An Unsupervised Acoustic Denoising Model for Water Leakage Detection

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Abstract

The global issue of water loss due to leakage in Water Distribution Networks (WDN) is considerable. Acoustic methods are preferred for leak detection because they are non-invasive, efficient, and cost-effective. However, distinguishing leaks from background noise remains a major challenge due to the reliance on predetermined thresholds in conventional methods and the substantial dependence of mainstream supervised deep learning approaches on the quality of training data. To overcome these obstacles, this study proposes an Unsupervised Acoustic Denoising Model (UADM), designed specifically for identifying and reducing noise to enhance leak detection accuracy within a WDN. This model uses an encoder-decoder architecture and incorporates domain-specific loss functions to guide the denoising process. Tests with publicly available datasets show that the proposed UADM significantly enhances the distinction between leak and non-leak signals. The improvements in accuracy, recall, F1 score, and precision were notable, with average increases of 8.1%, 14.5%, 8.0%, and 6.4%, respectively. The proposed UADM offers a stable and efficient tool for stakeholders involved in WDN management. By enhancing the anti-noise capability of acoustic leak detection systems, the UADM model contributes to the proactive identification and mitigation of water leaks, thereby minimizing water loss and associated financial costs.

Keywords: Domain Knowledge Integration, Unsupervised Leakage Detection, Encoder-Decoder Neural Networks, Water Distribution Networks

1. Introduction

The issue of water leakage in Water Distribution Networks (WDN) is a prevalent and significant global concern. Estimations (Liemberger and Wyatt 2018) projected the global non-revenue water (NRW), water that is pumped and then lost or unaccounted for, to reach an alarming 126 billion m^3 annually, incurring a staggering annual loss cost of approximately USD 39 billion. Notably, WDN leakage stands out as the primary contributor to NRW (Tornyeviadzi and Seidu 2023; Zyoud et al. 2016; Shao et al. 2023). In the United States, it is believed that WDN leakage contributes to over 20% of potable water loss (Momeni et al. 2022). Moreover, data from the "Urban Water Supply Statistical Yearbook of China" (Xinyue and Shihu 2018) for the year 2015 revealed a national average water loss rate of 14.32%. Recognizing the severity of this issue, the Chinese government has outlined an ambitious goal to reduce the leakage rate of the national urban public water supply network to below 9% by the year 2025 (Ministry of Housing and Urban-Rural Department of the Republic of China 2022). While this target signifies progress, it still represents a relatively high ratio of water loss within the system. The importance of reducing NRW is underscored by the fact that the United Nations (UN) has listed ensuring the availability and sustainable management of water and sanitation for all as UN Sustainable Development Goal (SDG) number 6. The UN's high prioritization of water and sanitation (SDG #6) is due to both being at the core of sustainable development, for the range of services both provide underpin health, poverty reduction, economic growth and environmental sustainability (United Nations, Department of Economic and Social Affairs Sustainable Development 2022).

Acoustic signal-based detection stands as one of the most prevailing and effective automated methods for monitoring WDN leaks. Dating back to the 1960s (Morgan 1966), the incorporation of acoustic equipment significantly revolutionized the prompt discovery and management of WDN leaks, enhancing the timeliness and convenience of monitoring tasks. The evolution of acoustic equipment hardware and signal analysis algorithms has sparked numerous studies proposing real-time or non-real-time solutions for WDN leakage detection. The prevalent framework for WDN leakage detection entails the use of acoustic sensors, such as hydrophones (Cody et al. 2018), noise loggers (El-Zahab et al. 2019), and more, to gather data, followed by time domain (Zhang et al. 2022), frequency domain (Yu et al. 2023), time-frequency analysis (Guo et al. 2021; Xie et al. 2020), or cross-correlation analysis (Guo et al. 2022). Advancements in analysis tools have progressed in chronological order, encompassing the Fourier Transform, Fast Fourier Transform, Wavelet Transform, Empirical Mode Decomposition (EMD), Variational Mode Decomposition (VMD) (Fazai et al. 2019; Song and Li 2021; Fan et al. 2022), and others for signal feature extraction. Following feature extraction, traditional classification algorithms (SVM, Random Forest, etc.) or deep learning algorithms (CNN, RNN, etc.) are employed to classify leak and non-leak signals. In recent years, the rapid advancements in deep learning technology have shown promise when fused with the aforementioned methods. Studies by Liu et al. (2024) and Guo et al. (2022)

showcased the successful application of advanced convolutional neural networks in analyzing acoustic data, reporting impressive leak monitoring accuracy of 90.77% and 100% for metal pipelines and 95% for non-metal pipelines, respectively. These studies demonstrate significant achievements in detection accuracy.

