

Article

Leak Location in Water Distribution Networks Using Deep Learning Techniques: A Synthetic Application

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Abstract

Leak localization and maintenance in water distribution networks (WDNs) are essential for reducing water losses and operating costs; however, they usually require extensive monitoring and large datasets. This work proposes a methodology that combines topological sectorization of a hydraulic node network and deep learning techniques to improve leak location by selecting representative nodes to reduce the spatial dimensionality of the WDNs. The network is partitioned using a Spectral Clustering algorithm to identify key nodes based on a weighted criterion that considers pressure variability, flow rate, and proximity to the centroid. Subsequently, a Bidirectional Long Short-Term Memory (Bi-LSTM) neural network classifies the cluster and sub-cluster where a leak occurs, using pressure and flow time series simulated in EPANET. This methodology was validated on the L-Town network, achieving an accuracy of 99.94% for cluster classification and 99.82% for sub-clusters, with a validation loss of 0.024%. During validation with 117 unseen leakage scenarios, the model reached an overall effectiveness of 85%. Moreover, Spectral Clustering outperformed K-Means in preserving physical connectivity. These results confirm the efficiency of the proposed methodology and highlight its potential for application in other hydraulic networks.

Keywords: leak location; Bi-LSTM; Spectral Clustering; representative nodes; water distribution network; deep learning



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1. Introduction

Efficient water management is a priority for operating agencies due to increasing resource scarcity and the demand for sustainability. Effective leak detection is crucial to minimizing water losses, reducing economic costs, and maintaining service quality. In Mexico City, it is estimated that more than 40% of water is lost due to leaks in the distribution network, primarily due to insufficient maintenance [1]. These losses not only have a negative impact on water resource availability but also cause significant economic losses and affect the quality of service. In this context, locating leaks in advance

is essential to guarantee user access and enhance operating agencies' efficiency through timely maintenance and saving costs [2].

Reducing operational costs through leak localization strategies enables the allocation of resources to technologies that modernize hydraulic infrastructure. For example, sensors installed in distribution networks enable real-time monitoring of pressure, flow, and level parameters. However, the required instrumentation involves high costs. Therefore, developing methodologies that optimize data collection and processing is essential. Hydraulic data simulation is an alternative for generating information that is representative of a system's behavior, which can then be used to train artificial intelligence algorithms with fewer instrumentation requirements, thereby facilitating decision-making in complex problems such as leak localization.

Over the last few decades, artificial intelligence (AI) has established itself as an effective tool for detecting and locating leaks, implementing various approaches within machine learning. For example, Gárete [3] used Support Vector Machines (SVMs) to classify pressure data, reporting accuracies between 50% and 90% that were affected by overfitting, while Zhang et al. [4] achieved 96.9% accuracy when processing and classifying acoustic signals. Likewise, Liu et al. [5] proposed a multi-class model based on Generalized Least Squares Twin SVM (GLT-KSVM) that reduced the model's sensitivity to variations. Artificial neural networks (ANNs) have also demonstrated a greater ability to adapt to the hydraulic complexity of networks, performing better than SVM algorithms with balanced data [6,7]. In a recent work, Mahdi et al. [8] designed an ANN model based on autocorrelation and signal energy parameters, achieving F1 detection and localization values of 86.5% and 86.2%, respectively. Subsequently, studies using convolutional neural networks (CNNs) for image classification have proven effective in leak detection by processing acoustic signals with 92.44% accuracy [9] and pressure data with 70% effectiveness [10]. Nevertheless, their performance depends on a large amount of data and careful preprocessing, which suggests the need to incorporate statistical methods to improve the results [9,11].

Recently, the use of recurrent neural networks, especially the Long Short-Term Memory (LSTM) architecture, has gained relevance for leak detection and localization due to their ability to retain relevant information in sequences and manage both short- and long-term dependencies. Due to its structure, which includes an input layer defining the feature space, this methodology is also distinguished as having hidden layers called memory cells.

Several studies have applied LSTM to hydraulic data, reporting detection accuracies close to 90% when analyzing water flows [12]. Likewise, Dong et al. [2] combined LSTM with K-Means to segment the network, obtaining 85% effectiveness in leak detection, and therefore, the authors proposed improving the method. In addition, to mitigate false alarms, Yang et al. [13] proposed a two-stage hybrid scheme based on an Optimally Pruned Extreme Learning Machine (OPELM) and Bi-LSTM, using pressure variations and improving accuracy compared to other traditional methods. This approach was also validated in various industrial oil and gas systems. In this regard, Peng et al. [14] proposed a Long Short-Term Memory Fully Convolutional Network (LSTM-FCN) architecture that explores local patterns based on high-frequency pressures to diagnose ruptures, emphasizing that the selection of time series and data preprocessing are directly linked to detection sensitivity and response speed. In a comprehensive review conducted by Korlapati et al. [15], it is highlighted that current methods use different types of input data, such as flow rates and pressures, negative pressure waves, acoustic signals, and simulation-based approaches. Previous methods, aiming to improve sensitivity, cost-effectiveness, and efficiency in detection, reinforce the need for hybrid approaches robust to signal noise.

Furthermore, transient test-based techniques (TTBTs) are a methodology for leak detection and localization in pressurized systems, taking advantage of the propagation

of pressure waves generated during transient events. Studies such as that of Brunone et al. [16] present a review of physical experiments for leak identification, analyzing both laboratory and field data, where it is demonstrated that the transient response is influenced by various factors, such as system configuration, the transient generation mode, pipe material and diameter, initial pressure and flow conditions, as well as leak characteristics. Similarly, Guo et al. [17] presented a review classifying these techniques into model-based and data-based approaches. These methods employ artificially generated pressure waves to extract information about the leak through time–frequency analysis, numerical models, or data science tools.

Despite these recent advances, leak localization in distribution networks remains a challenge due to the structural and operational complexity of the systems. These systems are characterized by large-scale and highly branched topologies, hydraulic transients resulting from valve operations and pumping schedules, non-stationary demands, and signal measurements that are sensitive to noise. Moreover, continuous population growth significantly modifies the structure and operation of hydraulic networks, complicating the networking operation. In this regard, simulated WDN models trained under specific scenarios require continuous retraining, increasing location time, and limiting their applicability in real-world scenarios. In addition, approaches in sectorized networks often focus on either hydraulic or spatial attributes, reducing the representativeness of the sectors. Therefore, a strategy is required that simultaneously integrates topological and hydraulic information, preserving the physical connectivity of the network, and enabling the selection of representative nodes, thereby reducing the number of monitoring points and training time without compromising localization accuracy.

In order to contextualize the characteristics of the models, Table 1 presents a summary of recent studies based on LSTM or Bi-LSTM, highlighting whether they incorporate network segmentation and which algorithm is applied. Likewise, the capability to locate leaks or whether the approach is applied only for leak detection is also included.

Table 1. Summary of recent studies on leak detection/location.

