consumption and maintenance. The need for back-up diesel pumps adds to the complexity and cost. The system is best suited to areas where there is a continuous power supply and no viable options for interim storage. In summary, while the pumping method offers flexibility and the ability to meet specific needs, it comes with higher costs and potential reliability issues, making it a critical choice for regions with challenging conditions. Choosing between a pumping system and a gravity system for a topography with a mild to medium slope requires a thorough analytical approach. A pumping system can be designed to accommodate any topographic configuration, making it versatile. Conversely, a gravity system is only viable if the input point is at a higher elevation than all withdrawal points. When the elevation difference is minimal, the gravity system would necessitate large pipe diameters, rendering it less cost-effective than a pumping system. Therefore, it is crucial to determine the critical elevation difference at which the costs of both systems are equivalent. The gravity system becomes more advantageous if the elevation difference exceeds this critical threshold. The authors in [7] have developed a criterion to estimate this critical elevation difference, providing a valuable guideline for the adoption of gravity mains. This criterion helps make an informed decision by comparing the economic feasibility of both systems based on specific topographic conditions[6],[7].

3. Combined gravity and pumping system

Combining pumping systems with gravity-fed reservoirs to effectively distribute water to users is known as an advanced water distribution technique. In this system, water is supplied to users by gravity after being pumped from the mains to an elevated storage reservoir. By keeping extra water in the reservoir, this method guarantees a consistent and dependable water supply, especially during times of high demand or emergency. Pumps may run at a constant speed according to the system's architecture, which increases efficiency, decreases mechanical wear, and lowers operating expenses. This technique is particularly helpful in hilly or high areas where gravity may help with distribution, lowering the energy required for pumping.

Advantages of this system include higher efficiency due to the constant operation of pumps and cost savings from reduced dependence on high-capacity pumps. The gravity-fed distribution also leads to energy conservation and offers flexibility, allowing different sections of the network to be supplied either by direct pumping or gravity, depending on the landscape [1],[9]. Furthermore, the storage reservoirs improve overall system resilience by offering a dependable backup during crises or maintenance intervals.

There are drawbacks as well, though. Because of the building of elevated reservoirs and the associated infrastructure, the initial setup might be expensive. Additionally, these reservoirs need a lot of room, which might be hard to come by in crowded or metropolitan settings. The system’s complexity demands careful planning and continuous management, along with regular maintenance of both pumps and reservoirs to ensure smooth operation. Furthermore, the effectiveness of the gravity-fed component is highly dependent on having suitable elevated ground, and managing the large storage volume required to balance demand can be challenging. Despite these challenges, the combined gravity and pumping system remains a highly effective solution for areas with varied topographies and water distribution needs[1], [9].

An effective distribution system must provide treated water to customers while retaining the same degree of purity. It should be inexpensive and simple to maintain and run, with pipe sizes designed to match demand levels. Furthermore, the system must be safeguarded from future pollution and provide an uninterrupted water supply, even during maintenance or repair activities. In Figure.2.8, different pipe types are used to implement DWNs, each of which is determined by the demands and the conditions.

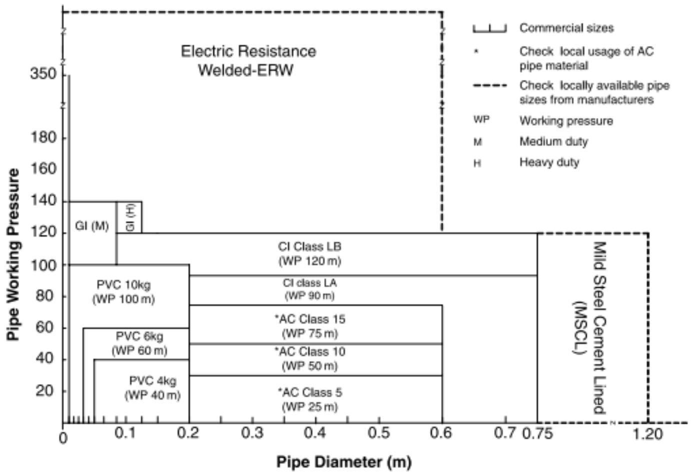

Figure.2.8 Selection of pipe materials based on different conditions. [7]

Because of the benefit of the water leak detection field in all the faces of life, irrigation, industry, daily life, and so on, a considerable number of researchers are interested in writing and publishing about this topic, as illustrated in the Figure.2.9 that discusses a sample of papers and shows the most country that publishes in the aim to solve this problem.

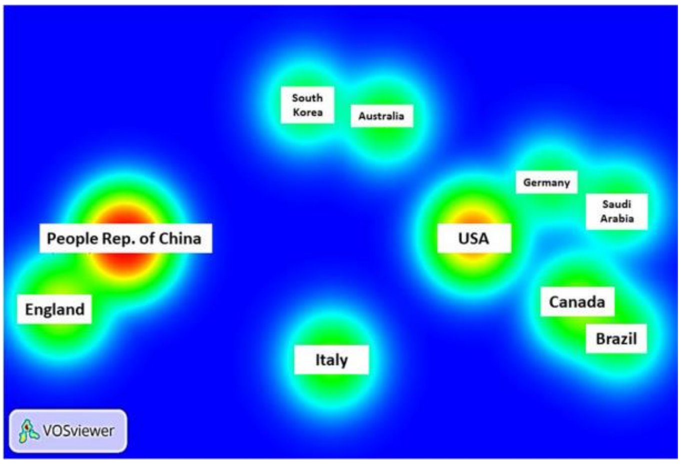

Figure.2.9 Bubble graph showing the nations with the most publications in the field of water leak detection worldwide.[13]

Based on the principles of operation of current detectors, we may divide them into four categories: acoustic, non-acoustic, transient, and others, as seen in the Figure.2.10. Each segment has unique qualities, benefits, and downsides. In the following, we describe each kind in each part, as well as examine the benefits and drawbacks of each detector, allowing you to select the most efficient and effective detector depending on your needs.

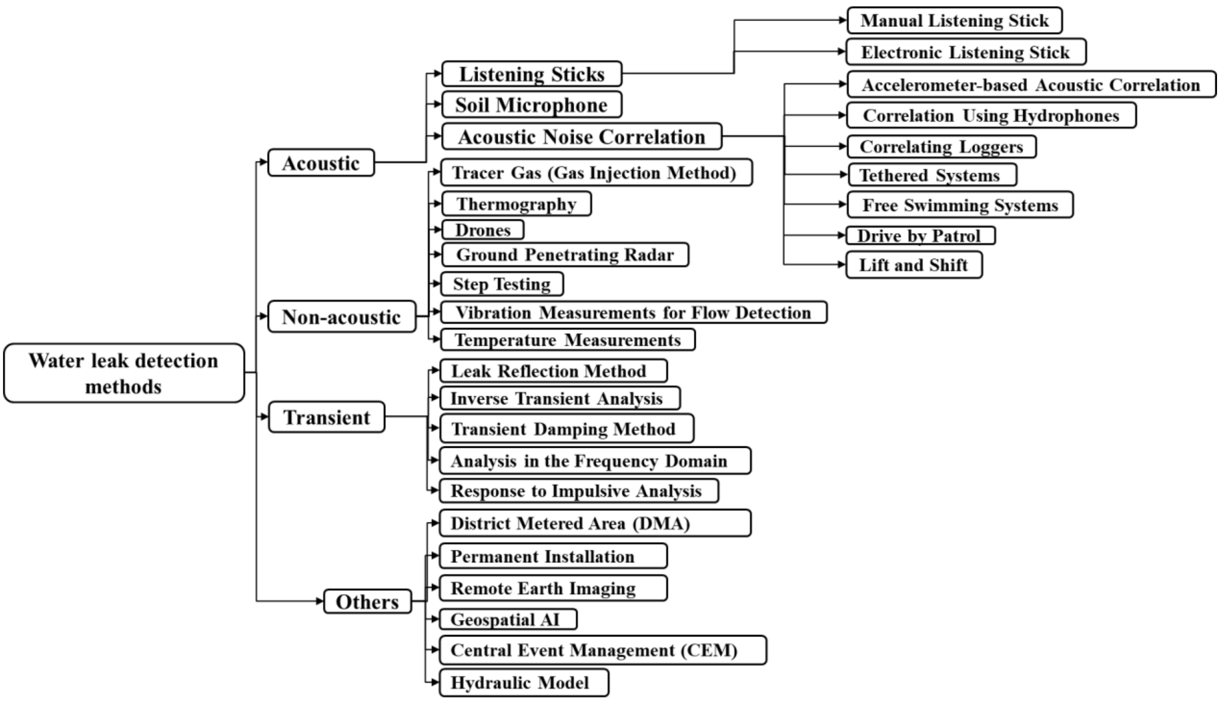

Figure.2.10 Water leak detectors classification.

III. Overview techniques

A. Acoustic Methods:

1. Listening Sticks

a. Manual Listening Stick

The manual listening stick, commonly referred to as a basic listening stick, is an essential tool for detecting and pinpointing leaks in water utility systems. This device features an earpiece and a sturdy bar, which can be made from metal, wood, or plastic, designed to transmit vibrations caused by leaks. The vibrations travel from the point of access, such as a fire hydrant, through the steel bar to a brass diaphragm housed within a resonant cavity. This cavity mechanically amplifies the vibration signals before they reach the diaphragm, which then converts them into audible sounds that the engineer can hear through the earpiece [14].

This technique relies entirely on the engineer's ability to discern the sound of the leak without any electronic enhancement. It is particularly effective for use on metallic pipelines with diameters ranging from 75 to 250 mm and operating under pressures above 10 meters head (15 psi). While the material or size of the pipe does not hinder the listening stick's ability to locate leaks from the surface, several factors can influence its effectiveness see the Figure.2.11. These include the type of leak, the ground backfill material, the pressure of the water escaping the pipe, background noise, and the engineer's skill and experience [4],[14].

The manual listening stick is best suited for environments where electronic equipment may not be practical or available, and where the conditions allow for clear transmission of sound through the pipeline and surrounding materials. Its simplicity and mechanical amplification make it a widely used and reliable tool for many water utilities in their efforts to maintain and repair their infrastructure [4].

Figure.2.11 Manual acoustic listening device. [14]

b. Electronic Listening "Stick" Accessory

Pipeline leaks may be found with the electronic listening stick (See Figure.2.12), an advanced acoustic device that locates leaks using a piezoelectric transducer. This transducer converts mechanical vibrations brought on by leaks into amplified electrical impulses. The user is able to hear the leak by use of a speaker or headphones that receive the amplified signals. The device also features an integrated noise filter to suppress background noise, enhancing the clarity of the leak signals [4].

The electronic listening stick is straightforward to use. While following the pipeline, the leak inspector listens for leak signals at several access points such stop taps, meters, valves, and hydrants. The level of noise suggests how near the leak is; the more noise, the closer the leak. Nevertheless, a number of variables, like the kind of pipeline, the makeup of the surrounding soil, the size and form of the leak, might affect the noises that arise from it. Small leaks under high pressure typically produce louder noises than larger leaks under low pressure. In some cases, large leaks under low pressure may produce minimal noise, making them challenging to locate. Additionally, other sources such as customer water usage and traffic can produce misleading sounds, complicating the detection process [14].

The effectiveness and accuracy of the electronic listening stick depend heavily on the user's experience, as the device does not provide visual indications or alarms for the presence of a leak. Users must distinguish between normal pipeline operation noises and those produced by leaks. For optimal performance, the device should be in direct contact with the pipe, especially metal pipelines. A hand-probe or extension rod can be used to listen at contact points, providing good sound pick-up. This method, once known as "bashing" when used with mechanical listening rods, helps narrow down the leak location through a process called localization. The leak is first localized to a general area between fittings and then pinpointed to an exact position before excavation. It is important to note that the point of maximum noise on pipe fittings may not indicate the exact leak position but rather the fitting closest to the leak [14].

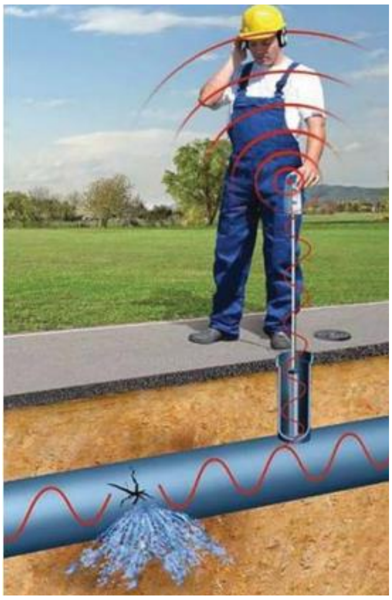

Figure.2.12 Electronic listening stick [14]

2. Soil Microphone

A soil microphone leak detector is a sophisticated device used to identify leaks in pipelines by directly contacting the surrounding soil, rather than the distribution network itself (Figure.2.13). This method involves moving the microphone along the ground at intervals along the pipeline and observing changes in sound volume as the microphone nears the leak. The device can be configured in contact mode for probing fittings or in study mode for locating leaks over shorter pipeline sections. Unlike traditional listening sticks, soil microphones offer superior sensitivity, detecting even weak leak signals directly above the ground surface without always needing access points for connection. The effectiveness of soil microphones, particularly in MDPE pipes, depends on various factors, including the distance between the monitoring point and the leak, as leak signals attenuate with distance. Acoustic leak detection using soil microphones is most effective at pipeline fittings like valves and hydrants, but closely spaced fittings are not always present in distribution networks, making detection challenging. Additionally, external factors such as traffic noise, water flow, and pipe depth significantly influence the performance of leak detection. The ground microphone is especially useful for pinpointing leaks after initial surveys, when no accessible contact points are available, or when dealing with non-metallic pipes where leak noise doesn't reach fittings. Operators move the ground microphone along the surface, noting changes in sound amplification to identify the area of maximum noise level, thereby aiding in accurate leak detection and localization [4],[15].

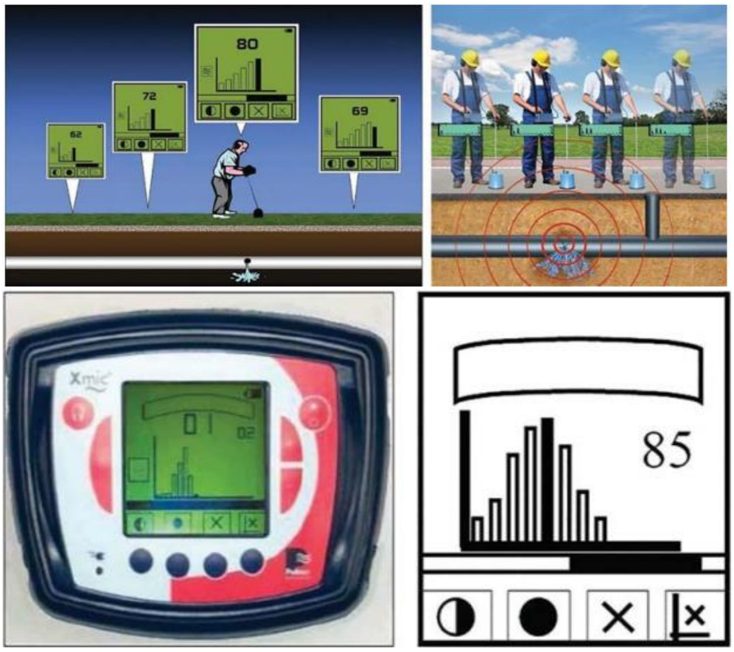

Figure.2.13 Leakage detection using soil microphone. [14]

Noise correlation leak detectors have established themselves as highly effective and efficient tools for pinpointing leaks in pipelines, surpassing traditional methods like listening sticks and ground microphones. These sensors are installed on exposed pipe materials such as valves, hydrants, and meter points, typically at intervals of up to 100 meters. By detecting the noise generated by leaks, noise correlators can accurately identify the exact location of a leak along the pipeline. Once the leak is detected, the crew marks the location for subsequent repair. The process of pinpointing leaks often involves the use of ground microphones and noise correlators, and may also incorporate non-acoustic methods such as thermography, ground-penetrating radar, and tracer gas techniques. Given that pinpointing leaks can be time-consuming, preliminary leak detection surveys are usually conducted to narrow down the potential leak area to specific pipe sections. This preparatory step helps streamline the pinpointing process, making it more efficient and effective. Overall, noise correlation leak detectors play a crucial role in modern leak detection strategies, offering precise and reliable results that facilitate timely and accurate repairs [14],[16].

3. Acoustic Noise Correlation

Acoustic Noise Correlation Theory

One method that is frequently used to find leaks in water distribution pipelines is acoustic noise correlation. It works on the premise that when a pressurized pipeline leaks, liquid escapes from a zone of high pressure into one of lower pressure, producing turbulent flow and audible indications. Along the pipeline, sensors like accelerometers and hydrophones can pick up these signals as shown in Figure.2.14.

The method involves measuring the time delay between the detection of leak-induced noise at two points along the pipeline. The noise travels at a constant velocity in both directions, assuming uniform pipe material and diameter. Sensors placed equidistant from the leak will detect the noise simultaneously, but if the leak is closer to one sensor, the noise will reach that sensor first. This time difference helps pinpoint the leak's location.

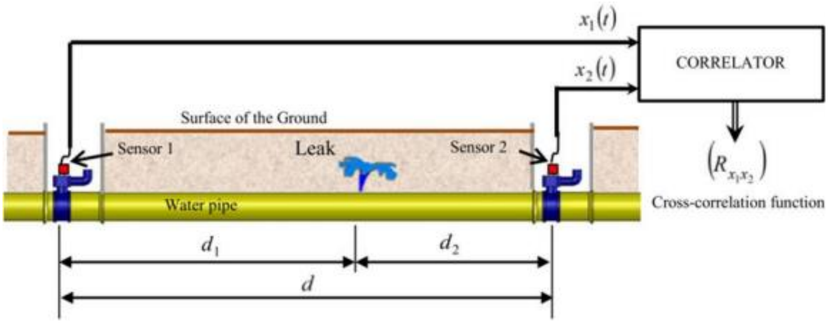

Figure.2.14 Schematic of leakage detection between two sensors. [16]

In practice, sensors are placed at known points on the pipeline, such as valves or fire hydrants, and the captured signals are analyzed using a correlation function. The time delay, or correlation peak, is calculated to determine the leak's location. The speed at which sound travels through a pipeline can be influenced by various factors, including wall thickness, pipe material, diameter, and ambient conditions. This can have an impact on the precision of the leak location [4].

Two primary types of sensors are utilized: hydrophones that record sound waves in the water, and accelerometers that measure vibrational signals on the pipe's surface. Both types can transmit data wirelessly to a processing unit for time delay calculation [14].

While effective, practitioners should note that any noise source on the pipeline can generate a correlation peak. Therefore, detected leak signals are treated as points of interest, requiring further on-site verification, typically with ground microphones. The accuracy of acoustic noise correlation also depends on factors like water pressure and background noise levels, which can affect the clarity of the leak signal [4],[14].

In summary, acoustic noise correlation offers a reliable and non-invasive means of detecting and localizing leaks in pipelines by analyzing the time delay in noise detection between two sensor points. Its accuracy and effectiveness make it a key technique in modern leak detection strategies, especially when supplemented by other confirmation methods.

3.a. Accelerometer-based Acoustic Correlation

Leak signals are detected using accelerometer sensors, which are non-intrusive devices attached to access points like fire hydrants and valves, or directly to the pipeline surface when possible. Common acoustic leak detection devices include Listening sticks, Ground microphones, Leak noise loggers, and Correlators.

Accelerometers measure vibrations that travel through the pipeline structure. Their installation is non-invasive, typically involving magnetic mounting onto pipe surfaces or fittings. Piezoelectric accelerometers are the most widely used due to their sensitivity and reliability in leak detection, as supported by various studies. Recent innovations include Microelectromechanical Systems (MEMS) accelerometers, which offer a compact alternative for leak detection. For example, El-Zahab et al. showcased a real-time monitoring system utilizing wireless MEMS accelerometers in water networks, demonstrating their effectiveness in laboratory tests on ductile iron and PVC pipes [17].

Further advancements in intelligent wireless sensor networks (WSNs) have broadened the capabilities of leak detection through real-time, non-destructive monitoring of underground pipelines. In this context, accelerometers measure vibrations on the pipeline surface. However, challenges persist, particularly regarding sensor node power management, bandwidth utilization, and time synchronization, as even minor time discrepancies in data can lead to significant errors in leak localization [18].

When used for correlation, accelerometers are typically mounted on pipe fittings or the external surface of the pipeline as shown in Figure.2.15, eliminating the need for access to the water inside the pipe, which simplifies installation. They are most effective on metallic pipes, where they can better detect higher-frequency noise. Their performance diminishes on non-metallic or large-diameter pipes due to rapid attenuation of high-frequency signals and impedance mismatches between the pipe material and fittings. Despite these limitations, their ease of use and cost-effectiveness make them a popular choice for many leak detection applications.

Figure.2.15 Accelerometer sensors paired with a radio-based correlator. [14]

For instance, the MicroCorr Touch leak noise correlator from HWM employs highly sensitive accelerometer sensors combined with an automated filtering system known as AFIS. This system optimizes filter settings by testing multiple filter combinations on the data, enhancing the accuracy of leak pinpointing across various pipe types [14]. Research indicates that integrating accelerometers with such advanced correlator technologies significantly improves the precision of leak detection efforts in diverse pipeline environments [19].

3.b. Correlation Using Hydrophones

Hydrophones, which are underwater microphones designed to capture acoustic signals in water, are frequently utilized in leak detection systems due to their capability to directly detect sounds within the water column (see Figure.2.16). Since hydrophones must be submerged during operation, their installation is intrusive and typically involves either suspending them along the centerline of the pipe or embedding them in the pipe wall, ensuring that their sensing surfaces are flush with the inner pipe surface. Traditional hydrophones are constructed from piezoceramic materials that leverage the piezoelectric effect to sense acoustic waves, as demonstrated in research by [17]. They also introduced a novel MEMS hydrophone that is significantly smaller (3.5 × 3.5 mm), more cost-effective, and efficient, facilitating easier installation in pipelines, even through small openings, making it particularly suitable for real-time in-pipe monitoring.

Hydrophones are particularly beneficial in situations where acoustic signals attenuate rapidly, such as in plastic pipes, which poses a common challenge for other detection methods like noise loggers. Due to their sensitivity, hydrophones have proven effective in monitoring leaks in both metallic and non-metallic pipes. A study by Gao et al. indicated that pressure responses captured by hydrophones were effective even in scenarios with low SNRs, although accelerometers provided sharper correlation peaks in certain instances. Another study emphasized that leak detection using hydrophones inside the pipe is especially effective in smaller-diameter pipes, though it may be less reliable in larger pipes [20].

In practical leak detection systems, a pair of hydrophones is positioned at two points along the pipeline where a leak is suspected. The system calculates the correlation between the signals received at each hydrophone to estimate the leak location based on the time delay between the signal arrivals. This method relies on accurate knowledge of the sound propagation speed in the fluid and the geometry of the pipeline [21]. However, the correlation method has limitations, such as its inability to detect multiple leaks simultaneously or leaks outside the placement boundaries of the hydrophones.

Figure.2.16 Example of hydrophone installation. [14]

Hydrophones are particularly effective in scenarios where high-frequency noise energy is quickly absorbed by the pipe material, which is common with plastic pipes or large-diameter mains. When combined with advanced filtering techniques, especially at low acoustic frequencies, hydrophones have proven successful in locating leaks in such challenging environments [14]. For example, they are ideal for use in pipelines with large distances between access points or in areas with significant background noise, such as those with heavy traffic.

Overall, hydrophone-based correlation techniques offer distinct advantages in specific applications, particularly in plastic or large-diameter pipes, and in cases where high background noise complicates detection using other methods.

Hydrophones and accelerometers are both commonly used for leak detection in buried and above-ground pipelines, but their effectiveness can vary based on the type of pipe and the nature of the leak. According to a study by Almeida et al., hydrophones are more sensitive to lower frequencies, making them ideal for situations where signals weaken due to factors like pipe shape, long distances between sensors, or damping effects. This sensitivity is particularly useful for plastic or large-diameter pipes, where higher frequencies are absorbed quickly. However, hydrophones are less effective at higher frequencies, which can limit their ability to detect small leaks. In Almeida's study, their sensing frequency was limited to 28 Hz, making them less suitable for identifying smaller, less noticeable leaks. In contrast, accelerometers performed better for detecting weak leaks and had a wider frequency range of up to 104 Hz, allowing for more accurate results in cross-correlation analysis. However, they can be more affected by low-frequency background noise, which may interfere with their performance in some cases [21].

In practical terms, hydrophones are generally more difficult and time-consuming to install than accelerometers. However, they tend to be more effective in challenging situations, such as when dealing with small leaks, high background vibration levels, or when sensors need to be placed far apart. Their sensitivity to low-frequency signals makes hydrophones particularly suitable for plastic and large-diameter pipes, where low-frequency sound waves are more common [17].

Interestingly, large leaks are not always the main cause of water loss, as they are usually detected and repaired quickly when water surfaces. Small leaks, on the other hand, can go unnoticed for long periods, leading to significant water loss. Paradoxically, small leaks can sometimes be easier to detect acoustically because they often produce more noise, making them easier to identify with hydrophones. However, leaks in difficult locations, such as under-stream crossings, are often the hardest to find and repair. Therefore, leak detection efforts should focus on these challenging areas to reduce water loss.

This analysis highlights the importance of choosing the right sensors based on the specific conditions of the pipeline, including its material, size, and environmental factors.

3.c. Correlating Loggers

Correlation loggers, widely used for leak detection in WDNs, employ advanced techniques to identify and localize leaks by analyzing the acoustic signals generated by water escaping from pipes. Typically, correlation loggers integrate piezoelectric accelerometers or hydrophones to detect leak signals. These sensors, coupled with programmable data loggers, capture and store the acoustic data for further analysis. Unlike traditional listening sticks that require manual intervention, correlation loggers are designed for both temporary and permanent deployment on accessible pipeline points such as hydrants and valves using magnetic fasteners (Figure.2.17). These loggers are strategically spaced, typically between 200 and 500 meters apart, based on the pipeline material and diameter, as plastic pipes require closer spacing than metal pipes due to higher acoustic attenuation [17].

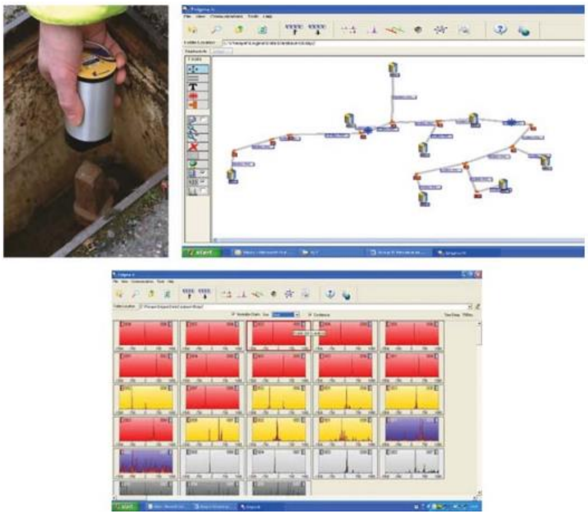

Figure.2.17 Correlating loggers to a pipe, as well as the resulting correlations. [14]

Leak noise correlation is a critical aspect of this process, wherein the sound recorded at two or more points along the pipeline is compared. This comparison uses the principle of cross-correlation, which involves measuring the time delay between the noise signals detected at two different locations. The position of the leak is determined by calculating the time shift of the maximum correlation, the distance between the sensors, and the sound propagation velocity in the pipe (Figure.2.18). This technique is highly sensitive and accurate for locating leaks, particularly when precise time synchronization is achieved between the loggers, ensuring a more reliable identification of leaks without the need to visit the site physically [4],[13].

One advantage of correlation loggers is that they can operate autonomously, often programmed to record data during off-peak hours (typically from 2 to 4 a.m.) when background noise is minimal [14]. The acoustic data collected during this time is analyzed to distinguish leak sounds from regular operational noise, such as consumer water use or traffic noise. This distinction is crucial for accurate leak detection. Some systems further enhance the accuracy of leak detection by incorporating Geographic Information System (GIS) data to optimize logger placement across the network.

Real-time data transmission via wireless communication systems, such as radio or cellular networks, has revolutionized the use of correlation loggers. These remote communication systems allow acoustic data to be transmitted to central servers, where it is processed to determine the presence and location of leaks. In more sophisticated systems, multi-point correlations across multiple loggers enhance the precision of leak localization. This eliminates the need to manually estimate sound velocities, a common challenge in older systems, and facilitates near real-time leak detection[15].

Figure.2.18 Reading from radio-based correlator on ductile iron pipe with 350m long. [14]

However, there are limitations and challenges. While correlation loggers are effective in identifying leaks, they can also mistakenly detect non-leak noises, such as consumer water use or other environmental sounds, leading to false alarms. Additionally, loggers that rely on radio transmitters may face deployment challenges in busy urban areas due to interference from local structures or adverse weather conditions. Moreover, the economic viability of correlation loggers, especially when deployed permanently, remains a debate among researchers. For example, it has been reported that the cost-effectiveness of loggers, particularly in comparison to skilled leak inspectors, is questionable, with some studies indicating that loggers may fail to detect around 40% of leaks identified by traditional methods[14].

In summary, correlation loggers represent a powerful tool for leak detection, offering a non-intrusive, automated approach to monitoring large areas of a water distribution network. They provide substantial advantages in precision, reduced human error, and the capacity to work under low-noise conditions. However, high initial costs, potential false alarms, and radio communication limitations must be considered when deploying these systems.

3.d. Tethered Systems

In the realm of water leak detection, inline acoustic leak detection sensors play a crucial role by traversing through operational pipes to identify sounds indicative of leaks. These sensors can be categorized into two distinct systems: tethered and free swimming, each offering unique advantages and limitations. Regardless of the system employed, both utilize an acoustic hydrophone that moves near potential leaks, enabling the detection of leaks of all sizes, regardless of the pipe material. Remarkably, inline technologies have demonstrated the capability to identify leaks as small as 0.2 liters per minute. Furthermore, since these systems do not depend on sound propagation through the water column or pipe walls, they exhibit exceptional sensitivity, making them effective even for the smallest leaks [4].

Tethered systems, such as the Sahara system (see Figure.2.19), represent a sophisticated acoustic-based technology for detecting leaks in water distribution pipelines. An umbilical cable that is placed into the pipeline while it is still in use is connected to a hydrophone sensor in these systems. Water leaks produce acoustic signals that are detected by the hydrophone, an underwater microphone. The cable makes sure that the sensor is continuously transmitting real-time data to a surface operator while it is being carried by the water flow. Unlike other acoustic leak detection methods that require multiple external sensors, tethered systems place the sensor inside the pipe, near potential leak sites. This proximity enhances the sensitivity and accuracy of leak detection, as supported by previous research. The internal positioning of the sensor allows it to capture the specific acoustic signatures of leaks more effectively than external sensors like accelerometers [18],[20].

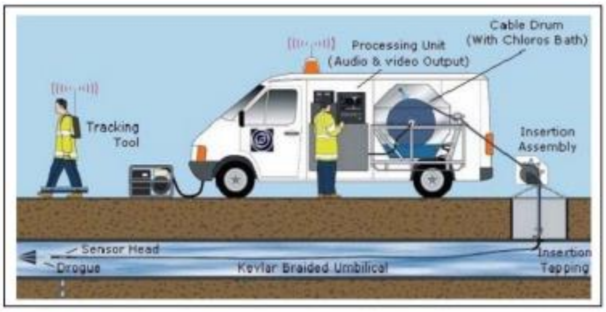

Figure.2.19 The principal of Sahara detector. [4]

Tethered systems address several challenges commonly encountered in pipeline leak detection. For example, free-swimming acoustic devices often suffer from noise interference due to movement, but tethered systems reduce this issue by being more stable, as they are pulled along by the water's flow using a drogue. Research has demonstrated that this setup minimizes noise interference, resulting in more precise acoustic readings. Additionally, the hydrophone's connection via an umbilical cable eliminates the need for battery-powered sensors, thereby avoiding the risk of power failure during extended inspections. The cable also ensures continuous communication with the surface, providing real-time feedback on leak locations, as evidenced by previous implementations of the Sahara system [4],[14].

One of the primary advantages of tethered systems is their ability to operate in live pipelines without disrupting service. Research shows that these systems can detect leaks as small as 0.25 gallons per hour, with a location accuracy within 2–3 feet, making them highly effective for detecting leaks in large water mains. Furthermore, the umbilical cable of the tethered system can extend up to 2 kilometers, allowing for long-distance inspections from a single insertion point. This capability is particularly beneficial for pipelines that are difficult to access or where minimal intervention is preferred. The sensor's ability to navigate up to 270 degrees of bends in the pipeline further enhances its flexibility in various pipeline configurations [14],[15].

Despite these strengths, tethered systems do face certain limitations. The primary drawback is the restriction imposed by the umbilical cable, which limits the distance that can be surveyed and the system's maneuverability, especially in pipelines with multiple branches. Research shows that in cases where inspections need to cover several kilometers, the tethered system becomes cumbersome due to the setup and breakdown process required at each insertion point [12]. Furthermore, the system is less effective in small-diameter pipes, which limits its application primarily to large water mains.

Recent advances in tethered systems, however, have expanded their functionality beyond leak detection. Many modern tethered systems are equipped with live video capabilities, allowing for additional asset intelligence to be gathered during the inspection. This includes identifying issues such as valve status, cement-lining delamination, and tuberculation, providing valuable insights into the overall condition of the pipeline [4]. As research continues to enhance these systems, they are becoming increasingly valuable not only for detecting leaks but also for broader pipeline management and maintenance tasks.

In conclusion, tethered systems like the Sahara offer a powerful and precise method for detecting water leaks in large-diameter pipelines. Their real-time data acquisition, ability to operate in live systems, and flexibility make them a robust solution in the field of leak detection. However, their effectiveness is limited by the length of the umbilical cable and the challenges of deployment in complex pipeline networks. Research suggests that with careful planning and appropriate application, tethered systems can significantly improve leak detection accuracy while minimizing disruption to water distribution services.

3.e. Free Swimming Systems

Free-swimming systems offer a state-of-the-art approach to detecting leaks in pipelines while they remain operational, functioning autonomously to effectively identify issues. Devices like the Sahara and Smart Ball are deployed directly into the pipeline, relying on the flow of water to move through the system. Unlike tethered systems, free-swimming devices are not constrained by a cable, allowing them to travel significant distances within the pipe. After the inspection, the devices are typically retrieved using a net, ensuring the pipeline can continue operating without interruption. As they traverse the pipeline, these systems continuously collect acoustic data and tracking information, which is later processed to locate leaks (see Figure.2.20) [4],[14].

An example of such technology is the SmartBall, developed by Pure Technologies. The SmartBall is a small, spherical device, designed to be smaller than the diameter of the pipeline, which enables it to travel quietly and efficiently. Its foam exterior encases an aluminum core that houses an acoustic sensor, data acquisition system, power supply, and additional instruments. By detecting the sound of water escaping the pipe, the system can identify leaks, with the acoustic data analyzed to determine the leak's exact position. The SmartBall can operate for up to 17 hours, allowing it to inspect up to 25 kilometers of pipeline per use, depending on water flow. One of its key strengths is its adaptability, as it can function in pipes made from various materials without being affected by the composition of the pipe [4].

Free-swimming technologies, such as SmartBall, provide several key benefits. A significant advantage is their ability to inspect pipelines with minimal intervention, requiring just two access points for insertion and retrieval, making them ideal for inspecting long stretches of pipeline. Their design also allows them to navigate tight curves and pass-through inline valves, such as butterfly valves, without difficulty. However, these systems do have limitations. They may be less effective in pipes with diameters under 125 mm and can struggle in high-pressure environments, which limits their application in certain industrial settings. Additionally, noise from pumps or nearby equipment can complicate leak detection by introducing interference. While these systems can pinpoint the location of leaks, they are unable to assess the size of the leak. Tracking their precise position within the pipeline can also pose challenges due to the absence of real-time positioning technology [4],[14].

In summary, free-swimming systems offer a versatile and efficient solution for detecting leaks in larger pipelines, especially over long distances. Their ability to operate autonomously without interrupting pipeline service makes them an appealing choice for many WDNs [14]. Despite some limitations, ongoing advancements are expected to improve their accuracy and broaden their application.

Figure.2.20 Deployment of a free-swimming sensor in the pipe. [14]

3.f. Drive by Patrol

The Drive-By Patrol method is a water leak detection technique that utilizes mobile data collection to monitor leaks in a water distribution network. This method involves the use of devices such as PERMALOG sensors, which are installed on the network to detect leaks automatically. These sensors are equipped with long-lasting batteries, offering over ten years of autonomy, and are designed to withstand immersion with an IP68 rating. They are easily attached to valve heads or other pipeline accessories using strong magnets, ensuring secure placement without the need for direct intervention [22].