However, the detection of leaks in WDN using acoustic methods faces substantial challenges when dealing with environmental noise interference. Given the relatively shallow depths at which WDN are typically buried (within 3m), environmental noise easily interferes with the effectiveness of acoustic methods (Wu and Liu 2017; Liu et al. 2022). The impact of environmental noise presents difficulties in various analytical domains. First, in time domain analysis, noise interference disrupts the waveform, as noise is reflected in amplitude, often complicating its differentiation from the signal. Second, in frequency domain analysis, noise manifests within specific frequency components, potentially overlapping with the frequencies of the target signal, thus complicating accurate discrimination. Narrowband noise or spurious signals further complicate the analysis, interfering with the desired frequency components. Efforts in time-frequency domain analysis aim to combine time and frequency information to enhance signal assessment. Despite being among the most effective analysis methods, this approach's reliance on short-term signal spectrum conversion makes it more susceptible to noise variations within brief periods. Abruptly changing or burst noise patterns can disrupt the time-frequency domain representation, challenging the separation of signal and noise. Existing research often integrates denoising into the input feature extraction process, typically under the constraints of pre-set threshold parameters. Traditional denoising methods, such as linear filtering, spectral subtraction, statistical model-based techniques, and methods based on mode decomposition like EMD, VMD, and Wavelet (Wu et al.

2018; Guo et al. 2016; Pan et al. 2018), heavily rely on the rationality of preset parameters. However, these parameters often lack generalizability due to the complex nature of target signals and noise in WDN scenarios, influenced by network topology, leak type, background noise, flow conditions, etc. The challenge is further compounded as a supervised deep learning model is difficult to implement due to the absence of a clear quantitative evaluation between target signals and noise, making it arduous to define the required input mapping for training purposes.

To address the aforementioned challenges, this study proposes an Unsupervised Acoustic Denoising Model, named UADM. The model utilizes an encoder-decoder framework and directs the noise reduction process of the input signal via domain knowledge-based innovative loss function design. This unique approach eliminates the need for preset threshold parameters or mode decomposition parameters. To validate the denoising efficacy of the proposed UADM model, this study employs various mainstream methods, including SVM, Random Forest, 1DCNN, RNN, and Wavelet-based algorithms for comparison and verification. Utilizing a public dataset from the Aghashahi et al. (2023) team at Texas A&M University, which encompasses hydrophone signals collected across different leak types, network topologies, background noise, and flow conditions, the experimental results reveal the UADM model's significant enhancement in acoustic leak detection accuracy within WDN. Comparative analysis against data pre-denoising showcases a noteworthy average improvement across five sets of verification experiments. The metrics, including *Accuracy*, *Recall*, *F1 score*, and *Precision*, exhibited an average improvement of 8.1%, 14.5%, 8.0%, and 6.4%, respectively. From a theoretical perspective, this research contributes a novel outlook on enhancing the anti-noise capability of acoustic WDN leakage detection, specifically by addressing the challenge through an unsupervised learning approach integrating domain knowledge. From an engineering standpoint, the UADM model offers a stable and efficient tool for detecting leaks within WDN system, proving beneficial for stakeholders in water distribution networks.

2. Related work

Acoustic-based leakage detection encounters an inherent challenge due to the amalgamation of environmental noise and leakage signals. Given the typical shallow burial depth of WDN, ambient noise from sources such as operating pumps, rain impacting chamber lids, and passing vehicles can easily infiltrate acoustic sensors (Fan et al. 2022; Aghashahi et al. 2023). Hence, the core objective of acoustic-based leakage detection revolves around the extraction of leakage-relevant patterns from the original signal by mitigating interference from ambient noise. These discernible patterns serve as the benchmark for distinguishing between leak and non-leak conditions. Notably, prevailing research in acoustic-based leakage detection encompasses various methodologies, including analysis in the time domain, frequency domain, time-frequency domain, and correlation analysis.

2.1 Time domain analysis

Time domain analysis is a method that employs time as the independent variable and tracks changes in the audio signal as the dependent variable. It serves as the most intuitive and fundamental approach for characterizing acoustic signals. Consequently, time domain analysis stands as the earliest method applied to leakage detection. Common techniques within this domain include Root Mean Square (RMS) (Banjara et al. 2020), Peak Analysis (Meng et al. 2012), and Envelope Analysis (Ahn et al. 2019), among others. Lim et al. (2014) proposed the utilization of the crest factor and acoustic emission energy features in the time domain to assess pipe leakage, successfully identifying four distinct leaks in various areas. Similarly, Zhang et al. (2022) reported a novel leak localization method for buried natural gas pipelines using four microphones placed in detection holes. While time domain analysis offers simplicity and clarity, with the substantial advantage of low computational load, it has limitations (Fazai et al. 2019; Duan et al. 2011). It might be inadequate for non-stationary signals and complex signal scenarios, as it is often insufficient to solely use time domain parameters to describe them. Additionally, methods based solely on time domain analysis might not detect leakage before the acoustic signal collection begins (Fan et al. 2022). Consequently, pure time domain analysis is scarcely used in contemporary applications.