Author	Algorithm	Data Used	Network Segmentation	Sectorization Algorithm	Leak Location
Yang & Zhao (2020) [13]	Bi-LSTM	Pressures	No	-	No
Shin et al. (2024) [18]	LSTM Autoencoder	Pressure and Flow (images)	No	-	No
Ullah et al. (2024) [19]	Bi-LSTM	Acoustic Emissions	No	-	No
Ladino-Moreno et al. (2024) [20]	Kalman Filter–Bi–LSTM–Monte Carlo	Pressure and Flow Rate	No	-	No
Guo et al. (2024) [21]	LSTM	Flow rate	No	-	Yes
Dong et al. (2024) [2]	LSTM combined with K-Means	Pressures	Yes	K-Means	Yes
Han et al. (2024) [22]	LSTM	Pressure and Flow Rate	Yes	DBSCAN	No
Gómez-Coronel et al. (2024) [23]	LSTM	Pressure and Flow Rate	Yes	Topological and operational criteria	Yes
Liu et al. (2025) [24]	Bi-LSTM	Wave dispersion	No	-	Yes
Peng et al. (2025) [14]	LSTM-FCN	Pressures	No	-	No
Present study	Spectral Clustering + Bi-LSTM	Pressure and Flow Rate	Yes	Spectral Clustering	Yes

The selection of representative nodes allows the amount of required data and the complexity of the problem to be reduced, achieving higher localization efficiency compared to approaches mainly based on pressure sensitivity, where it is necessary to simulate a large

number of leak scenarios at different network nodes, since the size, location, and type of leak influence pressure and flow rate [2]. Furthermore, there are studies in which the pressure sensor is installed at the cluster centroid [25]; however, this selection may be hydraulically insensitive to leak occurrences, providing a limited representation of local variations in pressure and flow rate. Despite these advances, several challenges remain: existing methods often fail to explicitly preserve the topological structure of WDN during partitioning, rely on an excessive number of sensors, and lack systematic strategies to reduce dimensionality while retaining relevant hydraulic information. To address these limitations, this study focuses on integrating existing methods to address the practical challenges encountered in real WDNs. Consequently, this work aims to address the limitations identified above through a leak localization methodology that can be applied to different WDNs. The main objective is to use Spectral Clustering to sectorize a WDN, subdividing with K-Means to similar hydraulic characteristics, and integrating topological and hydraulic features for leak localization.

2. Materials and Methods

The proposed methodology allows for the precise localization of probable leak zones using limited datasets through the analysis of pressure time series in WDN. This approach integrates hydraulic modeling and extended-period simulation (EPS) to generate reference data, combined with network sectorization using clustering techniques that preserve physical pipe connectivity. Then, representative nodes are selected using a weighting criterion that combines pressure variability, average flow, and distance to the sector centroid. Leak scenarios are simulated at these nodes using pressure-dependent emitters to generate time series. These signals are normalized and segmented into sliding windows that feed a Bi-LSTM model, which is designed to extract complex temporal patterns and classify the zone with a high probability of leakage. The sequential stages of this methodology are summarized in Figure 1.

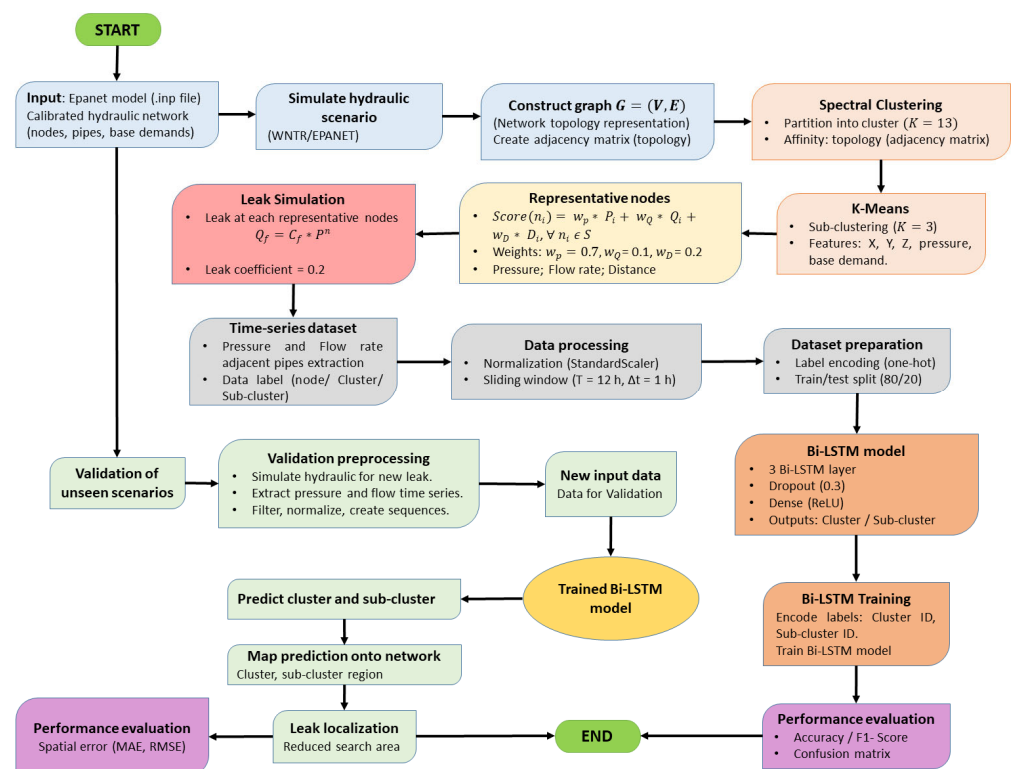


Figure 1. Proposed leak localization methodology.

2.1. Hydraulic Modeling

In this study, the proposed methodology assumes the availability of a previously calibrated hydraulic model. Therefore, the calibration process itself is not part of the scope of this work. Instead, the calibrated model is used as a reliable representation of the system to generate synthetic hydraulic data for training and validation purposes.

The hydraulic model was implemented in EPANET V2.2 software (U.S. Environmental Protection Agency, Cincinnati, OH, USA). The model must include spatial coordinates, base demands, and temporal variation patterns to be defined at the nodes, while pipe elements must be specified in terms of length, nominal diameter, material, and roughness. For the tanks, the model includes geometric characteristics and the corresponding dynamic storage levels. The operating conditions must also be defined, including pumping schedules and valve operations. The hydraulic analysis is based on the laws of energy and mass conservation, considering friction losses and local losses in the hydraulic network. The energy balance between nodes is based on Bernoulli's equation, and the relationship between pressure, topographic height, and kinetic energy is also considered, including friction head losses between pipe nodes. In addition, the flow balance is described by the continuity equation, using the Darcy–Weisbach expression for friction losses and the Colebrook–White expression to determine the friction factor.

A calibrated model accurately reflects real operating conditions; EPSs were executed under leak-free scenarios. This process yielded a time series of nodal pressures, pipeline flow rates, and tank storage levels. These datasets, coupled with the network topography, form the input dataset essential for the sectorization phase using Spectral Clustering and the subsequent identification of representative nodes.

2.2. Sectorization Using Spectral Clustering

Network partitioning was implemented through Spectral Clustering, an algorithm suited for identifying non-linear clusters within complex datasets. This approach is based on graphical theory, using information from the spectral decomposition of an affinity matrix, in which each element encodes the pairwise similarities between nodes [26]. Consequently, Spectral Clustering often outperforms traditional methods like K-Means by accounting for nodal connectivity, increasing its popularity in network analysis applications [27].