When a leak is detected, the PERMALOG sensors automatically calibrate to their environment and enter an "alarm" mode, transmitting a signal that indicates the presence and characteristics of the leak to a mobile data collector, referred to as a "patroller." This collector can be mounted in a vehicle, enabling rapid drive-by sweeps of an area. The patroller receives, analyzes, and identifies the source transmitter, allowing for the pre-location of the leak's position. This information is displayed on an LCD screen and stored for later review (Figure.2.21). The patroller can instantly check the position of leaks or review it at the end of the patrol, facilitating efficient leak localization and better planning of intervention efforts [4],[22].

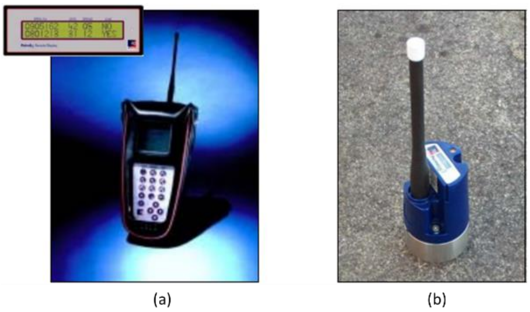

Figure.2.21 (a) (a) Patroller + LCD screen for patroller, (b) Permalog 3 with antenna.[22]

The Drive-By Patrol method (See Figure.2.22) offers several significant advantages. It provides comprehensive coverage of the distribution network, ensuring that 100% of the network is under surveillance for potential leaks. The method allows for quick leak identification, finding more leaks rapidly compared to other techniques, and enabling a prompt response to any detected leaks. Continuous monitoring is also a key benefit, allowing for the early detection of new leaks and helping to maintain the continuity of water distribution [22].

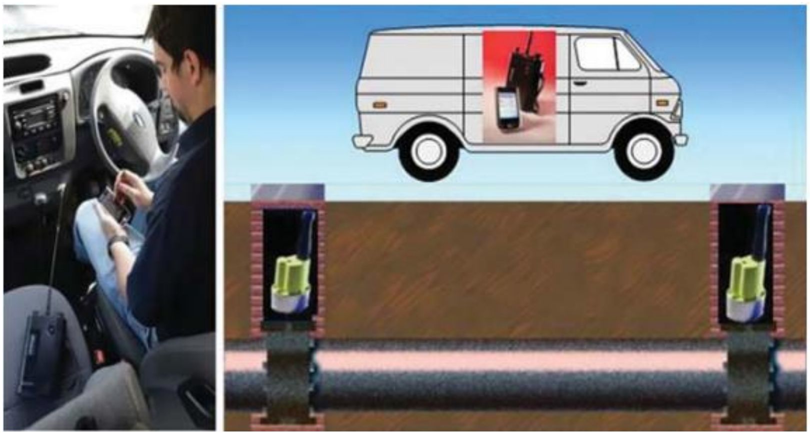

Figure.2.22 Drive by patrol method. [14]

This approach is highly automated and simplifies the leak detection process, reducing the chances of human error and eliminating ineffective searches. The method operates independently of the network's size or condition and is non-intrusive, meaning it does not cause any disruption to subscribers. This non-destructive nature allows it to function without causing disorder or inconvenience. Moreover, the Drive-By Patrol method improves overall efficiency by enabling technicians to focus on locating existing leaks rather than spending time in non-leaking areas, enhancing both efficiency and motivation [14].

Additionally, the system can function continuously for up to 10 years, making it easy to maintain low leak levels with minimal maintenance. The Drive-By Patrol method also offers flexible deployment strategies. In a fixed mode, loggers are permanently installed in an area for ongoing monitoring, particularly useful in open networks without district metered areas (DMAs). In survey mode, loggers are temporarily deployed in a specific area to detect and control leaks. Multiple sweeps may be necessary to optimize leak detection, as initial sweeps often reveal larger, quieter leaks masked by initial findings. Overall, the Drive-By Patrol method is a versatile and effective solution for water leak detection, capable of adapting to various network conditions and operational requirements while minimizing disruptions and maximizing efficiency[4],[23].

3.g. Lift and Shift

The "lift and shift" technique is a highly efficient methodology developed by the water leak detection industry to survey extensive areas rapidly. This approach involves the daily relocation of many loggers, which are devices used to detect and record data on potential leaks. The data collected by these loggers is automatically downloaded to handheld retrieval units via radio communication as shown in Figure.2.23. From these units, the leak data is transferred directly or remotely to a central office for detailed analysis and pinpointing of leak locations. When leaks are detected using noise logging, the most recent lift and shift noise loggers are also capable of capturing leak noise. This data can be correlated locally or transmitted along with noise logging data for correlation by cloud-based viewing systems. The evolution of technology has significantly enhanced the efficiency and effectiveness of the lift and shift technique. Modern advancements include the integration of GPS positioning and mapping tools, which aid in the precise placement and tracking of loggers. These tools enable operators to conduct highly efficient surveys by providing accurate location data and visual aids [14].

Recent developments have further streamlined the process through the use of mobile applications. These apps serve as both programming and data download devices, leveraging third-party technology to offer several benefits. Key features of these apps include [14]:

-GPS Location Tracking: Accurate positioning of sensors and points of interest.

-Offline Maps: Free maps that can be accessed without an internet connection, ensuring continuous operation in remote areas.

-Remote Data Upload: The ability to upload measurements from the site via cellular technology or WiFi, facilitating real-time data transfer.

-Deployment Photographs and Reports: The capability to take and upload photographs and generate reports remotely, enhancing documentation and communication.

These technological advancements have made the lift and shift technique a robust method for water leak detection and localization, enabling quick and accurate surveys of large areas with minimal manual intervention.

Figure.2.23 Deployment with lift and shift method and mapping with GPS. [14]

B. Non-Acoustic Methods:

1. Tracer Gas

- Gas Injection Method

The gas injection method is a leak detection technique used in water pipelines that involves the injection of non-toxic and insoluble gases, known as tracer gases, into the system. These gases, containing ammonia, halogens, and helium, with helium being the most sensitive, tend to escape through leaks and seep out through the soil or pavements. The gas injection approach is reliable in all types of materials, as it is not material-dependent, and can detect leaks in pipelines ranging from 75 mm to 1000 mm in diameter. This method relies on knowing the flow of the water and blocking the gas from finding easier routes to exit the system. This is achieved by closing branches and cutting off the suspected leak area, which may cause interruptions to the water distribution service. Additionally, the gas may exit the ground from a different location than that of the leak, which is common in buried pipelines [13].

The gas injection method has several advantages, including its high sensitivity, low false alarm rate, and wide range of application. It can find even the smallest breaches and is very helpful for locating leaks in non-metallic pipes. Nevertheless, it has several disadvantages, such as the requirement for a significant volume of gas to be injected into the system, which might raise the cost. Furthermore, because the approach needs a significant volume of gas to identify leaks, it is not appropriate for big low-pressure applications [13][18].

The gas injection method uses a non-hazardous gaseous tracer to be guided into the pipeline, which is detected by an electronic nose at the exact location of the leak as it diffuses through the ground surface. Helium is the most commonly used gas, due to its high sensitivity, but hydrogen is also used, due to its lower cost and high performance. The gas is typically diluted 5% in nitrogen and injected into the pipeline, and can be used with pipes of various diameters, from 75 mm to 1000 mm. It is essential to know the direction of water flow and block the gas from finding easier routes to exit the system. The pipeline can be empty of water or full, but less gas is required when the pipe is full. The gas comes to the surface after leaving the leak in the pipe, so the direction of the water flow must be known. The method is not affected by the mixing of the gas with water, and the material of the pipe has no effect on the gas injected. The gas injection method is a reliable and effective technique for detecting leaks in water pipelines, particularly in small-diameter [13].

2. Thermography

Thermal infrared imaging has emerged as a powerful tool for the inspection and maintenance of underground pipelines, offering a non-invasive and efficient method for leak detection (Figure.2.24). All objects emit infrared radiation, which can be visualized using advanced thermal imagers, allowing engineers to "see" heat and detect anomalies invisible to the naked eye. This technology is particularly effective for pipeline surveys, where it not only identifies potential leak points but also assesses the overall condition of the right-of-way, revealing construction activities and ground disturbances. Depending on the location and known course of the pipeline, these surveys are carried out at different altitudes; in open terrain, low-level surveys provide high-resolution pictures, while higher-level surveys optimize cost and coverage in rural regions. The use of drones has further revolutionized this process, offering a cost-effective alternative to traditional methods such as helicopters. Drones equipped with dual cameras one for general imagery and the other for thermal imaging can hover over suspect areas, zoom in for detailed analysis, and immediately relay findings to operators. This capability is invaluable in remote or obscured locations where direct access is challenging. Despite its advantages, infrared thermography does have limitations. It is most effective when the soil temperature is close to ambient, and it may be less reliable for pipelines carrying fluids at temperatures similar to the surrounding environment. The method also requires significant expertise in interpreting thermal images, as it can only provide a heat map without directly explaining the causes of temperature anomalies. Furthermore, the system's effectiveness can be influenced by weather conditions, soil composition, and the timing of the survey, emphasizing the need for skilled operators and advanced algorithms to enhance accuracy. Nonetheless, the versatility of infrared thermography makes it a vital technique in pipeline inspection, capable of detecting leaks, assessing environmental impacts, and offering insights that complement other diagnostic tools such as acoustic technologies[4],[21],[24].

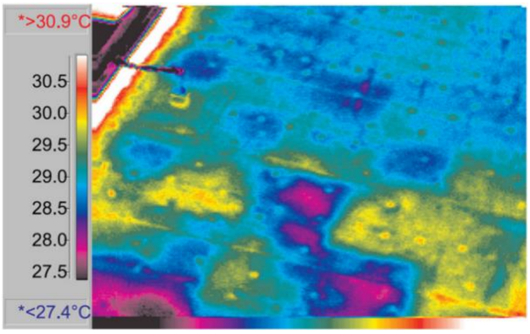

Figure.2.24 The picture depicts several loggers colored yellow and inserted into service openings of a pressurized water network [13]

3. Drones for Leak Detection Activities

To reduce water loss and find leaks, water companies all around the world use drones fitted with thermal or infrared cameras (Figure.2.25). Because these businesses have educated their employees to fly drones, leaks in difficult-to-reach places that are invisible to the unaided eye may be quickly discovered. In order to make it simpler to find subterranean leaks, leak assessments are usually carried out in the early morning when earth temperatures are at their lowest. Figure.2.25 shows that the Civil Aviation Authority certifies drone operators. On a thermal imaging camera, a warm-colored area often indicates that the water escaping from a leak is warmer than the surrounding soil [14].

Figure.2.25 Leak detection with drones equipped with cameras. [14]

4. Ground Penetrating Radar

By imaging subsurface anomalies and cavities caused by leaking water, Ground Penetrating Radar (GPR), a non-invasive geophysical technology, uses electromagnetic waves, usually between 125 MHz and 370 MHz, to identify water leaks in subterranean pipes. Electromagnetic radiation is released into the ground to be detected by GPR. The radiation is reflected back when it comes into contact with surfaces between materials that have differing electrical characteristics[13].

The basis of GPR technology is the idea that reflections between various mediums with differing electrical characteristics might occur at interfaces (Figure.2.26). GPR uses the time difference between the transmitted and reflected waves to precisely measure the depth of objects or subsurface abnormalities. After that, this data is processed using specialist software to create intricate three-dimensional representations of the subterranean structures, which offer important insights for leak detection and pipe assessment [23],[25].

Advantages [20]**:**

- Can be used in a variety of media.
- Capable of detecting objects, changes in material, voids, and cracks.
- Can penetrate up to 15 meters in dry soil.
- Provides detailed three-dimensional images of subsurface structures.

Disadvantages [20]**:**

- The depth of penetration is highly dependent on soil type.
- Requires considerable expertise to design, conduct, and interpret surveys.
- The equipment and software are relatively expensive.
- High energy consumption may necessitate large, cumbersome batteries for extensive surveys lasting more than 10 hours.
- An experienced operator is needed for the correct interpretation of radiograms.

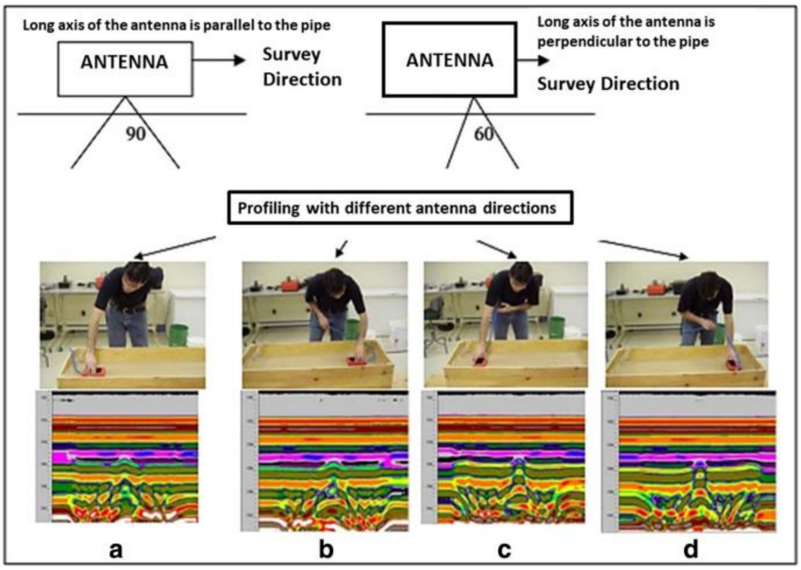

Figure.2.26 GPR leak detection. [13]

5. Step Testing

Step testing is a flow-based method used to localize water leaks within a zoned distribution system. This technique is particularly effective in areas with plastic pipes, where conventional acoustic methods may not be as reliable due to the absorption of leak noise by the pipe material. The process begins by monitoring the inflow of water into a specific zone, using either a data logger attached to the inlet water meter or manual recordings by an operator. The zone is then divided into sections, or "steps," by systematically closing valves to isolate these sections. An anticipated customer consumption rate for each step is calculated and compared to the actual flow drop recorded at the input meter during the isolation of the step. A significant difference between the expected and actual flow indicates potential leakage within that step [14].

To ensure accurate results, step testing requires detailed planning and precise execution. A well-thought-out plan identifies the pipe lengths and valves to use, as well as the order in which valves should be closed, and remains consistent for all subsequent tests unless the zone changes. The tests are ideally conducted during low-demand periods, typically between 1:00 and 4:00 am, to minimize fluctuations in water use and improve the accuracy of the measurements. Valve integrity is crucial to the success of step testing; all required valves must be located and tested before implementation, with a Zero Pressure Test (ZPT) ensuring they can be completely closed without allowing water to pass. Data transmission to the operator closing the valves can be facilitated through various methods, such as communication from another operator at the inlet meter or via a Radio/GPRS data logger transmitting live flow data [14].

While step testing is a powerful method for detecting leaks, particularly in plastic pipes, it does have some limitations. The process can be time-consuming, especially if too many steps are involved or if valve integrity issues arise. Additionally, performing the tests during low-demand periods, such as late at night, can pose safety concerns for operators. Despite these challenges, step testing provides a quantitative measure of water loss and helps pinpoint areas with high leakage. Complementary methods, such as acoustic surveys using noise loggers, acoustic listening tools, or leak noise correlators, can be used alongside step testing to further refine leak detection and localization, offering a comprehensive approach to managing water distribution systems [15].

6. Vibration Measurements for Flow Detection

The vibration-monitoring device is a handheld technological tool designed to expedite customer-side leakage surveys in water supply systems by detecting low-frequency vibrations associated with water flow through external stop taps (see Figure.2.27). The device features two vibration sensors: one positioned on the external stop tap and another for measuring background vibrations. It conducts simultaneous 30-second measurements from both sensors, storing up to 256 sets of readings, each of which is date and time-stamped and GPS-referenced, allowing for detailed geographic tracking of survey operations [14].

After data collection, readings are uploaded to a database where algorithms analyze the data and classify the flow status of each stop tap into categories such as definite flow, probable flow, possible flow, definite no flow, or problematic recording. This device is capable of detecting small leaks that produce minimal or no noise, as well as leaks located far from the stop tap where the noise does not travel, surpassing the capabilities of traditional acoustic methods. Its design eliminates reliance on human auditory skills or operator experience, making it simple to use with minimal training. Additionally, the system facilitates comprehensive survey tracking over time and space, with stored recordings available for retrospective analysis and enhancement of data interpretation through machine learning techniques [4].

Figure.2.27 Vibration logger. [14]

7. Leak Detection from Temperature Measurements

Water leak detection through temperature measurements relies on identifying variations in temperature between the water in pipes and the surrounding environment (Figure.2.28). This approach employs fiber optic technology with Brillouin acoustic scattering to detect small temperature changes, indicating potential leaks. In the UK, a system has been developed to monitor the temperature of water flowing through customer pipes. Since water is typically maintained at a temperature between 5 and 15°C, any significant deviation from this range compared to the surrounding ground temperature can suggest a leak. For example, on a warm summer day, water moving through a pipe may stay cooler than the surrounding soil, and continuous flow would create a noticeable temperature difference. Sensors placed on the stop tap detect these changes, and the data is logged, analyzed, and processed with automated algorithms. With the ability to detect breaches with flows as low as 1 liter per hour, this approach is a valuable tool for early leak identification and water usage monitoring. Since 2015, it has been in operation across the UK [14],[26],[27].

One of the many advantages of this temperature-based technique is its ability to continuously monitor water flow and identify leaks as little as one liter per hour. Moreover, it is vulnerable to minor leaks. Furthermore, it offers real-time data processing via cloud-based platforms, enabling quick leak identification and remediation. Additionally, it does not depend on acoustic signals, which makes it suitable for environments where traditional acoustic leak detection methods might be affected by external noises. However, there are some limitations. Installing sensors and data loggers at each monitoring location can be labor-intensive and expensive. Furthermore, the accuracy of detecting leaks can be influenced by external factors such as significant environmental temperature changes, seasonal variations, or ground composition, which may result in false alarms or missed leaks. Despite these challenges, temperature-based leak detection is a valuable method in water management, particularly in areas where water conservation and maintaining water quality are essential.

Figure.2.28 Temperature measurements device. [14]

C. Transient Methods:

Transient-based methods have emerged as an effective approach for detecting water leaks by analyzing transient pressure waves in piping networks. These methods capitalize on sudden pressure changes, or transients, caused by events like valve operations or pump failures, allowing engineers to identify anomalies that suggest leaks. Various techniques have been explored in this field, including the Leak Reflection Method, Inverse Transient Analysis (ITA), Transient Damping Methods, Analysis in the Frequency Domain, and Response to Impulsive Analysis [18],[28],[29].

Transient-based methods are particularly advantageous as they can detect leaks from greater distances compared to traditional techniques. Their non-intrusive nature and lower costs make them appealing, positioning them as a significant focus of ongoing research aimed at enhancing water distribution system management and minimizing the environmental and economic consequences of undetected leaks.

1. Leak Reflection Method

The leak reflection method is a transient-based technique for detecting leaks in pipelines by measuring and analyzing the transient pressure waves reflected by a leak. This method relies on the principle that leaks partially reflect a transient wave, sending a reflected wave back toward the point where the original pressure wave was generated and measured. The characteristics of the reflected wave, such as its amplitude and timing, depend on several factors, including the size of the leak and its distance from the measurement point. A larger leak generally produces a reflected wave with a greater amplitude. By analyzing the time difference between the incident transient wave and the reflected wave, the location of the leak can be determined[4].

Developed and refined through research by Brunone and others, the leak reflection method offers significant advantages in detecting and localizing leaks when using a well-formed transient wave. It provides a rapid response and real-time application, particularly in simpler pipeline systems, enhancing both the accuracy and efficiency of leak detection. However, this method has limitations in practice, as detecting the subtle pressure variations caused by leak reflections can be challenging, especially in complex or extensive piping networks. As a result, the application of the leak reflection method in real-world systems is still evolving. To achieve the best results, it is often combined with traditional leak detection methods, such as online surveillance and acoustic leak detection, which can effectively pinpoint smaller leaks [28]. This integrated approach leverages the strengths of different techniques to provide a comprehensive solution for water leak detection.

2. Inverse Transient Analysis

Hydraulic leak detection is a cost-effective and quick-response method, making it highly advantageous for both oil and water industries. This approach includes various pressure-based leak detection techniques, covering both steady-state and unsteady-state conditions, each with its own set of advantages and disadvantages. Inverse analysis, traditionally used in groundwater and transport problems, has been effectively applied to pipeline networks, especially in water distribution systems. The Inverse Transient Analysis (ITA) has emerged as a crucial methodology for leak detection in pipeline networks, particularly in water distribution systems. Originally proposed in 1994, the ITA method involves the development and calibration of a transient simulation model to analyze pressure changes within the network (see Figure.2.29). This technique is capable of identifying unknown leak nodal zones by comparing predicted pressures with actual measurements. By employing least squares regression techniques, ITA facilitates the precise location of discrete leak positions, addressing challenges related to system transitions and boundary conditions [4],[30],[31],[32].

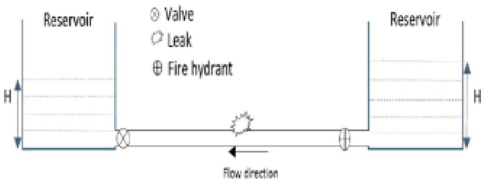

Figure.2.29 Method of Inverse Transient Analysis. [31]

The methodology enhances the estimation of the pipe friction factor, thus improving the accuracy of leak detection. Moreover, ITA has demonstrated its effectiveness in detecting and quantifying leaks of various sizes, with experimental results indicating a margin of error around 1% of the total pipe length. Advanced applications of ITA, including hybrid algorithms that combine Levenberg-Marquardt with Genetic Algorithms, have further refined the accuracy of leak localization. Through meticulous comparison of measured and simulated pressure signals, ITA effectively filters out perturbations, enabling the detection of multiple leaks within a network. Consequently, when paired with accurate characterization of the pipe system, ITA offers valuable insights for enhancing leak detection and management practices, significantly improving the operational efficiency of WDNs [4],[21],[30],[31].

3. Transient Damping Method

Transient Damping in water leak detection is a technique that leverages the damping effects of transient waves within a pipeline to identify and locate leaks. According to Wang et al. (2002), leaks in a pipeline contribute to the damping of transient waves, which can be expressed in terms of Fourier series. In a leak-free pipeline, all Fourier components are uniformly damped due to the constant friction of the pipeline. However, the presence of a leak causes each Fourier component to be damped differently. To detect leaks, the method involves comparing the frequency response of the measured pressure, which includes leak-induced damping, with the frequency response of calculated pressure values for the same pipeline without a leak. The amplitude of the damping indicates the size of the leak, while the different damping ratios of the Fourier components can be used to pinpoint the leak's location. The rate of leak-induced damping depends on several factors, including the characteristics of the leak, the pressure in the pipeline, the location where transient phenomena are generated, the pressure measurement point, and the shape of the generated transient phenomenon[17],[18].

In real-world scenarios, leaks and friction are not the only factors causing transient damping. Other physical elements such as joints, fittings, fire hydrants, and the pipeline wall can also contribute to transient damping. Modeling the transient behavior of these elements is complex, making it challenging to accurately calculate the leak-free damping for a real pipeline[23].

In summary, the Transient Damping Method is a sophisticated approach to water leak detection that utilizes the differential damping of transient wave components to identify and locate leaks. By analyzing the frequency response of pressure measurements and comparing them to theoretical leak-free responses, this method provides insights into both the size and location of leaks, despite the complexities introduced by other physical factors in the pipeline system.

4. Analysis in the Frequency Domain

Analyzing pipeline leaks using frequency domain techniques is an exceptionally efficient approach. By converting time-domain signals into the frequency domain using techniques such as the Fourier transform, one can observe clear differences in the frequency response of pipelines with leaks compared to those without. Leaks generate additional high-amplitude peaks in the frequency spectrum, which are either absent or much weaker in non-leaking pipelines. This difference allows for leak identification by comparing the dominant frequencies in the transient response of both scenarios. Moreover, the frequency domain approach has been successful in detecting multiple leaks, as shown by analytical models that consider pressure responses. Advanced techniques like the frequency response diagram utilize the resonance characteristics of the pipeline system to pinpoint the presence and location of leaks. These methods can identify multiple leaks by examining the pattern of resonant peaks and have been extended to detect leaks even when the leak loss accounts for up to 30% of the system's total flow. However, challenges persist, such as detecting leaks at specific points like the midpoint of a pipe, where the impact in the frequency domain might coincide with harmonic frequencies and thus go undetected. Despite these challenges, frequency domain analysis remains a powerful tool for pipeline leak detection, especially when combined with preprocessing steps that improve SNRs and attenuation coefficients, resulting in more precise leak localization and detection [4],[17],[25],[32].

5. Response to Impulsive Analysis

The impulsive response analysis method is a key technique in water leak detection, used to assess how a pipeline reacts when a unit impulse, such as a rapid pressure change, is introduced at its entry point. This impulse, typically generated by opening or closing a valve, propagates through the pipeline. Upon reaching a leak, the impulse behaves in distinct ways: part of it continues to travel, part scatters, and another portion reflects back towards the source. By analyzing the reflected signal and calculating its travel time, the location of the leak can be estimated with reasonable accuracy [4][18].

The amplitude of the reflected impulse also provides information about the size of the leak, making it possible to gauge the severity of the issue. However, in practice, detecting leaks can be challenging due to similar reflections caused by pipeline irregularities, such as bends, joints, or other discontinuities [28]. These factors complicate the interpretation of the signals, making it harder to distinguish between actual leaks and normal structural features of the pipeline. Despite these challenges, impulsive response analysis remains an effective tool for leak detection and pipeline integrity monitoring in water distribution systems.

D. Other Methods:

1. District Metered Area (DMA)

A District Metered Area (DMA) is a small, clearly defined area of a WDN that is typically supplied by a single main. A DMA's borders can occasionally be formed naturally, such as in a tiny community, but they are typically established by shutting the necessary valves to separate the area. Water providers mostly employ water audits as a means of locating leaks within a DMA. In order to do this, the total volume of water entering a DMA must be measured. A considerable difference over time in the volume of water entering and exiting a DMA that surpasses a level established by the water providers suggests the existence of one or more leaks [4].

2. Permanent Installation

Advancements in communication technologies like SMS, GPRS, 3G, 4G, NBIoT, and Radio, along with lower data transfer costs, have made it cost-effective to set up noise-logging networks in the field. In recent years, tens of thousands of these units have been installed permanently (Figure.2.30). Various methods for data transfer are available, and common download platforms integrated with AMR systems have been introduced. Permanent installations are ideal for areas with frequent bursts, hard-to-survey locations such as town centers and main roads, regions without DMA structures where acoustic noise logging is a cost-effective alternative, and previous DMA hotspots requiring ongoing monitoring to manage leakage levels. Leak noise data is automatically sent to a central monitoring station and often linked with GIS or mapping systems for a quick visual overview of the network. Immediate alarms help minimize leak run time, and effective repairs save significant water. The latest systems transmit noise files for leaks, which are used to pinpoint leak locations through cloud platforms and GIS maps [14].

This integration allows for 'autocorrelation' to identify and locate leaks automatically. Combining leak alarms with DMA flow data helps prioritize and optimize follow-up activities.

This approach reduces survey labor costs, making leak detection more specialized and focused on pinpointing and repair. The decision to deploy these systems now depends on comparing labor costs with capital investment and the additional benefits of immediate leak notifications.

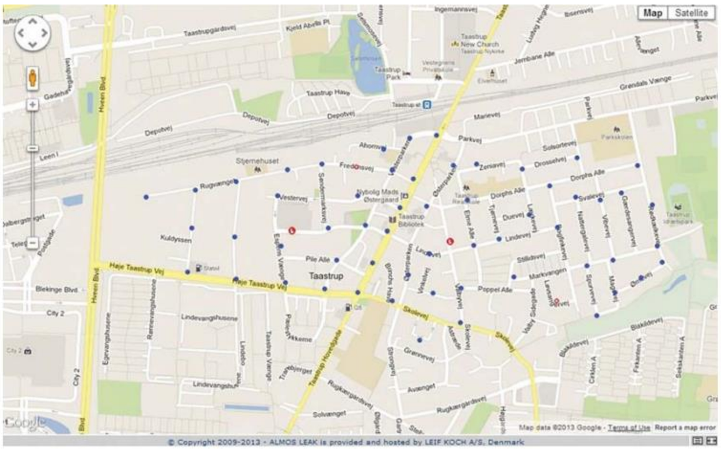

Figure.2.30 Map of Permanent Installation of noise loggers. [14]

3. Remote Earth Imaging

Seasat was the first satellite equipped with synthetic aperture radar (SAR) technology to monitor Earth's waters. SAR creates high-resolution 2D or 3D images by simulating a large antenna using radar movement, allowing for improved spatial resolution with fewer physical antennas. The system sends out radio wave pulses and records their echoes, which are processed to produce detailed images. Combining SAR's long-range imaging with radar’s ground-penetrating capabilities has enabled remote water leak detection via orbiting satellites (Figure.2.31). These satellites illuminate areas, and algorithms analyze the reflections to map potential leak locations. Field crews then verify and repair the leaks based on the map, optimizing efficiency. SAR is particularly useful for detecting underground water leaks, like in urban water systems. Water sources reflect electromagnetic (EM) waves at specific frequencies, allowing identification by their unique reflection patterns. However, unwanted reflections from nearby objects must be filtered out using multiple scans at different polarizations, such as horizontal-vertical (HV) and horizontal-horizontal (HH), to isolate water-related reflections [14].

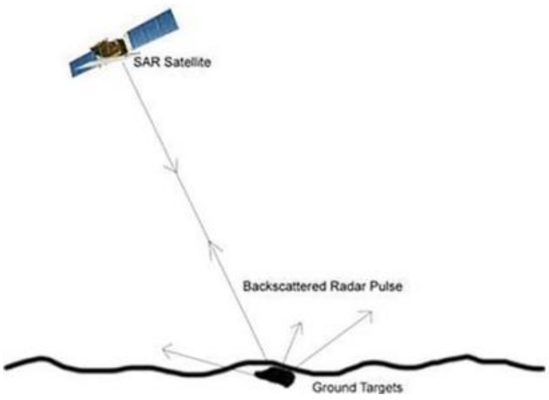

Figure.2.31 Principal of SAR schematic. [14]

4. Geospatial AI

Geospatial AI is used in water management to analyze environmental and pipeline data, such as soil type, weather, and pipeline characteristics, to predict potential network failures. By leveraging machine learning and historical failure data, it forecasts high-risk areas rather than pinpointing exact leaks. This technology helps prioritize regions for repair, optimize sensor placement, and reduce costs. Continuously updating with new data, Geospatial AI enables early interventions, preventing leaks and improving network management by focusing resources on the most vulnerable sections [14].

5. Central Event Management (CEM)

By combining data from several sources into a single, cohesive platform, this Central Event Management (CEM) system is all-inclusive and intended to supervise water infrastructure. Complementing the centralization of customer data that Customer Relationship Management (CRM) systems accomplish, CEM serves as a central clearinghouse for incident-related data, thereby reducing operational gaps among departments (see Figure.2.32). It analyzes, prioritizes, and finds, leaks, bursts, and malfunctioning assets in the network with the use of machine learning and data analytics. CEM controls every step of an event's lifetime, from identification and categorization to reaction planning and validation. For a complete picture of operations, it interfaces with various enterprise IT systems, including asset management platforms and Geographic Information Systems (GIS). Departmental cooperation is improved by this integration, guaranteeing speedier and more efficient event reaction times. By eliminating departmental silos, CEM fosters improved collaboration, reducing costs and delays while enhancing service quality. It also streamlines communication with external agencies, such as emergency services, during major incidents, and provides management with dashboards and reports for ongoing asset management and regulatory compliance. Ultimately, CEM boosts the overall efficiency and effectiveness of water infrastructure management by offering a holistic view of all operational activities [14].

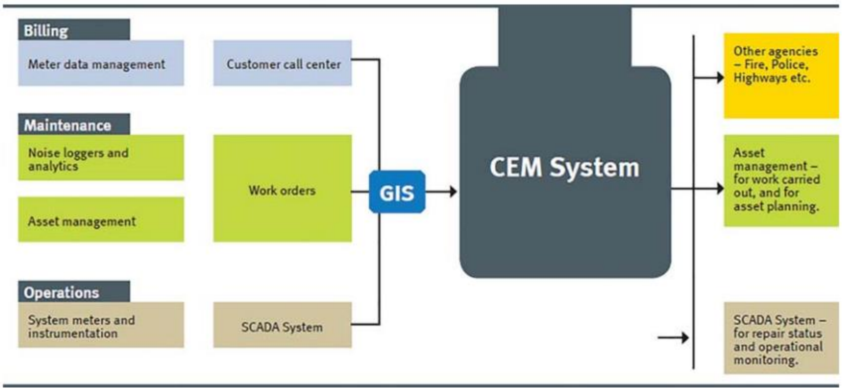

Figure.2.32 Combination of CEM with some enterprise IT systems. [14]

6. Hydraulic Model

A vital tool for finding water leaks is hydraulic modeling. It offers a trustworthy method for modeling the behaviors of water distribution systems and identifying possible leak locations. Engineers can replicate various operational scenarios by developing a hydraulic model and identifying anomalies that may indicate leaks. These models are progressively being combined with real-time data and sophisticated algorithms, which enhance their accuracy and predictive power. A key application of hydraulic modeling in leak detection involves the use of sensors to track critical parameters such as flow, pressure, and transient events within the pipeline. For example, sensors integrated with SCADA (Supervisory Control and Data Acquisition) systems and RTUs (Remote Terminal Units) deliver real-time data that is analyzed by specialized software. This software can assess the stability of the water supply system and detect potential leaks by examining the pressure loss ratio and utilizing head differences between sensors to identify leaks or bursts [16]. Anomalies identified through these techniques are subsequently analyzed to determine the characteristics of the suspected leak.

Numerous research studies have advanced the development and application of hydraulic models for leak detection. For instance, studies have explored the construction of hydraulic models to simulate pipeline operations under various leakage scenarios. These models address the inverse problem of pipeline network leakage by minimizing discrepancies between actual and simulated data, enabling precise leak localization. A method for solving the inverse problem of pipeline leakage through parameter identification has also been proposed [33].

Recent developments have also seen the incorporation of optimization and machine-learning techniques alongside hydraulic models. For example, particle swarm optimization (PSO) algorithms have been utilized with hydraulic models to improve the accuracy of leak detection and localization. Additionally, studies have employed the sensitivity matrix method, which compares measured network data with simulated values to identify leaks. This method has proven to be particularly effective, especially when the hydraulic model is accurately calibrated to reflect the network's characteristics. Hydraulic modeling has benefits, but there are drawbacks to using it for leak detection. The precision of the input data and the quality of the hydraulic model have a major impact on how successful leak detection techniques are [23],[28],[34],[35]. Nevertheless, model-based leak detection techniques are expected to be more and more important for guaranteeing the secure and effective operation of WDNs as pipeline modeling and system measurement technologies develop.

IV. Conclusion

Finally, water distribution leak detection techniques include a wide range of technologies, each with unique strengths and limits. Acoustic detectors, such as hydrophones and accelerometers, are extremely successful in detecting leaks by capturing sound emissions from pipes. Non-acoustic technologies, such as thermal imaging and gas injection, provide alternate options for identifying leaks in tough situations. Transient-based approaches use pressure wave analysis to provide precise leak identification by examining signal reflections. Furthermore, new technologies and hybrid systems that combine many methodologies continue to improve leak detection accuracy. As water scarcity becomes a greater problem, incorporating these approaches into contemporary water distribution systems is crucial for assuring effective water management and reducing resource loss.

References

[1] T. Mekuria, Y.Kifle, Y.Assefa, *Water Supply Distribution System Design*. 2009, In Holeta Town Wolmera West Shewa Zone of Oromia region, Ethiopia. [Online]. Available:https://www.academia.edu/download/55983127/Water_Supply_Distribution_System_Design.pdf

[2] N. K. Velayudhan, S. Aiswarya, A. R. Devidas, and M. V. Ramesh, "Delay and Energy Efficient Offloading Strategies for an IoT Integrated Water Distribution System in Smart Cities," *Smart Cities*, vol. 7, no. 1, pp. 179–207, 2024, doi: 10.3390/smartcities7010008.

[3] American Water Works Association, *Principles and Practices of Water Supply Operations Water Transmission and Distribution*., 4th ed, 2012.

[4] M. Bentoumi, " Développement de méthodes efficaces pour la localisation de fuites sur les canalisations d'eau potable",Ph.D. dissertation, Department of Electronics, Faculty of Technology, Mohamed Boudiaf University, M'Sila, Algeria, 2017.

[5] A. A. Abokifa, Y. J. Yang, C. S. Lo, and P. Biswas, "Water quality modeling in the dead end sections of drinking water distribution networks," *Water Res.*, vol. 89, pp. 107–117, 2016, doi: 10.1016/j.watres.2015.11.025.

[6] Maharashtra Jeevan Pradhikaran and CEPT University, *Basics of Water Supply System – Training Module for Local Water and Sanitation Management*, 1st ed. Maharashtra, India: Maharashtra Jeevan Pradhikaran, 2012.

[7] P. K. Swamee and A. K. Sharma, *Design of Water Supply Pipe Networks*. Hoboken, NJ: John Wiley & Sons, 2008.