2.2 Frequency domain analysis

Frequency domain analysis is an analytical method that dissects time domain signals into a series of combined sine and cosine waves through Fourier Transformation. By scrutinizing signal components at various frequencies and their overall statistical distribution patterns, frequency domain analysis enables the differentiation between leak and non-leak signals. Notable methods within frequency domain analysis encompass peak frequency, frequency centroid of a band, skewness, kurtosis (Fazai et al. 2019; Song and Li 2021), etc. Guo and Yang (2009) proposed a pipeline leak detection method solely relying on frequency domain analysis. Similarly, Yu et al. (2023) utilized energy distribution in the frequency domain as an indicator to classify WDN leakage signals. However, the straightforward frequency domain analysis method exhibits limitations when handling non-stationary signals (those with frequencies changing over time). It can only capture the frequency components encompassed within a segment of the signal as a whole, without identifying the specific moment when each component emerges. Consequently, this method entirely disregards valuable information inherent in the time series.

2.3 Time-frequency domain analysis

To address the limitations of solely analyzing acoustic signals in the time and frequency domains, a range of time-frequency domain analysis tools have emerged. The most classic among these is the Short-Time Fourier Transform (STFT), which conducts Fourier Transform on small signal segments via a sliding window and then combines these segments frame by frame. This technique aims to preserve both time-series relationships and frequency domain features simultaneously. For instance, in 2009, Lay-Ekuakille et al. (2009) developed an urban waterworks leakage detection tool based on STFT. Building upon the concept of localized signal decomposition from STFT, the Wavelet Transform (WT) was introduced in the 1980s (Grossmann and Morlet 1984). WT employs a more adaptable wavelet basis function for signal decomposition, addressing the limitation of fixed window size across frequencies. As various wavelet basis functions continually evolve, they are better suited for diverse and complex situations compared to single sine and cosine functions. WDN leakage detection based on WT has become one of the most extensively utilized analysis methods (Yang et al. 2010; Ahadi and Bakhtiar 2010; Ting et al. 2021). However, the wavelet base selection requires manual intervention based on the specific scenario. Due to the Heisenberg uncertainty principle, improvements in time accuracy come at the expense of frequency accuracy, and vice versa. Another significant approach, Empirical Mode Decomposition (EMD) (Huang et al. 1998), decomposes any signal, especially non-stationary nonlinear time series signals, into a series of linear steady-state signals (Intrinsic Mode Functions, IMF). By decomposing signals into multiple IMFs and a residual component, EMD aids in distinguishing between leak and non-leak signals (Guo et al. 2016; Bakhti et al. 2019). Furthermore, several analysis methods have evolved from these approaches and are widely employed in the field of WDN leakage detection. These include Variational Mode Decomposition (VMD) (Zhao et al. 2023; Xu et al. 2021), Hilbert-Huang Transform (HHT) (Lukonge et al. 2021), and various fusion methods (Fu et al. 2024; Spandonidis et al.

2022). These diverse time-frequency domain tools offer enhanced capabilities to tackle the complexities of acoustic signal analysis in identifying and differentiating leakage within water distribution systems. However, these methods also have shortcomings. For instance, VMD can be sensitive to noise and may require careful parameter tuning to ensure accuracy, while HHT often struggles with mode mixing issues, which can complicate the interpretation of transient signals in noisy environments. Additionally, fusion methods can be computationally intensive and require significant data preprocessing to achieve optimal results.

2.4 Correlation analysis

In addition to examining leakage characteristics in the time and frequency domains, there exists a specialized method known as Correlation Analysis. This technique utilizes the correlation between signals from two different sensors to ascertain whether a leak event has transpired. For instance, in 2017, Muntakim et al. (2017) presented a leak detection method founded on a function measuring the degree of correlation between two time series, successfully validating the method in a real metal WDN scenario in Canada. Similarly, Yang et al. (2013) proposed an algorithm to extract and evaluate signal self-similarity through approximate entropy, enabling leak detection even in the presence of non-leak noise within and outside the pipeline, achieving correct detection rates of 93.8% and 86.3%, respectively. Correlation analysis offers a new research perspective on acoustic WDN leakage; however, it does come with certain limitations. Firstly, the method necessitates multiple signal sources, rendering scenarios with only a single sensor impractical. Secondly, the results derived from correlation analysis are heavily contingent on the quality and accuracy of the data. Inaccurate, noisy, or missing sensor measurement data could bias the outcomes of correlation analysis.

2.5 Acoustic Leak Detection in WDN: Recent Deep Learning Approaches

Recent advancements in deep learning-based acoustic leak detection for WDN have focused on improving data quality, feature selection, and model robustness. Wu et al. (2024) emphasized a data-centric approach, demonstrating that advanced data augmentation techniques, such as IAAFT and masking, significantly enhance detection accuracy by increasing data diversity. Meanwhile, Xu et al. (2024) introduced an optimized feature selection framework (MDMR_ISFFS), identifying four key acoustic features that improve classification performance across multiple machine learning models (XGBoost and SVM). To address the challenge of long-range temporal dependencies in acoustic signals, Liu et al. (2024) proposed a Time-Transformer model, which outperforms CNN and CNN-LSTM models in accurately detecting leaks, especially in noisy environments. Additionally, data scarcity remains a bottleneck for training deep models, and Liu et al. (2024) tackled this issue by developing an LSTM-GAN approach that generates high-quality synthetic leak signals, enhancing the robustness of detection models. On the application side, Fares et al. (2023) validated deep learning-based leak detection in real-world WDNs, demonstrating that noise loggers combined with machine learning techniques (e.g., SVM, ANN, and deep neural networks), achieve stable and accurate performance across varying pipeline materials and conditions.