The .inp file (from EPANET software) defines the distribution network architecture, an undirected graph where the following model $G = (V, E)$ is constructed, where V denotes the set of hydraulic nodes, while E represents the physical connections (pipes). In this work, the affinity matrix (W) is constructed exclusively based on the network topology, using a binary adjacency matrix where $W_{ij} = 1$ if a pipe connects nodes i and j , and $W_{ij} = 0$ otherwise. This formulation ensures that the resulting clusters maintain the integrity of the network's physical connectivity, preventing the grouping of nodes that are not directly connected. The number of clusters is determined using a heuristic that assesses the network dimensionality, accounting for its scale and topological features. Subsequently, Spectral Clustering proceeds to calculate spectral embedding based on the Laplacian matrix (L), $L = D - W$, which satisfies the normalization conditions established in Equation (1).

$$\mathcal{L} = D^{-\frac{1}{2}} L D^{-\frac{1}{2}} \quad (1)$$

where $\mathcal{L}$ is the normalized matrix, and D called the degree matrix, which is a diagonal matrix, the elements of which are made up of the sum of the similarities of node i with all the nodes to which it is connected (node degree). This results in a dimensionality reduction, and each node is represented in a lower dimension without modifying the connectivity of the network.

The Laplacian matrix enables the connectivity structure of the network to be captured, and its decomposition allows the detection of natural clusters. To perform this process, the eigenvalues λ of the normalized matrix ($\mathcal{L}$) are calculated using Equation (2). Subsequently, the eigenvector (Z_1) associated with the second smallest eigenvalue (λ_1) is calculated [26].

The eigenvectors associated with the smallest eigenvalues of matrix $\mathcal{L}$ are the most relevant for dimensionality reduction. A new matrix is constructed using the eigenvectors, where each row corresponds to an original node represented in the reduced space.

$$\mathcal{L}_Z = \lambda Z \quad (2)$$

Finally, the K-Means clustering algorithm is applied to the rows of the new matrix in order to divide the nodes into the desired number of clusters and label them. This enables a group of nodes with similar properties to be identified and obtained, while maintaining the connectivity of the hydraulic network.

To capture the operational variations within each cluster, each cluster is further subdivided using the K-Means algorithm to group nodes based on hydraulic characteristics such as average pressure and average demand, obtained from the simulation over an extended period without leaks. This makes it possible to obtain sub-clusters with greater homogeneity, allowing the area searched for a leak location to be reduced. Each node is associated with a label related to the cluster and sub-cluster to which it belongs according to the grouping, and this label is used as the input in the selection of representative nodes.

2.3. Selection of Representative Nodes

When a leak occurs in a distribution network, the pressure and the water flow variations are more evident in nodes close to the leak point, while in distant points, they may be barely noticeable. In order to reduce the scenario simulation and model training times, this study selected one representative node for the sub-cluster that is highly informative in the event of leaks and representative of the group.

The selection of a representative node is based on a multi-criteria weighting approach that considers both the topological and hydraulic characteristics of each sub-cluster. Let $S_i = \{n_1, n_2, \dots, n_n\}$ be the set of nodes within sub-cluster i . For each node $n \in S_i$, three attributes are defined: an indicator of the informative capacity of hydraulics based on the temporal variance in pressure under leak-free operation P_i . Unlike the sensitivity matrices described by Liu et al. [28], which quantify the exact pressure response to a unit change in demand or leakage, our criterion identifies nodes with high signal dynamics for deep learning classification rather than measuring exact local sensitivity. Additionally, the selection considers the relevance of the normalized flow rate (Q_i), obtained from the average flow of the pipes adjacent to the node during leak-free simulations, and the normalized geometric proximity to the sub-cluster centroid (D_i), calculated using the distance normalized within the sub-cluster. This selection is executed through an objective function where specific weights are assigned to each attribute, as defined in Equation (3):

$$\text{Score}(n_i) = w_p * P_i + w_Q * Q_i + w_D * D_i, \forall n_i \in S \quad (3)$$

where w_p, w_Q, w_D are the weighting coefficients that adjust the relative importance of pressure, flow rate, and distance, respectively. These weights are assigned based on the physical relevance of each variable; specifically, pressure is considered the most informative factor for leak localization, as leaks directly disrupt the hydraulic grade line, making pressure variations highly sensitive indicators [29]. Flow-related variables provide complementary information, as nodes with higher flow rates often show significant changes in mass balance under leak conditions. Finally, spatial criteria are incorporated to ensure representativeness

within each sub-cluster, capturing both the hydraulic behavior and the physical structure of the WDN.

To ensure a balanced comparison between variables, pressure and distance-to-centroid values are normalized, while flow values are scaled within a $[0, 1]$ range. Consequently, each node receives a standardized score, enabling the identification of the most representative node. These nodes are used to simulate leak scenarios and provide the dataset for training the deep learning model. This procedure significantly decreases data dimensionality and reduces the number of simulation scenarios; in addition, it allows sensitivity to leak events to increase while enhancing the efficiency of deep learning models for leak localization in WDN.

2.4. Simulation of Scenarios with Leaks

Leaks can be simulated as an additional demand at a node, causing observable changes in the network's pressure and flow regimes [2]. In this study, single-leak events were simulated individually at each of the representative nodes selected in the previous stage. The leak was modeled as a pressure-dependent emitter at the node, using Bernoulli's equation for orifice flow, as expressed in Equation (4):

$$Q_f = C_f * P^n \quad (4)$$

where Q_f denotes the leakage flow rate, C_f is the discharge coefficient dependent on the orifice size and shape, P represents the nodal pressure, and n is the exponent characterizing the leak, ranging from 0.5 to 2.0. The coefficient C_f is categorized on three levels based on its magnitude relative to the network's average flow rate [30]: small or background leaks: 0–5%; moderate leaks: 5–10%; and large-scale leaks: 10%. This categorization ensures that the model is tested across a comprehensive spectrum of leak severities.

2.5. Data Processing and Bi-LSTM Model

The input data for the Bi-LSTM model consists of hydraulic time series extracted from the WDN simulation. Each leakage scenario was simulated with a 60-min window over a continuous 3-month period to account for operational variability; consequently, the number of resulting datasets is inherently dependent on the scale and topological magnitude of the WDN. Specifically, the model uses pressure from representative nodes within each sub-cluster, along with the flow rates from the pipes directly connected to those nodes. This same data structure is maintained throughout both the training phase and the leak localization process to ensure consistency in the model's performance. At this stage, the dataset is structured by labeling nodes to differentiate leak-free conditions from leak events, enabling the model to train the different hydraulic patterns associated with each scenario.

Subsequently, the labels were encoded using the one-hot format to generate the softmax output probabilities. Finally, the dataset is partitioned into training and validation sets, ensuring a class-based stratification that maintains a balanced representation of clusters and sub-clusters. In this study, 80% of the data was allocated for training, while the remaining 20% was used for validation. This procedure prevents spatial bias and ensures the model's capability to locate leaks across all sectors of the network.

Based on these sequences, LSTM networks are employed due to their suitability for time-series data. Their architecture incorporates memory cells and gating mechanisms that regulate information flow, enabling the capture of both short- and long-term dependencies. This design effectively mitigates the vanishing gradient problem, a common drawback in traditional artificial neural networks [12]. Specifically, each gate is composed of a fully connected neural network [31] that functions as a decision-making mechanism to control the data retained or discarded. These gates are generally composed of three elements:

a neural network layer, a sigmoid activation function, and a pointwise multiplication operator [32]. LSTM units use gating mechanisms to regulate the flow of information over time, as illustrated in the standard architecture shown in Figure 2. Arrows represent the flow of information within the LSTM architecture. The symbols indicate the activation functions and internal operations of the memory cell, including sigmoid gates, hyperbolic tangent transformations, and summation operations involved in updating the cell state and hidden state [31]. This structure enables the network to learn complex dynamic patterns and long-term dependencies. Since these formulations are well established in the literature, detailed mathematical expressions for individual gates are omitted here; a comprehensive description can be found in [31].