[8] A. Dongre, "Optimization of Water Distribution Network-A Review," International Journal of Science Technology & Engineering, vol. 2, no. 09, pp. 269–272, 2016, [Online]. Available: www.ijste.org

[9] N. Trifunović, *Introduction to Urban Water Distribution*, London, UK: Taylor & Francis, 2006.

[10] J. Thornton, R. Sturm, and G. Kunkel, *Water Loss Control*, 2nd ed. New York, NY, USA: McGraw-Hill, 2008.

[11] M. F. Ghazali, *Instantaneous Frequency Analysis for Leak Detection in Pipeline*

Networks. Sheffield, UK: University of Sheffield, 2012.

[12] Y. AWAISAH, M. Awawdeh, M. Zeidat, and Y. Shaheen, *Analysis and Design of Water Distribution Network and Wastewater Collection System for Al-Shoyoukh Town*, B.Sc. project report, Dept. Civ. & Archit. Eng., Palestine Polytechnic Univ., Hebron, Palestine, May 2012.

[13] S. El-zahab, T. Zayed, "Leak detection in water distribution networks: an introductory overview," *Smart Water,* vol. 4, no. 05, 2019. https://doi.org/10.1186/s40713-019-0017-x

[14] S. Hamilton and B. Charalambous, *Leak Detection: Technology and Implementation*, 2nd ed. London, UK: IWA Publishing, 2020. http://iwaponline.com/ebooks/book-pdf/1078453/wio9781789060850.pdf

[15] O. Hunaidi, A. Wang, M. Bracken, T. Gambino, and C. Fricke, "Acoustic methods for locating leaks in municipal water pipe networks," in Proc. Int. Conf. Water Demand Management, Dead Sea, Jordan, May 2004, pp. 1–14.

[16] Z. Ahmad Fuad, H. S. Eddy, Y. Badronnisa, and I. Syazwani, "Water leak detection method in water distribution network," *IOP Conf. Ser. Earth Environ. Sci.*, vol. 357, no. 1, 2019, doi: 10.1088/1755-1315/357/1/012033.

[17] H. Fan, S. Tariq, and T. Zayed, "Acoustic leak detection approaches for water pipelines," vol. 138, Jun. 01, 2022, *Elsevier B.V.* doi: 10.1016/j.autcon.2022.104226.

[18] K. B. Adedeji, Y. Hamam, B. T. Abe, and A. M. Abu-Mahfouz, "Towards Achieving a Reliable Leakage Detection and Localization Algorithm for Application in Water Piping Networks: An Overview," *IEEE Access*, vol. 5, pp. 20272–20285, 2017, doi: 10.1109/ACCESS.2017.2752802.

[19] Georgia Environmental Protection Division, *Water Leak Detection and Repair Program: EPD Guidance Document*, Watershed Protection Branch, Atlanta, GA, USA, Aug. 2007.

[20] T. Al Qahtani, M. S. Yaakob, N. Yidris, S. Sulaiman, and K. A. Ahmad, "A Review on water leakage detection method in the water distribution network," *J. Adv. Res. Fluid Mech. Therm. Sci.*, vol. 68, no. 2, pp. 152–163, 2020, doi: 10.37934/arfmts.68.2.152163.

[21] P. R. Quiterio, F. S. Silva, I. C. Mariscal, and J. A. M. Campana, “Comparative Analysis of Water Leak Detection Systems and Methodologies,” *Environ. Eng. Manag. J.*, vol. 15, no. 9, pp. 2063–2074, 2016, doi: 10.30638/eemj.2016.223.

[22] Le détecteur PERMALOG-3, http://www.hellotrade.com/allied-power-technology/permalog-3-acoustic-leak-noise-logger.html.

[23] U. Baroudi, A. A. Al-Roubaiey, and A. Devendiran, “Pipeline Leak Detection Systems and Data Fusion: A Survey,” *IEEE Access*, vol. 7, pp. 97426–97439, 2019, doi: 10.1109/ACCESS.2019.2928487.

[24] N. A. M. Yussof and H. W. Ho, “Review of Water Leak Detection Methods in Smart Building Applications,” *buildings*, vol. 12, no. 10, 2022, https://doi.org/10.3390/buildings12101535.

[25] A. Moubayed, M. Sharif, M. Luccini, S. Primak, and A. Shami, “Water Leak Detection Survey: Challenges Research Opportunities Using Data Fusion Federated Learning,” *IEEE Access*, vol. 9, pp. 40595–40611, 2021, doi: 10.1109/ACCESS.2021.3064445.

[26] A. Myles, “Permanent Leak Detection on Pipes using a Fibre Optic Based Continuous Sensor Technology,” *Pipelines 2011*, pp. 744–754, 2011,doi.org/10.1061/41187(420)69.

[27] T. Yuvaraj, N. Krishna, P. Manish, P. Naik, and P. Varsha, “Review paper on water monitoring and leakage detection,” *Int. J. Res. Sci. Innov. (IJRSI)*, vol. 4, no. 1, pp. 31–34, 2019.

[28] X. J. Wang, A. R. Simpson, M. F. Lambert, and J. P. Vítkovský, “Leak detection in pipeline systems using hydraulic methods: A review,” in *Proc. Conf. Hydraulics in Civil Engineering*, Inst. Eng., Australia, Hobart, Australia, Nov. 23–30, 2001, pp. 391–400.

[29] X. Wang, M. F. Lambert, A. R. Simpson, J. A. Liggett, and J. P. Vtkovský, “Leak Detection in Pipelines using the Damping of Fluid Transients,” *J. Hydraul. Eng.*, vol. 128, no. 7, pp. 697–711, 2002, doi: 10.1061/(asce)0733-9429(2002)128:7(697).

[30] M. F. Ghazali, S. B. M. Beck, J. D. Shucksmith, J. B. Boxall, and W. J. Staszewski, “Comparative study of instantaneous frequency based methods for leak detection in pipeline networks,” *Mech. Syst. Signal Process.*, vol. 29, pp. 187–200, 2012, doi:

10.1016/j.ymssp.2011.10.011.

[31] A. Abdulshaheed, F. Mustapha, and A. Ghavamian, “A pressure-based method for monitoring leaks in a pipe distribution system: A Review,” *Renew. Sustain. Energy Rev.*, vol. 69, no. August 2016, pp. 902–911, 2017, doi: 10.1016/j.rser.2016.08.024.

[32] S. H. Kim, “Multiple leak detection algorithm for pipe network,” *Mech. Syst. Signal Process.*, vol. 139, p. 106645, 2020, doi: 10.1016/j.ymssp.2020.106645.

[33] Q. Fang, J. Chen, and C. Xie, “Research on leakage area detection method in water distribution network based on gray wolf optimization,” *Water Supply*, vol. 23, no. 2, pp. 645–656, 2023, doi: 10.2166/ws.2023.014.

[34] I. Marzola, S. Alvisi, and M. Franchini, “A Comparison of Model-Based Methods for Leakage Localization in Water Distribution Systems,” *Water Resour. Manag.*, vol. 36, no. 14, pp. 5711–5727, 2022, doi: 10.1007/s11269-022-03329-4.

[35] W. Wang, H. Sun, J. Guo, L. Lao, S. Wu, and J. Zhang, “Experimental study on water pipeline leak using In-Pipe acoustic signal analysis and artificial neural network prediction,” *Meas. J. Int. Meas. Confed.*, vol. 186, 2021, doi: 10.1016/j.measurement.2021.110094.

Chapter03

DSP In Water Leak Detection Field

I. INTRODUCTION

In recent decades, there has been a major evolution in DSP techniques. Key components in many applications are the FFT, STFT, CWT, and DWT. This review outlines these methods chronologically, emphasizing their evolution and importance in signal processing. Through improved signal analysis and interpretation, each approach has experienced a substantial evolution, increasing leak detection capabilities. The discussion will center on the mathematical formulations and historical evolution of these techniques, emphasizing their applicability to the detection and identification of water leaks.

Given the complexity of the signals involved which frequently include vibrational disturbances, pressure variations, and auditory emissions the application of DSP techniques in water leak detection is especially important. According to, time-frequency analysis methods like FFT and STFT make it possible to identify water leaks even in the presence of background noise. By offering multi-resolution capabilities which are crucial for catching fleeting leak events that could be masked by other operational noises the CWT and DWT further improve this analysis [1],[2],[3]. Through the use of these cutting-edge methods, engineers and researchers can greatly increase the precision and effectiveness of leak detection systems, which will enhance water resource management and save operating expenses.

Furthermore, in WDNs, correlation techniques are critical for localizing leaks. It is achievable to determine a leak's location more accurately by comparing the data from various sensors. It is feasible to extract relevant information from complex datasets by combining DSP methods with correlation algorithms, which makes it simpler to react to leaks quickly and effectively [4]. We'll look at how different DSP techniques and correlation methods interact in this chapter and explain how they work together to enhance water leak detection technologies.

II. FFT

II.1. HISTORICAL BACKGROUND

Particularly in water leak detection, the FFT has emerged as a vital tool in signal processing. The basis of this method is the Discrete Fourier Transform (DFT), which transforms signals from the time domain to the frequency domain and provides informative data about signal properties. However, the DFT was computationally intensive, especially with big datasets. The FFT algorithm was developed to address this difficulty and drastically lower computational complexity, increasing the effectiveness and applicability of spectral analysis in practical settings [5].

In water distribution systems, leaks pose significant environmental and economic risks. The FFT has been effectively applied to detect leaks by analyzing the acoustic signals captured from within the pipeline. These signals are typically recorded using a microphone or hydrophone and then processed with the FFT to generate a frequency spectrum. This spectrum reveals characteristic peaks associated with leaks, which are absent in non-leak scenarios, enabling reliable distinction between different operating conditions. Early experiments involving various leak sizes, non-leak situations, and disturbances caused by external factors demonstrated the FFT's capability to identify these characteristic frequencies, thus confirming its utility in leak detection [5].

The FFT has been widely adopted in various commercial applications, such as LabView software, to perform spectral analysis efficiently. By transforming time-domain data into the frequency domain, FFT makes it easier to identify key signal components, simplifying many signal-processing tasks. Its ability to reduce the computational burden of DFT calculations is precious in DSP applications, including those involved in monitoring and diagnosing pipeline systems [6].

Despite its advantages, the FFT has some limitations in leak detection, especially when faced with transient signals or noisy environments. Factors such as fluid properties, fault geometry, and background noise can influence the accuracy of the results obtained using FFT alone. In response to these challenges, researchers have explored the use of other techniques, such as the STFT and wavelet transforms, which provide a more localized analysis of time-varying signals [7].

FFT is highly effective for transforming signals into their frequency components, making it a powerful tool for identifying characteristic leak signatures in pipelines. When a leak occurs, FFT can detect high-frequency peaks in the acoustic signal, which differ significantly from the low-frequency peaks observed in normal, no-leak conditions. This consistent difference in frequency response has made FFT a preferred method for detecting leaks over time. In large-scale studies, FFT has been applied to vast datasets, including thousands of samples from both leak and non-leak scenarios. These datasets were processed using FFT, which enabled accurate classification of leak conditions [8].

From a mathematical standpoint, the FFT operates by converting a set of time-domain samples into a corresponding set of frequency-domain values. This process allows for spectral analysis of digital signals, such as those obtained from sensors in pipeline systems. The FFT simplifies this transformation by utilizing the periodicity and symmetry properties of the signal, which reduces the complexity of the calculations involved [9]. This feature has made FFT a versatile tool for leak detection, especially in systems where it is necessary to monitor continuous signal fluctuations.

In cases where pipelines have complex geometries, such as zigzag paths or sections with smaller diameters, FFT is effective in identifying leaks. For example, experiments have demonstrated that FFT can accurately detect leaks in pipelines with diameters smaller than 20 cm, highlighting its adaptability to various pipeline configurations. However, for short-duration events like sudden valve closures, STFT often outperforms FFT due to its ability to analyze signals over short time intervals, providing better resolution in dynamic systems [10].

The FFT continues to play a crucial role in leak detection systems, especially when used alongside other techniques that complement its strengths and mitigate its weaknesses. Spectral analysis using FFT remains a valuable approach for monitoring pipelines, as it is fast, efficient, and well-suited for processing large datasets [11]. Additionally, FFT’s capability to work with various signal types and geometries has solidified its position as a go-to method for detecting leaks in water distribution systems [11],[12].

II.2. MATHEMATICAL EQUATION

To calculate the DFT, the FFT algorithm is optimized. The DFT's fundamental mathematical formula remains unchanged, however, the FFT increases processing performance. The FFT equation is the same as the DFT equation:

$$X(k) = \sum_{n=0}^{N-1} x(n) e^{-i2\pi kn/N}$$

- $X(k)$ is the frequency component at the index k,

- $x(n)$ is the n-th sample of the time-domain signal,

- N is the total number of samples,

- k is the index representing each frequency bin (ranging from 0 to $N - 1$),

- $e^{-i2\pi kn/N}$ is the complex exponential that performs the transformation,

- i is the imaginary unit (i^2 = -1).

While the DFT directly computes this formula, the FFT takes advantage of the symmetry and periodicity properties of the complex exponential, reducing the number of computations from (O (N^2)) to (O ($N \log N$) [9].

The FFT algorithm essentially breaks down the DFT into smaller parts, recursively applying the DFT in stages. This is why it's significantly faster for large datasets [6].

II.3. APPLICATION IN WATER LEAK DETECTION

The use of the FFT in water leak detection has attracted considerable interest due to its efficiency in analyzing signals produced by leaks in water supply systems. FFT is a computational technique that converts time-domain signals into their frequency-domain equivalents, facilitating the identification of specific frequencies linked to leak events. This feature is particularly advantageous in environments where noise and other disturbances can obscure the signals of interest.

One major application of FFT in leak detection involves analyzing vibrations and acoustic emissions generated by leaks in pipelines. For example, study have demonstrated that frequency analysis, including FFT, was crucial for characterizing signals from accelerometers in plastic water supply pipes, especially when acceleration values alone were insufficient to differentiate between leaking and non-leaking conditions. Similarly, other research has noted that traditional methods, including FFT, are widely used in the literature for leak detection, although they pointed out limitations in the FFT approach, suggesting that while FFT is useful, it may not always provide the most comprehensive analysis [13],[14].

Additionally, integrating FFT with other signal processing techniques has been explored to enhance leak detection capabilities. For instance, Martini et al. developed a detection algorithm that uses standard deviation metrics alongside FFT to distinguish between leaking and non-leaking conditions in buried plastic pipes [4]. This approach highlights the importance of combining FFT with statistical methods to improve detection accuracy. Furthermore, research has emphasized the effectiveness of instantaneous frequency analysis, which can complement FFT techniques, in identifying leaks and other features within pipeline networks [15].

In another the paper, the authors discuss the application of the FFT as a traditional technique for detecting leaks in pipeline systems. FFT is utilized for spectral analysis of pressure signals, allowing for the transformation of time-domain data into the frequency domain. This transformation helps identify frequency components that may indicate the presence of leaks. However, the authors point out that while FFT is effective in many scenarios, it has limitations, particularly in complex pipeline configurations such as zigzag designs. The accuracy of leak detection using FFT can be compromised due to noise and the ill-posed nature of the eigenvalue problems involved. The paper contrasts FFT with the filter diagonalization method (FDM), which the authors propose as a more robust alternative, particularly for handling the complexities of pipeline systems. Despite its limitations, FFT remains a valuable tool in the analysis of pipeline signals, and the authors suggest that integrating FFT with FDM could enhance the overall reliability of leak detection and localization efforts in water distribution systems.[1]

Another paper offers complete research on the use of FFT for leak detection in pipelines, with an emphasis on identifying distinctive frequencies related to leakage events. The experimental setup included a microphone inserted within the pipe, as well as a data gathering device (NIcDAQ-9178) and a pressure transducer, to record the sound produced by leaks under various situations in the time domain Figure.3.1[5].

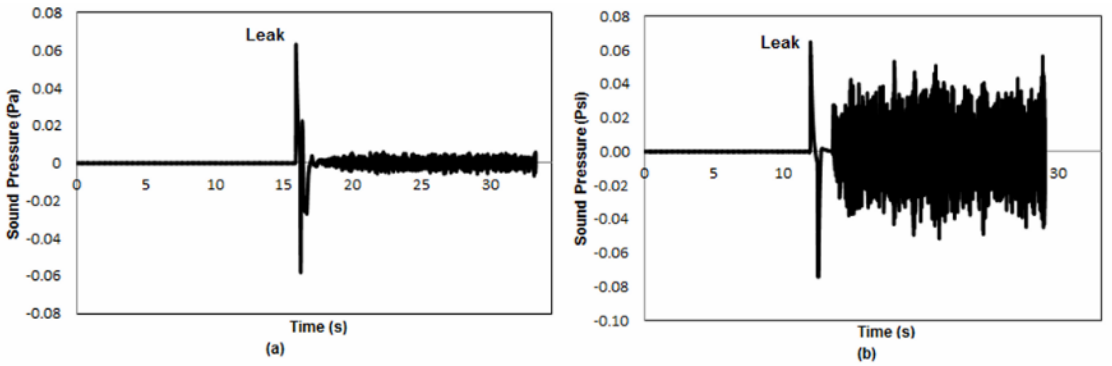

Figure.3.1 Time-domain representation of microphone signal (in sound pressure). a) Leak size of 2 mm b) Leak size of 5 mm.[5]

The FFT was used to examine the frequency response across various operating states, demonstrating differential spectrum features between leakage and non-leakage scenarios. The study specifically looked at leak sizes ranging from 1mm to 5mm and compared them to situations without leaks and those with external influences on the pipe. The results showed that particular frequency peaks appeared only in the presence of leaks and were missing in non-leak situations, making it easier to detect leaks using spectral analysis Figure.3.2. Notably, while leaking scenarios did not have a single dominant frequency, they did have a constant range of prominent frequencies across time, which contrasted dramatically with the lack of such regions in non-leak conditions. The study also used LabVIEW software to develop a real-time monitoring interface, allowing for continuous observation of pressure fluctuations and sound wave propagation, which are longitudinal mechanical waves that require a medium to transmit. This study highlights the effectiveness of FFT in discriminating between typical operational noises Figure.3.3, and those suggestive of leaks, making a substantial contribution to the area of pipeline monitoring and maintenance. [5]

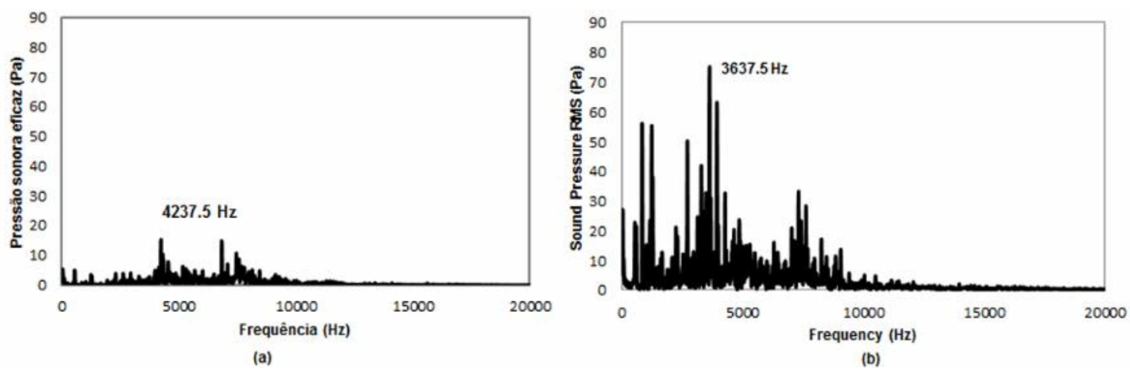

Figure.3.2 A microphone signal in the frequency domain with leakage. a) Leak size: 2 mm. c) Leak size of 5 mm. [5]

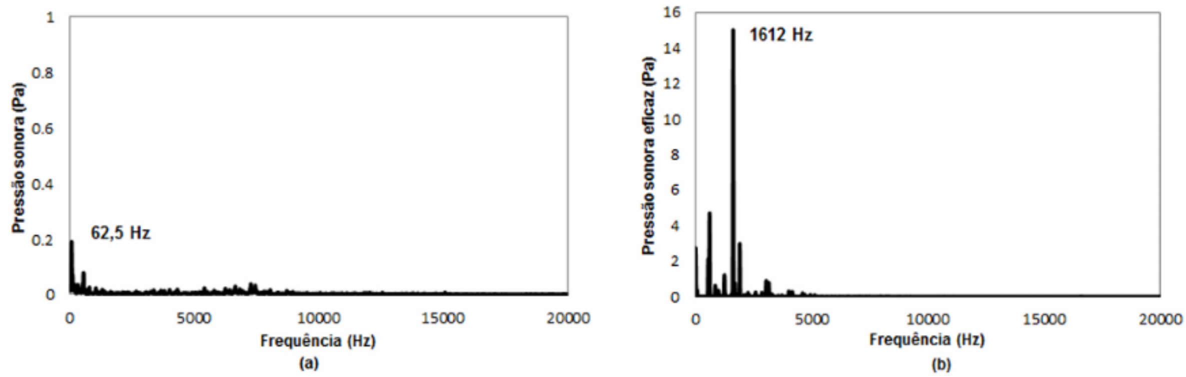

Figure.3.3 Microphone signal in the frequency domain with no leakage. a) Only sounds from the lab, air conditioner turned on, and people walking. b) Continuous blows with a metallic instrument in the pressure vessel. [5]

The FFT has found significant applications in addressing the limitations of leak detection in smaller pipelines, especially those with complex geometries. In the current scientific literature, traditional approaches often face challenges in effectively detecting leaks in compact and zigzag-shaped pipeline sections, primarily due to limited access and reduced accuracy in vibration measurements. The use of FFT enables the analysis of vibration signals from smaller pipelines those under 20 cm in length overcoming these inherent limitations and improving the precision of leak detection. By applying FFT, spectral analysis techniques can be utilized to break down the frequency components of the vibrations generated by leaks, distinguishing them from normal operational conditions. This method is particularly beneficial for detecting leaks in zigzag pipelines, where conventional methods might fail to recognize subtle changes due to the pipeline's structural complexity. Despite some trade-offs in accuracy for very small sections, FFT-based analysis presents a promising solution to detect and prevent leaks by leveraging the distinct spectral characteristics observed in the frequency domain and thus enhancing reliability even in challenging pipeline layouts. [11][12]

Researchers investigate the use of the FFT as a vital analytical approach for the detection and localization of leaks in water supply systems, with an emphasis on plastic pipe infrastructure. The work tackles the inherent issues of leak detection in contexts where running water causes vibrations that might disguise modest leak indicators. To reduce interference produced by these vibrations, the scientists employ FFT to translate time-domain vibration signals acquired using accelerometers into the frequency domain. This modification is critical because it reveals different frequency components that are common during leak events. According to the study's findings, leak signals display substantial frequency activity between

270 and 370 Hz. This frequency range is a key differentiator, as non-leak signals often exhibit less activity in this region. The authors undertake a systematic investigation of FFT data from various signal types, including leak situations with and without water flow. Through this comparison research, they develop a strong criterion for leak identification based on frequency analysis. The study expands on its findings by using cross-power spectral density (CPSD) and wavelet analysis, which give supplementary validation to the FFT results and reinforce the conclusions' credibility. Along with their analytical advances, the authors create a MATLAB-based system to automate the analysis process. This technique assesses the closeness of local maxima in FFT graphs to determine the likelihood of leaks. This method is automated, which not only simplifies leak detection but also underlines the significance of training the system with known leak signals to enhance accuracy and dependability. Finally, the article illustrates the effectiveness of FFT as a sophisticated tool for distinguishing leak-related vibrations from background noise. This skill significantly contributes to the evolution of approaches for detecting and localizing water leaks, enabling more effective water resource management. The findings illustrate the potential of FFT to increase operational efficiency in water delivery systems, emphasizing its importance in modern infrastructure management methods. [13]

Also, another research investigates the use of wireless sensor networks (WSN) to monitor the operating status of wall-mounted water pipes via low-power vibration sensors, especially accelerometers. The major goal is to determine the viability of leak detection in these pipelines. The study is divided into two parts: (1) examining the effect of various pipeline components, including clamps, bends, and leaks, on vibration signals, and (2) identifying the best sensor location to detect leaks of various sizes. The study found that medium-sized leaks are particularly difficult to detect because their vibration patterns closely mimic those of no-leak situations. Furthermore, vibrations detected farther from the leak spots are less useful for detection. To increase leak detection accuracy, the scientists use three distinct learning models on data acquired from various sensors. The Support Vector Machine (SVM)-based model beats others by dramatically improving leak detection and size classification accuracy when four sensors are used instead of one. The paper utilizes the FFT to analyze vibration signals, allowing the authors to better understand the frequency components influenced by different pipeline components and leak conditions. FFT helps in distinguishing subtle differences in the vibration signals, thereby aiding in the detection of leaks, particularly for challenging cases such as medium-size leaks.[16]

The application of FFT in water leak detection is multifaceted, encompassing vibration analysis, acoustic emission monitoring, and integration with smart sensor technologies. While FFT provides a robust framework for frequency analysis, ongoing research continues to explore its limitations and potential enhancements through complementary techniques. The combination of FFT with other analytical methods and technologies holds promise for improving the reliability and efficiency of leak detection systems in water supply networks.

III. STFT

III.1. HISTORICAL BACKGROUND

The STFT technique has its roots in the need to analyze non-stationary signals, which are prevalent in various fields, including engineering and signal processing. Introduced by Dennis Gabor in 1946, the STFT was developed as a method to window a signal and then apply the Fourier Transform (FT) to the windowed segments, allowing for the analysis of time-varying frequency content. This technique addresses the limitations of the traditional Fourier Transform, which is effective for stationary signals but fails to provide time-localized frequency information for non-stationary signals. The STFT operates by segmenting the signal into smaller, overlapping portions, each treated as stationary, thus enabling the capture of temporal variations in frequency components [17],[18],[19].

The application of STFT has been particularly significant in the field of leak detection in pipelines, where identifying leakage signals amidst noise is a critical challenge. The STFT allows for the transformation of pressure and flow signals from the time domain to the time-frequency domain, facilitating the identification of anomalies such as leaks by establishing a spectral imprint associated with these events. The spectrogram generated from the STFT provides a two-dimensional representation of the signal's power spectrum, illustrating how frequency components evolve over time, which is essential for detecting variations indicative of leaks [20],[21].

Despite its advantages, the STFT has limitations, particularly regarding its fixed window size, which can lead to trade-offs between time and frequency resolution. Narrow windows yield better time resolution but poorer frequency resolution, while wider windows improve frequency resolution at the expense of time accuracy. This limitation has led to the exploration of alternative methods, such as the Wavelet Transform (WT), which offers variable window sizes and better adaptability to non-stationary signals. However, the STFT remains a widely used tool due to its simplicity and effectiveness in many applications, including urban waterworks leak detection, where it has been successfully employed to analyze acoustic signals and identify leaks based on spectral characteristics [17],[19],[22].

In conclusion, the STFT technique has evolved as a crucial method for time-frequency analysis, particularly in applications requiring the detection of transient phenomena such as leaks in pipelines. Its historical development from Gabor's initial concept to its current applications underscores its importance in modern signal processing, despite the ongoing challenges related to resolution and noise management. As research continues to advance, integrating STFT with machine learning and other analytical methods may enhance its effectiveness in real-world applications [21].

The STFT technique is a time-frequency analysis method that emerged as an evolution of the classical Fourier Transform (FT) to address its limitations in analyzing non-stationary signals. The FT, which decomposes a signal into its constituent frequencies, is well-suited for stationary signals where frequencies do not change over time. However, real-world signals, such as those encountered in leak detection for water distribution systems or gas pipelines, often exhibit non-stationary behavior. This motivated the development of STFT, designed to capture the frequency content of signals that evolve by applying a sliding window over the signal, allowing for localized frequency analysis [10].

The roots of STFT trace back to the early 20th century, with Dennis Gabor's work in 1946 on signal representation using elementary functions. He proposed that any signal could be represented as a sum of modulated Gaussians, forming the basis for time-frequency representations, which directly influenced the development of STFT. In essence, Gabor’s work laid the foundation for analyzing signals in both time and frequency simultaneously, rather than treating them as static phenomena [23]. Later on, as computational techniques advanced, Gabor’s ideas were translated into a more practical form with the introduction of the STFT, providing engineers and researchers with a tool to handle non-stationary signals effectively.

The limitations of classical FT in handling signals with time-varying frequencies became more apparent as technology advanced and more complex signals required analysis. In the late 20th century, researchers working in fields like speech processing and radar technology began to utilize STFT to handle the temporal variations in signal frequencies. The early applications of STFT involved speech signal processing, where the short-time behavior of frequencies is crucial for understanding the nuances of speech [10]. The method became essential in identifying how certain frequencies change within short intervals, enabling better insights into signal characteristics over time.

By the late 1970s and early 1980s, STFT became increasingly popular in fields such as biomedical engineering, sonar, and leak detection. Its ability to provide time-localized frequency information allowed researchers to identify anomalies like water or gas leaks by distinguishing between the signals' normal and abnormal spectral content [24]. Because of the method's simplicity, ease of implementation, and capacity to handle complicated and noisy data, it was widely adopted.

The fixed window size of the STFT, which forces a trade-off between time and frequency resolution, is one of its main disadvantages. While large windows offer superior frequency resolution at the expense of time accuracy, narrow windows produce good time resolution but poor frequency resolution. This limitation led to the development of other techniques, such as the Wavelet Transform (WT), which allows for adaptive windowing. However, the STFT remains a crucial method in various domains because of its computational simplicity and effectiveness for many practical applications, especially when the goal is to obtain a general overview of time-varying frequency components[25].

In recent years, STFT has been widely applied in fields like water leak detection, where time-frequency characteristics of signals play an essential role in identifying the precise location of leaks. Its historical importance and adaptability make it an indispensable tool in signal processing. The continuous refinement of STFT algorithms, paired with advances in machine learning techniques, has expanded its utility in modern engineering applications, providing robust insights into the time-frequency dynamics of non-stationary signals [6],[24].

Scientists examine the processing of electroencephalogram (EEG) signals, which represent the electrical background activity of the brain generated by the nerve cells of the cerebral cortex. A crucial preprocessing step is the application of Independent Component Analysis (ICA) to improve signal quality. The STFT is utilized for signal frequency denoising in the time-frequency domain as shown in Figure.3.4, comprising three principal steps: (1) STFT computation, wherein the Fourier Transform is applied to overlapping windowed segments of the signal; (2) thresholding, during which spectrogram values beneath a predetermined range are nullified, facilitating effective reconstruction Figure.3.5; and (3) inverse STFT computation, which reconstructs the denoised signals. This method guarantees the retention of essential characteristics in the ECG signals while efficiently diminishing noise[26].

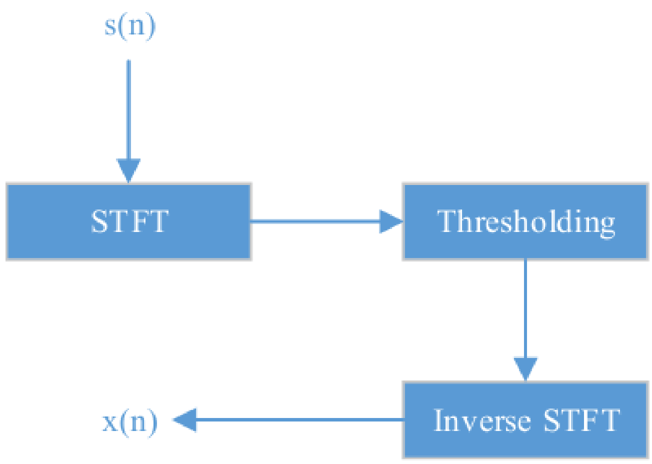

Figure.3.4 Block schematic of denoising using STFT. [26]

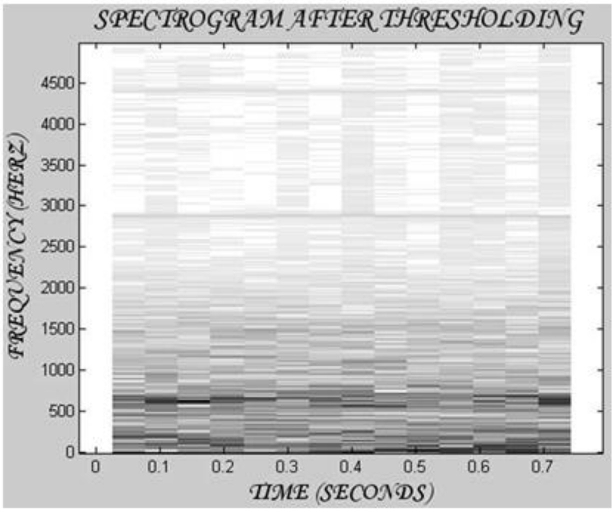

Figure.3.5 Spectrogram shows the signal after thresholding using STFT. [26]

III.2. MATHEMATICAL EQUATION

The STFT is a widely used method in signal processing for analyzing non-stationary signals. The mathematical equation for the STFT is given by [10],[24],[25]:

$$STFT\{x(t)\}(\tau,\omega) = \int_{-\infty}^{\infty} x(t)\omega(t-\tau)e^{-i\omega t}dt$$

where:

- $x(t)$ is the original pressure signal,

- $\omega(t-\tau)$ is the sliding window function centered at the time τ,

- ω is the angular frequency, and

- t is the time variable.

The STFT is performed by multiplying the signal $x(t)$ with a window function $\omega(t-\tau)$, shifting the window across the signal in time τ, and computing the Fourier transform of the windowed signal for each segment. This allows the identification of frequency components within small time windows, making STFT suitable for analyzing non-stationary signals with varying frequencies over time [24][25].

The spectrogram, which represents the squared magnitude of the STFT, is given by:

$$P(\tau,\omega) = |STFT\{x(t)\}(\tau,\omega)|^2$$

This spectrogram provides a two-dimensional representation of the signal's power spectrum, allowing for the identification of variations in frequency and intensity over time, which is particularly useful for detecting anomalies like leaks in hydraulic systems. The fixed window size in STFT introduces a trade-off between time and frequency resolution; narrow windows provide better time resolution but worse frequency resolution, while wider windows yield better frequency resolution but worse time resolution [10],[24],[25] ,[27].

III.3. APPLICATION IN WATER LEAK DETECTION

The efficiency of the STFT in evaluating non-stationary signals has drawn increasing attention to its application in the localization and detection of water leaks in recent years. Because STFT can record the transient sounds generated by pipeline leaks, it is particularly useful for acoustic leak detection. This technique allows for the monitoring of underwater acoustic signals over time, enabling the identification of leakage signatures that can be further analyzed using wavelet transforms for enhanced localization in the time-frequency domain [28].

Recent studies have demonstrated the efficacy of STFT in conjunction with machine learning techniques for leak detection. For instance, the integration of STFT with convolutional neural networks has shown promise in improving signal quality and feature extraction from acoustic emissions during both normal and leak conditions. This hybrid approach not only enhances the detection capabilities but also aids in distinguishing between noise and actual leak signals, which is crucial for accurate localization [2].

Work focuses on using the STFT for spectrum analysis to identify underground water pipeline leaks. STFT, which has traditionally been used to interpret speech signals, is successful at recognizing leak signs in WDNs. To emulate real-world circumstances, a 1-inch-diameter pipeline system was built. The study uses pressure transducers to collect data. STFT is used to break the signal into successive short frames, offering insight into both frequency content and time when signal occurrences occur, but with limited precision [10].

In addition to its application in acoustic monitoring, STFT has been utilized in various methodologies aimed at improving the overall efficiency of leak detection systems. For example, the combination of STFT with other signal processing techniques, such as wavelet transforms, has been shown to yield better results in terms of leak localization accuracy.

In spite of that, the STFT is a widely used time-frequency analysis method that employs a time-shifting window to capture frequency characteristics over time. However, it has limitations when applied to non-stationary signals with varying frequencies, as its fixed window size cannot adapt to the changing nature of such signals [2],[23]. This is the rationale for using the wavelet transform, which has two varieties: CWT and DWT.

IV. CWT

IV.1. HISTORICAL BACKGROUND

A reliable technique for time-frequency analysis that may be used to examine both stationary and non-stationary data is the CWT. The goal of using time-frequency analysis, and specifically the CWT, is to record the acoustic signals' temporal evolution of spectral features. Particularly useful for differentiating between stationary processes and those that fluctuate weakly over time is this strategy. Because of its computational effectiveness and capacity to examine the behavior of background and leak-induced acoustic waves in water networks, the CWT was selected [29].

The CWT's capacity to detect non-stationary power at different frequencies throughout time is one of its main features, which makes it a useful instrument in a variety of applications, including fault diagnosis, structural health monitoring, and acoustics. It is hypothesized that leak-induced acoustic waves in the context of water leak detection are stationary, whereas weakly time-varying waves are produced by normal network conditions. Therefore, CWT is the best method for evaluating signals in systems with small temporal variations due to its rapid convergence and robust performance [29],[30]. The CWT can identify the prominent frequencies in the signals, also known as leak signatures, and determine if these frequencies are associated with periodic or ongoing oscillations in the water.