3. Methodology

3.1 Framework

The proposed UADM model primarily comprises an autoencoder architecture with multiple loss functions, as outlined in Fig. 1. It features two main modules: the encoder and the decoder. The encoder, composed of a single linear layer followed by a ReLU activation function, focuses on diminishing the input audio's dimensionality from its original size to 128 units. Subsequently, the decoder takes the 128-dimensional representation from the encoder and reverts it back to the original input dimension. Utilizing the Tanh activation function, the output values are scaled to a range of -1 to 1, a common practice for audio data. To summarize, the UADM model operates by encoding the input audio into a lower-dimensional representation via the encoder and then reconstructing it back to the original dimensions using the decoder. This model serves as the foundation for unsupervised learning, examining differences between the input and output data within the autoencoder architecture. The WDN leakage acoustic signal undergoes denoising through the model's loss functions (MES, TC, Spectral, and MAE loss) designed based on pertinent domain knowledge, refined through continuous iterations.

3.2 Loss function design

The functional implementation of the proposed UADM model centers around the design of its loss functions. Given the characteristics of unsupervised learning, the structure of the UADM model itself does not markedly influence the denoising process but serves to establish an ongoing iterative framework for learning. The denoising path of the input acoustic signal is entirely steered by the loss functions designed within the model. Drawing from a comprehensive literature review and pertinent domain knowledge in acoustic-based WDN leakage detection, this section elaborates on the concept of the four core loss functions within the UADM model: MSE, Temporal Consistency, Spectral, and MAE loss.

3.2.1 Mean Square Error loss

The primary role of Mean Square Error (MSE) loss is to prevent excessive noise reduction that might distort the acoustic signal. Within the influence of the UADM model, the original input signal undergoes continuous compression and reconstruction in a loop iteration. If the entire training process remains unconstrained, the final output could lose the original leak signal characteristics while reducing noise. This scenario might significantly diminish the effectiveness of leak detection. Hence, the UADM model employs MSE loss to compare the average error between the input and the reconstructed output in each cycle of unsupervised learning. MSE loss serves to control the iterative process, ensuring that the reduction in noise remains within certain bounds to avert signal distortion. This control maintains a balance between noise reduction and signal preservation. For the detailed calculation formula of MSE loss, please refer to formula (1), where *n* represents the number of samples, *y* represents the input before each iteration cycle, and $\hat{y}$ denotes the output signal after reconstruction.

$$MSE\ loss = \frac{1}{n} * \sum (y - \hat{y})^2 \tag{1}$$

3.2.2 Temporal Consistency loss

The Temporal Consistency (TC) loss is an innovative loss function designed for guiding the UADM model to retain components of the signal that persist over time, particularly focusing on preserving the persistent nature of the leak signal. In instances of WDN leakage, barring occasional bursts, the leakage primarily exhibits a continuous pattern. This continuous pattern often endures throughout the entire signal cycle, as opposed to environmental noise, which typically occurs intermittently, like the sound of rain or passing cars (Fan et al. 2022). Leveraging this disparity, the study devises a novel loss function to suppress burst-like components during the unsupervised learning process. This approach aims to better preserve the continuous leak signal to enhance detection accuracy. The TC loss accomplishes its function by comparing the one-dimensional convolution outcomes of the audio data before and after the unsupervised loop, as depicted in formula (2). Since signal components in the original signal with sustained temporal characteristics exhibit minimal change following the 1D convolution operation, the TC loss effectively filters out sporadic noise while retaining more persistent leak signals. In formula (2), *Conv1D(y)* and *Conv1D(ŷ)* respectively represent the input and output of the 1D convolution after each learning iteration.

$$TC\ loss = \frac{1}{n} * \sum(Conv1D(y) - Conv1D(\hat{y}))^2 \qquad (2)$$

3.2.3 Spectral loss

The Spectral loss serves as an innovative tool within the UADM model, aiming to enhance the retention of low-frequency signals. In the context of water distribution networks leakage detection, the primary essence lies in measuring the sounds emitted by the turbulent jet of water escaping the pipes (Khulief et al. 2012). Studies have revealed that the predominant characteristics of the leak signal primarily reside within the low-frequency portion of the audio spectrum (Sitaropoulos et al. 2023). To reinforce the prominence of these critical low-frequency components carrying leak-related information, this study introduces the Spectral loss. This novel loss function accentuates the low-frequency segments in the original signal, magnifying the features of the leak signal component. The specific calculation formula for the Spectral loss is depicted in formula (3). Here, *STFT(y)* and *STFT(ŷ)* respectively represent the results of the input and output signals before and after each unsupervised learning cycle, processed via the Short-Time Fourier Transform (STFT). Low-frequency signals, occupying a wider spectrum range, are more readily captured by STFT during spectrum calculations. Additionally, the mean squared error calculation tends to be more sensitive to the larger amplitude of the low-frequency parts within the spectrum. Consequently, the Spectral loss prioritizes preserving the low-frequency segment, which is more likely to encompass the leak signal, compared to the high-frequency portion. This emphasis helps retain critical components integral to leak identification.