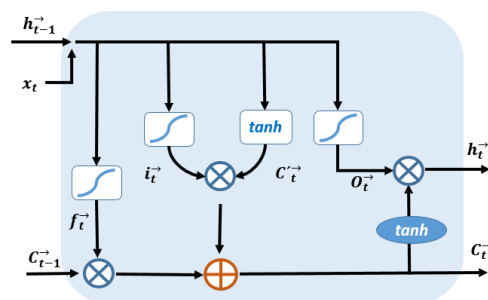


Figure 2. LSTM structure.

To enhance sensitivity to subtle variations that are best identified by analyzing sequences in both temporal directions, the Bi-LSTM architecture is used. This variant processes each time window in both forward ($h_t^{\rightarrow}$) and backward ($h_t^{\leftarrow}$) directions, concatenating both representations to obtain the final information and overcoming the limitations of traditional LSTMs [19]. The final output of the Bi-LSTM at time t , is the result of this concatenation, as shown in Equation (5):

$$h_t = [h_t^{\rightarrow}; h_t^{\leftarrow}] \quad (5)$$

where $(;)$ represents the concatenation of the outputs of the unidirectional LSTM at time t [33].

Therefore, a Bi-LSTM classifier with two output categories (cluster and sub-cluster) was used to locate the leaks. The Bi-LSTM architecture used a tensor of dimensions T and F as an input parameter, where T denotes the time steps and F represents the features needed to produce a representation that summarizes the dynamics of the given time window. Stacking several Bi-LSTM layers enables the capture of temporal hierarchies, where lower layers model local variations and upper layers integrate long-range dependencies. Between each block, a dense layer is added to project the representation into a separable space, followed by two independent softmax outputs, one to predict the cluster and the other for the sub-cluster. This results in a multi-output configuration that shares the same parameters, thereby reducing inconsistencies between the related classification tasks.

Dropout was incorporated into each block to randomly deactivate a fraction of neuron activations during training, ensuring that the network does not rely on specific combinations and thus preventing overfitting. The network was trained using the Adam optimizer, which employs an adaptive gradient to minimize the composite loss function. In addition, to avoid performance degradation due to overtraining, an Early Stopping strategy was implemented to monitor validation loss and restore the optimal weights.

2.6. Performance Evaluation

To carry out the performance evaluation of the multi-class classification algorithm, a confusion matrix of dimensions $n \times n$ was employed, where n denotes the total number

of classes (see Table 2). In this framework, rows represent the actual classes while columns represent the predicted classes. This matrix allows the quantification of True Positives (TPs), False Negatives (FNs), and False Positives (FPs) for each category. Such a class-specific analysis facilitates the identification of systematic classification errors, highlighting the scenarios where the model confuses a cluster or sub-cluster during leak localization.

Table 2. Multi-class confusion matrix.

		Predicted Class			
		Class 1	Class 2	...	Class n
Actual Class	Class 1	C 1,1	FP	...	C 1, n
	Class 2	FN	TP	...	FN
	...	...	...	...	...
	Class n	C n ,1	FP	...	C n , n

In addition, the model is evaluated using the accuracy metric for the entire confusion matrix using Equation (6):

$$A_{CC} = \frac{\sum_{i=1}^N TP(C_i)}{\sum_{i=1}^N \sum_{j=1}^N (C_{i,j})} \quad (6)$$

where A_{CC} is the accuracy metric; i is the total number of classes; C_i is the correct predictions for the class i ; $\sum_{i=1}^N$ is the sum of the entire diagonal; and $C_{i,j}$ represents the number of samples of the actual class i that were predicted as j . For example, if $i = j$ this is the correct prediction, but if $i \neq j$, this is a classification error.

To analyze the model's capacity, an evaluation under unknown scenarios during the training phase was performed. In this procedure, leak nodes were selected from the set of nodes not used as representative points to ensure a true test of robustness. For each of the 39 sub-clusters, three nodes were selected using a random sampling. This sampling was designed to cover different topological positions within each sub-cluster, providing a diverse set of unseen nodes during the training phase. A single leak was simulated at each selected node with a discharge coefficient of 0.05 to generate pressure and a flow rate time series. This specific coefficient was chosen to evaluate the model under more demanding conditions compared to the training phase, where a coefficient of 0.2 was used. By testing the model against smaller leakage intensities at unseen nodes, we simultaneously assessed its robustness and sensitivity to subtle hydraulic variations closer to real scenarios. These series were processed using the same criteria applied during training. Finally, the classifier performance was calculated for this new dataset in order to verify its ability to locate leak zones at non-instrumented points within the network.

2.7. Comparison of Partitioning Algorithms and Input Variables

To evaluate how the network partitioning method influences the leak localization performance, a comparative study between Spectral Clustering and K-Means was conducted. To ensure a fair benchmark, both algorithms used an identical cluster number. Representative nodes for each sub-cluster were selected using the weighting criterion described in Section 2.3. Following the generation of leak scenarios, the Bi-LSTM classifier was trained by maintaining a fixed architecture, temporal windows, and normalization protocols. This rigorous control of variables ensures that any observed differences in localization effectiveness are only attributable to the choice of the partitioning algorithm.

3. Case Study

The methodology was validated in the WDN called L-Town, widely known in the literature. This network comprises a total length of approximately 42 km of pipelines, consisting of 905 pipes interconnected through 782 nodes (junctions). The hydraulic system includes two supply reservoirs and a water storage tank, as well as a pump and three pressure-reducing valves (PRVs), which regulate the hydraulic behavior in the different sections of the WDN [30]. The hydraulic model was developed in EPANET (.inp) format, available for download at <https://battledim.ucy.ac.cy/> (accessed on 25 November 2025), and the validation networks were sourced from <https://uky.edu/WDST/database.html> (accessed on 18 December 2025). These files include geometric characteristics, elevations, roughness parameters, and operational schemes such as valve control and pumping schedules. This calibrated model serves as the basis for EPS and the generation of the dataset utilized in subsequent procedures.

Network partitioning was performed using Spectral Clustering with a precomputed affinity using the proximity matrix, where the number of clusters was chosen by applying the heuristic, $K = \sqrt{782}/2 = 13.9$, resulting in $K = 13$. The equation `random_state = 0` was set to preserve reproducibility of the partitioning. Each cluster was then subdivided into three sub-clusters using K-Means based on the characteristics of each node, including coordinates (X , Y , Z), average pressure, and base demand. In a cluster with fewer than three nodes, a single sub-cluster was assigned. Finally, geometric centroids were calculated at both cluster and sub-cluster levels to determine the Euclidean distances to the respective centroid.

The selection of representative nodes per sub-cluster was performed by assigning weights in Equation (3), where $w_p = 0.7$, $w_Q = 0.1$ and $w_D = 0.2$. For each sub-cluster, the node with the highest score was selected as a representative node. In addition, the node closest to the cluster centroid was added to the list, and duplicates were removed to generate the final set of representative nodes.