Unlike the Fourier Transform (FT), which employs infinite sinusoids and is only appropriate for stationary signals, the CWT makes use of wavelets, which are unique functions with finite duration and energy. The core component of the CWT is the "mother wavelet" function, which generates a family of "daughter wavelets" by scaling and translating. This process essentially enables the CWT to capture both the high-frequency and low-frequency components of a signal. The convolution of the input signal with functions produced by the mother wavelet is the mathematical definition of the CWT, where the behavior of the wavelet in the time and frequency domains is determined by the scaling parameter (α) and the translation parameter (b) [31],[32].

A scalogram, which shows a two-dimensional depiction of wavelet energy over time and frequency ranges, is frequently used to visualize the CWT. One noteworthy benefit of CWT is its ability to track oscillatory activity and frequency transients by utilizing a complex analytic wavelet as the mother wavelet. The ‘Morlet’ wavelet, which is renowned for its accuracy in both the time and frequency domains, is one of the most widely used wavelets for CWT. The ‘Morlet’ wavelet is a popular option for studying water network acoustic signals since studies, including those by Kumar et al., have demonstrated that it is particularly effective in leak identification and localization [29][30].

Because it can analyze signals at several frequency resolutions, CWT's multiresolution capabilities are what gives it its power. It is better than the STFT because of this feature, which offers consistent resolution at all frequencies. Leak detection systems require the identification of singularities in high-frequency signals, and the CWT is well-suited for this task due to its capacity to conduct local analysis capturing breakdown sites and discontinuities. The CWT is a useful tool for leak detection in WDNs since it can record brief pressure drops [31],[32].

The CWT is utilized in passive leak detection techniques to evaluate transient flow signals produced by fresh leaks and separate them from ambient noise and typical network circumstances. Through the isolation of high-frequency signal components linked to pressure drops, the CWT coefficients can efficiently draw attention to the existence of leaks. Furthermore, wavelet transforms and mother wavelet selection advancements further boost the method's capacity to extract leakage characteristics [30].

IV.2. MATHEMATICAL EQUATION

CWT is defined as the convolution of a signal with a set of scaled and translated versions of a mother wavelet function. The general mathematical expression for the CWT of a signal $x(t)$ is given by:

$$W_{\psi}(a,b) = \int_{-\infty}^{\infty} x(t)\frac{1}{\sqrt{|a|}}\psi^{*}\left(\frac{t-b}{a}\right)\,dt$$

- $W_{\psi}(a,b)$ represents the wavelet coefficient at scale a and translation b.

- $x(t)$ is the input signal.

- $\psi(t)$ is the mother wavelet function, which is scaled by a and translated by b.

- a is the scale parameter, controlling the dilation (compression or stretching) of the wavelet.

- b is the translation parameter, determining the location in time where the wavelet is centered.

- ψ^{*} the complex conjugate of the mother wavelet function.

- The factor $\frac{1}{\sqrt{|a|}}$ ensures that the wavelet is normalized across different scales.

This equation enables the decomposition of the signal $x(t)$ into different frequency components by adjusting the scale parameter a, with each wavelet coefficient $W_{\psi}(a,b)$ providing information about the signal's frequency content at a specific time b [29],[30],[31],[32].

IV.3. APPLICATION IN WATER LEAK DETECTION

The CWT has established itself as a vital tool for detecting and localizing water leaks, primarily because of its effectiveness in analyzing transient signals in a time-frequency context. This capability is essential for identifying the acoustic emissions associated with leaks in pipelines, as these emissions typically exhibit non-stationary patterns. CWT enables the decomposition of signals into wavelet coefficients, effectively capturing the varying frequency components of leak-related signals over time, thereby enhancing detection capabilities[3]. In recent advancements, a hybrid deep learning technique has been developed to improve pipeline leak detection by using STFT spectrograms and CWT scalograms produced from acoustic emission (AE) signals. The data is denoised with Sobel and wavelet filters, which prepare the signals for further analysis. The technique effectively extracts features from processed scalograms and spectrograms using CNN. The AE signals are divided into leak and normal situations in two steps: dimensionality reduction using Principal Component Analysis (PCA), followed by classification using t-distributed Stochastic Neighbor Embedding (t-SNE) and Artificial Neural Networks (ANN). This work focuses on real-world applications and exhibits successful leak detection by classifying signal pictures after denoising and filtering.[2]

Recent research has underscored the effectiveness of CWT in boosting the accuracy of leak detection systems. For instance, CWT has been utilized to create acoustic emission (AE) images that represent time-frequency scales, facilitating the identification of leak signatures with high-energy representations. This method not only aids in detecting leaks but also helps in pinpointing their sources by providing detailed information about the signal characteristics. The integration of CWT with deep learning techniques has further improved detection accuracy, as machine learning models can exploit the rich features extracted from CWT scalograms to distinguish between normal operational sounds and leak-induced signals [2], [3],[33].

On the other hand, research on leak detection in plastic pipes employed vibration data collected by high SNR accelerometers. The study focused on determining vibration frequency variations induced by leak events. The data were analyzed using wavelet analysis, which allowed for signal segmentation onto several spatial and temporal scales, successfully separating important information from external noise. At leak detection scales, the authors predicted interference if noise levels exceeded the flow signal. However, their results demonstrated that noise was limited at these scales, reducing its influence on the identification process and validating the resilience of wavelet analysis in this setting. [13]

Moreover, studies have demonstrated that CWT can effectively reduce signal noise, enhancing the clarity of leak detection and localization efforts Figure.3.6, where researchers analyzed non-stationary vibration signals from water pipelines using the ‘Haar’ mother CWT in conjunction with double thresholding to differentiate between leak and no-leak conditions Figure.3.7. The signals were segmented, and for each segment, a partial binary decision was made based on two thresholds determined experimentally. The final binary decision was reached using the ‘K out of L’ fusion rule. The study highlights that wavelet analysis offers the advantage of long-time intervals for better precision at low frequencies, while shorter intervals capture high-frequency components. The method also requires the use of two sensors for accurate leakage detection, with the ‘Haar’ wavelet particularly suited to detect sudden changes in the signals. [14]

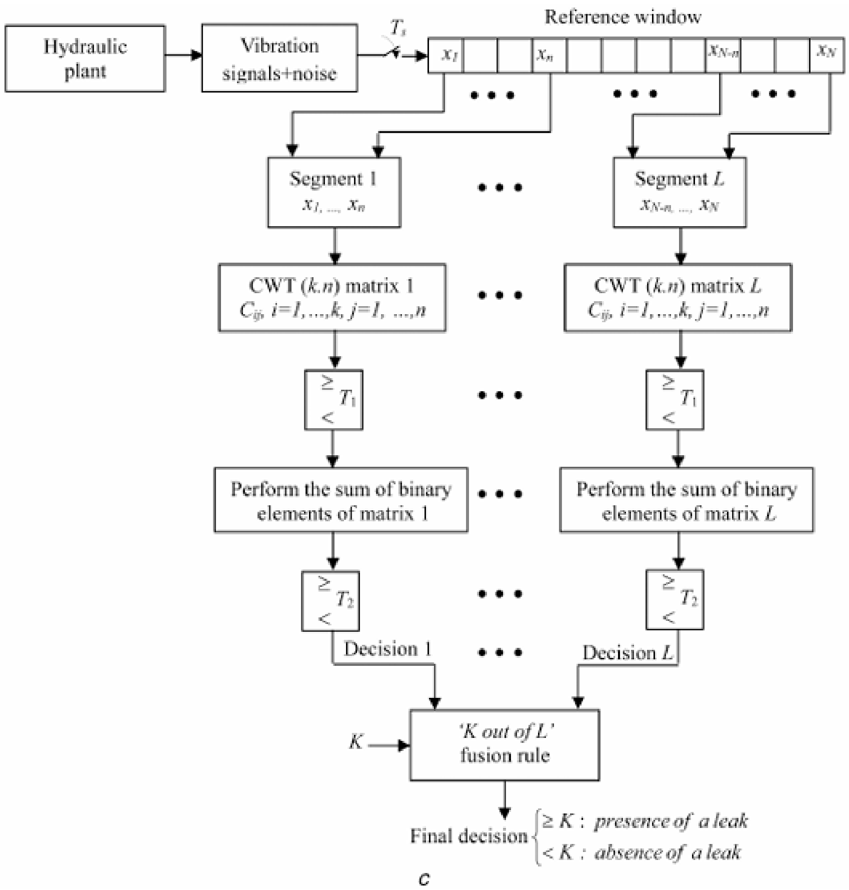

Figure.3.6 Flowchart of water leak detecting technology in pipelines. [14]

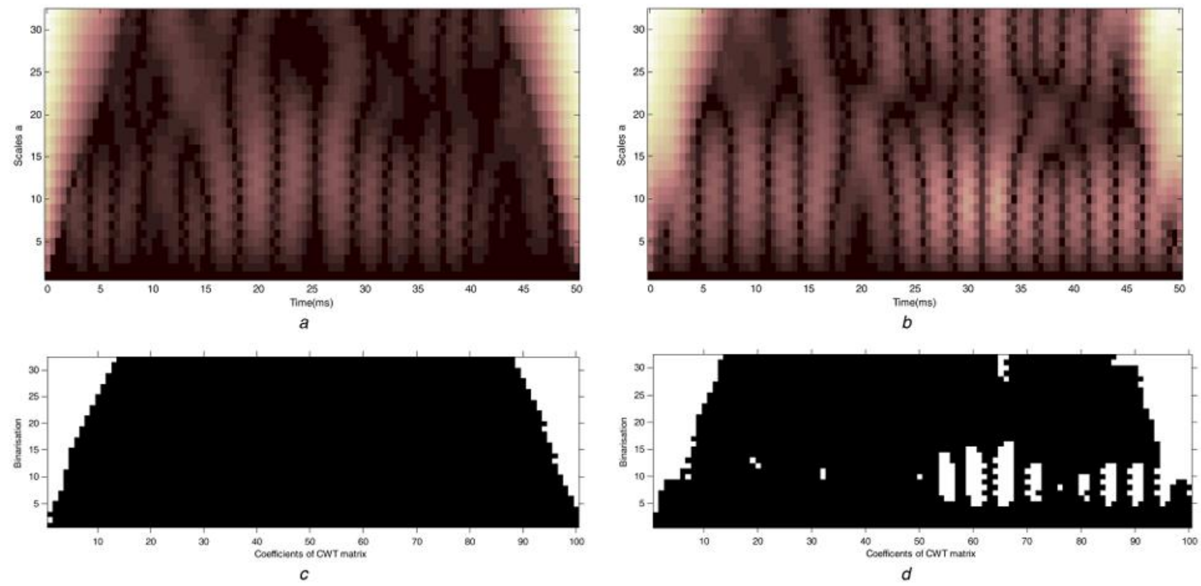

Figure.3.7 Time/scale representation and the corresponding binary matrices of segment one (a) Time/scale representation without a leak, (b) Time/scale representation with a leak at 1.6 m, (c) Binary matrix without a leak, (d) Binary matrix with a leak at 1.6 m. [14]

Another research addresses the use of wavelet transformations to differentiate transient (brief, rapid changes) and steady-state (continuous, stable) signals by identifying sharp data changes. The analysis of experimental data was done utilizing the wavelet transform (WT) in conjunction with the FFT to increase the identification of power quality. In this technique, steady-state signals were largely recognized using FFT, whereas transient disturbance signals were investigated using WT for singularity identification. The research uses the Daubechies mother wavelet for this reason. [18]

In summary, the CWT is instrumental in advancing water leak detection and localization technologies. Its ability to analyze transient signals in a time-frequency domain, coupled with its integration into machine learning frameworks, significantly improves the accuracy and reliability of leak detection systems. As water utilities continue to seek efficient methods for managing leaks, the application of CWT is likely to play an increasingly important role.

V. DWT

V.1. HISTORICAL BACKGROUND

The DWT is acknowledged as an efficient signal processing method, especially for enhancing the SNR in both stationary and non-stationary signals. It is an adaptable instrument for signal de-noising, essential for applications that need the analysis of noisy data. The DWT separates the input signal into two components low and high frequency utilizing filter banks, with the low-frequency components designated as approximation coefficients and the high-frequency components as detail coefficients [10]. The DWT serves as a discretization of the CWT, enabling efficient operation inside digital systems.

Mallat (1989) significantly enhanced the implementation of DWT using filters by introducing an efficient technique for signal decomposition utilizing a sequence of low-pass and high-pass filters at each level of decomposition. At each level, the signal is down-sampled by a factor of two, and the approximation and detail coefficients are obtained. This procedure may be replicated over several tiers, with each tier contributing to the subsequent one, incrementally enhancing the signal representation [34]. The DWT is contingent upon the noise level in the data. A single level of DWT decomposition may be enough for signals with low noise densities, whereas greater noise densities need further decomposition [31].

Wavelet de-noising includes the use of thresholding methods, such as hard and soft thresholding, to remove noise from the signal. The hard thresholding approach is more successful in decreasing noise, whereas the soft thresholding method may keep signal smoothness. Wavelet-based de-noising substantially improves signal quality, particularly in applications such as wireless sensor networks, where noise is more common [34]. The DWT's multi-resolution capacity enables it to adapt to various frequency bands, offering high-resolution analysis at lower frequencies and low-resolution analysis at higher frequencies [32].

The multi-resolution analysis (MRA) employed in DWT comprises putting a signal through a high-pass filter G and a low-pass filter H, followed by down-sampling to obtain approximation and detail coefficients. This process is depicted in a two-level wavelet decomposition tree, where the original signal is successively decomposed into coarser approximations and finer details at each level. The reconstruction step of the DWT comprises up-sampling and filtering of the deconstructed components to recover the original signal without losing substantial information [32]. Although flawless reconstruction is sometimes not achievable owing to noise interference, the DWT offers a very effective technique for decreasing noise and enhancing signal quality.

In image processing, DWT is especially beneficial for lowering the computing burden by concentrating exclusively on the changes between successive resolutions of the signal. This dyadic scaling mechanism allows DWT to work effectively, storing just the needed information for signal reconstruction. The signal is successively deconstructed via several filter banks, with low-pass filters collecting the coarse information and high-pass filters recording the finer features. This iterative breakdown continues until the necessary resolution is obtained. Finally, the DWT is computationally efficient and well-suited for applications needing data compression or noise reduction. However, this efficiency comes at the expense of missing certain finer details, particularly when the purpose is to study the underlying data for hidden information. Overall, the DWT offers a strong technique for signal analysis, balancing efficiency, and accuracy in varied applications such as biological signal processing, picture compression, and water leak detection [9],[27].

V.2. MATHEMATICAL EQUATION

The mathematical equation of the DWT is derived from the discretization of the CWT, which entails scaling and translating the mother wavelet to evaluate a signal at multiple frequencies and resolutions. The DWT is stated as follows:

$$DWT_{m,c} = \sum_{n=0}^{N-1} x(n)\psi^{*}\left(\frac{n-2^{m}c}{2^{m}}\right)$$

- $DWT_{m,c}$ represents the wavelet coefficients for the discrete scale m and translation c values.

- $x(n)$ is the discrete input signal.

- ψ signifies the mother wavelet, which is scaled and shifted for various m and c.

- m is the scale parameter setting the resolution level.

- c is the translation parameter that governs the location of the wavelet in time.

- N is the total number of samples in the signal.

- ψ^{*} is the complex conjugate of the mother wavelet function.

- The component 2^{m} refers to the dyadic scaling, indicating that the mother wavelet is compressed or stretched by powers of two [10],[34].

This equation specifies how the signal is divided into approximation and detail coefficients at various resolution settings. Each coefficient correlates to unique time-frequency content, offering a multi-resolution analysis that is crucial for signal processing tasks like denoising and feature extraction in water leak detection [32].

V.3. APPLICATION IN WATER LEAK DETECTION

The use of DWT in water leak detection and localization has attracted substantial interest owing to its capacity to evaluate signals in both time and frequency domains. DWT is especially good in spotting transitory signals, such as those caused by leaks in water distribution systems. By dividing signals into distinct frequency components, DWT allows the identification of abnormalities that indicate the existence of leaks.

One noteworthy work by Liang et al. stresses the combination of predictive analytics and intelligent sensing to detect high-risk regions in water mains before breakdowns occur. Their technique leverages DWT to evaluate data from smart sensors, which optimizes the priority of investigations in sensitive zones of the water network [35]. This proactive technique not only assists in leak detection but also improves the location of sensors, hence boosting overall system efficiency. Another similar research investigates the use of pressure waves generated by the fast opening and closing of a solenoid valve for leak detection. A pressure transducer is utilized to gather these transient signals, which are then processed using the DWT to eliminate DC offsets and unwanted low and high frequencies. The study discovers leaks by monitoring the time difference between the initial pressure pulse and its reflection. The appearance of additional peaks in the signal indicates the existence of a leak. Experiments were conducted with different leak sizes, and the results showed that the amplitude of the processed peak increased according to the cube root of the leak diameter. [19]

Moreover, a study indicates the usefulness of vibration measurements in leak identification inside underground plastic pipes. Their experimental studies revealed that monitoring vibrations may effectively locate leaks, provided that external water flow does not interfere with the data. The introduction of DWT in this context allows for the extraction of significant characteristics from the vibration signals, boosting the detection capabilities [4]. This correlates with the results of [36], who stress the usefulness of advanced metering infrastructure (AMI) in monitoring water consumption and discovering leaks using data analytics. Their work reveals that DWT may be applied to examine consumption patterns, resulting to timely notifications for suspected breaches.

In addition to these applications, the use of DWT in combination with other approaches has been studied. For instance, scientists explore the employment of ground microphones and noise recorders in combination with DWT for identifying leak sites following initial leak identification by step testing. This combination of technologies guarantees that repairs may be handled successfully, decreasing water loss in distribution networks [37]. Furthermore, the ability of DWT to provide time-frequency information makes it a valuable tool for analyzing acoustic signals related to leaks, as demonstrated in the study by [38], which employed DWT alongside Support Vector Machine techniques for gas pipeline leak detection.

Overall, the synthesis of these investigations demonstrates that DWT acts as a significant analytical tool in the area of water leak identification and localization. Its flexibility to deconstruct signals into numerous frequency components enables for the detection of small changes indicative of leakage, hence boosting the reliability and efficiency of water distribution systems.

VI. CORRELATION TECHNIQUE IN WATER LEAK DETECTION

VI.1. OVERVIEW

The correlation approach is a widely established method for leak detection and localization in water distribution systems. This approach largely depends on the study of acoustic signals created by leaks, which may be detected by strategically positioned sensors along the pipeline. The primary premise underlying correlation approaches is to detect the temporal difference in the arrival of these acoustic signals at two or more sensors, which may then be used to determine the leak's location.

One of the primary benefits of the correlation approach is its ability to employ several pressure sensors to boost detection accuracy. Research notes that by adopting a time-series-based approach with numerous sensors, the correlation between data points across time can be fully harnessed, resulting in enhanced leak detection performance compared to typical single-time model-based techniques. This multi-sensor technique allows for a more extensive examination of the pressure variations that occur due to leaks, hence boosting the reliability of the detection procedure[39].

The efficiency of the correlation approach is further confirmed by a work, who underline the necessity of precisely measuring temporal delays in acoustic signals for successful leak identification. They propose that correlation approaches give optimum time delay estimators, which are critical for recognizing different peaks in cross-correlation functions that signal the existence of a leak. This is especially crucial in cases where the acoustic signals may be impacted by multiple ambient conditions, making exact time delay estimates vital for correct localization[40].

Additionally, study reveals that although correlation approaches have demonstrated excellent results in metal pipes, their performance might be more varied in plastic pipes owing to changes in acoustic qualities [41]. This constraint demands the development of more precise correlation techniques that can adjust to the individual properties of various pipe materials. Further emphasize that despite the obstacles faced by complex settings, correlation techniques remain a popular option in the water business owing to their simplicity and high accuracy[42].

The cross-correlation method, a specific implementation of the correlation technique, has been extensively studied for its application in leak localization. Authors discuss how this approach exploits the time lag between acoustic signals recorded by two sensors to infer the leak's location. This technique has been tested in many experiments, proving its capabilities to reliably detect leak sites based on the study of acoustic wave propagation and the temporal variations in signal arrival[43].

Moreover, the combination of sophisticated signal processing techniques, such as empirical mode decomposition (EMD) and adaptive independent component analysis (ICA), with correlation approaches has shown promise in boosting leak detection capabilities. For instance, a work describes a hybrid EMD-correlation strategy that efficiently identifies and localizes leaks by first denoising the recorded signals and then performing correlation analysis [6]. This combination of approaches provides for enhanced signal clarity and more precise leak location.

The correlation methodology is a stable and effective method for leak detection and localization in water distribution systems. Its dependence on acoustic signal analysis, along with developments in sensor technology and signal processing methodologies, continues to expand its application and accuracy in varied pipeline materials and environmental situations.

VI.2. COMBINATION BETWEEN CORRELATION TECHNIQUE and FFT, STFT, CWT, and DWT

In the field of DSP, correlation approaches are critical for evaluating and interpreting information. Among the methods used, the FFT, STFT, CWT, and DWT are especially noteworthy. Each of these approaches has distinct qualities that make them appropriate for a variety of applications, particularly correlation analysis. The FFT is a popular technique for calculating the discrete Fourier transform (DFT) and its inverse. It is especially useful for stationary signals, which have a constant frequency content across time. FFT gives a global frequency representation, which is useful for evaluating periodic signals. However, it does not give time-localized frequency information, which might be a drawback in non-stationary signal analysis [44]. FFT has been used to evaluate vibration signals in applications such as fault diagnostics in induction motors, proving its ability to identify particular problem features. Nonetheless, its inability to handle time-varying inputs has prompted academics to investigate more sophisticated approaches[45].

The STFT overcomes the restrictions of the FFT by using a windowing approach that enables frequency components to be localized across time. This technique is especially beneficial in situations where signal properties vary over time, such as voice processing and biological signal analysis [46]. The STFT has been compared to other correlation approaches, such as Canonical Correlation Analysis (CCA), demonstrating that, although STFT is simpler, CCA may provide more insightful findings without needing much training [47]. Furthermore, the STFT has been used in a variety of applications, including speech enhancement and fetal heart rate signal analysis, where its capacity to capture temporal dynamics is critical [26][48].

The CWT is a more adaptable technique for time-frequency analysis because it uses wavelets that can adapt to the signal's properties. CWT, unlike STFT, has variable window sizes, allowing for improved resolution in both the temporal and frequency domains. Because of its versatility, CWT is especially useful for evaluating non-stationary data since it may catch fleeting aspects that other approaches may overlook. For example, while examining soil spectral reflectance, CWT has been demonstrated to correlate strongly with numerous soil parameters, giving a strong framework for environmental monitoring. Furthermore, CWT has been effectively employed in defect diagnostic situations, exhibiting the capacity to extract significant characteristics from complicated signals [49], [50],[51].

Another significant tool in the wavelet analysis family is the DWT, which allows for multi-resolution signal analysis. DWT is especially useful for applications that need data compression and noise reduction because it can successfully separate signal components at various scales. In correlation analysis, DWT has been used to improve the performance of various signal processing applications, including flaw identification in machinery and biological signal analysis. Its capacity to break down signals into multiple frequency bands enables a more sophisticated understanding of the underlying processes, making it an invaluable tool in engineering and scientific studies. We will provide more in-depth explanations and detailed applications of the cross-correlation technique and DWT[52],[53].

VII. CONCLUSION

In conclusion, the correlation approaches of FFT, STFT, CWT, and DWT each have unique benefits and disadvantages. FFT is useful for stationary signals, but it lacks temporal localization. STFT improves on this by including time-frequency information, while CWT and DWT provide more flexibility and resolution for non-stationary signals. The approach used is ultimately determined by the precise properties of the signal being examined as well as the study's aims.

References

[1] A. Lay-Ekuakille, C. Pariset, and A. Trotta, “Leak detection of complex pipelines based on the filter diagonalization method: Robust technique for eigenvalue assessment,” *Meas. Sci. Technol.*, vol. 21, no. 11, 2010, doi: 10.1088/0957-0233/21/11/115403.

[2] M. F. Siddique, Z. Ahmad, N. Ullah, and J. Kim, “A Hybrid Deep Learning Approach: Integrating Short-Time Fourier Transform and Continuous Wavelet Transform for Improved Pipeline Leak Detection,” *Sensors*, vol. 23, no. 19, 2023, doi: 10.3390/s23198079.

[3] S. Ahmad, Z. Ahmad, C. H. Kim, and J. M. Kim, “A Method for Pipeline Leak Detection Based on Acoustic Imaging and Deep Learning,” *Sensors*, vol. 22, no. 4, 2022, doi: 10.3390/s22041562.

[4] A. Martini, M. Troncossi, and A. Rivola, “Automatic Leak Detection in Buried Plastic Pipes of Water Supply Networks by Means of Vibration Measurements,” *Shock Vib.*, vol. 2015, pp. 11–15, 2015, doi: 10.1155/2015/165304.

[5] R. B. Santos, W. S. De Almeida, F. V. Da Silva, S. L. Da Cruz, and A. M. F. Fileti, “Spectral analysis for detection of leaks in pipes carrying compressed air,” *Chem. Eng. Trans.*, vol. 32, pp. 1363–1368, 2013, doi: 10.3303/CET1332228.

[6] H. Bakhti, M. Bentoumi, A. Harrag, and K. El-Hadi, “Experimental validation of hybrid EMD-correlation acoustic digital leaks detector in water distribution network system,” *Instrum. Mes. Metrol.*, vol. 18, no. 6, pp. 535–545, 2019, doi: 10.18280/i2m.180604.

[7] B. Bakhtawar, A. Fares, and T. Zayed, “AI-based smart water leak detection using hydrophones,” *Res. Sq.*, 2022, doi: 10.21203/rs.3.rs-2149154/v1.

[8] R. Vanijjirattikhan *et al.*, “AI-based acoustic leak detection in water distribution systems,” *Results Eng.*, vol. 15, Sep. 2022, doi: 10.1016/j.rineng.2022.100557.

[9] A. Kourgli, *Traitement Numérique du Signal: Notes de cours*, Master 1 Systèmes de Télécommunications, Univ. des Sciences et de la Technologie Houari Boumediene (USTHB), Algiers, Algeria, 2020, doi: 10.13140/RG.2.1.2991.6000.

[10] A. Lay-Ekuakille, G. Vendramin, A. Trotta, and P. Vanderbemden, “STFT-based spectral analysis of urban waterworks leakage detection,” *19th IMEKO World Congr. 2009*, vol. 2, pp. 674–678, ISBN 978-963-88410-0-1,2009.

[11] A. Lay-Ekuakille, A. Trotta and G. Vendramin, "FFT- based spectral response for smaller pipeline leak detection," 2009 IEEE Instrumentation and Measurement Technology Conference, Singapore, 2009, pp. 328-331, doi:10.1109/IMTC.2009.5168469.

[12] A. Lay-Ekuakille, A. Trotta, G. Vendramin, and P. Vanderbemdem, "FFT-based algorithm improvements for detecting leakage in pipelines," *2009 6th Int. Multi-Conference Syst. Signals Devices, SSD 2009*, pp. 3–6, 2009, doi: 10.1109/SSD.2009.4956691.

[13] K. Marmarokopos, D. Doukakis, G. Frantziskonis, and M. Avlonitis, "Leak detection in plastic water supply pipes with a high signal-to-noise ratio accelerometer," *Meas. Control (United Kingdom)*, vol. 51, no. 1–2, pp. 27–37, 2018, doi: 10.1177/0020294018758526.

[14] M. Bentoumi, D. Chikouche, A. Mezache, and H. Bakhti, "Wavelet DT method for water leak-detection using a vibration sensor: An experimental analysis," *IET Signal Process.*, vol. 11, no. 4, pp. 396–405, 2017, doi: 10.1049/iet-spr.2016.0113.

[15] M. F. Ghazali, S. B. M. Beck, J. D. Shucksmith, J. B. Boxall, and W. J. Staszewski, "Comparative study of instantaneous frequency based methods for leak detection in pipeline networks," in *Mechanical Systems and Signal Processing*, 2012, vol. 29, pp. 187–200. doi: 10.1016/j.ymssp.2011.10.011.

[16] M. U. R. A. Virk, M. F. Mysorewala, L. Cheded, and I. M. Ali, "Leak detection using flow-induced vibrations in pressurized wall-mounted water pipelines," *IEEE Access*, vol. 8, pp. 188673–188687, 2020, doi: 10.1109/ACCESS.2020.3032319.

[17] S. Theodoridis *et al.*, *Time-Frequency Signal Analysis and Processing: A Comprehensive Reference*. 2015. doi: 10.1016/B978-0-12-398499-9.09983-0.

[18] Y. Q. Peng, F. Wang, J. Zhang, J. Li, and D. M. Zhang, "Research of a new power quality detection system based on ARM," *Appl. Mech. Mater.*, vol. 568–570, pp. 1825–1833, 2014, doi: 10.4028/www.scientific.net/AMM.568-570.1825.

[19] M. Taghvaei, S. B. M. Beck, and W. J. Staszewski, "Leak detection in pipelines using cepstrum analysis," *Meas. Sci. Technol.*, vol. 17, no. 2, pp. 367–372, 2006, doi: 10.1088/0957-0233/17/2/018.

[20] H. Hosseini Giv, "Directional short-time Fourier transform," *J. Math. Anal. Appl.*, vol. 399, no. 1, pp. 100–107, 2013, doi: 10.1016/j.jmaa.2012.09.053.

[21] S. Atanasova, S. Maksimović, and S. Pilipović, "Directional Short-Time Fourier Transform of Ultradistributions," *Bull. Malaysian Math. Sci. Soc.*, vol. 44, no. 5, pp. 3069–3087, 2021, doi: 10.1007/s40840-021-01093-z.

[22] S. Atanasova, S. Pilipovic, and K. Saneva, "Directional short-time Fourier transform and directional regularity," pp. 1–14, 2017, [Online]. Available: http://arxiv.org/abs/1707.02831

[23] L. Zhao, Z. Cao, and J. Deng, "A review of leak detection methods based on pressure waves in gas pipelines," *Meas. J. Int. Meas. Confed.*, vol. 236, p. 115062, 2024, doi: 10.1016/j.measurement.2024.115062.

[24] R. Patil, "Noise Reduction using Wavelet Transform and Singular Vector Decomposition," *Procedia Comput. Sci.*, vol. 54, pp. 849–853, 2015, doi: 10.1016/j.procs.2015.06.099.

[25] Ç. P. Dautov and M. S. Özerdem, "Introduction to Wavelets and their applications in signal denoising," *Bitlis Eren Univ. J. Sci. Technol.*, vol. 8, no. 1, pp. 1–10, Jun. 2018, doi: 10.17678/beuscitech.349020.

[26] K. Sivasankari and K. Thanushkodi, "An improved EEG signal classification using Neural Network with the consequence of ICA and STFT," *J. Electr. Eng. Technol.*, vol. 9, no. 3, pp. 1060–1071, 2014, doi: 10.5370/JEET.2014.9.3.1060.

[27] E. O. Ladino-Moreno and C. A. García-Ubaque, "Leak Detection in Urban Hydraulic Systems Using the K-BiLSTM-Monte Carlo Dropout Model," *Civ. Eng. J.*, vol. 10, no. 7, pp. 2066–2087, 2024, doi: 10.28991/CEJ-2024-010-07-01.

[28] D. Kumar, D. Tu, N. Zhu, R. A. Shah, D. Hou, and H. Zhang, "The free-swimming device leakage detection in plastic water-filled pipes through tuning the wavelet transform to the underwater acoustic signals," *Water (Switzerland)*, vol. 9, no. 10, 2017, doi: 10.3390/w9100731.

[29] K. Sitaropoulos, S. Salamone, and L. Sela, "Frequency-based leak signature investigation using acoustic sensors in urban water distribution networks," *Adv. Eng. Informatics*, vol. 55, Jan. 2023, doi: 10.1016/j.aei.2023.101905.

[30] X. Wu, S. Peng, G. Zheng, X. Fang, and Y. Tian, "Leakage Detection in Water Distribution Networks Based on Multi-Feature Extraction from High-Frequency Pressure Data," *Water (Switzerland)*, vol. 15, no. 6, 2023, doi: 10.3390/w15061187.

[31] S. Rashid, S. Qaisar, H. Saeed, and E. Felemban, "A Method for Distributed Pipeline Burst and Leakage Detection in Wireless Sensor Networks Using Transform Analysis," *Int. J. Distrib. Sens. Networks*, vol. 2014, 2014, doi: 10.1155/2014/939657.

[32] R. Aggarwal, J. Karan Singh, V. Kumar Gupta, S. Rathore, M. Tiwari, and A. Khare, "Noise Reduction of Speech Signal using Wavelet Transform with Modified Universal Threshold," *Int. J. Comput. Appl.*, vol. 20, no. 5, pp. 14–19, Apr. 2011, doi: 10.5120/2431-3269.

[33] M. F. Siddique, Z. Ahmad, N. Ullah, S. Ullah, and J. M. Kim, "Pipeline Leak Detection: A Comprehensive Deep Learning Model Using CWT Image Analysis and an Optimized DBN-GA-LSSVM Framework," *Sensors*, vol. 24, no. 12, 2024, doi: 10.3390/s24124009.

[34] I. A. Tijani, S. Abdelmageed, A. Fares, K. H. Fan, Z. Y. Hu, and T. Zayed, "Improving the leak detection efficiency in water distribution networks using noise loggers," *Sci. Total Environ.*, vol. 821, 2022, doi: 10.1016/j.scitotenv.2022.153530.

[35] B. Liang *et al.*, "A Data Driven Approach for Leak Detection with Smart Sensors," *2020 16th International Conference on Control, Automation, Robotics and Vision (ICARCV)*, Shenzhen, China, 2020, pp. 1311-1316, doi: 10.1109/ICARCV50220.2020.9305403.

[36] W. Schultz, S. Javey, and A. Sorokina, "Smart Water Meters and Data Analytics Decrease Wasted Water Due to Leaks," *J. Am. Water Works Assoc.*, vol. 110, no. 11, pp. E24–E30, 2018, doi: 10.1002/awwa.1124.

[37] E. Azwar, D. S. Irawan, and M. Naufal, "Study of Physical Water Loss in Water Distribution Network using Step Test Method and Pressure Calibration," *Reka Buana J. Ilm. Tek. Sipil dan Tek. Kim.*, vol. 6, no. 1, pp. 88–103, 2021, doi: 10.33366/rekabuana.v6i1.2293.

[38] R. Xiao, Q. Hu, and J. Li, "Leak detection of gas pipelines using acoustic signals based on wavelet transform and Support Vector Machine," *Meas. J. Int. Meas. Confed.*, vol. 146, pp. 479–489, 2019, doi: 10.1016/j.measurement.2019.06.050.

[39] Y. Shao, X. Li, T. Zhang, S. Chu, and X. Liu, "Time-series-based leakage detection using multiple pressure sensors in water distribution systems," *Sensors (Switzerland)*, vol. 19, no. 14, 2019, doi: 10.3390/s19143070.

[40] Y. Ma, Y. Gao, X. Cui, M. J. Brennan, F. C. L. Almeida, and J. Yang, "Adaptive phase transform method for pipeline leakage detection," *Sensors (Switzerland)*, vol. 19, no. 2, 2019, doi: 10.3390/s19020310.

[41] Y. Gao, M. J Brennan, and P.F Joseph, "Cross-Correlation For Leak Detection In Buried Plastic Water Pipes," Journal of Sound and Vibration, vol. 26, pp. 127–138, 2004.

[42] S. Na, J. Liu, Q. Li, Y. Liu, and Y. Tie, "An adaptive method for water pipeline leak localization," Advances in Engineering Research,vol. 173, Wartia, pp. 146–153, 2018, doi: 10.2991/wartia-18.2018.24.

[43] G. Liu, J. Liu, W. Ji, and S. Liu, "Research on pipeline leakage identification method based on lyapunov exponent spectrum," *Vibroengineering Procedia*, vol. 23, pp. 61–65, 2019, doi: 10.21595/vp.2019.20701.

[44] G. Pan, S. Li, and Y. Zhu, "A time-frequency correlation analysis method of time series decomposition derived from synchrosqueezed S transform," *Appl. Sci.*, vol. 9, no. 4, 2019, doi: 10.3390/app9040777.

[45] Z. Wang, J. Yang, H. Li, D. Zhen, Y. Xu, and F. Gu, "Fault identification of broken rotor bars in induction motors using an improved cyclic modulation spectral analysis," *Energies*, vol. 12, no. 17, 2019, doi: 10.3390/en12173279.

[46] L. Mondada, M. E. Karim, and F. Mondada, "Electroencephalography as implicit communication channel for proximal interaction between humans and robot swarms," *Swarm Intell.*, vol. 10, pp. 247–265, 2016, doi: 10.1007/s11721-016-0127-0.

[47] G. Averbuch, "The spectrogram, method of reassignment, and frequency-domain beamforming," *J. Acoust. Soc. Am.*, vol. 149, no. 2, pp. 747–757, 2021, doi: 10.1121/10.0003384.

[48] A. M. Ponsiglione , C. Cosentino, G. Cesarelli, F. Amato, and M. Romano, "A Comprehensive Review of Techniques for Processing and Analyzing Fetal Heart Rate Signals," *Sensors*, vol. 21, no. 6136, pp. 1–31, 2021, https://doi.org/10.3390/s21186136.