$$Spectral\ loss = \frac{1}{n} * \sum(|STFT(y)| - |STFT(\hat{y})|)^2 \qquad (3)$$

3.2.4 Mean Absolute Error loss

The role of Mean Absolute Error (MAE) loss is to prevent the inadvertent deletion of leak signals owing to their relatively small energy content compared to background noise. From an energy perspective, the energy carried by the leak signal is relatively small compared to the background noise. The input signal, being a time domain signal, exhibits an amplitude that strongly correlates with the energy of the relevant signal. To safeguard signals with lower energy levels, the MAE loss is employed, computing the average of the absolute differences between predicted and true values, as depicted in formula (4). The linearity of MAE loss sensitivity to error size ensures that each error contributes equally to the total error. As a result, it robustly reflects the average error and mitigates the risk of disproportionately discarding signals with lower energy content due to power operations within other loss functions.

$$MAE\ loss = \frac{1}{n} * \sum |y - \hat{y}| \qquad (4)$$

In summary, the overall loss function of the proposed UADM model can be expressed as formula (5).

$$Total\ loss = MSE\ loss + TC\ loss + Spectral\ loss + MAE\ loss \qquad (5)$$

3.3 Evaluation metrics

The core objective of acoustic-based WDN leakage detection is to classify unknown input signals into leak and non-leak categories. To validate the efficacy of the unsupervised denoising model proposed in this study, various prevalent detection models from existing research were employed, both with and without UADM model processing. Consequently, this study employed the four primary binary classification evaluation metrics in the machine learning domain to assess the effectiveness of the proposed model: *Accuracy, Recall, F1,* and *Precision*.

These evaluation metrics are determined by the counts of samples categorized by the four models: TP (True Positive), TN (True Negative), FP (False Positive), and FN (False Negative) in accordance with the actual classification outcomes, as demonstrated in Table 1. The specific calculation formulas for *Accuracy, Recall, F1,* and *Precision* are displayed in formulas (6), (7), (8), and (9), respectively.

$$Accuracy = (TP + TN) / (TP + FP + TN + FN) \tag{6}$$

$$Recall = TP / (TP + FN) \tag{7}$$

$$Precision = TP / (TP + FP) \tag{8}$$

$$F1 = 2 * Precision * Recall / (Precision + Recall) \tag{9}$$

These metrics aid in quantitatively assessing the model's performance in distinguishing between leak and non-leak signals, providing a comprehensive evaluation of its classification effectiveness. *Accuracy* is the proportion of correctly predicted instances to the total instances, measuring overall correctness. *Recall* is the proportion of true positive predictions to all actual positives, assessing the model's ability to find relevant instances. *Precision* is the proportion of true positive predictions to all positive predictions, indicating the accuracy of positive predictions. *F1* score is a harmonic mean of precision and recall, offering a balance between precision and recall for binary classification.

4. Experiments

4.1 Data collection

To assess the applicability of the proposed UADM model, this study utilized a public dataset provided by Aghashahi et al. (2023) from Texas A&M University in 2023 (https://data.mendeley.com/datasets/tbrnp6vrnj/). It's essential to note that the original dataset encompasses three distinct data types: hydrophone, accelerometer, and dynamic pressure sensor. For this study, only the hydrophone data, widely employed in engineering practice, was utilized. The dataset was curated through controlled leak experiments conducted within a laboratory-scale water distribution testbed, featuring 152.4 mm diameter PVC pipes and a total pipe length of 47 meters, as depicted in Fig. 2. During the data collection process, various factors were altered, as detailed in Table 2, including network topology (looped and branched), leak types (orifice, longitudinal, circumferential, and gasket), and non-leak conditions. Background flow rates, ranging from 0 to 0.47 L/s, and transient flow changes from 0.47 to 0 L/s, were also manipulated. Furthermore, background noise sources such as traffic and tool noise were introduced.

4.2 Data processing

To adapt the dataset introduced in Section 4.1 for various acoustic-based leakage detection methods, this study undertook specific preprocessing steps. Initially, the original dataset was in a RAW format, which was then converted to the more accessible WAV format for ease of data reading and processing. Moreover, the original dataset contained an imbalance between the number of leak and non-leak signal samples. To avert potential decreases in detection accuracy due to this imbalance, the study performed data augmentation on the original dataset. Through a process of offsetting and introducing random noise enhancement, as shown in Fig. 3, the data underwent a balancing operation. Following this augmentation procedure, both the leak and non-leak signal samples were equated to 100 instances each.