Using the representative nodes as specific points of interest, leak scenarios were generated in EPS by coupling the WNTR Python library version 1.2.0 with the EPANET V2.2 hydraulic engine. Each simulation focused on a single-leak event per node, modeled via a pressure-dependent emitter as defined in Equation (4). A leakage coefficient of 0.2 was selected, with the leak active throughout the simulation, indicating that it was not repaired during that period. This procedure allowed us to use the extracted time-series data for nodal pressures and flow rates from pipes adjacent to the representative nodes. Ultimately, these records were organized into a structured dataset labeled by node, cluster, and sub-cluster, providing the input necessary for subsequent classification stages.

For data preprocessing, independent normalization was implemented using `StandardScaler` to ensure that all numerical variables represented a unit variance. To adapt the time series to the classifier's architecture, the data were transformed into overlapping sequences using a sliding window of length $T = 12$ steps with unit displacement. Since the simulations use a 1 h time step, each window represents a 12 h period of system operation. All windows correspond to steady leak conditions, as these are introduced at the beginning of the simulation and remain active throughout the entire time horizon. Consequently, no transition from normal to leak conditions is included in the input sequences. Labels were encoded using `LabelEncoder` followed by a one-hot transformation, linked to the softmax optimization function. Finally, the dataset was partitioned into 80% for training and 20% for internal validation, employing stratified sampling by cluster to preserve class proportion across both subsets and prevent data imbalances.

The multi-output Bi-LSTM model consists of three Bi-LSTM layers, as specified in Table 3. The first two layers operate with 64 units per direction, with a total of 128 per layer,

and are configured to maintain the dimensionality of the input window (12 and 128). The third bidirectional layer subsequently compacts the sequence into a fixed feature vector of 64 neurons. To mitigate overfitting, a dropout rate of 0.3 was implemented. This is followed by a dense layer with 64 neurons and ReLU activation, serving as a shared representation that feeds the two outputs. These outputs utilize a softmax function to generate probability distributions proportional to the number of categories for both the cluster and sub-cluster, respectively, and the Adam algorithm was used to optimize the model.

Table 3. Bi-LSTM network architecture summary.

Layers	Output Shape	Param #
Bidirectional_1	(None, 12, 128)	119,808
Bidirectional_2	(None, 12, 128)	98,816
Bidirectional_3	(None, 64)	41,216
Dropout	(None, 64)	0
Dense	(None, 64)	4160
Cluster_output (Dense)	(None, 13)	845
Sub-cluster_output (Dense)	(None, 3)	195

To mitigate overfitting, an Early Stopping strategy was implemented by monitoring the global loss with a patience of 5 epochs and the restoration of the optimal weights. The training phase was capped at 50 epochs using a batch size of 64 sequences, while simultaneously validating both outputs. The evaluation was performed using the method to calculate both total and task-specific losses, from which the independent accuracy for each output was derived. Finally, a confusion matrix was constructed to identify systematic error patterns and confusion between classes.

4. Results

The partitioning of the L-Town network is visualized in Figure 3, which shows the spatial distribution of the 13 clusters identified within the studied network using Spectral Clustering. Different colors are used to distinguish each cluster, while the numerical labels correspond to the assigned cluster identifiers employed in the subsequent classification and leak localization stages. The results demonstrate that sectorization effectively adheres to the network's physical connectivity, ensuring that the nodes are grouped based on their actual connections while avoiding arbitrary pipeline intersections or the grouping of disconnected components.

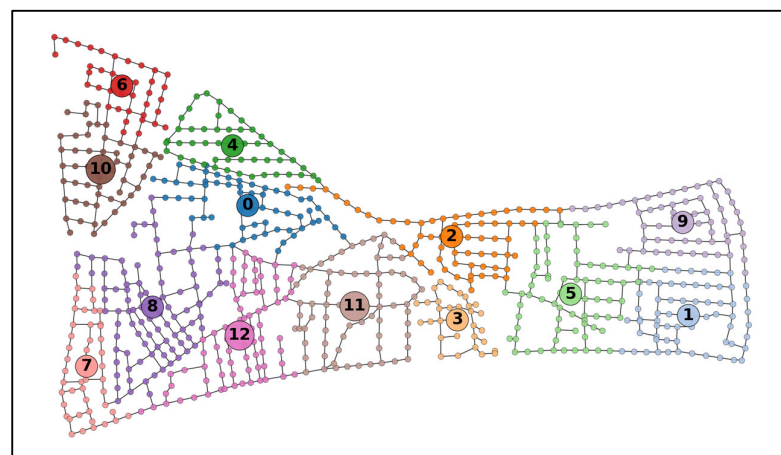


Figure 3. Network sectorized using Spectral Clustering.

The subdivision of clusters using K-Means yielded a partition that is consistent from both topological and hydraulic perspectives, resulting in the identification of 50 representative nodes. This strategy significantly streamlined the simulation phase, reduced the overall data volume for training, and enabled the generation of scenarios that provide more granular information for leak localization, enhancing the model's ability to distinguish between leak events. This represents a reduction of 93.6% compared to the full network, without compromising hydraulic representativeness. This significant reduction confirms that the representative node selection criterion preserves the most informative hydraulic patterns required for leak localization.

Figure 4 illustrates the learning curves of the multi-output model, demonstrating rapid and stable convergence. The global loss decreases sharply during the initial epoch and continues a steady decline until stabilizing at approximately 0.024, which triggers the Early Stopping at 12 epochs. The validation loss closely tracks the training curve throughout the process. Regarding the cluster-level output, the accuracy reaches 0.9994, achieving stability well before the conclusion of the training phase.

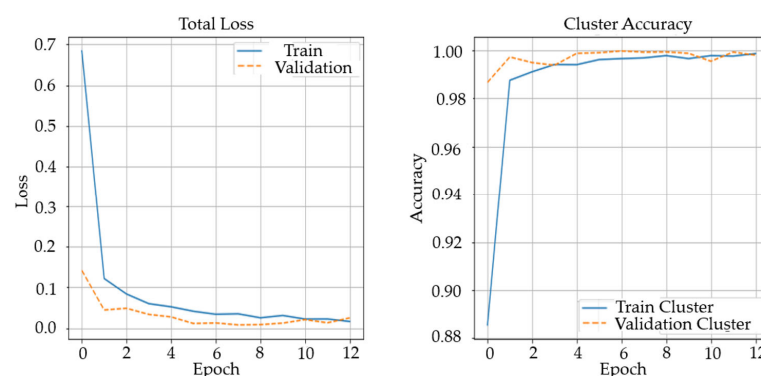


Figure 4. Loss and accuracy curves for training and validation.

To evaluate the classification performance of the model, the cluster-level confusion matrix is presented in Figure 5a. The results exhibit a near-perfectly diagonal matrix, with off-diagonal values approaching zero, thereby confirming the effective separation between the 13 clusters defined by Spectral Clustering. Reading the sub-cluster classification performance, the confusion matrix in Figure 5b demonstrates the model's high precision in identifying sub-clusters with leakage. This effectiveness is further quantified by the accuracy (Equation (6)), which yields a value of 0.9984, validating the robustness of the dual-output architecture for leak localization.