[49] J. A. Schulte, "Statistical hypothesis testing in wavelet analysis: theoretical

developments and applications to Indian rainfall," *Nonlinear Process. Geophys.*, vol. 26, no. 2, pp. 91–108, 2019, doi: 10.5194/npg-26-91-2019.

[50] B. Guo *et al.*, "Retrieving zinc concentrations in topsoil with reflectance spectroscopy at Opencast Coal Mine sites," *Sci. Rep.*, vol. 11, no. 1, pp. 1–20, 2021, doi: 10.1038/s41598-021-99106-1.

[51] D. Zhen, Z. Wang, H. Li, H. Zhang, J. Yang, and F. Gu, "An improved cyclic modulation spectral analysis based on the CWT and its application on broken rotor bar fault diagnosis for induction motors," *Appl. Sci.*, vol. 9, no. 18, 2019, doi: 10.3390/app9183902.

[52] H. Cai, C. Xu, S. Zhou, H. Yan, and L. Yang, "Study on the thick-walled pipe ultrasonic signal enhancement of modified s-transform and singular value decomposition," *Math. Probl. Eng.*, vol. 2015, 2015, doi: 10.1155/2015/312620.

[53] O. Yüce, U. Aslan, C. Hanilçi, E. Korkmaz, O. A. İsen, and E. Cantez, "Fault Diagnosis: Spectral Analysis of the Vibration Signals in Transfer Press," *Acad. Perspect. Procedia*, vol. 3, no. 1, pp. 1–9, 2020, doi: 10.33793/acperpro.03.01.7.

Chapter04

Research Methodology

I. INTRODUCTION

This chapter outlines the methodologies developed in this thesis to address the challenges of water leak detection and localization in WDNs. The proposed approaches combine mathematical modeling, advanced signal processing techniques, and optimization algorithms to provide comprehensive solutions. The chapter is structured around three independent contributions, each focusing on a distinct aspect of leak detection.

The first approach involves the development of a mathematical model based on the principles of fluid mechanics, enhanced through the optimization of critical parameters using the BBO method. BBO, an evolutionary algorithm introduced by Dan Simon in 2008, draws inspiration from the migration patterns of species and has proven effective in solving complex optimization problems. By optimizing parameters such as the friction factor and discharge flow through leak points, we aim to refine existing mathematical models, allowing for a generalized application across various leak scenarios and enhancing the accuracy of leak detection in WDNs [1],[2],[3],[4].

The second contribution addresses signal noise and false alarms in leak detection systems. Using a custom-built experimental setup, pressure signals were collected with two high-precision transmitters and acquired through an Arduino Due board. The collected data were denoised using the S.G filter, optimized for window size and polynomial degree. The denoising process was evaluated by calculating the SNR, ensuring improved data quality. Leak localization was achieved by computing the time difference in signal arrivals at the transmitters, which was incorporated into a mathematical equation to pinpoint the leak [5],[6],[7]. The experimental prototype consisted of a zigzag-shaped WDN using high-density polyethylene (HDPE) pipes (26 m length, 40 mm diameter), a water tank, and an electric pump, facilitating the implementation of this approach. Validation tests are conducted to corroborate the leak positions, leveraging the known distances between the sensors and the simulated leak points.

The third contribution further advances leak detection with a more refined setup and additional experimental conditions. A larger prototype with circular shape was constructed using 100 m of HDPE pipe (40 mm diameter) with the same pressure transmitters but paired with a high-precision Miclobaox Dspace unit for data acquisition. Four different leak sizes (4 mm, 6 mm, 8 mm, and 12 mm) were tested at varying distances to validate the approach. The collected pressure data were processed using discrete wavelet transform (DWT) for decomposition, followed by Donoho thresholding to remove noise while retaining useful information. The reconstructed signals, processed through inverse discreet wavelet transform (IDWT), were analyzed for signal quality using SNR, NCC, and MSE. The time difference in signal arrival, calculated through a normalized cross-correlation technique, was included in a mathematical equation to accurately localize leaks. This approach demonstrated high precision in validation tests, confirming its robustness across varying leak sizes and distances.

In summary, this chapter presents a comprehensive exploration of innovative leak detection techniques for WDNs, combining evolutionary optimization, mathematical modeling, and advanced signal processing. By addressing the persistent challenges of signal quality and ambient noise, these methodologies contribute to reducing water losses, enhancing WDN integrity, and promoting sustainable water management practices.

II. Part 1: Mathematical Modeling and Parameter Optimization

II.1. Fluid Mechanics in Leak Detection Modeling

II.1.a. Definition of Mathematical model

This section will present the component equations of the thoughtful mathematical model. It is largely concerned with the basic concepts of fluid mechanics, which serve as the theoretical framework for understanding the behavior of water flow in distribution networks. Using these rules, the technique creates a strong foundation for modeling and studying the dynamics of fluid flow, pressure fluctuations, and leak-induced disturbances in pipeline systems. This method not only emphasizes the significance of fluid mechanics in understanding the complex interactions inside WDNs, but it also makes it easier to create precise and reliable leak detection and localization algorithms. Figure.4.1. depicts the process, demonstrating how these concepts and equations work together to solve the complexity of leak detection and localization[8]. The horizontal line represents the pipe with leak, while the inclined line shows the Energy Grade Line (EGL) for a leaky pipe. By analyzing pressure head, velocity head, and flow rate variations, we can detect and locate leaks. The key idea is that a leak causes a pressure drop and flow imbalance, which we quantify using Bernoulli's and continuity equations. This approach lays the foundation for accurate leak localization in real-world pipeline systems.

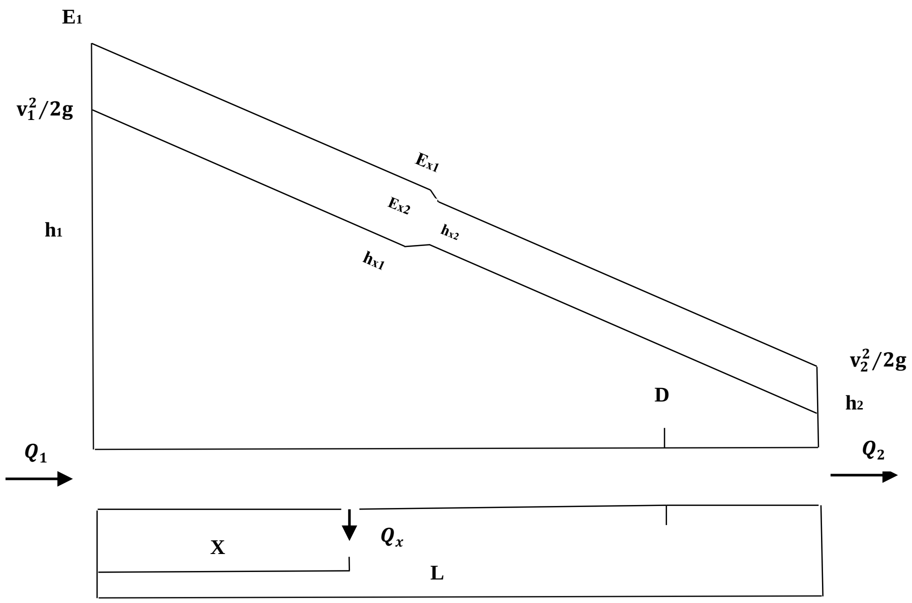

Figure.4.1. The flow scenario under discussion [8].

Q_1 **:** The inlet discharge into the pipe.

$\boldsymbol{h_1}$ **:** the static head in the intake portion.

$\boldsymbol{Q_2}$ **:** the discharge exiting the pipe.

$\boldsymbol{h_2}$ **:** the static head on the outlet.

$\boldsymbol{Q_x}$ **:** the discharge issuing from the orifice.

$\boldsymbol{g}$ **:** Gravitational Acceleration.

$\boldsymbol{v}$ **:** Velocity of the fluid.

$\boldsymbol{h_{x2}}$ **:** The static head is immediately downstream of the orifice site.

$\boldsymbol{h_{x2}}$ **:** The static head is immediately downstream of the orifice site.

$(\boldsymbol{c_d A_x})^*$: The effective flow area through the hole is calculated by multiplying the hole's real area $\boldsymbol{A_x}$ by its discharge coefficient, $\boldsymbol{c_d}$).

X: The leak location as measured from the intake section.

The equation of the energy per unit weight is the following

$$E_i = h_i + v_i^2/2g \tag{1}$$

Obviously, we need to know nine factors in order to determine the precise position of the leak site using the mathematical model. However, measuring the discharge and pressure at the pipe's intake and output requires five equations to solve the issue.

Continuity equation:

$$Q_1 - Q_2 = Q_x \tag{2}$$

The friction losses in the segment of pipe of length X, upstream from the hole, may be represented in the form

$$h_1 - h_{x1} = f_1 \frac{X}{D} \frac{Q_1^2}{A^2 2g} = K_1 X Q_1^2 \tag{3}$$

The losses due to friction in the piece of pipe with a length L-X downstream from the hole may be stated in the form

$$h_{x2} - h_2 = f_2 \frac{X}{D} \frac{Q_2^2}{A^2 2g} = K_2 (L - X) Q_2^2 \tag{4}$$

The discharge through the hole is derived from the equation that describes the flow through an orifice.

$$Q_x = c_d A_x \sqrt{2gE_{x1}} \tag{5}$$

Finally, by applying the overall energy balance to the system under discussion, the total energy lost in the hole H is

$$H = Q_1 E_1 - Q_2 E_2 - Q_1 (E_1 - E_{x1}) - Q_2 (E_{x2} - E_2) \tag{6}$$

The following equation is valid for an incompressible flow and shows that the overall energy lost in the hole is equal to the overall energy in minus the sum of the overall energy out plus the overall energy lost in the part of the pipe before and after the hole. After the algebraic transformation, we obtain

$$H = Q_1 E_{x1} - Q_2 E_{x2} \tag{7}$$

When the flow spouts into the atmosphere

$$H = (Q_1 - Q_2)\, v_x^2 / 2g \tag{8}$$

Where:

$$v_x = Q_x / c_d A_x \tag{9}$$

v_x**:** is the fluid's speed as it emerges from the hole.

By replacing $\boldsymbol{v_x}$ with the discharge per unit effective flow area via the hole, we can demonstrate with ease that

$$H = C (Q_1 - Q_2)^3 \tag{10}$$

Where:

$$C = 1/2g (c_d A_x)^2 \tag{11}$$

Equating the two expressions for **H,** expressing $\boldsymbol{E_{x1}}$ and $\boldsymbol{E_{x2}}$ as static and dynamic head sums, and representing the constant $\mathbf{1/2gA^2}$ by $\boldsymbol{B}$**.**

$$B = 1/2gA^2$$

Two expressions for $\boldsymbol{E_{x1}}$ and $\boldsymbol{E_{x2}}$**:**

$$E_{x1} = h_{x1} + v_1^2/2g \tag{12}$$

$$E_{x2} = h_{x2} + v_2^2/2g \tag{13}$$

The rate of flow will be computed as follows

$$Q = V_f.A \tag{14}$$

V_f: The flow velocity (m/s) is the speed with which a fluid moves in a certain direction.

A: The cross-sectional area (m²) of the fluid-flowing pipe or channel.

One substitutes the equation (14) in (12) and (13)

$$E_{x1} = h_{x1} + Q_1^2/2gA^2$$

$$E_{x2} = h_{x2} + Q_2^2/2gA^2$$

$$E_{x1} = h_{x1} + BQ_1^2 \tag{15}$$

$$E_{x2} = h_{x2} + BQ_2^2 \tag{16}$$

Multiply equations (15) and (16)in $\boldsymbol{Q_1}$and $\boldsymbol{Q_2}$respectively

$$Q_1E_{x1} = Q_1h_{x1} + BQ_1Q_1^2 \tag{17}$$

$$Q_2E_{x2} = Q_2h_{x2} + BQ_2Q_2^2 \tag{18}$$

(17) Minus (18) **:**

$$Q_1E_{x1} - Q_2E_{x2} = Q_1(h_{x1} + BQ_1^2) - Q_2(h_{x2} + BQ_2^2)$$

$$= Q_1h_{x1} + Q_1BQ_1^2 - Q_2h_{x2} - Q_2BQ_2^2$$

$$= Q_1h_{x1} - Q_2h_{x2} + B(Q_1^3 - Q_2^3)$$

$$= Q_1h_{x1} - Q_2h_{x2} + (Q_1 - Q_2)B(Q_1^2 + Q_2^2 + Q_1Q_2)$$

$$= Q_1h_{x1} - Q_2h_{x2} + (Q_1 - Q_2)(BQ_1^2 + BQ_2^2 + BQ_1Q_2) \tag{19}$$

Equality between the two equations (10)and (19) we get:

$$Q_1h_{x1} - Q_2h_{x2} + (Q_1 - Q_2)(BQ_1^2 + BQ_2^2 + BQ_1Q_2) = C(Q_1 - Q_2)^3$$

$$Q_1 h_{x1} - Q_2 h_{x2} = C(Q_1 - Q_2)(Q_1 - Q_2)^2 - (Q_1 - Q_2)(BQ_1^2 + BQ_2^2 + BQ_1Q_2)$$

$$= (Q_1 - Q_2)[C(Q_1^2 + Q_2^2 - 2Q_1Q_2) - BQ_1^2 - BQ_2^2 - BQ_1Q_2]$$

$$= (Q_1 - Q_2)[CQ_1^2 + CQ_2^2 - 2CQ_1Q_2 - BQ_1^2 - BQ_2^2 - BQ_1Q_2]$$

$$= (Q_1 - Q_2)[(C - B)Q_1^2 - (2C + B)Q_1Q_2 + (C - B)Q_2^2]$$

$$= \lambda(Q_1 - Q_2)$$

One gets:

$$Q_1 h_{x1} - Q_2 hx_2 = (Q_1 - Q_2)[(C - B)Q_1^2 - (2C + B)Q_1Q_2 + (C - B)Q_2^2] = \lambda(Q_1 - Q_2) \tag{20}$$

$$\lambda = (C - B)Q_1^2 - (2C + B)Q_1Q_2 + (C - B)Q_2^2$$

Through (3) and (4) we conclude

$$h_{x1} = h_1 - K_1 X Q_1^2 \tag{21}$$

$$h_{x2} = h_2 + K_2(L - X)Q_2^2 \tag{22}$$

Multiply equations (21) and (22)in $\boldsymbol{Q_1}$and $\boldsymbol{Q_2}$respectively:

$$h_{x1}Q_1 = h_1Q_1 - K_1XQ_1Q_1^2 \tag{23}$$

$$h_{x2}Q_2 = h_2Q_2 + K_2Q_2(L - X)Q_2^2 \tag{24}$$

(23) Minus (24) **:**

$$h_{x1}Q_1 - h_{x2}Q_2 = h_1Q_1 - K_1XQ_1Q_1^2 - h_2Q_2 - K_2Q_2(L - X)Q_2^2$$

$$= h_1Q_1 - h_2Q_2 - K_2Q_2LQ_2^2 - K_1XQ_1Q_1^2 + K_2Q_2Q_2^2X$$

$$= h_1Q_1 - h_2Q_2 - K_2Q_2LQ_2^2 + X(K_2Q_2Q_2^2 - K_1Q_1Q_1^2)$$

$$= (Q_1 - Q_2)\lambda = \lambda Q_1 - \lambda Q_2$$

$$\lambda Q_1 - \lambda Q_2 - h_1Q_1 + h_2Q_2 + K_2Q_2LQ_2^2 = X(K_2Q_2Q_2^2 - K_1Q_1Q_1^2)$$

$$X = \frac{\lambda Q_1 - \lambda Q_2 - h_1Q_1 + h_2Q_2 + K_2Q_2LQ_2^2}{(K_2Q_2Q_2^2 - K_1Q_1Q_1^2)}$$

$$= \frac{Q_2(-\lambda\ Q_1/Q_2 + \lambda\ Q_2/Q_2 + h_1\ Q_1/Q_2 - h_2\ Q_2/Q_2 - K_2 L\ Q_2^3/Q_2)}{Q_2(\ K_1\ Q_1^3/Q_2 - K_2\ Q_2^3/Q_2)}$$

$$= \frac{-\lambda\ Q_1/Q_2 + \lambda + h_1\ Q_1/Q_2 - h_2 - K_2 L Q_2^2 + h_1 - h_1}{(\ K_1\ Q_1^3/Q_2 - K_2 Q_2^2)}$$

$$= \frac{h_1 - h_2 + \lambda - \lambda\ Q_1/Q_2 + h_1\ Q_1/Q_2 - h_1 - K_2 L Q_2^2}{(\ K_1\ Q_1^3/Q_2 - K_2 Q_2^2)}$$

$$X_c = \frac{(h_1 - h_2) + \lambda(1 - Q_1/Q_2) + h_1(Q_1/Q_2 - 1) - K_2 L Q_2^2}{(\ K_1\ Q_1^3/Q_2 - K_2 Q_2^2)}$$

$$X_c = \frac{(h_1 - h_2) + \lambda(1 - Q_1/Q_2) - h_1(1 - Q_1/Q_2) - K_2 L Q_2^2}{(\ K_1\ Q_1^3/Q_2 - K_2 Q_2^2)}$$

$$X_c = ((h_1 - h_2) - k_2 Q_2^2 L + (Q_1/Q_2 - 1)(h_1 - \lambda))/(k_1 Q_2^2\ Q_1/Q_2 - k_2 Q_2^2) \tag{25}$$

$\boldsymbol{X_c}$**:** represents the computed value of **X**.

There are two unknown factors are the friction factor and the discharge flow through the hole, we should optimize them in the leak localization by BBO to locate the leak position, because we can’t measure them.

II.2. Parameter Optimization with BBO

II.2.a. Introduction to BBO

Charles Darwin and Alfred Wallace, two nineteenth-century naturalists, are credited with establishing biogeography. Prior to the 1960s, biogeography was mostly descriptive and historical. Robert MacArthur and Edward Wilson's 1967 landmark book, The Theory of Island Biogeography, was the culmination of their early 1960s cooperation on mathematical models of biogeography. In 2005, 25,452 publications on biogeography were published. In 2008, Dan Simon proposed the revolutionary evolutionary algorithm (EA) known as "biogeography-based optimization". [9].

Species migration promotes information transmission via BBO, an evolutionary mechanism. Information exchange is achieved via the movement and emigration of species across islands. Each island represents a possible solution, with a good problem solution including a significant number of favorable biotic (living) and abiotic (non-living) characteristics that attract more species to the island than those on other islands. Each feature is referred to as the suitability index variable (SIV), which is the independent variable in such a problem in BBO. BBO's dependent variable is the island suitability index (ISI), which changes in parallel with these features. The following is an issue with n-independent variables and k-islands or individuals (equation (26)) [9],[10],[11]

$$\mathrm{ISI_i} = \mathrm{f}(\mathrm{SIV_1}, \mathrm{SIV_2}, \ldots \mathrm{SIV_n}) \quad \mathrm{i} = 1,2, \ldots .\mathrm{k} \tag{26}$$

BBO is divided into two sections: migration and mutation, with an optional part for elitism. Figure.4.2. depicts an island-wide species migratory model based on a number of species [12].

S_0: is the equilibrium species count.

S: is the number of species with probability $p_s(t)$.

I and E represent the highest conceivable immigration and emigration rates, respectively. λ and μ represent the immigration and emigration rates, respectively.

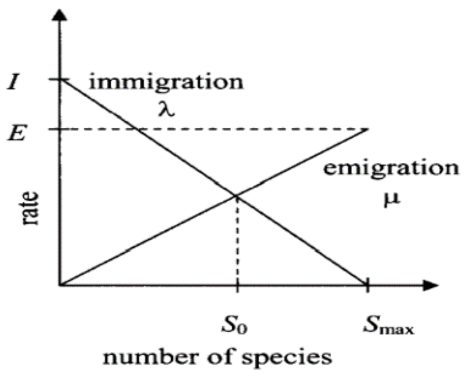

Figure.4.2. An island-specific species migratory model based on a number of species [12].

The change from $p_s(t)$ to $p_s(t + \Delta t)$ may be expressed as

$$p_s(t + \Delta t) = p_s(t)(1 - \lambda_s \Delta t - \mu_s \Delta t) + p_{s-1}(t)\lambda_{s-1}\Delta t + p_{s+1}(t)\mu_{s+1}\Delta t \tag{27}$$

$$\mu_s = \frac{E}{S_{max}} s \qquad , 0 < \mu_s < 1 \tag{28}$$

$$\lambda_s = 1 - \mu_s = \mathrm{I}\,(1 - \frac{s}{S_{max}}) \tag{29}$$

1. Migration

The migration process uses high ISI islands as a source of modification to share their traits with low ISI islands, enabling poor solutions to be probabilistically upgraded and maybe even outcompete better ones [11].

2. Mutation

According to the island hypothesis, some external variables might cause the species' equilibrium point to deviate significantly. The overall number of species will fall dramatically as a consequence of events such as predators from nearby islands, tsunamis, volcanoes, diseases, or earthquakes [12]. The mutation rate (m) may be computed as follows

$$m = m_{max}\left(1 - \frac{p_s}{p_{max}}\right) \tag{30}$$

m_{max} is a maximum mutation rate that m can reach, which is set by the user, and $p_{max} = \max(p_s)$

3. Elitism

After the processes of mutation and migration, it is quite likely that the best habitats will have perished with the development of new populations. We use the elitist strategy to rule this option out. It recognizes that the next generation will emulate one or more of the more desirable environments. This elitism keeps the most successful individual from fading during replacement. [13].

4. BBO algorithm

The BBO algorithm is given by [13]:

start

Generate a random set of initial solutions (islands).

while the stop criterion is not **do**

Rank the solutions based on their fitness (HSI).

Calculate the number of species S, the rate of λ_s immigration and emigration μ_s for each solution.

This phase is optional; however, it involves starting the elitist process to save the best ideas needed for the following generation.

Modify islands on a migration basis.

Mutation.

End **while**

end

Algorithm.1: standard BBO algorithm.

The General Flow Chart of the BBO algorithm is provided in Figure.4.3.

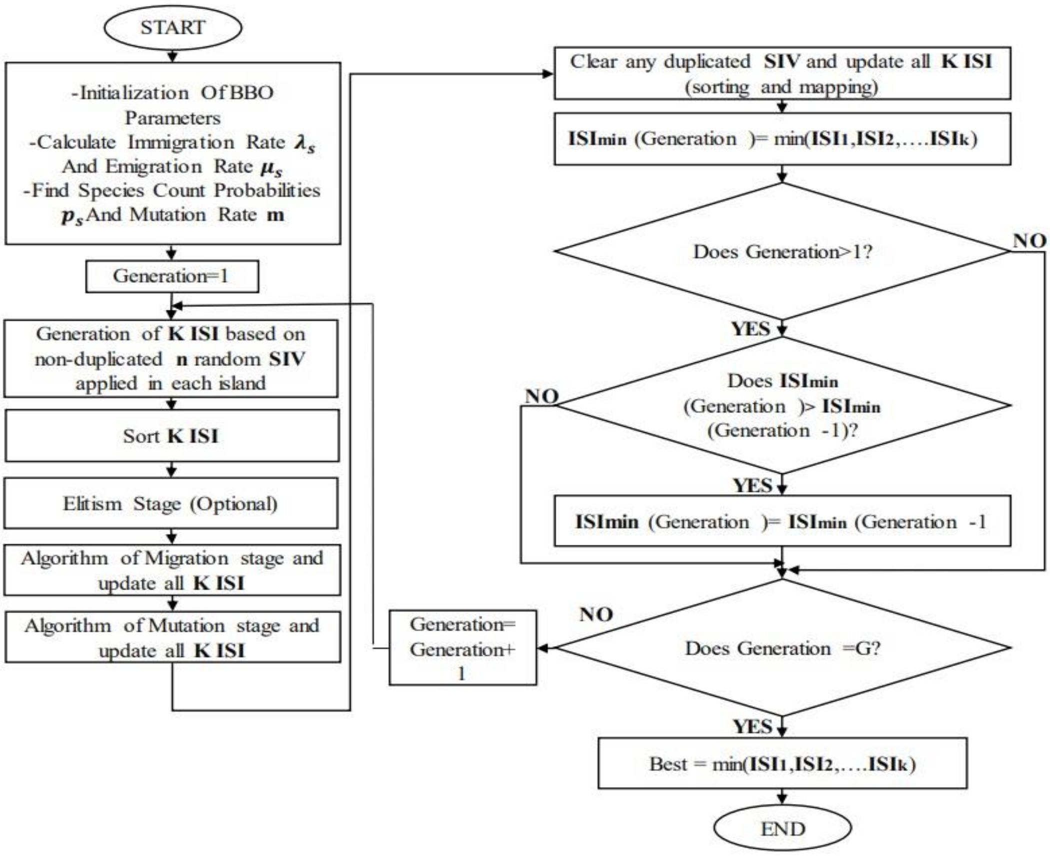

Figure.4.3. General Flow Chart of the BBO Algorithm. [11]

III. Part 2: Experimental Signal Processing and Leak Localization

This section focuses on the design of a low-cost leak detection system for WDNs, addressing the economic and environmental implications of water loss. In the laboratory, two pressure transmitters were mounted on a test pipe to create a prototype system. The prototype pipe was divided into two parts: hydraulic and electrical. The hydraulic section is made up of a closed hydraulic circuit that forms a serpentine and includes a variety of components such as pipe, tank, pump, elbows, accessories, and so on. We placed it horizontally to remove characteristics that have a link with distances in the equations of continuity and mass conservation in the pipe's mathematical models. The electrical component has a signal conditioning step.

Signals obtained from these transmitters were often contaminated with noise, requiring the employment of digital filtering methods. The S.G filter was used to denoise the signals, and its efficacy was shown by increased SNR estimates.

After denoising, the signals were evaluated to establish the existence of leaks. Based on the time difference in signal arrivals, a mathematical model was employed to compute the precise location of the leak in relation to one of the sensors. Validation testing on the prototype system validated the accuracy of the method in locating leaks.

III.1. Prototype Hydraulic Model Setup

To achieve the objectives of this approach, a prototype WDN was constructed in our laboratory. Seven leaks of 10 mm in size were simulated at different positions along the pipeline to evaluate various scenarios. The prototype setup includes a high-density polyethylene (HDPE) pipe, a plastic water tank, an electric pump, and additional accessories to replicate realistic hydraulic conditions. A detailed description of this hydraulic prototype is provided below.

III.1.a. Description of the Physical Setup

Figure.4.4. shows the hydraulic circuit of the WDN prototype. The setup includes a 26 m long Polyethylene Height Density (PEHD) pipe with a diameter of $\emptyset = 4$ cm. To mimic a leak, holes with a diameter of $\emptyset$=10 mm were bored at various sites P1 to P7,

Figure.4.4. Experimental setup

III.1.b. Positioning of Sensors

To monitor pressure fluctuations, a pressure transmitter was installed at the beginning of the pipeline, positioned 3.55 m from the leak. Another transmitter was placed 24.36 m downstream from the first, ensuring both transmitters were located on either side of the leak. The position of the first transmitter remained fixed, while the second transmitter was moved to specified locations for measurement. The hydraulic system utilized a PENTAX JM100 water pump with the following specifications: a flow rate of 10–50 L/min, a power of 0.74 kW, and a rotation speed of 2800 rpm. A 100-liter polyethylene tank was also included in the setup.

III.2. Data Collection Process

Figure.4.5. shows a synoptic representation of the overall blocks required for the data collecting procedure.

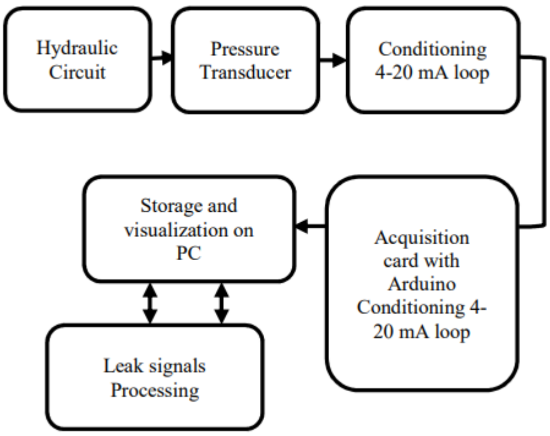

Figure.4.5. The acquisition system's overall view.

Bellow is a detailed description of the conditioning circuit and the system acquisition board.

III.2.a. Signal Acquisition

The acquisition was done using an Arduino DUE card. We used two pressure transmitters put in different places to capture two signals at separate points along the pipe. They will be recorded in duration of 1 second and analyzed. To collect signals, a software component is necessary. Obviously, we used MATLAB's Simulink to use functional blocks for communication and data transfer. MATLAB-based programs analyze data to determine position.

Our leak detection system is essentially built on high-precision pressure transmitters. The pressure transmitters use a 4-20 mA loop to create a current that represents the pressure in a particular location in the pipe. The latter will be converted into volts. This voltage is displayed on a PC, enabling us to monitor the pressure's temporal evolution. The visual signals may be digitized and recorded as an Excel file, which will be evaluated by our MATLAB-based programs. Figure.4.5. shows a synoptic schematic of the acquisition chain, which consists of seven functional blocks. It is made out of a block that resembles a hydraulic circuit, with two pressure transducers and a solenoid valve placed to simulate a leak.

The ARDUINO DUE is used for data acquisition from pressure sensors. Simulink blocks are also necessary for our application. The following function from his datasheet delineates a model of the transducer current function.

$$\mathrm{I(mA)} = \mathrm{a} \times \mathrm{P(PSIG)} + \mathrm{b(mA)} \tag{31}$$

Where a=0.16 and b=4mA.

I: Courant in mA

P: Pressure in PSI

III.2.b. Denoising by S.G filter

External noise from traffic and human activity, as well as mechanical noise and the effect of digital to noise converters on signals and flow turbulence, all have an ongoing impact on the acquired data. As a consequence, we needed to denoise our data to increase the accuracy of leak localization. We use for this the S.G filter.

The S.G filter is a digital smoothing filter that improves the quality of noisy data by fitting successive subsets of neighboring data points to a low-degree polynomial using least-squares minimization. Originally developed for spectroscopic data processing, it has now been widely used for denoising applications in a range of industries because of its ability to keep high-frequency components while decreasing noise, thereby improving the SNR. Unlike moving average filters, which may blur important characteristics, the S.G. filter maintains the form and breadth of peaks, making it especially useful in time-series and pressure signal analysis, where signal preservation is vital [14]. The fundamental equation for the S.G smoothing process can be expressed as follows:

$$Y_i = \sum_{j=-k}^{k} b_j X_{i+j} \tag{32}$$

Y_i : The smoothed value at the i-th data point.

X_{i+j}: The original data points in the range of the smoothing window.

b_j: Convolution coefficients derived through least-squares polynomial fitting.

k: Half-width of the smoothing window, where the window size is $2k + 1$

The coefficients b_j are calculated to minimize the sum of squared differences between the original data points and the polynomial fit within each window [15]. These coefficients depend on:

- The **polynomial order** (p) used for fitting.

- The **window size** $2k + 1$.

The S.G filter is particularly advantageous because it not only smooths the data but also preserves important features such as peak heights and widths, which are critical in applications like spectroscopy. This is achieved by fitting a polynomial to the data points within the moving window, thus allowing for a more nuanced representation of the underlying signal compared to simpler methods like moving averages. The polynomial order and the window size are crucial parameters that influence the performance of the filter, as they determine the trade-off between noise reduction and signal distortion [16],[17],[18].

In practical applications, the S.G filter has been shown to outperform other smoothing techniques, such as moving average filters, by minimizing distortion in the spectral data. For instance, studies have demonstrated that using S.G smoothing leads to less variation in vegetation indices derived from hyperspectral data compared to moving average smoothing, which can introduce significant artifacts. Additionally, the filter's ability to reduce noise while maintaining the integrity of the signal makes it a preferred choice in fields such as medical signal processing and environmental monitoring [19],[20],[21].

The S.G smoothing equation and its implementation provide a robust method for enhancing data quality in various scientific disciplines. Its polynomial fitting approach allows for effective noise reduction while preserving essential signal characteristics, making it a standard tool in data analysis [22].

III.2.c. Calculation of the performance of the filtered signal by SNR

To know the filtering performance of our signals, we used the SNR (Signal Noise Ratio) as a means of discrimination widely used in these cases. For this, we need to calculate the power of the signals, before and after filtering and calculate their power ratios to be able to determine their SNR and subsequently their SNR in decibels (dB) over a given time window. The total mean power of the signal is given by

$$P_s = \frac{1}{N}\sum_{i=0}^{N-1}|x_i|^2 \tag{33}$$

The noise power is obtained by subtracting the power of the signal before filtering and that after filtering.

$$P_B = \frac{1}{N}\sum_{i=0}^{N-1}(|x_i|^2 - |y_i|^2) \tag{34}$$

$$SNR = \frac{P_s}{P_B} \tag{35}$$

$$SNR(dB) = 10log_{10}(SNR) \tag{36}$$

x_i: Sample of the signal with noise,

P_s: The total mean power of the signal (W).

P_B: The noise power (W).

y_i: Sample of the signal without noise,

N: Number of samples.

III.3. Leak Localization Using Analysing of Pressure Signals

III.3.a. Mathematical Equation for Leak Localization

Figure.4.6. depicts a pipe section with two pressure transmitters at a distance from L. We simulated a leak at an arbitrary location that was not in the middle of our section. When we found a singularity in our signals indicating depression, we noted an anomaly in our section (a leak). There are many approaches for detecting leaks. One of the most common methods used in low-cost detectors is based on the cross-correlation technique.

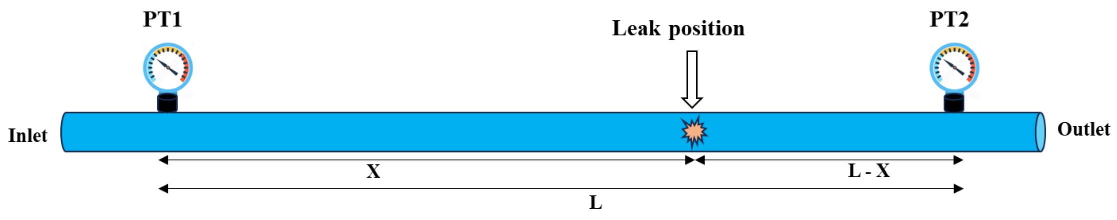

Figure.4.6. Location of the leak on a segment of the pipe.

X and L-X denote the distances between the leak and sensors A (PT1) and B (PT2), respectively.

The distance from sensor A (PT1) is determined by

$$X = Vt1 \tag{37}$$

Similarly, sensor B (PT2)

$$L - X = Vt2 \tag{38}$$

According to Figure.4.6, we have

$$L - X - X = V(t2 - t1); L - 2X = V.\Delta t$$

$$\Delta t = t2 - t1 \tag{39}$$

$$X = (L - V\Delta t)/2 \tag{40}$$

L: Distance between the two sensors (m)

Δt: Time difference between the two signals (s)

V: The speed of propagation of the pressure wave.

X: Position of the leak relative to sensor A.

IV. Part 3: Water Leak Detection and Localization Improvement Using Novel Discrete Wavelet Transform Detector Experimental Study

The concept for our detector was inspired by research on denoising non-stationary vibration signals using the FFT. To achieve efficient filtering, the authors utilized a Parseval's theorem-based threshold. They then recreated the denoised signal using the inverse fast Fourier transform (IFFT). Finally, they employed cross-correlation to calculate the delay between the two reconstructed signals. Figure.4.7. illustrates these stages. FFT analysis only provides frequency information, resulting in the loss of temporal information. FFT cannot offer spectrum changes over time or cope with non-stationary signals [23],[24],[25],[26],[27].

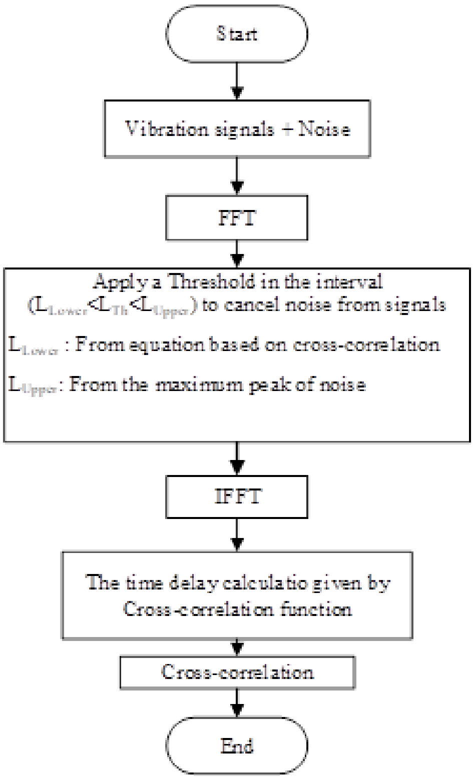

Figure.4.7. Frequency noise reduction approach for leak identification.[23]

In this section, we introduce a novel Discrete Wavelet Transform Detector (DWTD) that leverages high-precision pressure transmitters (CT114-357) as illustrated in Figure.4.8.