4.3 Experiment configurations

4.3.1 UADM

The proposed UADM model was implemented as a single-layer autoencoder with 128 bottleneck nodes. Each input was a full-length normalized waveform loaded from a .wav file with a sampling rate of 44,100 Hz. For 1-second recordings, this corresponds to an input dimension of 44,100 samples. Each signal was normalized between -1 and 1, and further standardized to have zero mean and unit variance before being processed. The autoencoder was trained independently for each signal using the Adam optimizer with an initial learning rate of 0.001, for 50 epochs. Due to per-sample training, batch processing was not used, and early stopping was not applied.

During training, the combined loss function was implemented by summing four components directly in the training loop. MSE and MAE were calculated in the time domain, while the spectral loss was computed from the STFT magnitude (FFT size = 2048, hop length = 512). The temporal consistency loss was applied by convolving the reconstructed waveform with a fixed smoothing kernel of size 5 before comparison. All loss terms were equally weighted and added to form the total loss.

4.3.2 Downstream leakage detection

In the downstream leakage detection task, we evaluated the effectiveness of the denoising process by comparing the performance of several mainstream classifiers, including traditional machine learning models (e.g., SVM, Random Forest) and deep learning models (e.g., 1D-CNN, RNN, and Time-Transformer). All models were trained and tested on the dataset both before and after denoising by the UADM model. Table 3 summarizes the architecture and training configurations for each model. To ensure fair comparison, all models were trained using identical data splits and evaluated using Accuracy, Precision, Recall, and F1 score.

4.4 Experiment results

To validate the denoising effect of the proposed UADM model in acoustic-based WDN leakage detection task, this study implemented two prevalent traditional classification methods (MFCC + SVM and MFCC + Random Forest) and three classification methods based on deep learning (Wavelet + 1DCNN, MFCC + 1DCNN, MFCC + RNN, MDMR_ISFFS and Time-Transformer). Among these methods, MFCC (Mel-scale Frequency Cepstral Coefficients) stands as the most utilized time-frequency analysis feature in the domain of speech recognition. Additionally, the Wavelet + 1DCNN method employs the widely used Haar wavelet base as the feature extraction algorithm in the wavelet domain to contrast with MFCC. Table 4 presents the leakage detection metrics results of all methods before and after applying the UADM model for input denoising. For a more visually comprehensible comparison among the various models, Fig. 4 illustrates a comparative analysis of these approaches. This detailed analysis enables an assessment of the effectiveness of the UADM model in denoising input data and its impact on the performance of diverse leakage detection methods. A detailed analysis of these results is presented in Section 5.

5. Discussions

5.1 Performance impact of UADM denoising

The experimental results in section 4.4 demonstrate notable improvements in almost all leakage detection indicators across both traditional and deep learning-based methods following the noise reduction process of the UADM model. On average, the *Accuracy* and *Precision* indicators increased by approximately 8.1% and 6.4%, respectively. Additionally, the *Recall* and *F1* witnessed an average increase of around 14.5% and 8.0%, respectively. These findings highlight the significant enhancement effect of the UADM model on the task of acoustic-based WDN leakage detection. However, there were two metrics that exhibited a drop after denoising. The *Recall* of the MFCC + Random Forest method decreased by 11%. Yet, it is noteworthy that the *Recall* value prior to denoising was exceptionally high at 1.00. Post noise reduction, although the *Recall* value dropped, the other three indicators (*Accuracy*, *F1*, and *Precision*) all showcased improvements. This suggests that the model's ability to accurately differentiate between leaks and non-leaks before denoising was poor. While all leak signals were classified as positive, this resulted in an extremely high *Recall*. However, many non-leak signals were incorrectly categorized as leak instances. The second metric that experienced a decrease was the *Precision* value of the Wavelet + 1DCNN method, dropping by 3%. Similar to the previous case, the remaining three metrics (*Accuracy*, *Recall*, and *F1*) exhibited improvements post-denoising. This reflects the trade-off between *Recall* and *Precision* in the model. Considering the more comprehensive benefit indicated by the *F1* score, which increased by 12%, the classification effect of the Wavelet + 1DCNN method was evidently better after denoising. After applying the UADM model, the MDMR_ISFFS method achieved a slight improvement in *F1* score while maintaining perfect *Recall*, suggesting enhanced robustness in leak detection, although a marginal drop in *Accuracy* and *Precision* indicates a possible trade-off in overall classification balance. For the Time-Transformer model, UADM denoising significantly boosted both *Recall* (from 0.72 to 1.00) and *F1* score (from 0.80 to 0.85), highlighting a substantial gain in sensitivity and overall detection capability, despite a decrease in *Precision* due to more false positives.

5.2 Ablation experiments

The core functional implementation of the proposed UADM model hinges on the design of its loss functions. To delve deeper into its operational mechanics, this study conducted ablation experiments on the model. Ablation experiments involve systematically removing parts of the system to observe their impact on the system's function or performance.

The steps involved in the ablation experiments were as follows: First, the total loss part of the UADM model was modified, and one loss function was removed at a time in a sequential manner. Subsequently, the modified UADM model was employed to denoise the original dataset, generating four distinct datasets (lacking MSE, TC, Spectral, and MAE loss, respectively). Finally, these four datasets served as inputs, and their performance, processed under the five mainstream leakage detection methods detailed in Section 4.3, was recorded. Table 5 presents the comprehensive results of these experiments, which are also illustrated in Fig. 5. This comparative visualization aids in discerning the impact of each removed loss function on the performance of the model in the context of leakage detection methods.