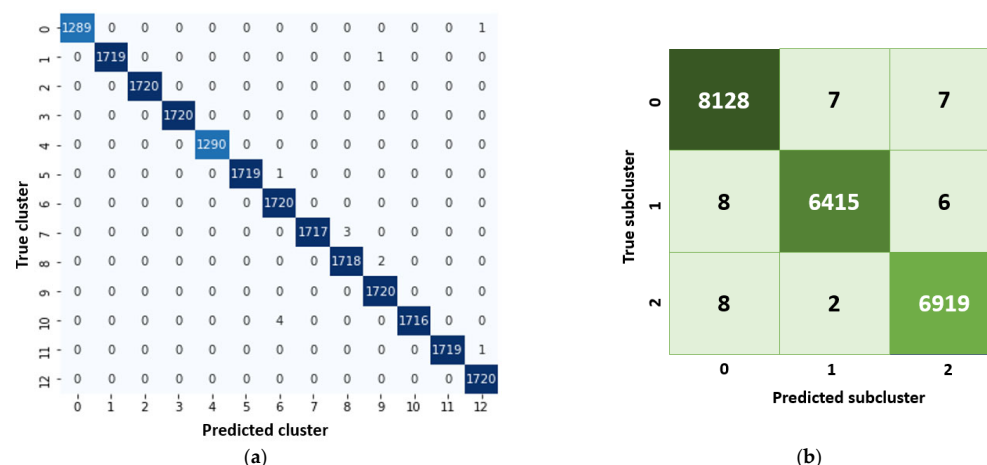


Figure 5. (a) Confusion matrix for cluster. (b) Confusion matrix for sub-cluster.

The performance is further quantified in Table 4, where the model achieved an overall accuracy, Balanced Accuracy, and Macro-F1 Score of 0.9997. As detailed in the cluster-specific report, the architecture maintained precision and recall across all sectors; notably, seven out of the thirteen clusters achieved a perfect recall of 1.00, while the remaining clusters remained above 0.9983.

Table 4. Summary of cluster-level localization performance.

Cluster	Precision	Recall	F1-Score
0	0.9992	1.0000	0.9996
1	1.0000	0.9983	0.9991
2	0.9988	1.0000	0.9994
3	0.9994	1.0000	0.9997
4	1.0000	0.9992	0.9996
5	1.0000	0.9988	0.9994
6	1.0000	1.0000	1.0000
7	1.0000	1.0000	1.0000
8	1.0000	1.0000	1.0000
9	0.9983	1.0000	0.9991
10	1.0000	1.0000	1.0000
11	1.0000	0.994	0.9997
12	1.0000	1.0000	1.0000

4.1. Validation

The model performance was evaluated using unseen pressure and flow datasets to ensure the robustness of the proposed approach. These new data series underwent the same normalization and preprocessing protocols as the training set to maintain consistency and reliability. For this validation task, node 558 was randomly selected to simulate a leak event with a leak coefficient of 0.05. It is important to note that this node represents the ground truth of the leak scenario and is not directly predicted by the model. As illustrated in Figure 6, the model successfully classified cluster 12 (green nodes) and its corresponding sub-cluster (red nodes) as the most probable leak location. Notably, node 558 is located within this predicted area, confirming that the model is effective in narrowing down the leak location rather than identifying the exact leaking node. Furthermore, the model maintained its localization accuracy even when the leak intensity was reduced from a training coefficient of 0.2 to a validation value of 0.05, demonstrating its sensitivity to smaller leak events.

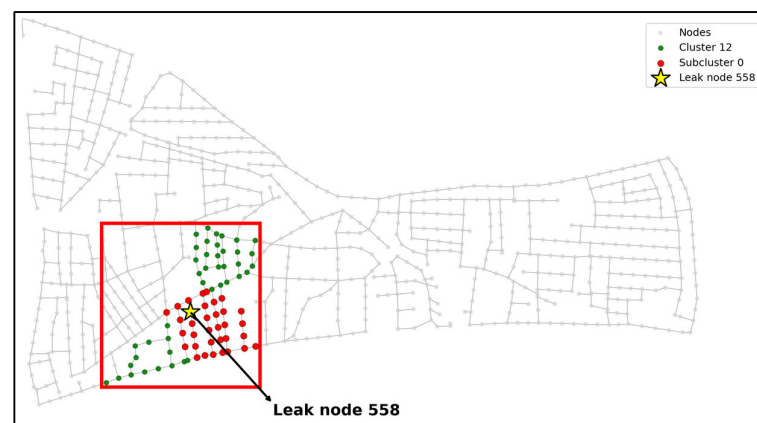


Figure 6. Cluster and sub-cluster with presence of leak.

To further validate the model's robustness, we extended this procedure by randomly selecting three independent leak scenarios for each of the 39 sub-clusters, resulting in a total of 117 distinct events. Under these conditions, the model achieved an 85.5% accuracy rate in correctly identifying the cluster containing the leaking node.

The lower bar chart in Figure 7a shows the classification performance per cluster; notably, clusters 0 and 8 exhibited the lowest success rates. This localized decrease in performance may be attributed to classification ambiguities arising from nodes positioned along the geographical boundaries of each cluster, where an overlapping hydraulic profile can lead to marginal error patterns.

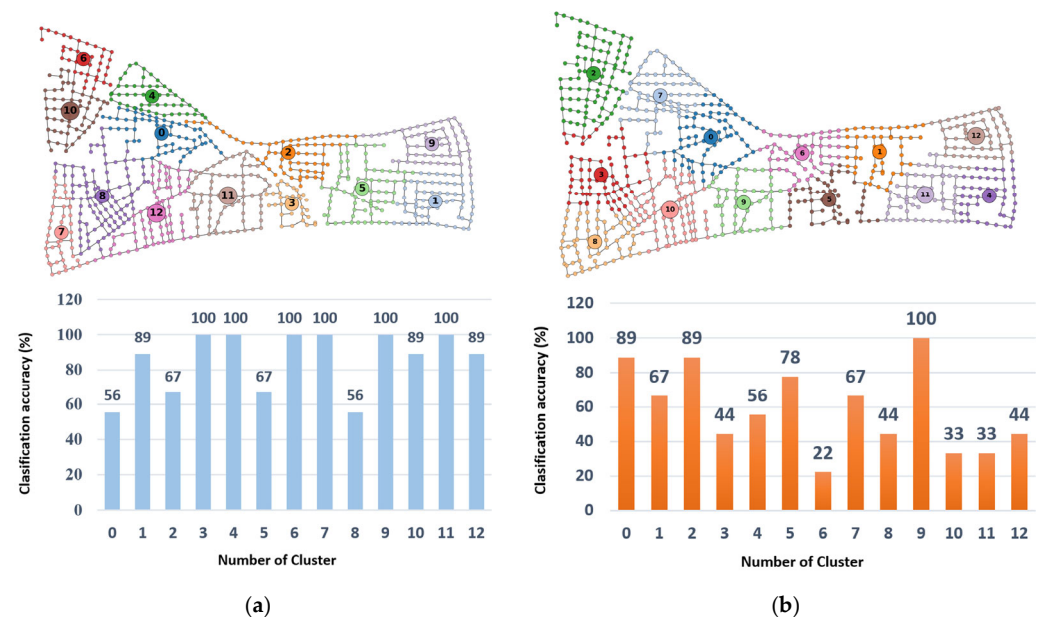


Figure 7. Sectorization and accuracy of the Bi-LSTM model with partitioning using (a) Spectral Clustering and (b) K-Means.