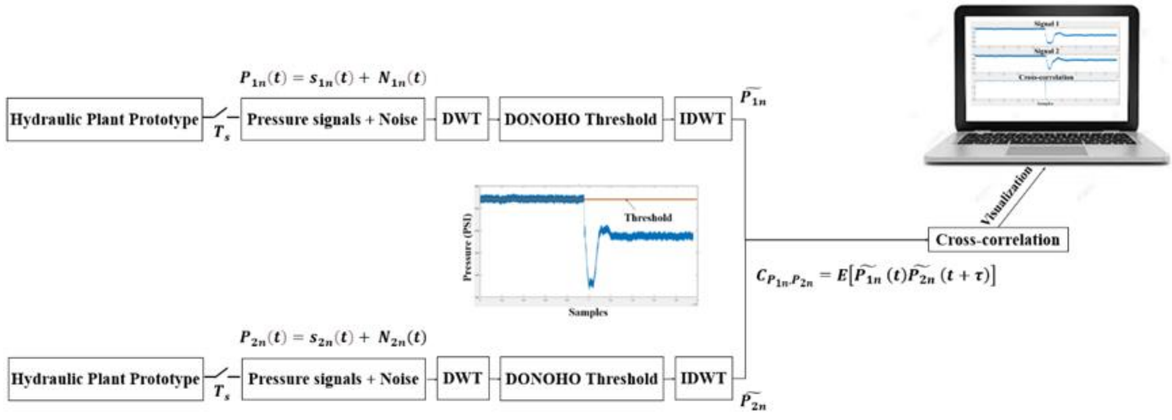

Figure.4.8. The suggested detector stages.

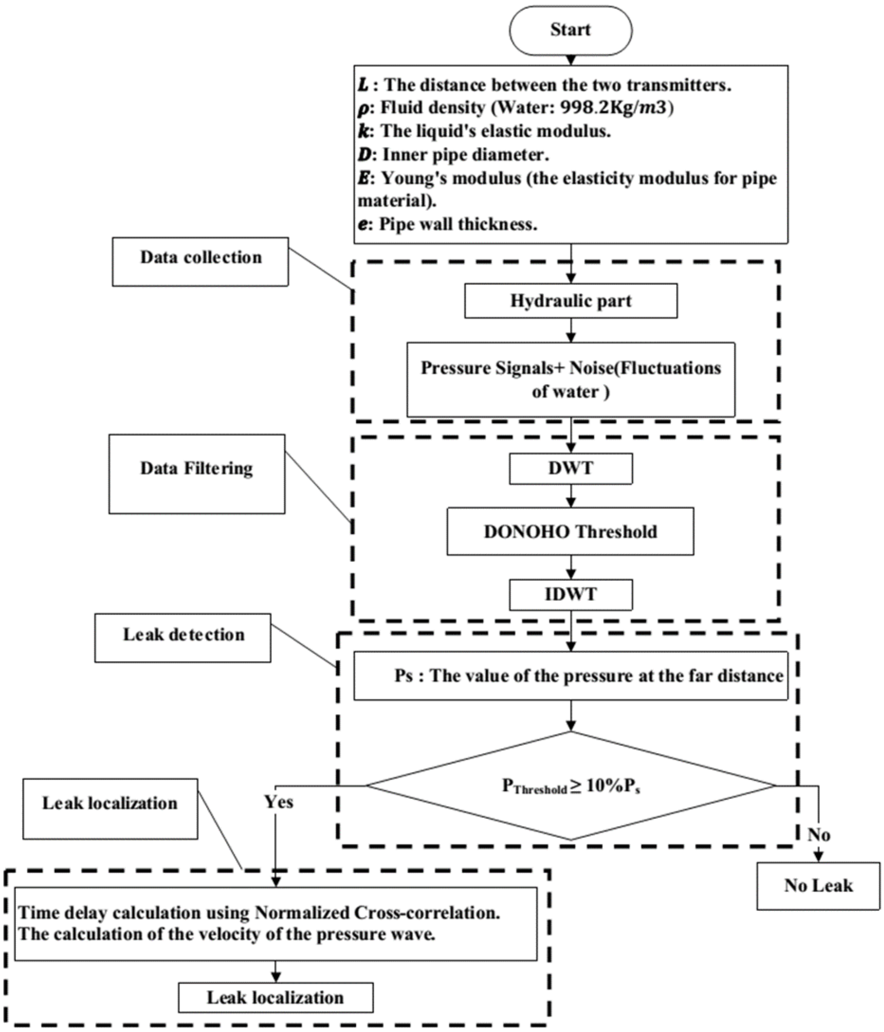

Figure.4.9. DWTD detector flow diagram.

These transmitters are strategically positioned on each side of the leak location: one is fixed at a predefined distance from the leak, while the other may be moved along the pipe up to 76m. The latter is triggered by pushing a push button that operates a solenoid valve. The transmitters provide analog, linear data via a 4-20mA loop, reflecting the pressure on the pipe as a current. An adapter card is needed to convert the two transmitters' current values to voltages that may be utilized as inputs to the DSpace MicroLabBox acquisition board. The latter uses two software packages (ControlDesk and MATLAB Simulink) to transform analog values to digital values at a sampling rate of 1 kHz.

A recording duration of 20ms is sufficient to acquire the singularity and restore it to our signal. The acquired pressure data is stored as files with the extensions.txt and.mat. The data gathered is used offline for analysis and processing. On the latter, we shall use the DWT. A DONOHO threshold is used to filter the obtained signals, improving the quality of the leakage signals. Calculating the SNR, NCC, and MSE measures evaluates performance quality. The IDWT will recreate the signals. To establish the existence of the leak, the signals will be subjected to a threshold equal to 10% of the lowest pressure value recorded experimentally at the furthest distance. Once a leak has been reported, the correlation function is used to establish its location. Figure.4.9. shows the flowchart of our proposed DWTD detector.

The data gathering step is divided into four major sections: the hydraulic circuit, pressure transmitters, acquisition system, and software. Figure.4.10. depicts the data collecting method. We begin by obtaining pressure data from the hydraulic circuit using two pressure transmitters. This information is then collected by the acquisition system, which is linked to a computer and stored, processed, and visualized using software such as ControlDesk and MATLAB. The dataset consists of 135 pressure measurements arranged into five categories. Each folder contains pressure signals collected under different situations, including the absence of leaks and leaks with sizes of 4mm, 6mm, 8mm, and 12mm, labeled as S_N_L, S_L_4mm, S_L_6mm, S_L_8mm, and S_L_12mm. The acquisition system records this data in.csv and.mat formats during a 20-second period and at a frequency of less than 1 KHz. Good measurements imply good leak detection, localization, and evaluation in water distribution pipes; thus, we used accurate and high-precession pressure transmitters, and we adjusted their position every time we wanted to record pressure information, as well as in each of the five cases mentioned above. The dSPACE MicroLabBox was also used for real-time data processing, which ensured efficient operations.

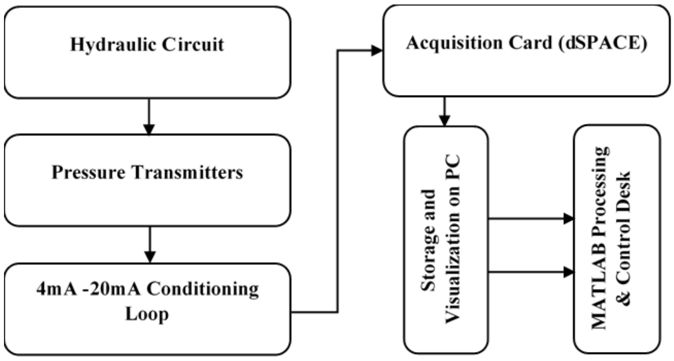

Figure.4.10. Data Acquisition System Synoptic Scheme

IV.1. Hydraulic Circuit

In the laboratory, to implement the hydraulic circuit we used a PHDE pipe with 100m length and 0.04m diameter, and a Tank with 150L volume. A water pump was employed to transfer water from the tank to the pipeline. Additionally, various accessories were utilized to facilitate the assembly of the water pipe network. The layout of the pipe network resembles a circular configuration, as illustrated in Figure.4.11.

Figure.4.11. The whole hydraulic circuit.

The pipe is from the K-PLAST TUBES industry in Sétif, Algeria. Where its characteristics are stated in Table.1.

Table 1. Characteristics of the pipe.

Characteristics and test methods	PE 100
Dimensional characteristics	Standard: NA 7700
Melt index at 190°C-5Kg(g/10min) NA 357 /ISO 1113	0,2-0,3 g/10 min
Density NA 7603/ISO 1183	956Kg/m3
Traction characteristics NA 7701/ISO 6259	at 20°C σ = 12 MPa
Hot shrink NA 7615 /ISO 2505	≤ 3%
Hydraulic pressure resistance NA 7517/ ISO 1167	à 20°C σ = 12 MPa
Oxidation stability at 210°C NA 7705 ISO 10837	t ≥ 20 min
Dispersion of carbon black NA 7601/ISO 11420	La note < 3
Carbon black content NA 7665 /ISO 6964	< 3%
Roughness coefficient	K=0.020mm
Volatile matter content NA 7715/ISO 1269	≤ 350 mg/kg

To provide the water for the pipeline, A 150-liter tank has been used. The water went back to the tank after his circulation. Coupling, 90 Degree Elbow, Ball Valve Coupling, and PHDE Clamp Saddle, are very important accessories to implement our water network prototype.

IV.2. Electrical part

The pump is the core element of our hydraulic system, it pumps the water into the WDN.

The table below Table.2 describes the electrical characteristics of the pump.

Table 2. Electrical characteristics of the pump

Type	PMC 3
Alimentation voltage	220v
Frequency of alimentation	50HZ
r.p.m	2850
PH~A	3.5
P2(KW)	0.6
. HP	0.8
P1(KW)	0.8
Q	100 l/min
. H	35

To achieve the objective of this section we need to collect the pressure signals of different leak diameters 4mm, 6mm, 8mm, and 12mm, to do that we used a drill with four different types of drill-bits to make holes in the pipe. The pressure transmitters catch up the signals of 20 second period under a 1Khz frequency. During the recording, we create leaks with a solenoid valve approximately 10s after the beginning of the recording process.

IV.3. Pressure Transmitters

Figure.4.12. illustrate the pressure transmitter used which is from Pratt & Whitney (CT114-357), and has an operating range between 1 and 100 PSIG. The pressure signals require a conditioning circuit. Due to this, these transmitters include an analog board inside of them that converts the reading's value into a value between 4 and 20 mA. Also, it has an output total error of 0.2%. The current image of the real values of pressure is modeled by equation (31).

The acquisition board can only read voltage signals; thus, a resistor is required to make it possible to read the value of the current flowing from the pressure transmitters.

Figure.4.12. The pressure transmitter

The acquisition board can only read voltage signals; thus, a resistor is required to make it possible to read the value of the current flowing from the pressure transmitters.

IV.4. Acquisition System

Using two transmitters at different points along the pipe, we were able to gather pressure data from our hydraulic network. We then read and stored the data using the dSPACE processing unit, MATLAB, and ControlDesk software, after building a Simulink circuit to connect the transmitters and the process unit, as seen in Figure.4.13. below.

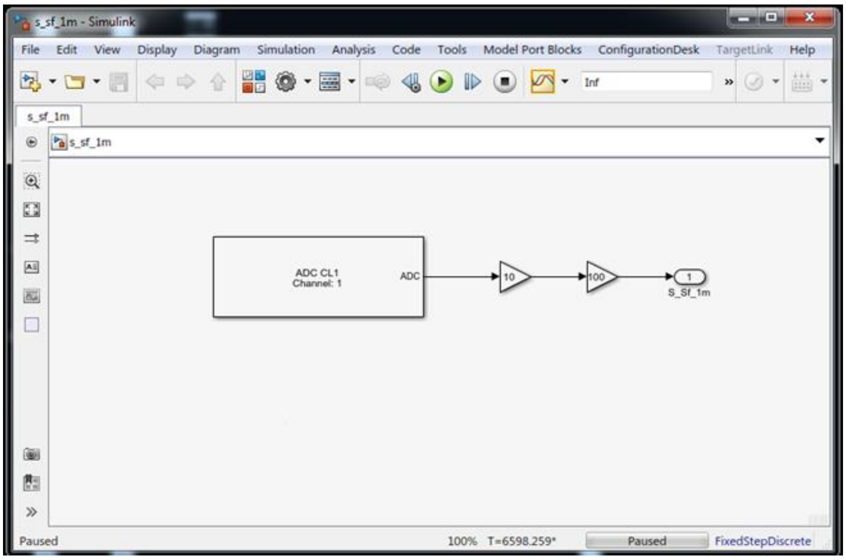

Figure.4.13. Simulink circuit for the acquisition process.

IV.4.1. Acquisition MicroLabBox

To record large amounts of data in real-time, we employ the dSPACE MicroLabBox. The DS1104 (Master PPC) board is a data acquisition board that has 8 digital-to-analog converters (DACs) with an input voltage range of -10V to +10V, and 8 analog-to-digital converters (ADCs) with an output voltage range of -10V to +10V. It also has several interfaces, including digital input/output, incremental encoders, etc. The DS1104 also has a slave digital signal processor (DSP), the TMS320F240 DSP.

In our case, the two transmitters' pressure signals are read by analog-to-digital converter ADC1. which is a high-precision with a 16-bit resolution and a ±10 V voltage range. It has an offset error of ±5 mV and a gain error of ±0.25%, as well as a SNR of >80 dB at 10 kHz. These features make it a versatile converter for measuring, controlling, and monitoring analog signals.

IV.5. Discrete Wavelet Transform (DWT)

The DWT is chosen to analyze and denoise the pressure signals for its ability to provide a time-frequency representation of the signal, which is essential for non-stationary signals such as pressure signals in pipes. Unlike FFT, which only includes frequency information, DWT uses a variable window to capture time and frequency information. In different fields, researchers used the discrete wavelet transform (DWT) algorithm for signal noise reduction [27]-[32].

"Wavelet transform" was first appeared in the early nineteenth century (1909). Unlike the Fourier transforms, this approach lets us utilize a changeable window based on what we require. If precision in low-frequency components is desired, a longer window is utilized; While for information in high-frequency components, a shorter window is employed. It offers a signal analysis at many resolutions. Figure.4.14. Illustrates multiple levels of the wavelet decomposition. Discrete wavelet transform (DWT) was applied to our non-stationary pressure signals to denoise them. The transformation equation (41) is below [28],[32].

$$DWT[a,b] = \sum_{n=0}^{N-1} x(n).\,\psi_{a,b}[n] \tag{41}$$

a, b:The scale and translation coefficient, respectively.
$x(n)$:The discrete signal.
$\psi_{a,b}[n]$:The discretized mother wavelet function.

$$\psi_{a,b}[n] = \frac{1}{\sqrt{a}}\psi\left(\frac{n-b}{a}\right) \tag{42}$$

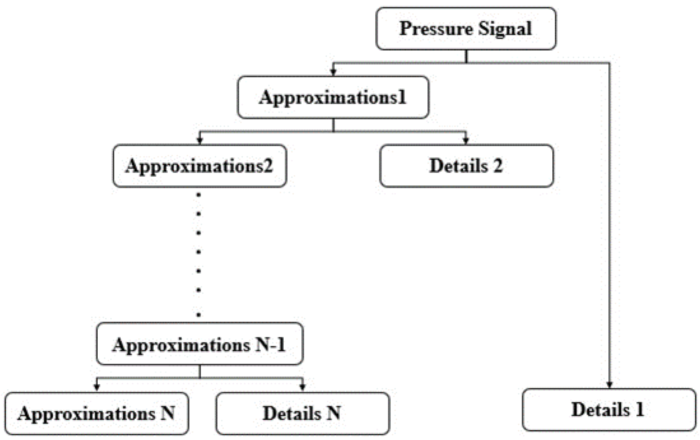

Figure.4.14. Multiple-level wavelet decomposition [28].

IV.5.1. Denoising with DWT

The denoising process involves applying DWT to the pressure signals, followed by soft and hard thresholding based on the DONOHO threshold to remove noise [29][31]. The inverse DWT (IDWT) is then used to reconstruct the denoised signals. Metrics such as SNR, NCC, and MSE are calculated to evaluate the performance of the denoising process.

Soft and Hard thresholding was given by equation (43) and equation (44)

Soft

$$C_s = \begin{cases} 0 & , \quad |C| < T_{thr} \\ sign(C).(|C| - T_{thr}), & |C| \geq T_{thr} \end{cases} \tag{43}$$

Hard

$$C_h = \begin{cases} 0, & |C| < T_{thr} \\ C, & |C| \geq T_{thr} \end{cases} \tag{44}$$

C: The wavelet coefficients.

Donoho Thresholding

$$T_{thr} = \sigma\sqrt{2\log_2(N)} \tag{45}$$

σ: The standard deviation estimation from the median of the noisy signal.

$$\sigma = \frac{Median\ of\ wavelet\ coefficients}{0.6745} \tag{46}$$

N: The length of the noisy signal (number of samples).

T_{thr}: DONOHO coefficient threshold.

IV.6. Cross-Correlation Improvement

In the event of a leak, waves propagate along the entirety of the pipe to its extremities. The interaction of physical factors, including friction, the distances between the two ends of the water transfer pipe, and the leak's location, introduces a time difference in the arrival of signals to the sensor. This time difference can be deduced by calculating the correlation between the two signal values measured simultaneously, considering the same frequency and number of samples.

In our investigation, we process pressure signals $P_{1n}[n]$and $P_{2n}[n]$ (vectors), following the procedural steps outlined in Figure.4.15. To understand their correlation, we use the cross-correlation calculation by (51). Before performing the cross-correlation calculation, a normalization of the two vectors is typically applied using a specific equation (47) [33]. This normalization step ensures that the signals are on a comparable scale, providing a more accurate correlation measure.

$$R_{P_{1n}P_{2n}}[k] = \sum_{n=-\infty}^{\infty} P_{1n}[n]P_{2n}[n+k] \tag{47}$$

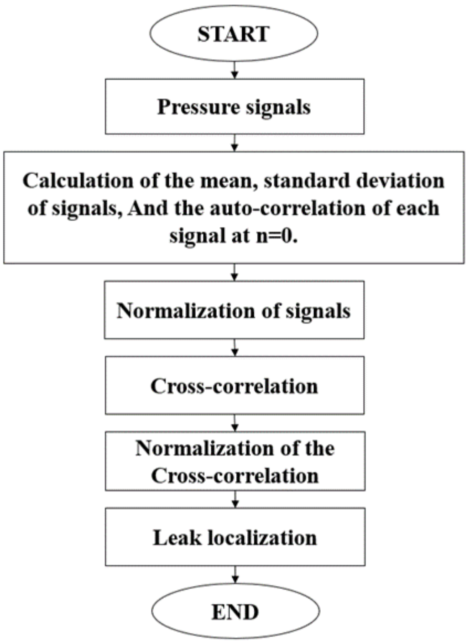

Figure.4.15. Normalized Cross-correlation flowchart

To achieve cross-correlation normalization, we compute both the mean and the Traditional standard deviation of the signal. Usually calculating the mean and standard deviation enables us to account for the baseline and variability of the signals, thereby enhancing the reliability of the cross-correlation analysis [33].

$$y[n] = \frac{P[n]-\mu}{\sigma'} \tag{48}$$

$$\mu = \frac{\sum_{n=0}^{N-1} P[n]}{N} \tag{49}$$

μ :The mean of P[n].

$$\sigma' = \sqrt{\left|\frac{\sum_{n=0}^{N-1}(P[n]-\mu)^2}{N}\right|} \tag{50}$$

σ':Traditional Standard Deviation Equation.

$$\rho_{P_{1n}P_{2n}}[k] = \frac{R_{P_{1n}P_{2n}}[k]}{\sqrt{R_{P_{1n}P_{1n}}[0]R_{P_{2n}P_{2n}}[0]}} \tag{51}$$

$$\Delta t = \left(N - 1 - k_{peak}\right)/f_s \tag{52}$$

$\rho_{P_{1n}P_{2n}}[k]$:The cross-correlation between $P_{1n}[n]$ and $P_{2n}[n]$.

$R_{P_{1n}P_{1n}}[0]$, $R_{P_{2n}P_{2n}}[0]$: The autocorrelation of $P_{1n}[n]$ and $P_{2n}[n]$ at n=0.

Δt : The time difference between the two signals.

f_s : The sampling frequency.

The following equation [34] is used to compute the velocity of the pressure wave

$$v = 1 \Big/ \sqrt{\rho\left(\frac{1}{k} + \frac{D}{E.e}\right)} \tag{53}$$

ρ: Fluid density (Water: 998.2Kg/m^3)

k: The liquid's elastic modulus.

D: Inner pipe diameter.

E: Young's modulus (the elasticity modulus for pipe material).

e: Pipe wall thickness.

In our case the calculated velocity v=229.785504 m/s.

After determining the Δt value and concurrently deducing the velocity v, it becomes possible to ascertain the leakage position by employing the equation (40).

VI. CONCLUSION

This chapter has provided a thorough approach to the important problems of locating and detecting water leaks in WDNs. By combining sophisticated signal processing methods, mathematical modeling, and optimization algorithms, the suggested strategies provide creative ways to increase the precision and effectiveness of leak detection.

The first contribution improved parameter estimates for leak situations by using a mathematical model based on fluid mechanics that was optimized using the BBO technique. This method showed promise for improving current models and allowing for their wider use.

The second contribution focused on mitigating noise and false alarms in leak detection systems. Using a custom-built experimental setup, the S.G filter effectively denoised pressure signals, which were then used to localize leaks based on time differences in signal arrival to the pressure transmitters. The denoising process was assessed through SNR calculations, ensuring improved data reliability. Validation tests further confirmed the efficacy of this approach in localizing leaks within a controlled experimental environment.

Leak detection is significantly improved in the third contribution by adding more experimental situations and a more sophisticated setup. With the same pressure transmitters and a high-precision Miclabox Dspace unit for data gathering, a bigger, circular prototype was built out of 100 meters of HDPE tubing with a 40 mm diameter. The method was validated by testing four distinct leak sizes (4 mm, 6 mm, 8 mm, and 12 mm) at various distances. The discrete wavelet transform (DWT) was used to decompose the pressure data that had been obtained. Donoho thresholding was then used to eliminate noise while keeping relevant information. SNR, MSE, and NCC were used to assess the signal quality of the reconstructed signals after they had been processed using inverse DWT (IDWT). A mathematical formula was developed to precisely pinpoint leaks by using the temporal difference in signal arrival, which was determined using a normalized cross-correlation approach. In validation experiments, this method showed excellent accuracy, demonstrating its resilience to changes in leak sizes and distances.

To sum up, the techniques described in this chapter mark important developments in WDN water leak detection. These contributions provide workable and scalable strategies that improve the accuracy and dependability of leak detection systems by tackling issues including signal noise, data scarcity, and fluctuating leak circumstances. When combined, they open the door to more effective management of water resources and the protection of vital infrastructure.

References

[1] B. Xing and W. J. Gao, "Biogeography-based Optimization Algorithm," *Intell. Syst. Ref. Libr.*, vol. 62, pp. 81–91, 2014, http://dx.doi.org/10.1007/978-3-319-03404-1_5.

[2] B. Li, H. Deng, and J. Wang, "Optimal Scheduling Of Microgrid Considering The Interruptible Load Shifting Based On Improved Biogeography-Based Optimization Algorithm," *Symmetry (Basel).*, vol. 13, no. 9, 2021, doi: 10.3390/sym13091707.

[3] Z. Wang, P. Liu, M. Ren, Y. Yang, and X. Tian, "Improved Biogeography-Based Optimization Based On Affinity Propagation," *ISPRS Int. J. Geo-Information*, vol. 5, no. 8, 2016, doi: 10.3390/ijgi5080129.

[4] X. Li, D. Wei, C. Lei, Z. Li, and W. Wang, "Statistical Process Monitoring with Biogeography-Based Optimization Independent Component Analysis," *Math. Probl. Eng.*, vol. 2018, 2018, doi: 10.1155/2018/1729612.

[5] O. B. Haddad, S.M. Hosseini-Moghari, and H. A. Loáiciga, "Biogeography-Based Optimization Algorithm for Optimal Operation of Reservoir Systems," *J. Water Resour. Plan. Manag.*, vol. 142, no. 1, 2016, doi: 10.1061/(asce)wr.1943-5452.0000558.

[6] M. Q. Duong, T. D. Pham, T. T. Nguyen, A. T. Doan, and H. Van Tran, "Determination of optimal location and sizing of solar photovoltaic distribution generation units in radial distribution systems," *Energies*, vol. 12, no. 1, 2019, doi: 10.3390/en12010174.

[7] X. Chen, H. Tianfield, C. Mei, W. Du, and G. Liu, "Biogeography-based learning particle swarm optimization," *Soft Comput.*, vol. 21, no. 24, pp. 7519–7541, 2017, doi: 10.1007/s00500-016-2307-7.

[8] A. H. A. Baghdadi and H. A. Mansy, "A mathematical model for leak location in pipelines," *Appl. Math. Model.*, vol. 12, no. 1, pp. 25–30, 1988, doi: 10.1016/0307-904X(88)90020-0.

[9] D. Simon, "Biogeography-Based Optimization," *IEEE Trans. Evol. Comput.*, vol. 12, no. 6, pp. 702–713, 2008, doi: 10.1109/TEVC.2008.919004.

[10] N. F. Hordri, S. S. Yuhaniz, and D. Nasien, "A comparison study of biogeography based optimization for optimization problems," *Int. J. Adv. Soft Comput. its Appl.*, vol. 5, no. 1, pp. 1–16, 2013.

[11] A. R. Alroomi, F. A. Albasri, and J. H.Talaq, “Solving the Associated Weakness of Biogeography-Based Optimization Algorithm,” *Int. J. Soft Comput.*, vol. 4, no. 4, pp. 1–20, 2013, doi: 10.5121/ijsc.2013.4401.

[12] R. H. MacArthur and E. O. Wilson, *The Theory of Island Biogeography*, Princeton, NJ: Princeton University Press, 1967.

[13] A. Akka, "Commande par l’utilisation des techniques du soft computing et leurs optimisations: Application à la commande d’un quadruple réservoir," Ph.D. dissertation, Dept. Elect. Eng., Univ. Sci. Technol. Oran, Oran, Algeria, 2018.

[14] A. Savitzky and M. J. E. Golay, “Smoothing and Differentiation of Data by Simplified Least Squares Procedures,” *Anal. Chem.*, vol. 36, no. 8, pp. 1627–1639, 1964, doi: 10.1021/ac60214a047.

[15] H. L. Kennedy, “Improving the frequency response of Savitzky-Golay filters via colored-noise models,” *Digit. Signal Process. A Rev. J.*, vol. 102, 2020, doi: 10.1016/j.dsp.2020.102743.

[16] P. J. Ochieng, Z. Maróti, J. Dombi, M. Krész, J. Békési, and T. Kalmár, “Adaptive Savitzky–Golay Filters for Analysis of Copy Number Variation Peaks from Whole-Exome Sequencing Data,” *Inf.*, vol. 14, no. 2, 2023, doi: 10.3390/info14020128.

[17] A. Homšek, B. Marković, N. Bogavac-Stanojević, S. Vladimirov, and K. Karljiković-Rajić, “Method Transfer Evaluation for Digital Derivative Spectrophotometry Through its Resolution Parameter Comparison of Different Computer Programs,” *Appl. Spectrosc.*, vol. 74, no. 5, pp. 525–535, 2020, doi.org/10.1177/0003702819889374.

[18] O. O. Dutra, L. H. C. Ferreira, G. D. Colletta, and L. B. Zoccal, “A Low Power R-peak Detector Clocked at Signal Sampling Rate,” *J. Integr. Circuits Syst.*, vol. 19, no. 1, 2024, doi: 10.29292/jics.v19i1.798.

[19] H. G. Schulze, R. B. Foist, A. Ivanov, and R. F. B. Turner, “Fully automated high-performance signal-to-noise ratio enhancement based on an iterative three-point zero-order savitzky-golay filter,” *Appl. Spectrosc.*, vol. 62, no. 10, pp. 1160–1166, 2008, doi: 10.1366/000370208786049079.

[20] K. Chen, H. Zhang, H. Wei, and Y. Li, “Improved Savitzky–Golay-method-based fluorescence subtraction algorithm for rapid recovery of Raman spectra,” *Appl. Opt.*, vol.

53, no. 24, p. 5559, 2014, doi: 10.1364/ao.53.005559.

[21] Y. Liu, B. Dang, Y. Li, H. Lin, and H. Ma, "Applications of Savitzky-Golay Filter for Seismic Random Noise Reduction," 2016. doi: 10.1515/acgeo-2015-0062.

[22] A. V. Agberien and B. Örmeci, "Monitoring of cyanobacteria in water using spectrophotometry and first derivative of absorbance," *Water (Switzerland)*, vol. 12, no. 1, 2020, doi: 10.3390/w12010124.

[23] D. B. Yoon, J. H. Park, and S. H. Shin, "Improvement of cross-correlation technique for leak detection of a buried pipe in a tonal noisy environment," *Nucl. Eng. Technol.*, vol. 44, no. 8, pp. 977–984, Dec. 2012, doi: 10.5516/NET.09.2011.067.

[24] A. Lay-Ekuakille, G. Vendramin, A. Trotta, and P. Vanderbemden, "STFT-based spectral analysis of urban waterworks leakage detection," *19th IMEKO World Congr. 2009*, vol. 2, pp. 674–678, ISBN 978-963-88410-0-1,2009.

[25] A. Lay-Ekuakille, A. Trotta, G. Vendramin and P. Vanderbemdem, "FFT- based algorithm improvements for detecting leakage in pipelines," 2009 6th International Multi-Conference on Systems, Signals and Devices, Djerba, Tunisia, 2009, pp. 1-4, doi: 10.1109/SSD.2009.4956691.

[26] A. Lay-Ekuakille, C. Pariset, and A. Trotta, "Leak detection of complex pipelines based on the filter diagonalization method: Robust technique for eigenvalue assessment," *Meas. Sci. Technol.*, vol. 21, no. 11, 2010, doi: 10.1088/0957-0233/21/11/115403.

[27] P. Karthikeyan, M. Murugappan, and S. Yaacob, "ECG signal denoising using wavelet thresholding techniques in human stress assessment," *Int. J. Electr. Eng. Informatics*, vol. 4, no. 2, pp. 306–319, 2012, doi: 10.15676/ijeei.2012.4.2.9.

[28] E. W. C. and C. K. Chui, "An Introduction to Wavelets.," *Math. Comput.*, vol. 60, no. 202, p. 854, Apr. 1993.

[29] R. Aggarwal, J. Karan Singh, V. Kumar Gupta, S. Rathore, M. Tiwari, and A. Khare, "Noise Reduction of Speech Signal using Wavelet Transform with Modified Universal Threshold," *Int. J. Comput. Appl.*, vol. 20, no. 5, pp. 14–19, Apr. 2011, doi: 10.5120/2431-3269.

[30] S. Lahmiri, "Comparative study of ecg signal denoising by wavelet thresholding in empirical and variational mode decomposition domains," *Healthc. Technol. Lett.*, vol. 1,

no. 3, pp. 104–109, Sep. 2014, doi: 10.1049/htl.2014.0073.

[31] Ç. P. Dautov and M. S. Özerdem, "Wavelet transform and signal denoising using Wavelet method," *2018 26th Signal Processing and Communications Applications Conference (SIU)*, Izmir, Turkey, 2018, pp. 1-4, doi: 10.1109/SIU.2018.8404418.

[32] Ç. P. Dautov and M. S. Özerdem, “Introduction to Wavelets and their applications in signal denoising,” *Bitlis Eren Univ. J. Sci. Technol.*, vol. 8, no. 1, pp. 1–10, Jun. 2018, doi: 10.17678/beuscitech.349020.

[33] J. Li, S. Chen, Y. Zhang, S. Jin and L. Wang, "Cross-Correlation Method for Online Pipeline Leakage Monitoring System," *2009 2nd International Congress on Image and Signal Processing*, Tianjin, China, 2009, pp. 1-4, doi: 10.1109/CISP.2009.5302839.

[34] P. Ostapkowicz, “Leakage detection from liquid transmission pipelines using improved pressure wave technique,” *Eksploat. i Niezawodn.*, vol. 16, no. 1, pp. 9–16, 2014.

Chapter05

Experimental Results And Discussion

I. Introduction

This chapter summarizes the three key contributions results of this thesis, each addressing essential areas of water leak detection and localization.

The first portion focuses on calculating two unknown variables: the friction factor and the discharge flow via the leak. This part also investigates the behavior of the cost function minimization process, focusing on its development across multiple generations.

The second portion delves into the analysis of pressure signals recorded in a controlled laboratory setting. The raw signals were processed by the S.G filter for noise reduction using a denoising approach, and the process's efficacy was measured quantitatively using SNR measurements. Leak localization was accomplished by estimating the time difference between the arrival of pressure signals at two strategically located pressure transmitters. The suggested technique was then validated to ensure its robustness and dependability.

The third component looks at additional pressure data collected from a separate prototype created in our laboratory. To improve data quality, a new approach based on DWT was used. The signals were decomposed into wavelet coefficients, denoised using the Donoho thresholding approach to extract valuable information, then reconstructed using the IDWT. The time difference between arrivals at both sides of the leak was estimated using the normalized cross-correlation approach on these reconstructed signals. When combined with the pressure wave velocity, these temporal discrepancies allowed for precise leak status identification and localization.

This phase's denoising procedure was evaluated using SNR, Mean Squared Error (MSE), and NCC metrics. The suggested detector's resilience was further tested with additional data from the same WDN prototype. Finally, a comparison with previous work was carried out to assess the performance and efficiency of the suggested approach.

II. Results and discussion

II.1. Part one

II.1.1. Simulation outcomes of the use of BBO in parameter optimization

In this part, we will examine the optimization results while taking into account the following information. The test rig is made up of a 26-meter-long PEHD pipe with an inner diameter of 40 millimeters, and we consider $Q_1 = 10\ l/min$, $Q_2 = 7.5\ l/min$, $h_1 = 1m$, $h_2 = 1m$. Here is the result Figure.5.1. The objective function in this research is the minimization of the difference between the calculated value of the leak position and the measured one using the pipe length, diameter, gravity, and flow rate values at the inlet and the outlet of the pipe where we the leak is located between them.

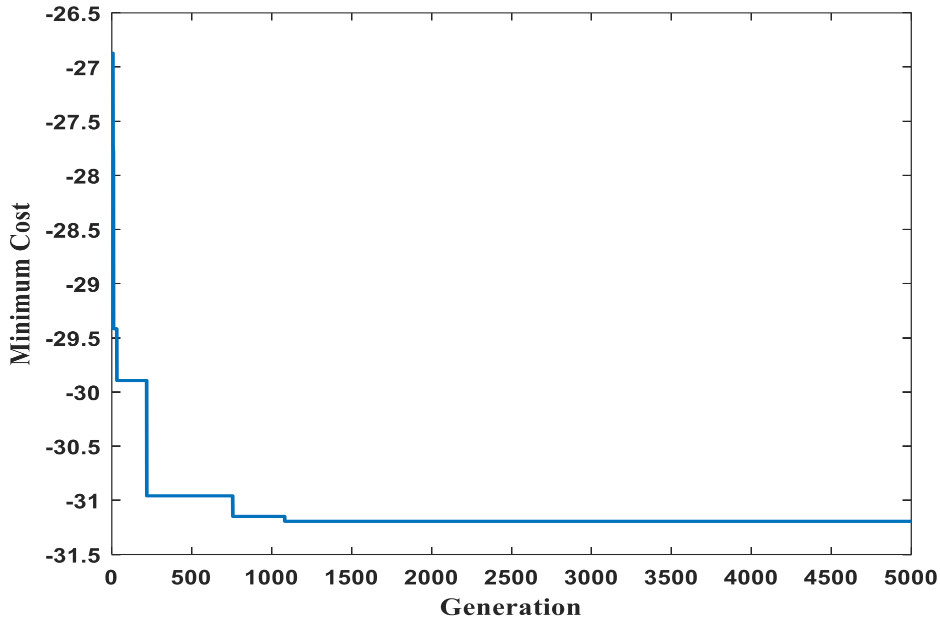

Figure.5.1. Curve of the mathematical model's fitness functions using BBO.

The curve in Figure.5.1. depicts how the cost function changes as the number of iterations increases (generations). To get the optimal model reduction, we consider a number of iterations equal to 5,000. We also selected a mutation probability of 0.03, a population size of 250, and a number of variables in each solution (problem dimension) of 2. The elitism stage is used to retain the best answer in each iteration. In the estimation of the two unknown parameters, the friction factor f and the discharge flow through the hole $c_d A_x$, it is essential to define realistic constraints that align with the physical properties of the system being studied. These constraints ensure that the optimization algorithm operates within a valid range, avoiding non-physical or impractical solutions. The friction factor f represents the resistance to flow caused by the pipe's surface roughness and flow conditions. Typical values for the friction factor range from very low (for smooth pipes with laminar flow) to relatively high (for rough pipes with turbulent flow) [1]. For this reason, we constrained f between 0.0025 and 1. The lower bound of 0.0025 represents a smooth pipe in near-ideal conditions, often seen in laboratory setups or newly installed pipelines. The upper bound of 1 captures the higher resistance that may occur in older or rougher pipes under turbulent flow regimes [2]. This range ensures that the friction factor remains physically meaningful while accounting for various possible scenarios in the WDNs.