The results obtained from the ablation experiments revealed the significance of the four proposed loss functions in the denoising performance of the UADM model. When the individual loss functions were removed sequentially, the evaluation metrics *Accuracy*, *Recall*, *F1*, and *Precision* displayed fluctuations. Upon the removal of MSE loss, there was an average decrease of 6.8% in *Accuracy*, 4.2% in *Recall*, 7.2% in *F1*, and 8.2% in *Precision*. Elimination of TC loss resulted in an average decrease of 4.6% in *Accuracy*, 5.4% in *Recall*, 4.8% in *F1*, and 5.2% in *Precision*. The removal of Spectral loss led to an average reduction of 12.8% in *Accuracy*, 2.4% in *Recall*, 7.8% in *F1*, and 14.0% in *Precision*.

Finally, eliminating MAE loss caused an average reduction of 6.0% in *Accuracy*, 4.2% in *Recall*, 5.4% in *F1*, and 6.8% in *Precision*. These findings highlight that the proposed MSE, TC, Spectral, and MAE loss functions each contribute to varying degrees in the denoising functionality of the UADM model. Moreover, certain metrics displayed significant increases post-ablation experiments. For instance, after removing MSE loss, the MFCC + RNN method experienced a 16% increase in the *Recall*. However, this increase was accompanied by varying declines in *Accuracy*, *F1*, and *Precision*. This suggests that the model tends to emphasize capturing true positive instances at the cost of overall accuracy, resulting in more negative examples being misclassified as positive. In summary, the results indicate that the four proposed loss functions play significant roles in enhancing the denoising task for acoustic-based WDN leakage detection.

5.3 Architecture

The encoder-decoder structure adopted by the proposed UADM model is relatively straightforward and only contains one layer of structure. In order to discuss its rationality, the study conducted denoising experiments using a more complex structure with three layers in both encoder and decoder modules, while maintaining all other parameters unchanged, as demonstrated in Table 6. In this modified model, the encoder was expanded to include additional layers, incrementally growing from 128 hidden units to 512 hidden units in several steps. The decoder's architecture mirrored that of the encoder, progressively expanding the dimension back to the original input size, as illustrated in Fig. 6.

The experimental outcomes reveal that escalating the model's complexity does not effectively enhance the performance of acoustic-based leakage detection tasks. Only the MFCC + Random Forest method displayed improvements across all evaluation metrics following denoising with the more intricate model. The MFCC + SVM method experienced an increase solely in the *Precision*, while other indicators remained unchanged or decreased. Notably, all deep learning methods, apart from the mentioned conventional methods, witnessed decreases in their evaluation metrics. The rationale behind this trend is attributed to the fact that as the model's complexity increases—particularly in terms of layer count and parameter volume—it typically demands more data to learn these parameters. The autoencoder, possessing an encoder-decoder structure, exhibits symmetry, signifying that with an increase in layer count, the network's width also exponentially expands. This exponential growth contributes to a rapid rise in the number of parameters. Especially within deeper autoencoders, the representation of latent space may become more intricate, necessitating more complex computations for encoding and decoding. Insufficient data volume might limit the model's capability to adequately learn the data features, subsequently leading to a decline in model performance. Furthermore, the heightened complexity of the model structure incurs substantial computational burden, particularly concerning the exponential growth of the encoder-decoder model.

5.4 Impact of preprocessing on acoustic leak detection performance

Preprocessing plays a crucial role in acoustic leak detection, particularly when dealing with high-frequency sensor data. Raw vibration and acoustic signals often contain significant background noise, and their key discriminative features may exist at much lower frequencies than the original sampling rate. If the sampling frequency is too high, deep learning models may struggle to extract meaningful patterns, potentially leading to suboptimal detection accuracy.

To explore the impact of different preprocessing methods on the accuracy of the WDN leakage detection task, this section conducts experiments using preprocessing approaches: Raw data, Down sampling (Moderate), Down sampling (Aggressive), Statistical features, and UADM (proposed). The experimental methodology involves applying each preprocessing technique to the dataset and then evaluating the processed data using all leakage detection methods mentioned in Section 4.3 (MFCC + SVM, MFCC + Random Forest, Wavelet + 1DCNN, MFCC + 1DCNN, MFCC + RNN, MDMR_ISFFS, and Time-Transformer). Finally, the results obtained from all methods are averaged to provide a comprehensive performance assessment, as shown in Table 7.

The results presented in Table 7 demonstrate that the choice of preprocessing method has a considerable impact on the overall performance of acoustic-based WDN leakage detection. Across all models and configurations, it is observed that directly using raw high-frequency audio signals results in relatively lower performance, with an average *Accuracy* of 0.80 and an *F1* score of 0.82. This can be attributed to the fact that critical discriminative patterns for leakage detection often reside in lower frequency bands and exhibit temporal persistence, which raw signals at high sampling rates tend to obscure. Moderate and aggressive downsampling help mitigate this issue by suppressing high-frequency noise, yielding improved *Accuracy* (0.86) and *F1* scores (0.85), although still limited by the lack of task-specific temporal feature extraction.