4.2. Comparison of K-Means vs. Spectral Clustering

The upper diagrams in Figure 7a,b provide a comparative visualization of the network partitioning achieved with Spectral Clustering and K-Means, respectively. The results demonstrate that Spectral Clustering yields superior homogeneity while strictly adhering to the topological constraints of the pipeline connections. Conversely, the K-Means-based model generates irregular sectoral boundaries and, in several instances, defines clusters containing nodes with no topological connectivity as evidenced by the disjoint components in the cluster labeled 3. Furthermore, the lower bar charts illustrate a significant disparity in classification performance.

For the Spectral Clustering approach, accuracy reached 100% for specific sectors, with a minimum of 56% and an overall average of 85.5%. In contrast, the K-Means partition exhibited significantly lower precision in leak localization, with accuracy dropping to 22% in certain clusters and an overall performance of only 58.97%.

To further evaluate the model's performance, an analysis of classification errors was conducted. Table 5 presents the leak nodes that were incorrectly classified, comparing the true cluster against the predicted one. A critical finding is that in 100% of the misclassification cases, the predicted cluster was topologically adjacent to the true cluster. This indicates that while the model may fail to identify the exact cluster, it remains spatially consistent, pointing to the immediate neighboring area. Quantitatively, the physical distance between the true leak location and the predicted cluster showed a median distance of 94 m and a mean distance of 208 m. In addition, the localization errors ranged from a minimum

of 42.12 m to a maximum of 673.69 m. The significant difference between the mean and median is attributed to these few outliers in larger clusters. However, the consistently adjacent topological relation suggests that the proposed methodology ensures that the search area is restricted to the immediate vicinity of the actual leak.

Table 5. Summary of leak localization classification errors.

Leak Node	True Cluster	Predicted Cluster	Distance (m)	Topological Relation
n24	10	6	42.12	Adjacent
n248	2	9	49.19	Adjacent
n144	0	12	52.77	Adjacent
n289	5	1	53.45	Adjacent
n519	8	0	54.31	Adjacent
n69	8	0	62.98	Adjacent
n149	8	12	82.39	Adjacent
n137	8	7	93.2	Adjacent
n582	12	11	94.04	Adjacent
n686	5	1	111.9	Adjacent
n87	0	11	241.49	Adjacent
n442	0	11	254.07	Adjacent
n714	5	9	393.52	Adjacent
n331	1	5	474.41	Adjacent
n451	2	3	599.87	Adjacent
n83	2	3	673.69	Adjacent

In addition to this classification metric, a broader spatial error metric analysis was performed across all 117 evaluated scenarios to determine the overall precision of the methodology. For correctly classified cases, an error of zero was assigned, while for misclassified instances, the Euclidean distance between the true leak node and the predicted cluster was used. For the entire dataset, the proposed method achieved a Mean Absolute Error (MAE) of 28.56 m and a Root Mean Square Error (RMSE) of 106.84 m. These results indicate that the vast majority of predictions are exact, while the remaining errors are spatially limited.

4.3. Validation Across Alternative WDN

To evaluate the scalability and robustness of the methodology, the framework was applied to two additional WDNs by modifying their respective .inp configuration files. In the first case, using the RedNet 2 topology, the Spectral Clustering algorithm successfully partitioned the network into five topologically coherent clusters, as illustrated in Figure 8a. The Bi-LSTM model demonstrated high performance on this network, achieving a training accuracy of 0.9995 and a global loss of 0.02. Furthermore, the cluster-level confusion matrix presented in Figure 8b exhibits a strong diagonal structure, with off-diagonal elements approaching zero, thereby confirming the model's consistent discriminative power across different hydraulic architectures.

For the second validation case, the ZJ network was utilized to further test the model's adaptability. Figure 9a illustrates the sectorization achieved via Spectral Clustering, comprising five distinct clusters. For this specific topology, the Bi-LSTM model yielded an accuracy of 0.8960. The corresponding confusion matrix, presented in Figure 9b, indicates that misclassifications are primarily concentrated within cluster 1.

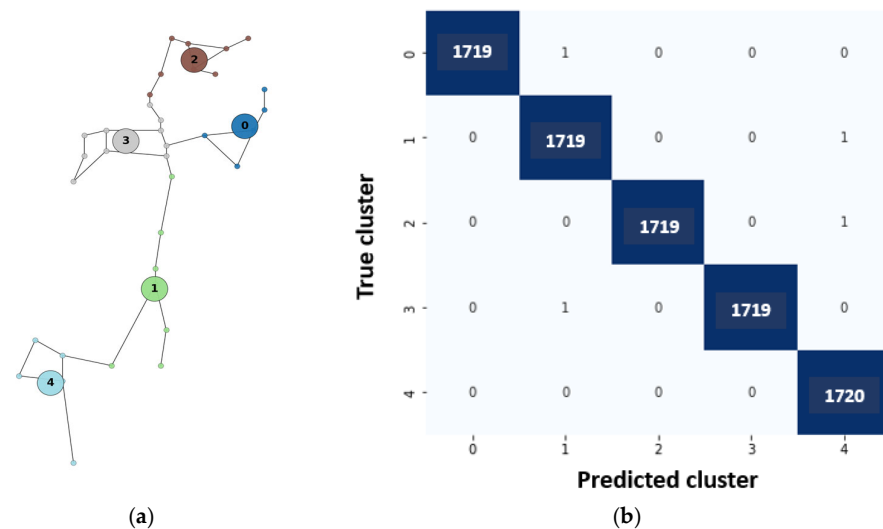


Figure 8. (a) Sectorization of RedNet2. (b) RedNet2 confusion matrix.

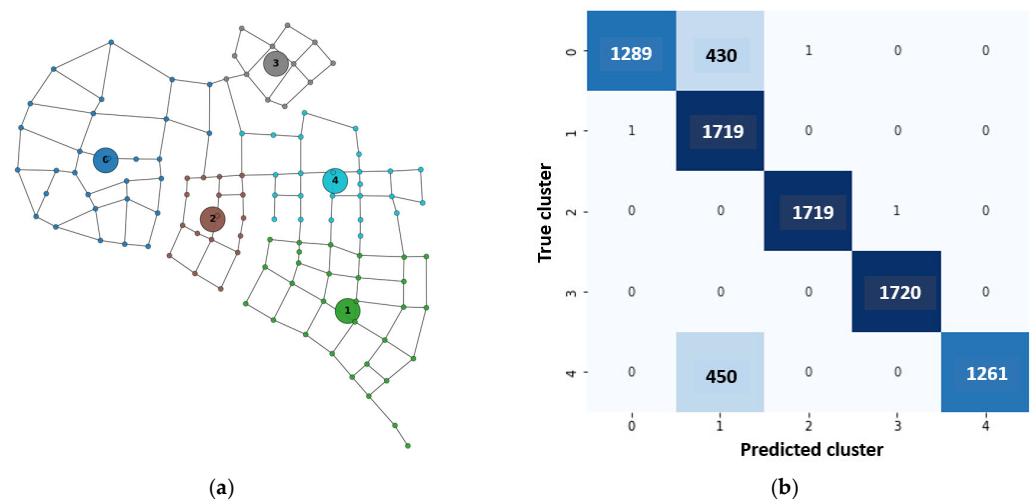


Figure 9. (a) ZJ network sectorization. (b) ZJ network confusion matrix.