The discharge flow through the hole $c_d A_x$ reflects the rate at which water escapes through a leak in the pipe. Its constraints were set between 0.4 and 1.7, based on experimental observations and practical leakage conditions. The lower bound 0.4 corresponds to a small leak, where the flow rate is minimal but measurable, while the upper bound 1.7 represents a larger, more significant leak. These values were determined from laboratory experiments and calibrated to match the operational characteristics of the water distribution system and the measurement equipment used. The range avoids unreasonably low values, which might represent negligible or undetectable leaks, and excessively high values that could indicate conditions beyond the scope of the experimental setup. By incorporating these constraints, we guided the optimization process to search within a feasible solution space. This approach balances realism with flexibility, allowing for accurate estimation of f and $c_d A_x$ while ensuring the results are consistent with the physical system. Additionally, these constraints prevent the algorithm from diverging toward extreme or erroneous values, thus enhancing the reliability and robustness of the parameter estimation process.

Following the optimization, we discovered that the optimal parameters are as follows

$f = 0.99981$, and $c_d A_x = 0.85094\ [m^2]$

After executing the optimization procedure, we discovered that the Elapsed Time was 10.789098 seconds. Depending on the improved outcomes, we evaluate how quickly the design's variables should be calculated utilizing the BBO technique. In our optimization, we measure the exact position, which is 0.9 metres. To check the technique's success, we inserted the obtained values of the two unknown factors into the equation that determines the specific leak location (equation (25)), and we observed that the calculated value is 1.0724 meters, which is almost identical to the real value.

II.2. Part two

II.2.1. Signals without leak

Following the collection of pressure data, certain visualizations were given to get an understanding of pressure behavior under normal circumstances and when a leak exists. In this case, we displayed signals without a leak for a randomly selected point. Figure.5.2. The x-axis shows time in seconds (s), while the y-axis represents pressure in PSIG.

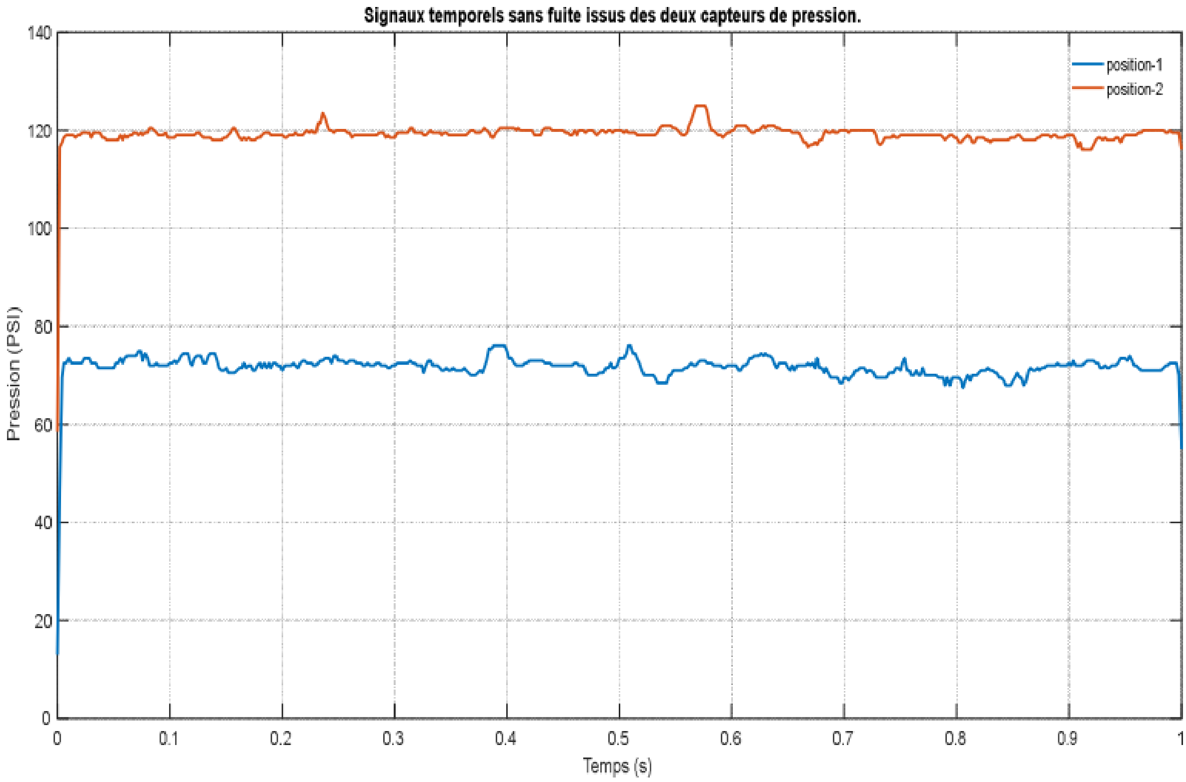

Figure.5.2. Time signals without a leak from both pressure transducers.

By carefully studying the two data sets, we can see that the pressures reported by the two transmitters are almost consistent throughout time, suggesting a steady flow situation. However, slight changes are detected in the recorded data. The turbulent character of the system's flow may explain these changes. Turbulence, a frequent feature of fluid dynamics, results from irregular and chaotic fluctuations in velocity and pressure when fluid particles interact with one another and with the conduit's walls.

In this particular scenario, the transmitters detect these slight fluctuations, which have no substantial effect on the overall stability of the observed pressure. Such behavior is common in systems where the flow regime shifts into or remains in a turbulent state, as shown by random and multi-scale vortices. The virtually constant pressure numbers imply that the mean flow stays consistent, but turbulence generates small-scale pressure changes that superimpose on this mean.

From a practical perspective, these insights are critical for understanding flow dynamics and determining the trustworthiness of pressure measurements. Understanding these fluctuations aids in the differentiation between typical turbulent-induced variations and abnormalities like leaks or blockages in applications such as water distribution systems or leak detection.

II.2.2. Signals with leak

Figure.5.3. shows the raw pressure time data (without filtering) from the two transmitters for a pipe with a leak. Signal analysis indicates that a singularity occurred at t = 0.4S for the first signal in purple and at t = 0.43S for the second transducer in orange. We also discovered that both signals appear in noise and that filtering is required.

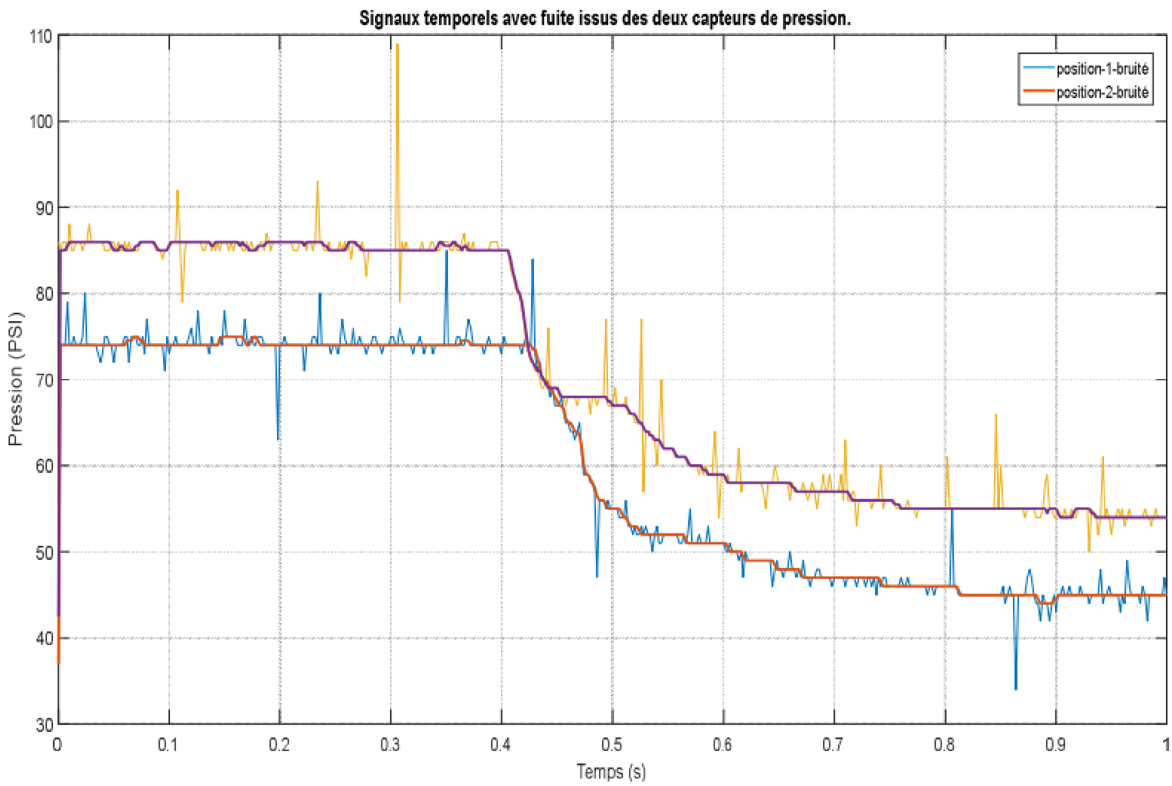

Figure.5.3. Leaked time signals from both pressure transmitters.

II.2.3. Filtering of signals by the SG filter

To denoise the leak signals, a four-order S.G filter [3] was applied to each signal having the leak. These latter originate from two transmitters. (transmitter A and B). The SG filter is a digital filter that may be used to a series of digital data points to smooth the data, hence increasing accuracy without altering signal tendency. Figure.5.4. depicts the results received after executing the MATLAB program designed for this filter.

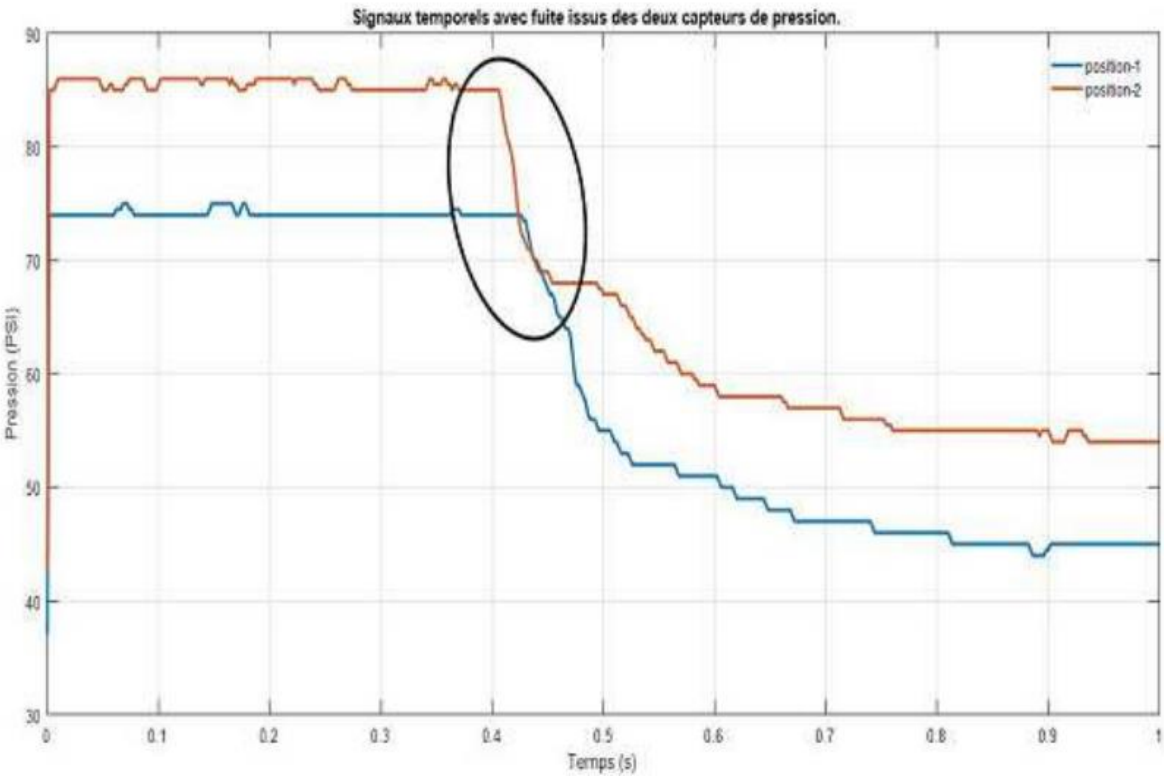

Figure.5.4. Time signals with leakage from the two pressure transmitters filtered

The S.G filter proved to be an effective filter for both signals. We can also see that there is a temporal lag between the two filtered time signals, indicating that they arrive at the transmitters later. At time t = 0.4 s, a depression develops, indicating the presence of a leak observed by the transmitter nearest to the leak, while the second transmitter detects the depression phenomena at time t = 0.43 s. Three acquisitions were randomly selected from the collected signals. The table below (Table.1.) groups the various locations of the selected leaks. After analyzing the performance of our signals from the two transmitters, we discovered that the latter are high-performance signals with less noise, higher powers, and higher SNR.

Table.1. Signal performance by SNR

Position	Signal	Transmitter A (PT1)	Transmitter B(PT2)
P_2	Power of signal (mW)	5.33×10^3	6.97×10^3
	Power of noise	3.97×10^2	1.77×10^2
	SNR	13.42	39.40
	SNR (dB)	11.2	15.95
P_4	Power of signal (mW)	5.74×10^3	7.03×10^3
	Power of noise	2.66×10^2	79.37
	SNR	21.59	89.03
	SNR (dB)	13.34	19.49
P_7	Power of signal (mW)	6.24×10^3	7.34×10^3
	Power of noise	1.98×10^2	2.16×10^2
	SNR	31.54	33.98
	SNR (dB)	14.98	15.31

II.2.4. LEAK LOCALIZATION

In our application, we used a distance of 24.36m between the two transmitters. The speed at which a pressure wave propagates in a pipe is determined by the pipe's material (HDPE, PVC, STEEL) and size. X and L-X are the distances between the leak and the transmitters A and B, respectively. In our investigation, we picked two leak sites at random. We put together the various leak distances selected to transmitter A (Position 1 = 20.92 m, Position 2 = 15.89 m).

To estimate the leak location, we use Equation (40) from the fourth chapter. First, we determine the time difference between the arrival times of the two pressure signals, as observed in the visualization figures below. Next, we calculate the fluid velocity and incorporate these values into the leak localization process for both testing and validation cases.

a. Time difference between the two signals

Figure.5.5. depicts the time signals from the two pressure transducers at position 1, which illustrate the recorded pressure fluctuations over time. These signals give vital information for studying the propagation of pressure waves throughout the pipeline, which is required for detecting abnormalities and accurately determining the leak site.

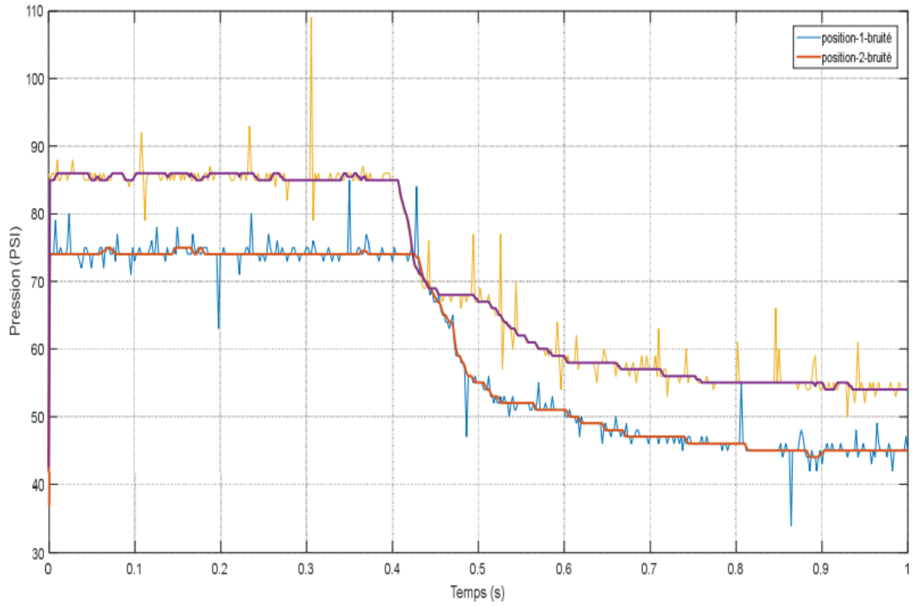

Figure.5.5. Time signals from the two pressure transmitters (position 1).

After denoising the obtained signals using S.G filter. Figure.5.6. shows a temporal difference of

$$\Delta t = 0.028\ s$$

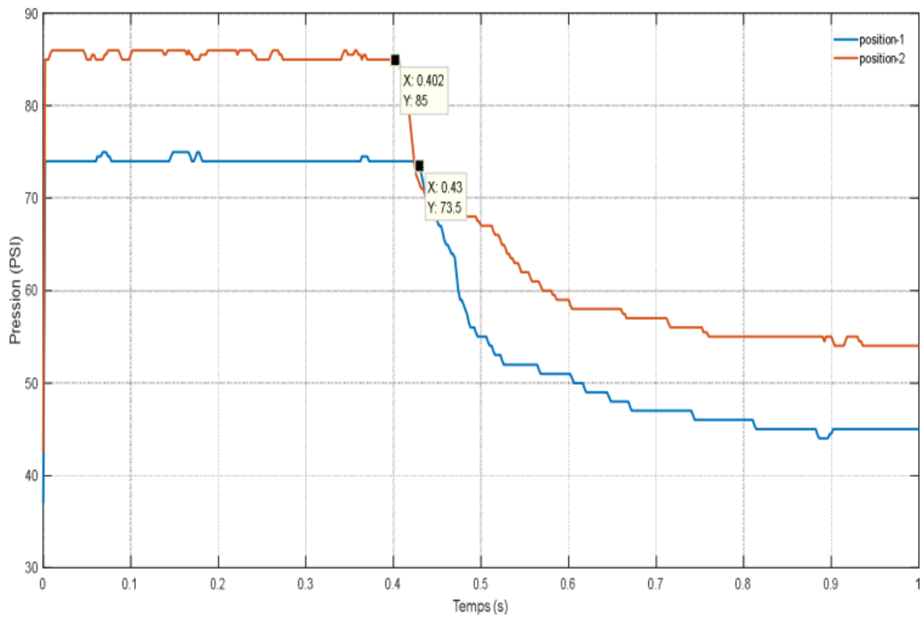

Figure.5.6. Time difference between the two signals position 1

b. Speed of propagation pressure wave

Based on experimental measurements and using the equation (36), we found that the pressure wave speed propagation's is $V = 576\ m/s$. This result provides a critical parameter for accurately localizing leaks within the pipeline system.

II.2.5. VALIDATION

Figure.5.7. shows the time signals from the two pressure transmitters (position 2).

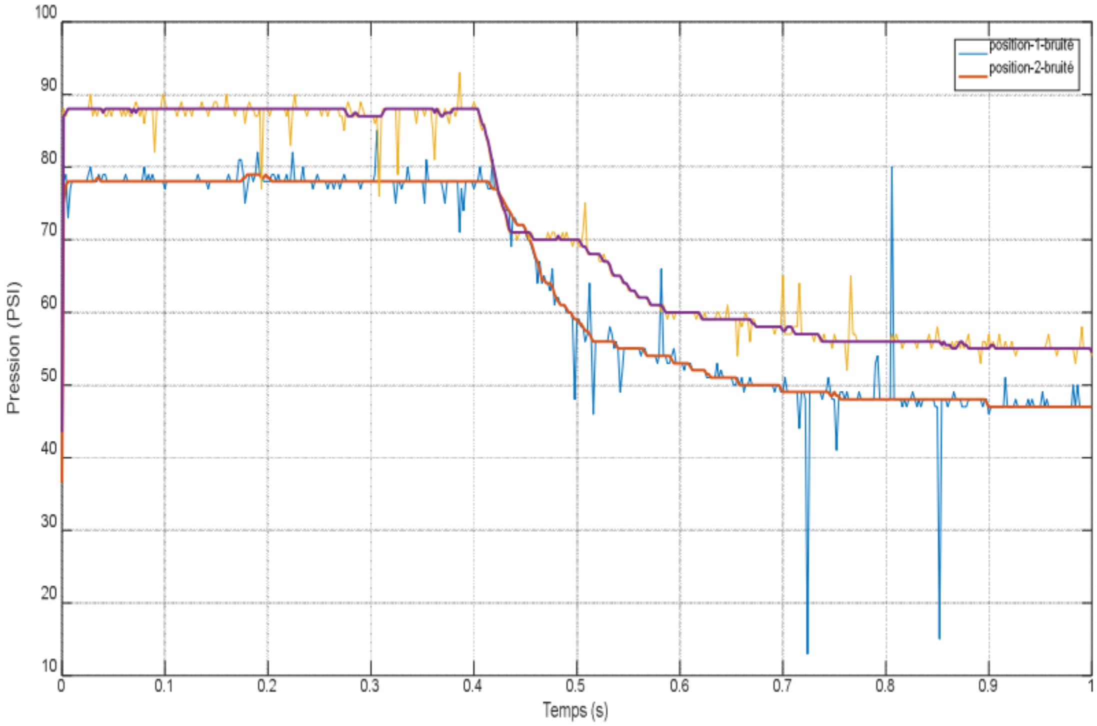

Figure.5.7. The time signals from the two pressure transmitters (position 2).

Figure.5.8. shows the processed results of denoising the time data from the two pressure transmitters. This chart shows the timing difference between the two signals to be

$$t_2 - t_1 \rightarrow \Delta t = 0.422 - 0.402 \rightarrow \ \Delta t = 0.020s$$

The numerical application of equation (37) in position 2, yields the actual position of transmitter A.

$$X = 576 \times 0.02 = 11.52m$$

To determine the precise location of the leak, add 3.63 m, which represents the distance between the leak and transmitter A. The actual location relative to transmitter A is

X=15.15 m.

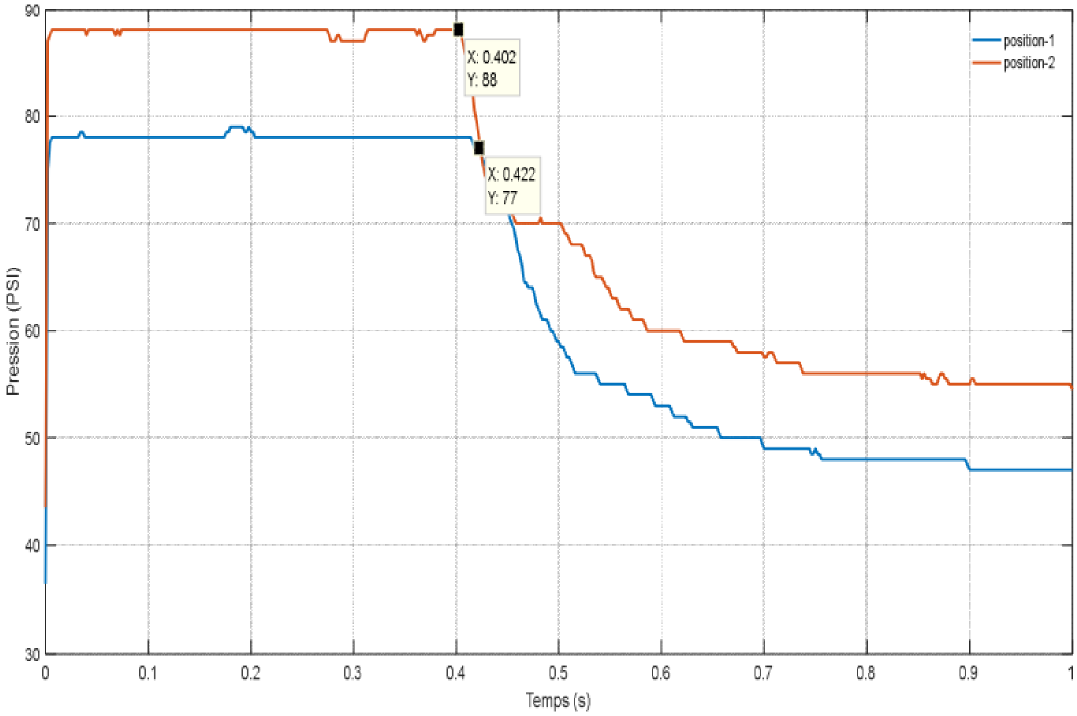

Figure.5.8. Denoised time signals from the two-pressure transmitter' position (2)

II.3. Part three

This section explores four leak-size situations produced by our prototype to imitate real-world settings, and provides an analysis of the resulting data processing results. Data collecting method: We began by drilling a 4mm hole in the pipe and installing a closed collar on a solenoid valve operated by a push button, imitating the leak by opening it, so that we could gather data. The size of the orifices is then progressively adjusted in the same locations, and the data is collected again. To improve signal charting clarity, an amplification factor of 100 was used. Figure.5.9. (a) shows that for the signal without a leak from transmitter1 positioned 76m from the pump, the pressure image stays steady at roughly 1.22 volts throughout the recording time. In the instance of a 4mm leak located 2m from the leak point, see Figure.5.9. (b). The pressure image remains steady at around 1.53 volts until the solenoid valve that mimics the leak is engaged. About 10 seconds into the recording, a singularity is detected, causing the pressure to decrease to 1.33 volt. The curve then stabilizes at 1.45 volts. When the wavelet is applied to the signal data for both without leak and leak situations at a predetermined distance, it is clear that no major events occur for the signal without leak Figure.5.9. (a), as indicated in Figure.5.9. (c). However, for the signal with a leak Figure.5.9. (b), the wavelet application Figure.5.9. (d) shows spots at t=10 seconds, suggesting an increase in the energy of the wavelet coefficients, notably at t=10 seconds and scale=10, as shown by the color palette.

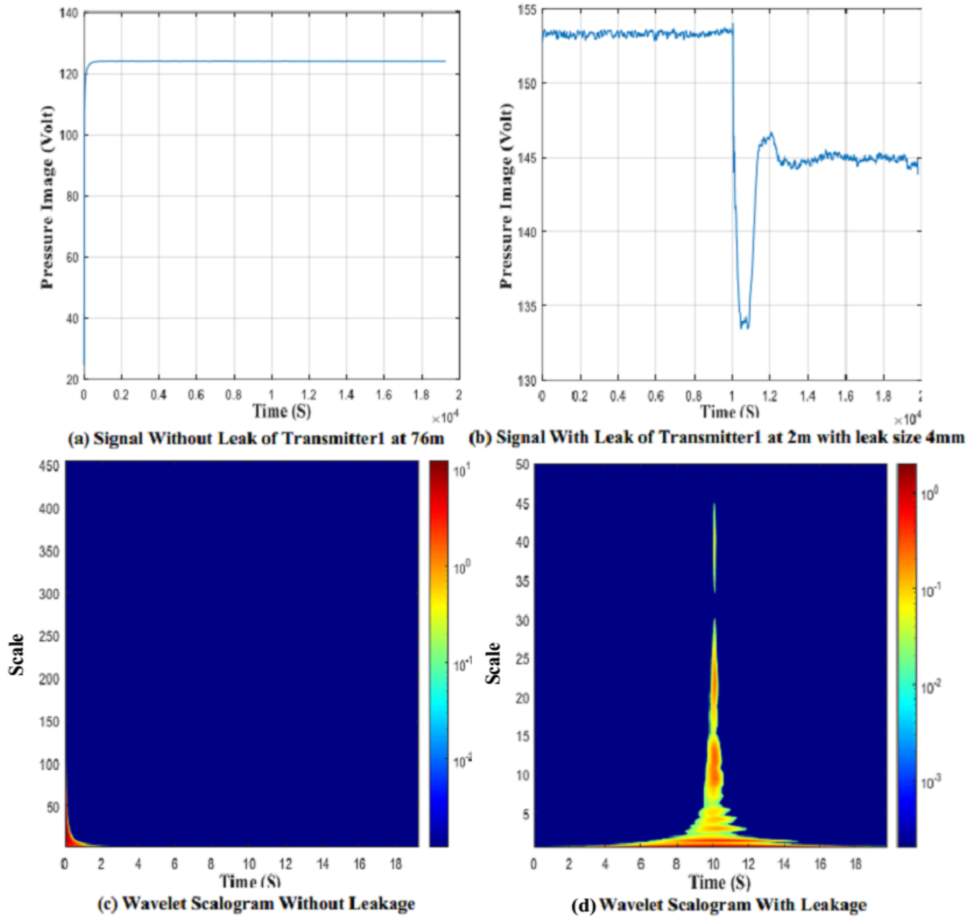

Figure.5.9. Pressure Signal Time-Frequency Representation with Wavelet Scalograms

II.3. 1. Integral State Feedback Controller

Figure.5.10 shows two pressure signals when the first transmitter is placed 2 meters (before the leak) and the second 70 meters (after the leak). The difference between the two signal amplitudes is large, with the first amplitude being about 1.5 volts and the second being roughly 1.28 volts. The two signals at (9303,154.942) and (9669,128.636) clearly indicate a decline. They then progressively grow and stabilize at levels lower than before the leak was created. The temporal delay between the two signals is due to the differing placements of the two transmitters.

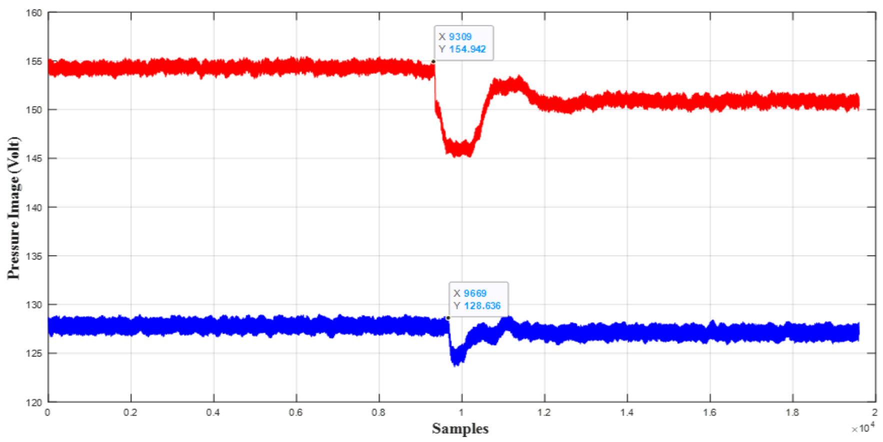

Figure.5.10. Illustration of two pressure indications after a leak occurred (the first 2m, and the second 70m distant from the leak position)

II.3.2. Leak size of 6mm (Noisy signal)

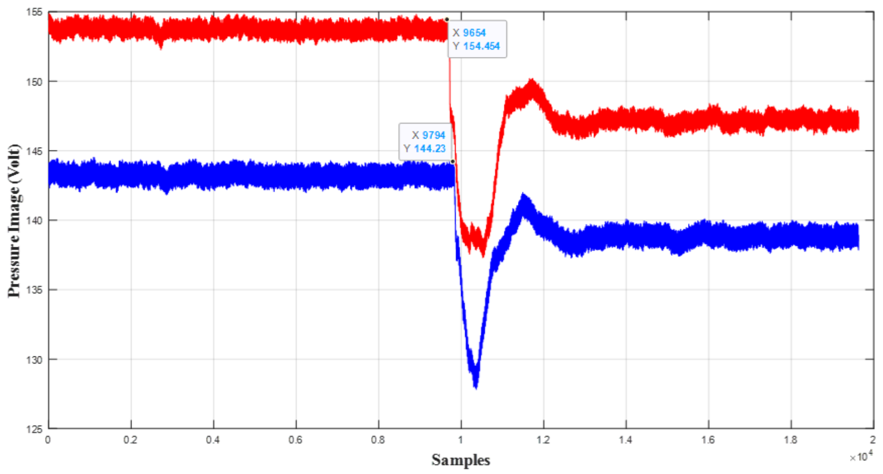

Figure.5.11. Illustration of two pressure signals when a leak occurred (the first 2m and the second 28m away from the leak position)

In this scenario, transmitter one is 2 meters and transmitter two is 28 meters distant from the leak location. The amplitudes for the first and second transmitters were 1,54454 and 1,4423 volts, respectively, prior to the leak. After the leak, the two signals sank at locations (9654,154.454) and (9794,144.23), as shown in Figure.5.11, before rising again and stabilizing.

II.3.3. Leak size of 8mm (Noisy signal)

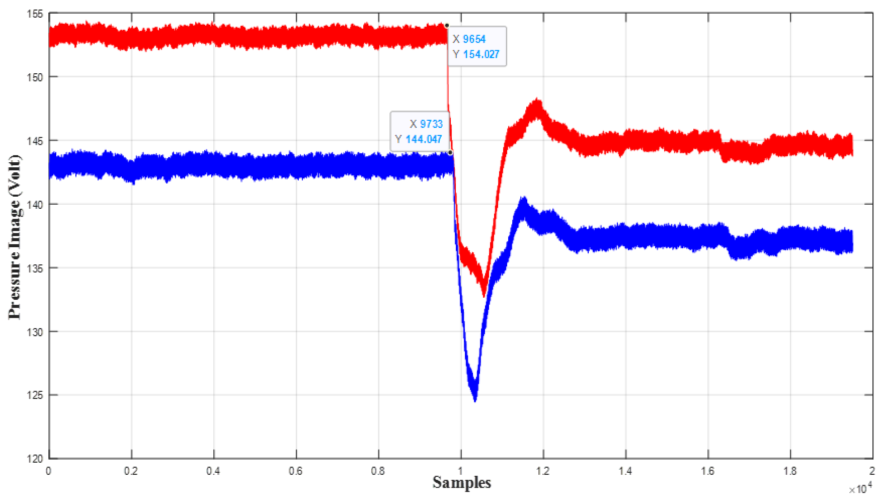

Figure.5.12. Illustration of two pressure signals when a leak occurred (the first 2m and the second 28m away from the leak position)

In this case, transmitter one is 2 meters away from the leak, while transmitter two is 28 meters distant. Figure.5.12 shows that both signals behaved nearly similarly before and after the pipe rupture, with just minor shifting and amplitude differences.

II.3.4. Leak size of 12mm (Noisy signal) (Noisy signal)

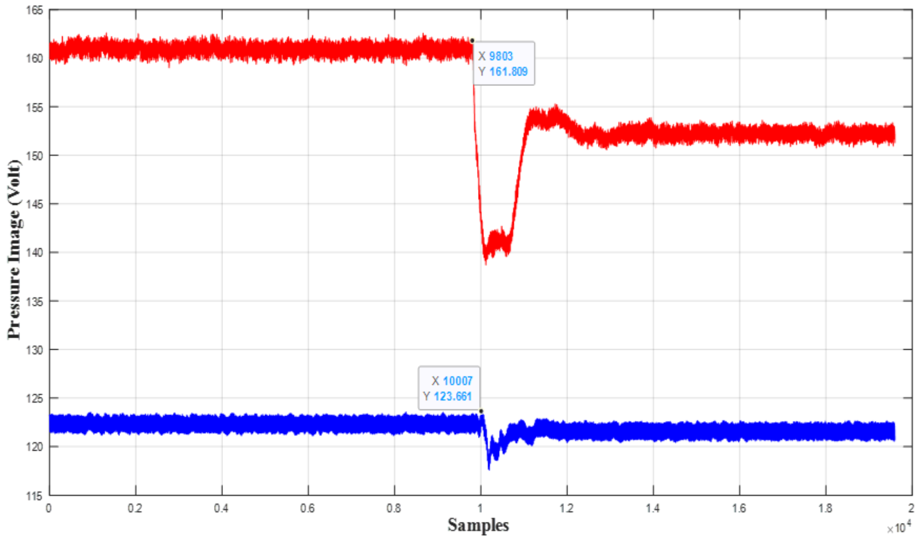

Figure.5.13. Illustration of two pressure signals when a leak occurred (the first 13.5m and the second 76m away from the leak position)

In the last scenario, when the leak has a diameter of 12mm, the positions of the two pressure transmitters are modified, with the first at 13.5 meters and the second at 76 meters from the leak spot. Figure.5.13 shows the signals.

II.3.5. Denoised signals

After filtering our leakage signals, obtained in the laboratory using the DWT approach, we plotted the pressure signals at specific transmitter locations. This was done to illustrate the differences and results observed during the data collection process for leaks. Two mother wavelets (Daubechies4, Haar) at different levels were applied with the ‘Soft’, and ‘Hard’ thresholding in addition to the ‘DONOHO’ threshold. The following examples are given at level 4.