The use of handcrafted statistical features (min, max, mean, variance) over fixed time windows introduces temporal aggregation, aiming to capture lag-based or segment-level characteristics. However, this approach yields mixed results, with a slight drop in *Accuracy* (0.76–0.77) and *F1* scores (0.73–0.74) despite a relatively stable recall. This suggests that while statistical features can retain some relevant patterns, they may also lose important nuances, especially under aggressive downsampling. In contrast, the proposed UADM model consistently achieves the best overall performance, with an accuracy of 0.88, a recall of 0.93, and an F1 score of 0.90. This can be attributed to its unique design, which integrates multiple domain-specific constraints into the learning objective through four loss components. The MSE and MAE losses help maintain signal fidelity while suppressing noise. The Temporal Consistency loss encourages the preservation of leak-related features that persist over time, which are commonly observed in real leakage events. Additionally, the Spectral loss emphasizes low-frequency components, where leak signals are most prominent. By combining these complementary objectives, UADM effectively balances denoising and feature preservation, allowing downstream classifiers to better distinguish leak from non-leak patterns. This demonstrates that embedding preprocessing principles into model design can lead to more robust and generalizable leakage detection performance.

5.5 Limitations

This study encounters two primary limitations. Firstly, obtaining real-world leakage data is inherently challenging. The acoustic signals used in this study were primarily collected from controlled laboratory experiments, as acquiring authentic leakage signals from operational WDNs for validation is highly difficult due to the unpredictability and rarity of actual leak events. Although our dataset encompasses diverse leakage scenarios under controlled conditions, it may not fully capture the variability encountered in complex real-world environments, including different pipeline materials, hydraulic conditions, and background noise sources. Nevertheless, it is important to emphasize that the public dataset used in this study was meticulously curated by a specialized research team under stringent experimental protocols, ensuring reproducibility and reliability as a benchmark for further studies. Secondly, the study's scope of investigation encompassed a limited number of leakage detection methods. Acoustic-based WDN leakage detection is a burgeoning field, marked by numerous studies proposing a wide array of methods to address the classification task of distinguishing leak and non-leak signals. In this study, only five relatively representative methods were selected for analysis. Exploring a more extensive array of methodologies could provide a more comprehensive understanding of the field's landscape and the potential for further advancements.

5.6 Future works

In the future, the field of WDN leakage research holds several promising directions: 1) Unsupervised Learning: In contrast to the prevalent supervised learning models, unsupervised learning offers a unique avenue to explore unlabeled data. It facilitates the discovery of inherent data structures, patterns, and correlations, allowing for a more comprehensive understanding without relying on pre-existing knowledge. This approach is instrumental in addressing data labelling cost and scarcity issues often encountered in engineering practices. 2) Integration of Domain Knowledge: The distinction between general artificial intelligence and its application in professional fields lies in the indispensable role of domain knowledge in enhancing model capabilities. Future research should emphasize leveraging scientific or engineering knowledge specific to WDN, thereby advancing the intelligent evolution of the industry. 3) Hardware Innovation: The extensive use of contact acoustic sensors in existing research has limited widespread adoption. Exploring contactless acoustic-based solutions from a hardware perspective remains a challenging yet pivotal area for innovation and development. 4) While our current study focuses on leak detection rather than precise localization, future work will explore advanced leak localization techniques using both data-driven and model-based approaches. One potential direction is multi-sensor triangulation, where signals from multiple hydrophones are fused to estimate the leak's location based on time delays and frequency shifts. Additionally, physics-informed deep learning models that incorporate fluid dynamics and acoustic wave propagation principles could be investigated to improve localization accuracy in complex pipeline networks. These approaches would enhance the practical applicability of AI-driven leak detection, enabling both detection and precise localization for real-world water distribution networks.

6. Conclusion

WDN leakage is one of the most common issues encountered in the operation and maintenance of underground infrastructure. To address the challenge of noise interference in acoustic-based WDN leakage detection, this study proposed an unsupervised learning denoising model, UADM. This model, based on an encoder-decoder structure, implements noise reduction using innovative loss functions derived from domain knowledge. Results from experiments conducted on publicly available datasets demonstrate that the proposed UADM model significantly improves the performance of acoustic-based WDN leakage detection. The evaluation metrics, including *accuracy, recall, F1 score*, and *precision*, display an average improvement of 8.1%, 14.5%, 8.0%, and 6.4%, respectively. The research contributes a novel theoretical perspective to knowledge by enhancing the anti-noise capability of acoustic WDN leakage detection, particularly through an unsupervised learning approach that integrates domain knowledge. From an engineering standpoint, the UADM algorithm provides a stable and efficient tool for detecting leaks within WDN systems, proving beneficial for stakeholders in water distribution networks.

Data Availability Statement

Some or all data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request.

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