The consistent performance obtained in L-Town, RedNet2, and ZJ networks demonstrates that the proposed scoring function exhibits a good level of transferability across different topological and hydraulic conditions.

5. Discussion

The findings demonstrate that sectorization strategies prioritizing the physical connectivity of the network significantly enhance cluster coherence and mitigate classification ambiguities at sector boundaries. This is consistent with previous research [34], which advocates for spectral approaches and adjacency matrices to partition distribution networks, noting their superiority over traditional heuristic methods. By preserving topological integrity, Spectral Clustering ensures that spatial adjacency reflects actual hydraulic connections, thereby preventing the erroneous grouping of disconnected nodes. This structural consistency is fundamental for the model, as it allows the neural network to learn pressure-flow profiles that are grounded in the real physical constraints of the WDN.

When comparing the approaches summarized in Table 1, significant advantages are identified regarding the use of spatial connectivity. It is important to highlight that, while part of the consulted literature focuses on leak detection, identifying only its existence [13,14,18–20], this research focuses on localization, which is the immediate step after

detecting the leak. Even in studies that do address localization [21,24], variants of LSTM architectures applied directly to hydraulic variables are implemented, but they omit network segmentation, which can limit the model's ability to work with large-scale networks, making the localization of leak events difficult.

On the other hand, the works that include network sectorization utilize K-Means and DBSCAN algorithms [2,22] based mainly on proximity within the feature space, which does not guarantee that the resulting sectors will align with the physical connectivity of the pipes. Therefore, the present study uses Spectral Clustering for the network partition based on a graph that represents the connection between pipes and the hydraulic characteristics. Additionally, this methodology proposes dimensionality reduction through the selection of representative nodes with a multi-output Bi-LSTM model that does not appear in the analyzed works, allowing the search area for leak localization to be narrowed down in WDN.

In addition, the proposed methodology reduces the dimensionality of the problem by training the model on representative nodes rather than relying on exhaustive simulations or dense instrumentation. A key aspect for real applicability is the availability of measurements at these selected representative nodes; in practice, they can be interpreted as candidate sensor locations, although further work is required to adapt the methodology to existing configurations in the operation of WDNs. This approach has a significant advantage over current trends identified in the recent literature, which often highlight dependency on massive historical datasets as a primary barrier to implementation. By decoupling the model's effectiveness from the need for extensive, often unavailable, real databases, this strategy mitigates one of the most persistent limitations in applying deep learning to WDN, particularly in data-scarce environments. However, it is important to note that the weighting coefficients used in the node selection criterion were defined heuristically, and a formal sensitivity analysis has not yet been conducted to evaluate their influence on the final set of nodes. Consequently, how variations in these weights affect the stability and optimality of the selection process remains to be analyzed.

Classification errors tend to cluster at the boundaries of hydraulically similar clusters, where pressure and flow rate gradients exhibit minimal variance, rendering the signals nearly indistinguishable. This phenomenon is particularly evident at the edges of adjacent sectors, where hydraulic profiles lack the contrast necessary for the model to perform definitive spatial separation. Likewise, misclassifications at the sub-cluster level are anticipated when leak-induced signal fluctuations fall below the threshold. These limitations underscore the challenge of isolating failure events in zones with high hydraulic redundancy, where the similarity in nodal responses complicates the precise identification of the affected area. This limitation can be addressed by integrating additional variables that enable a clearer identification of the corresponding cluster; as indicated by Tornyeviadzi and Seidu [35], multivariate frameworks that incorporate additional hydraulic parameters are instrumental in minimizing false alarms and improving overall predictive accuracy. Consequently, training the Bi-LSTM model with multivariate temporal series significantly strengthens the network's capacity for leak localization.

The comparative analysis of clustering algorithms demonstrates that Spectral Clustering outperforms K-Means, a finding consistent with the current literature. This superiority stems from the ability of Spectral Clustering to preserve the topological integrity of the network. By maintaining physical connectivity within each cluster, the algorithm avoids the erroneous clustering of hydraulically similar yet disconnected nodes, thereby ensuring spatial and functional consistency. This structural coherence facilitates the Bi-LSTM model's ability to characterize zone-specific temporal dynamics, effectively reducing classi-

fication ambiguities at cluster boundaries and enhancing the overall precision of the leak localization framework.

The results obtained for RedNet 2 confirm that the proposed methodology maintains high classification accuracy across varying network topologies and scales, provided the training data is appropriately curated. Conversely, the decline in performance observed in the ZJ network is a specific limitation in zones characterized by high nodal connectivity or complex intersections. In such configurations, the sensitivity of pressure and flow variations to leak events is reduced, thereby increasing classification ambiguity at the boundaries of hydraulically similar clusters. To reduce this effect, the strategic installation of isolation valves is suggested to establish well-defined hydraulic boundaries, ideally utilizing a single feed point while keeping secondary interconnections closed. The creation of district measurement areas (DMAs) is a practice in water loss management [36]. By minimizing interconnections and delimiting sectors, the contrast in hydraulic signals between zones is significantly enhanced, thereby improving the resolution of the Bi-LSTM model for leak localization.

6. Conclusions

This study introduces a methodology for leak localization in WDNs by integrating Spectral Clustering for sectorization with a multi-output Bi-LSTM classification framework. The results suggest that leveraging spectral approaches can help ensure the preservation of the network topological integrity, which appears to be a relevant factor for accurate hydraulic modeling. Furthermore, the selection of representative nodes based on weighted criteria allows for a significant reduction in required instrumentation rather than exhaustive nodal simulations. Unlike traditional approaches that depend on massive datasets and dense sensor deployment, this strategy prioritizes hydraulically informative nodes, effectively streamlining the data-driven training process. The results demonstrate that integrating physical connectivity with deep learning architectures not only enhances localization precision in this study but also provides a potentially scalable solution for WDN monitoring in scenarios where historical data is limited.

In the L-Town case of this study, the model demonstrated a robust capability, achieving an overall accuracy of 85.5% during blind validation using unseen scenarios. Complementing this performance, a spatial error analysis across all evaluated scenarios revealed an MAE of 28.56 m and RMSE of 106.84 m. These quantitative results indicate that the vast majority of predictions are exact, and even in misclassified instances, the model maintains high spatial consistency. Notably, in 100% of the misclassification cases, the predicted cluster was topologically adjacent to the true leak localization, ensuring that the search area remains restricted to the immediate vicinity of the actual event.

These findings illustrate the advantages of Spectral Clustering over the K-Means geometric partitioning algorithm under the conditions analyzed. While the former maintains the hydraulic and topological coherence of the network, the latter achieved an overall accuracy of only 58.97%. This significant performance gap suggests that physical connectivity may be a functional requirement for high-precision leak localization in complex distribution systems such as L-Town. Future work will focus on expanding the model's scope to incorporate concurrent leak events and varying initiation times, further aligning the simulations with real operating conditions. Additionally, we aim to implement optimization frameworks, the temporal window length, and the weighting parameters of node representativeness variables that were kept static in the current study. Finally, validating this methodology using data from real networks will be a crucial next step. This includes assessing performance across diverse hydraulic regimes and complex topographies, par-

ticularly in regions with significant changes in elevation where rugged terrain introduces non-linear pressure variations that may influence localization accuracy.

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