II.3.5.1. With "Daubechies4" mother wavelet (Db4)

a. Soft Thresholding

Transsmiter1

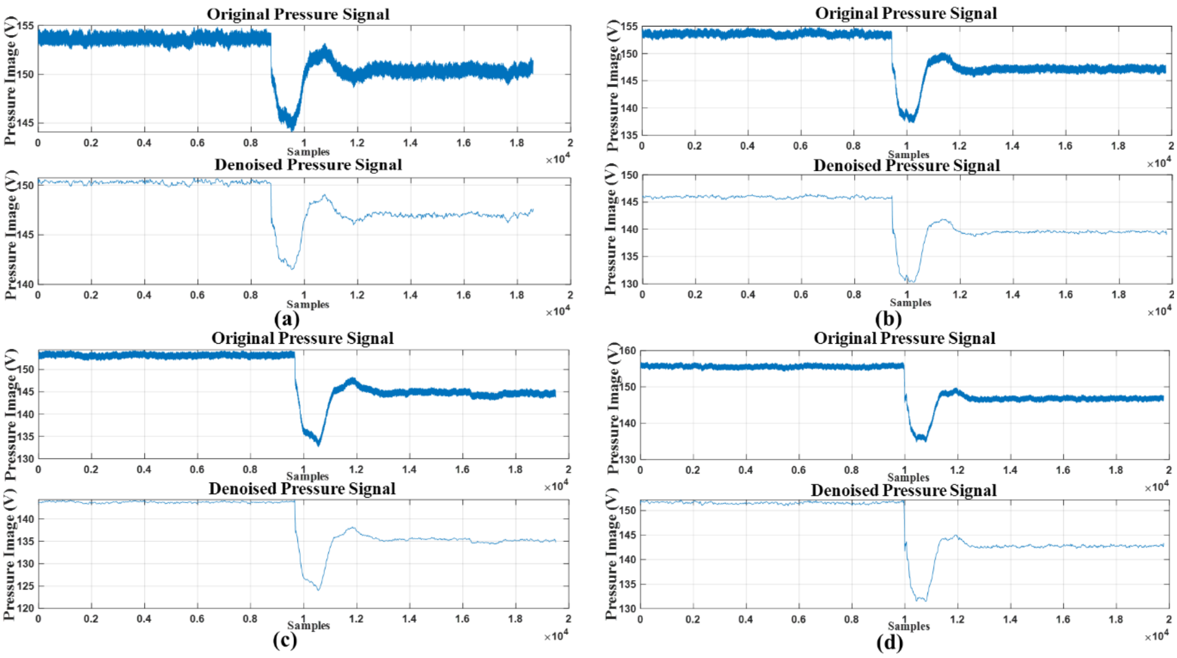

Figure.5.14. The illustration of the denoised pressure signal captured by transmiter1 where it located 2m away from the leak in four cases: (a) At leak with size 4mm, (b) At leak with size 6mm, (c) At leak with size 8mm, (d) At leak with size 12mm.Transsmiter2

Transsmiter2

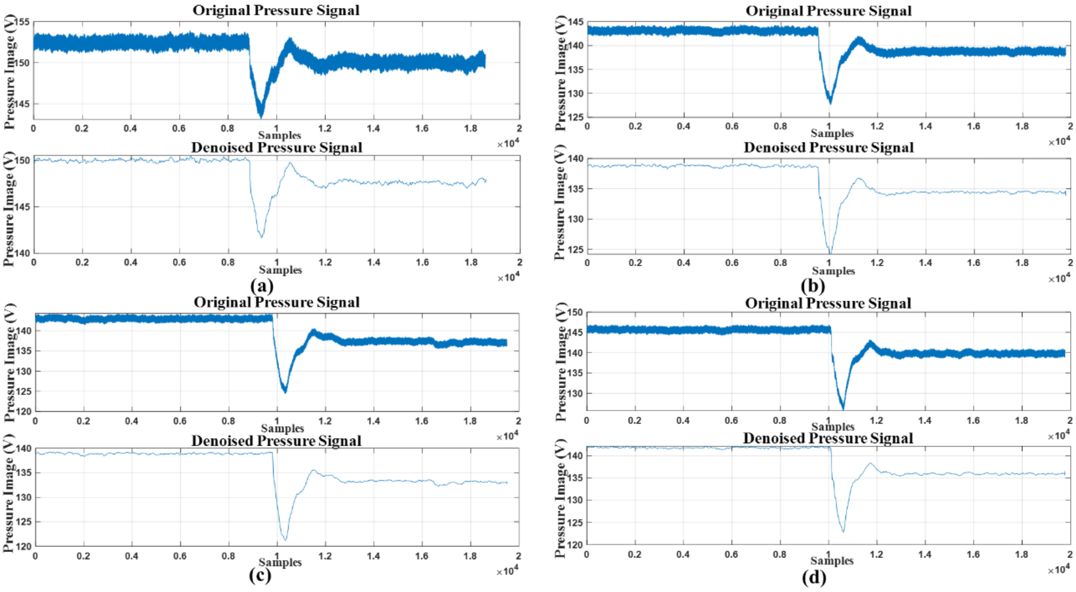

Figure.5.15. The illustration of the denoised pressure signal captured by transmiter2 which is located 28m away from the leak in four cases: (a) At leak with size 4mm, (b) At leak with size 6mm, (c) At leak with size 8mm, (d) At leak with size 12mm

b. Hard Thresholding

Transsmiter1

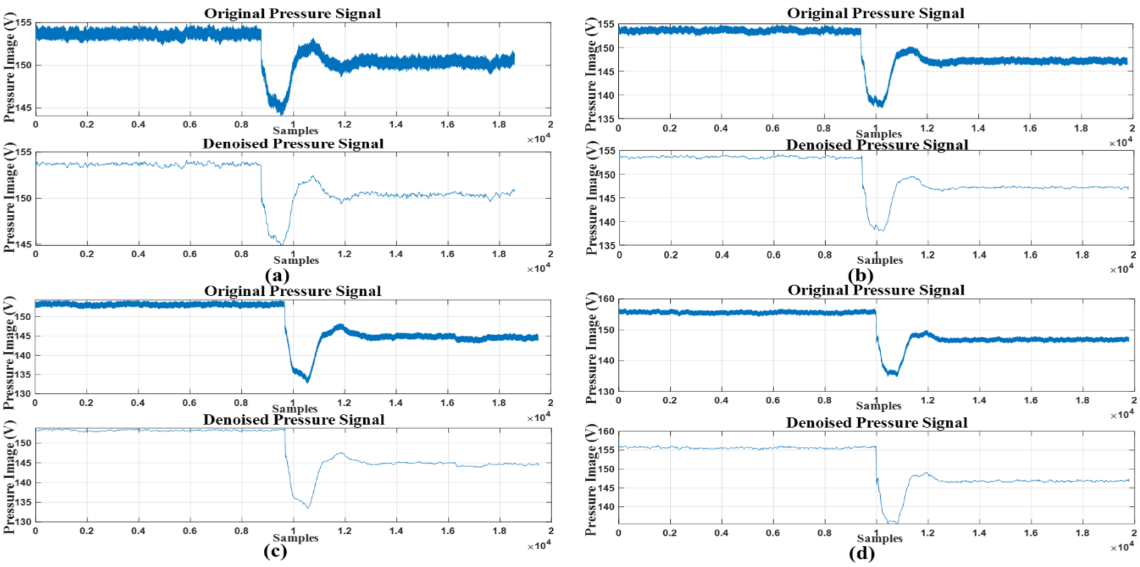

Figure.5.16. The illustration of the denoised pressure signal captured by transmiter1 which is located 2m away from the leak in four cases: (a) At leak with size 4mm, (b) At leak with size 6mm, (c) At leak with size 8mm, (d) At leak with size 12mm

Transsmiter2

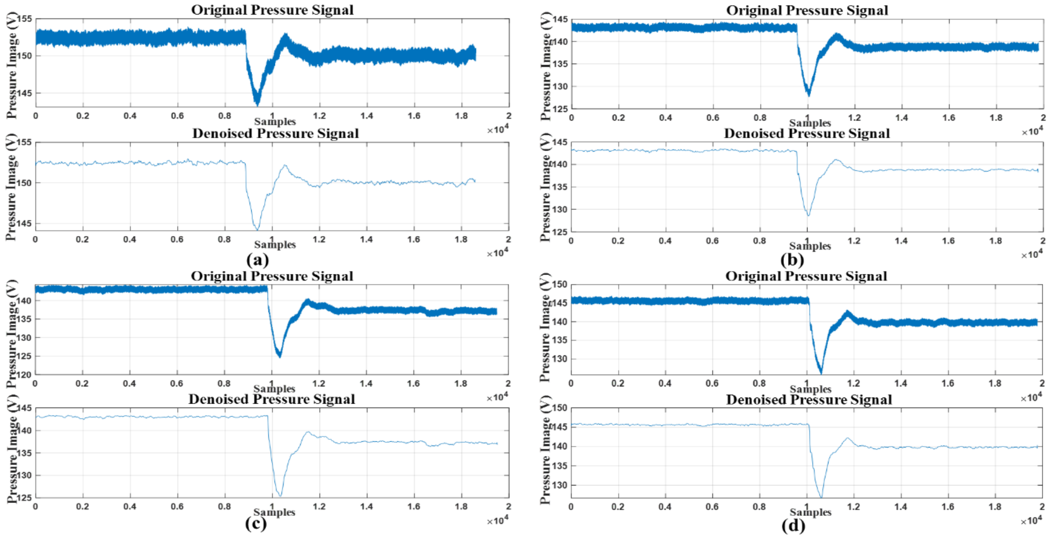

Figure.5.17. The illustration of the denoised pressure signal captured by transmiter1 which is located 2m away from the leak in four cases: (a) At leak with size 4mm, (b) At leak with size 6mm, (c) At leak with size 8mm, (d) At leak with size 12mm

II.3.5.2. With "Haar" mother wavelet

a. Soft Thresholding

Transsmiter1

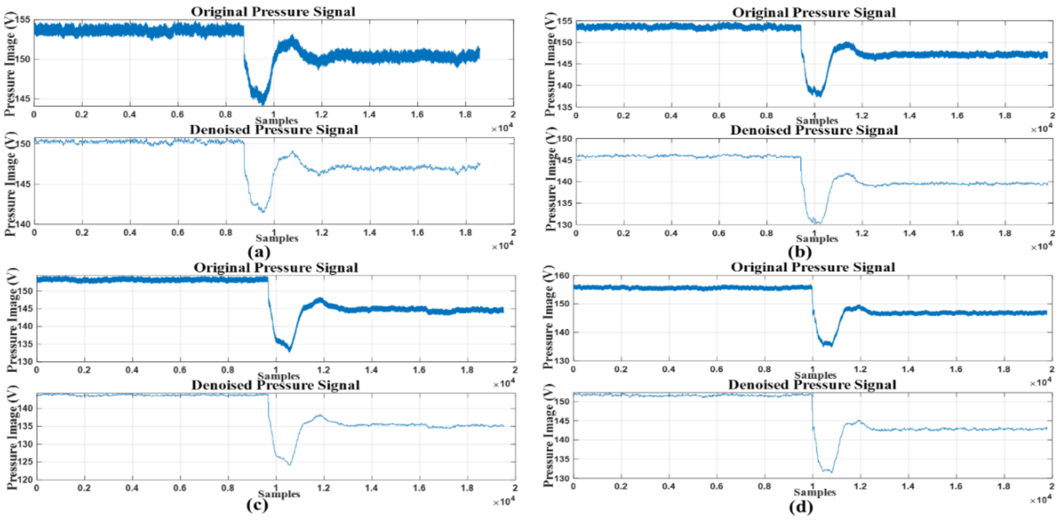

Figure.5.18. The illustration of the denoised pressure signal captured by transmiter1 where it located 2m away from the leak in four cases: (a) At leak with size 4mm, (b) At leak with size 6mm, (c) At leak with size 8mm, (d) At leak with size 12mm

Transsmiter2

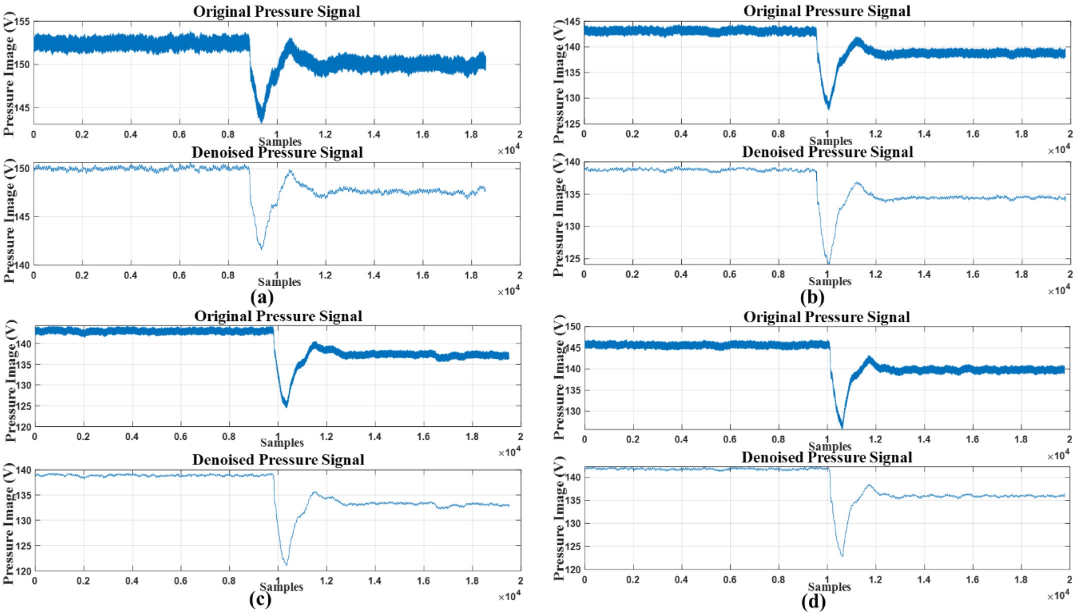

Figure.5.19. The illustration of the denoised pressure signal captured by transmiter2 where it located 28m away from the leak in four cases: (a) At leak with size 4mm, (b) At leak with size 6mm, (c) At leak with size 8mm, (d) At leak with size 12mm

b. Hard Thresholding

Transsmiter1

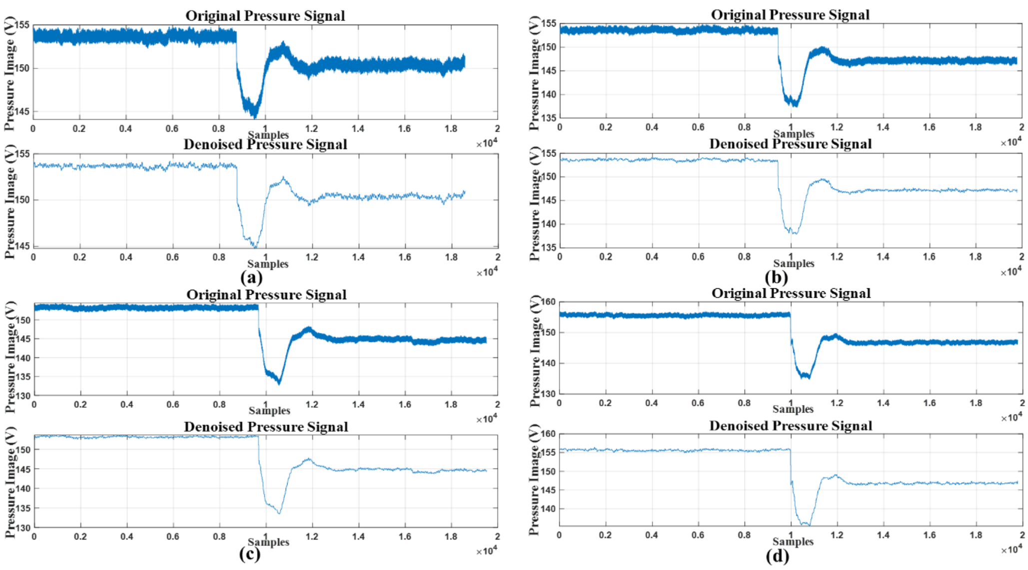

Figure.5.20. The illustration of the denoised pressure signal captured by transmiter1 where it located 2m away from the leak in four cases: (a) At leak with size 4mm, (b) At leak with size 6mm, (c) At leak with size 8mm, (d) At leak with size 12mm

Transsmiter2

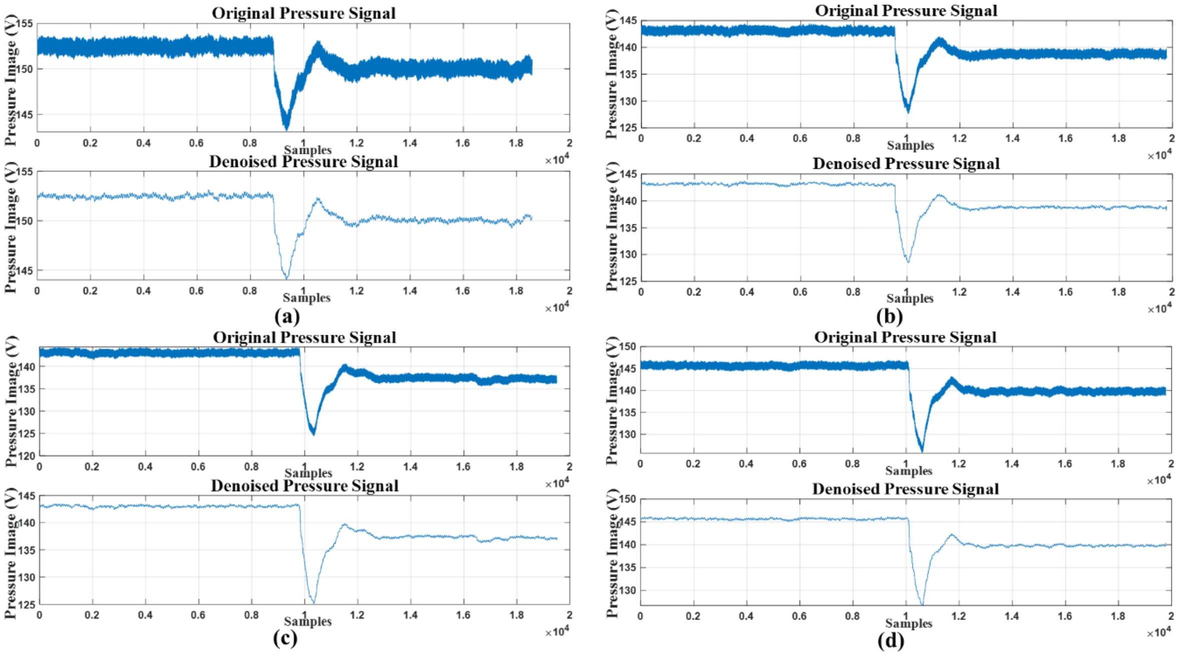

Figure.5.21. The illustration of the denoised pressure signal captured by transmiter2 where it located 28m away from the leak in four cases: (a) At leak with size 4mm, (b) At leak with size 6mm, (c) At a leak with size 8mm, (d) At leak with size 12mm

Figure.5.14-21 illustrate the pressure signals in four cases of leakage size (4mm, 6mm, 8mm, and 12mm), where one of the cases was randomly selected in which the first transmitter is located 2m and the second 28m before and after the real leak location. The leak is 14.5m from the entrance to the pipe network. It can be observed that the signals after filtering became smooth and no longer exhibited vibrations caused by external noise. It can be seen that as the size of the leak increases, the singularity of the signal representing the pressure decreases and varies for the wavelets Db4, Haar, and a level4 between 1.42V and 1.24V for the orifices 4 mm to 12 mm.

Table.2. displays the calculated Mean Squared Error (MSE), NCC, and SNR values for our filtered signals. These parameters provide insight into how closely the filtered signals match the original data in terms of quality, fidelity, and similarity. A lower MSE indicates less error between the filtered and original signals, and a higher SNR indicates a greater signal-to-noise ratio. To assess the effectiveness of the filtering method, the NCC calculates the degree of similarity between the filtered signals and the appropriate references.

Table.2. Metrics of evaluation

Mother wavelet	Level	Soft threshold		Hard threshold		Soft threshold		Hard threshold		Soft threshold		Hard threshold	
		SNR (dB)				NCC				MSE			
		PT1	PT2	PT1	PT2	PT1	PT2	PT1	PT2	PT1	PT2	PT1	PT2
Db4	Level4	26.6763	31.1535	50.2488	48.8281	0.99338	0.98435	0.99338	0.98435	48.4761	15.2076	0.21295	0.25978
	Level5	29.6672	34.0899	50.2099	48.8185	0.99332	0.98432	0.99332	0.98432	24.3464	7.7344	0.21486	0.26036
	Level10	42.4097	45.1296	48.1564	48.2039	0.98311	0.97756	0.98926	0.98191	1.2947	0.60877	0.34476	0.29993
Haar	Level4	26.6769	31.1568	50.3985	49.0283	0.9936	0.98506	0.9936	0.98506	48.4694	15.1961	0.20573	0.24807
	Level5	29.6673	34.0921	50.2166	48.8862	0.99333	0.98456	0.99333	0.98456	24.3458	7.7304	0.21454	0.25633
	Level10	42.4495	44.7279	48.3158	47.8657	0.98388	0.97433	0.98965	0.98043	1.2829	0.66776	0.33233	0.32422

The analysis of Table.2. reveals a positive outcome in assessing the filtered pressure signals through the metrics SNR, NCC, and MSE. These metrics serve as crucial indicators for evaluating the efficacy of the filtration process of the signals gathered by the pressure transmitters 1 and 2 (PT1, PT2 respectively). The results indicate a notable enhancement in signal quality and a big similarity and match with the original pressure signal, substantiated by higher SNR values (SNR > 26.6763 dB), and minimized MSE (NCC≈1) values, alongside NCC (0.20573 < MSE < 48.4761) values approaching unity. Particularly noteworthy is the superior performance observed when employing a hard threshold in conjunction with a DONOHO threshold, surpassing outcomes associated with a soft threshold. This comparison underscores the significance of methodological nuances in optimizing signal filtration.

To investigate and validate the efficiency of the new proposed detector, we fill the Table.3. below. By a comparison of the results obtained, we can note that in general there is a great convergence between the position of the real transmitter and the calculated position, where the most estimated error was about 5 meters, and this is related to a set of factors, including the real positioning of the two transmitters. Additionally, after the creation of the leak, water erupts from the pipeline creating a turbulent jet that may indicate that the water was not at its steady state when the measurements were taken.

Table.3. Experiments validation of results

Leak size	Real position(m)		Cross-correlation value (s)	Position calculation(m)	
	PT1	PT2		PT1	PT2
4 mm	2	3	0.002	2.2702	2.7298
	2	12	0.092	3.5701	17.5701
	2	28	0.164	-3.8424	33.8424
	2	38	0.12	6.2129	33.7871
	2	60	0.216	6.1832	55.8168
	2	70	0.304	1.0726	70.9274
	2	76	0.336	0.3960	77.6040
6 mm	2	3	0.002	2.2702	2.7298
	2	12	0.044	1.9447	12.0553
	2	21	0.094	0.7001	22.2999
	2	28	0.082	5.5788	24.4212
	2	38	0.16	1.6172	38.3828
	2	60	0.256	1.5875	60.4125
	2	70	0.306	0.8428	71.1572
	2	76	0.324	1.7747	76.2253
8 mm	2	3	0.002	2.2702	2.7298
	2	12	0.046	1.7149	12.2851
	2	21	0.08	2.3086	20.6914
	2	28	0.118	1.4427	28.5573
	2	38	0.15	2.7661	37.2339
	2	60	0.282	-1.3998	63.3998
	2	70	0.326	-1.4550	73.4550
	2	76	0.328	1.3152	76.6848
12mm	1.5	9	0.044	0.1947	10.3053
	1.5	14	0.084	-1.9010	17.4010
	1.5	18	0.054	3.5458	15.9542
	1.5	20.5	0.058	4.3362	17.6638
	1.5	25	0.064	5.8969	20.6031
	1.5	28.5	0.092	4.4299	25.5701
	1.5	32	0.114	3.6522	29.8478
	1.5	35	0.136	2.6246	33.8754
	1.5	38	0.132	4.5842	34.9158
	1.5	45.5	0.148	6.4959	40.5041
	1.5	66	0.234	6.8651	60.6349
	1.5	71.5	0.334	-1.8742	74.8742
	1.5	76	0.32	1.9843	75.5157
	4.5	76	0.276	8.5396	71.9604
	8	76	0.262	11.8981	72.1019
	11	76	0.254	14.3172	72.6828
	13.5	76	0.228	18.5545	70.9455

Table.3. presents our analysis of pressure measurements taken at various transmitter positions to calculate the change in time (ΔT) using equations (51) and (52). This analysis forms the basis for determining the distance between the leak location and each transmitter,

enabling leak localization based on collected pressure signals. For leak sizes of 4mm, 6mm, and 8mm, we positioned the first transmitter 2 meters from the actual leak, while varying the position of the second transmitter to observe different outcomes. In the case of a 12mm leak, the first transmitter was placed 1.5 meters from the leak. These variations were introduced to validate the effectiveness of our proposed detector. A comparison between the actual transmitter positions and the calculated positions revealed mostly consistent results, with occasional discrepancies of up to 5 meters. This variance may be attributed to transmitter placement affecting signal quality, particularly if obstructed by structural elements or resulting in susceptibility to external noise interference.

Table.4. Comparison with existing work.

	Type	DSP	Threshold	Noise source	detection	Localization
Proposed DWTD Detector	Pressure Transmitters	DWT. IDWT.	DONOHO for filtering. 10% of the value of pressure at the far distance for leak detection.	Water turbulence fluctuations.	Yes	Yes
[4]	Vibration Sensors	FFT. IFFT.	$L_{Lower} < L_{Th} < L_{Upper}$ $L_{Lower:}$ From equation based on Cross-correlation. $L_{Upper:}$ From the maximum peak of noise.	Simulation of environmental noise, they consider the machinery noises as periodic signals.	Yes	Yes

Based on the content of Table.4, our comparative analysis reveals significant insights into the methodologies employed for leak detection and localization within WDNs. Our approach, utilizing the DWT and DONOHO threshold on pressure signals directly collected from transmitters, focuses on minimizing the impact of water fluctuations noise. This method ensures enhanced signal quality through precise noise reduction techniques, thereby improving the accuracy of leak detection and localization. In contrast, the existing study adopts FFT and Parseval thresholding on vibration signals, which are susceptible to external noise. Despite both studies employing cross-correlation for time delay calculation to pinpoint leak positions, our emphasis on DWT highlights its effectiveness in mitigating turbulent water fluctuations' noise, contributing to more robust leak detection systems. The comparative study underscores the importance of applied signal processing techniques in advancing the reliability and accuracy of leak detection technologies under varying environmental conditions.

III- Conclusion

This chapter offers the experimental findings and debates generated from the thesis's three main contributions, which provide vital insights into water leak detection and localization. The first research established a reliable methodology for predicting the friction factor and discharge flow via leaks, illustrating the dynamic development of the cost function reduction procedure across numerous generations. This investigation underscored the suggested approach's dependability and efficiency in dealing with these essential hydraulic variables.

The second research focused on the controlled assessment of pressure signals, which employed the S.G filter to reduce noise. The efficiency of this method was statistically confirmed by increasing the SNR. Leak localization was accomplished by calculating the time difference between signal arrivals from two pressure sensors, and the method's durability was proven by experimental validation.

The third and final contribution built on these results by using sophisticated signal processing methods to analyze additional data from a second prototype. The DWT, together with Donoho thresholding and the IDWT, allowed for exact signal denoising and reconstruction. Leak detection and localization were subsequently refined using normalized cross-correlation analysis of the recovered signals. The usefulness of denoising was shown using measurements like as SNR, Mean Squared Error (MSE), and NCC.

This chapter emphasizes the dependability, accuracy, and resilience of the suggested procedures via careful examination and comparison to past methodologies. The findings highlight the importance of this study in enhancing water leak detection and localization approaches, providing a platform for further improvement and use in real-world WDNs.

References

[1] B. R. Munson, D. F. Young, T. H. Okiishi, and W. W. Huebsch, *Fundamentals of Fluid Mechanics*, 6th ed. Hoboken, NJ, USA: John Wiley & Sons, 2009. ISBN: 978-0-470-26284-9.

[2] V. L. Streeter and E. B. Wylie, Fluid Mechanics, 7th ed. New York, NY, USA: McGraw-Hill, 1979. ISBN: 0-07-062232-9.

[3] A. Savitzky and M. J. E. Golay, "Smoothing and Differentiation of Data by Simplified Least Squares Procedures," *Anal. Chem.*, vol. 36, no. 8, pp. 1627–1639, 1964, doi: 10.1021/ac60214a047.

[4] D. B. Yoon, J. H. Park, and S. H. Shin, "Improvement of cross-correlation technique for leak detection of a buried pipe in a tonal noisy environment," *Nucl. Eng. Technol.*, vol. 44, no. 8, pp. 977–984, Dec. 2012, doi: 10.5516/NET.09.2011.067.

Conclusion

And Recommendations

6.Conclusion

This thesis examines innovative approaches for water leak detection and localization, addressing key difficulties in sustainable water management. With urban water distribution systems being pressured by aging infrastructure and expanding worldwide demand, precise and dependable leak detection technologies are more important than ever. This study combines modern DSP techniques with older approaches to provide a novel framework for accurate leak location.

Parametric modeling, based on fluid mechanics concepts, is essential in the creation of mathematical models for water leak detection. These thesis gives a parametric description of the physical mechanisms governing fluid flow and leak dynamics by optimizing two unknown parameters using a BBO approach. The parameters being optimized are critical for properly forecasting the system's behaviour under different situations. The optimization procedure is critical since it directly influences the model's accuracy in localizing the leak, increasing the efficacy of leak detection tactics.

Central to this study is the application of DSP techniques, including FFT, CWT, and DWT. These methods have proven highly effective in analyzing complex and noisy signals, enabling the extraction of critical features linked to leaks. Through these tools, the research develops a novel mathematical model that leverages the temporal characteristics of pressure wave propagation and reflection to pinpoint leak locations within pipeline networks. This model significantly enhances the precision and adaptability of existing methodologies.

The practicality of these advances has been proven by considerable testing. High-precision pressure measurements were gathered and evaluated using a hydraulic prototype created to imitate real-world WDNs. The experimental system, which included a high-density polyethylene (HDPE) pipeline, tank, and electric pump, enabled for controlled testing of the suggested framework under a variety of conditions. The findings repeatedly show the approach's resilience and dependability, even under difficult operating situations.

Beyond its technical contributions, this study contributes to larger aims such as resource conservation and operational efficiency. Water losses from leaks not only cost money, but they also put additional pressure on scarce freshwater supplies. The solutions offered in this thesis directly address these concerns, providing tools for utilities and governments to use to decrease losses, preserve resources, and improve the sustainability of WDNs.

This study emphasizes the relevance of water management innovation by bridging the gap between theoretical advances and actual application. The use of DSP approaches and experimental validation emphasizes the interdisciplinary character of the difficulties addressed.

Furthermore, this study lays the groundwork for future research, notably the combination of machine learning and IoT technologies, which might improve leak detection and monitoring capabilities.

In conclusion, this thesis advances the state-of-the-art in water leak detection by presenting a robust and practical framework that enhances accuracy and dependability. This study helps to solve an issue of scientific and social importance by combining novel signal processing methods with real-world applications. It emphasizes the potential for technical innovation to play a critical role in maintaining one of the world's most important resources, water.

6.1 Research contributions

In Chapter 2, the literature review provided the framework by examining current water leak detection technologies as well as existing WDNs design. This study not only highlighted the benefits and downsides of various methodologies, but it also identified critical gaps in current practices. This chapter underlined the need for innovative solutions that employ advanced signal processing approaches to improve leak detection abilities in complex urban environments by synthesizing the existing body of knowledge.

Chapter 3 examined several DSP techniques, such as the FFT, STFT, CWT, DWT, and cross-correlation algorithms. The investigation of these approaches highlighted wavelet transforms' distinct benefits, specifically their ability to handle non-stationary signals common to water leak circumstances. This chapter's results underline the need of choosing suitable signal processing algorithms to improve leak identification and localization, ultimately adding to overall monitoring system efficacy.

Chapter 4 describes the methods used in this study to solve the issues of water leak detection and localization in WDNs. It explains the major contributions on which the proposed solutions are based.

i. The first contribution, begins by constructing a mathematical model based on fluid mechanics principles. The BBO approach is utilized to improve this model by altering critical parameters such as friction and discharge flow. The optimization technique increases the model's accuracy and applicability for a variety of leak scenarios.
ii. The second contribution, discusses the experimental setup for signal processing and noise reduction. Pressure signals are gathered using high-precision transmitters and processed using the S.G filter, which is ideal for denoising. The temporal difference between signal arrivals at sensors is computed and used in a mathematical model for

leak location. The experimental prototype, which was made of zigzag-shaped HDPE pipes, serves as a platform for confirming leak spots based on known distance.

iii. The third contribution, progresses to a bigger and more sophisticated experimental setup with circular HDPE pipes. This configuration consists of pressure transmitters and high-precision data-gathering equipment. Various leak sizes and distances are tried to verify the method. The pressure signals are decomposed using the DWT, followed by Donoho thresholding to eliminate noise. SNR, NCC, and MSE are among the metrics used to examine the reconstructed signals. The time difference in signal arrival is then utilized to locate leak positions.

Chapter 5 summarizes the important discoveries and outcomes from this thesis, concentrating on crucial areas of water leak detection and localization. It starts by describing the process of selecting critical system parameters and assessing optimization behavior across numerous iterations. The chapter then delves into the processing of experimental data acquired in controlled environments, focusing on noise reduction techniques and methods for precisely detecting and pinpointing leaks. Advanced signal processing approaches are presented, with a focus on enhancing data quality and detection accuracy. The latter was assessed by the calculation of some metrices. The chapter also examines the performance of the suggested methodologies using experimental validation and compares them to current methods, demonstrating their efficiency and dependability.

6.2 Recommendations

1. Use machine learning techniques (such as CNNs and RNNs) in conjunction with DSP methodologies to automate feature extraction and decision-making.
2. Validate in large-scale real-world systems: Apply suggested methodologies to complex WDNs to ensure scalability and robustness under changing conditions.
3. Improve Scalability and Complexity: Develop adaptive frameworks capable of handling large datasets, real-time processing, and a variety of network configurations.
4. Use Hybrid Approaches: Combine deep learning models with DSP approaches such as wavelet transforms and STFT to improve leak detection accuracy in noisy environments.
5. Improve Sustainable Water Management: Create cost-effective, automated solutions for water conservation and infrastructure monitoring.

Finally, this thesis not only contributes to our theoretical understanding of water leak detection methods, but it also gives practical solutions that can be used in real-world scenarios. The merging of modern DSP techniques with traditional leak detection methods represents a significant advancement in the industry, paving the way for more efficient and trustworthy systems capable of addressing the difficulties posed by water leaks in urban infrastructure. The findings presented here have the potential to influence future research directions and technological improvements in water resource management, therefore contributing to the long-term management of this essential resource.

Appendix A

List Of Publications

Publication(s):

- S. Meftah, M. Bentoumi, D. Burhanuddin, H. Bakhti, and C. Chabira, "Novel Leak Detector Based on DWT: An Experimental Study," International Journal of Robotics and Control Systems, vol. 4, no. 3, pp. 1109-1134, 2024, doi:10.31763/ijrcs.v4i3.1458.

Conference(s):

- S. Meftah, M. Bentoumi, H. Bakhti, and C. Chabira, "Parameterization and Validation of the Physical Coefficients of a WDNs by BBO," in 2022 International Conference of Advanced Technology in Electronic and Electrical Engineering (ICATEEE), Nov. 2022, pp. 1–5.
- M. Bentoumi, H. Bakhti, C. Chabira, and S. Meftah, "SG Filter and Speed of Pressure Wave Applied to Locate Leak in Water Pipe Networks," in 2022 International Conference of Advanced Technology in Electronic and Electrical Engineering (ICATEEE), Nov. 2022, pp. 1–5.
- M. Bentoumi, H. Bakhti, C. Chabira, and S. Meftah, "DWT and STFT Applied to Detect and Locate Leaks in WDNs," Participant Statistics, p. 216.
- M. N. Ribuan, D. Hanafi, A. M. Kwad, H. Abdurman, S. Bandri, and S. Meftah, "Wiener Model Structure Estimation of DC Motor Through Online Neural Network System Identification," in 2024 IEEE 15th Control and System Graduate Research Colloquium (ICSGRC), Aug. 2024, pp. 325–330.

Appendix B

VITA

The author, Sabir Meftah, was born on August 11, 1996, in M'sila, Algeria. He received the B.S. degree in Electronics from the University of M'sila, Algeria, in 2018, with a project focused on PWM control of an H-bridge chopper using the PIC 16F84 Microcontroller. He further pursued an M.S. degree in Instrumentation at the same university in 2020, where his master's thesis was titled Control of a Single-Phase Inverter with Harmonic Elimination based on the PIC 18F4431 Microcontroller. In 2022, he began his Ph.D. journey in the Department of Electronics, College of Technology, University of Mohammed Boudiaf, M'sila, Algeria.

From 2021 to 2022, he worked as an ordinary worker at Enterprise Wafa Plastics.

His research interests include water leak detection, optimization techniques, instrumentation systems, and control systems. Proficient in MATLAB, Python, and Assembly programming languages, he is also skilled in using software such as Proteus, LabVIEW, Arduino IDE, and MICRO C. He has practical experience working with hardware platforms like Arduino, PIC, and DSP.