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Leak location and magnitude estimation in water distribution networks using an optimised two-stage leak localisation model

Authors:



Hillary M. Zodape, MCE

Visvesvaraya National Institute of Technology
Nagpur India

Department of Civil Engineering

h zodape@gmail.com

Corresponding author



Assist.Prof. **Shilpa R. Dongre**, PhD. CE

Visvesvaraya National Institute of Technology
Nagpur India

Department of Civil Engineering

shilpadongre@civ.vnit.ac.in

Original research paper

Hillary M. Zodape, Shilpa R. Dongre

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Water loss from urban water distribution networks (WDNs) challenges sustainable water management and utility operations. Early leak detection and accurate localisation are crucial for reducing non-revenue water and maintaining network efficiency. This study proposes a machine learning-based framework integrating EPANET-generated static hydraulic simulations with an artificial neural network (ANN) optimised using particle swarm optimisation (PSO) for effective feature extraction. Pressure data under various leak and no-leak scenarios were simulated, and sensitive sensor nodes were strategically selected to enhance accuracy. By bridging simulation and reality, this method successfully integrates hydraulic modelling with data-driven learning, demonstrating the hybrid framework's strong potential for scalable and accurate leak detection, localisation, and magnitude estimation in WDNs.

Key words:

water distribution network, hybrid machine learning, PSO, leak localization, leak magnitude

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Hillary M. Zodape, Shilpa R. Dongre

Procjena lokacije i veličine curenja u vodoopskrbnim mrežama primjenom optimiranoga dvostupanjskog modela lokalizacije curenja

Gubici vode u urbanim vodoopskrbnim mrežama velik su izazov u održivome upravljanju vodnim resursima i radu komunalnih poduzeća. Rano otkrivanje curenja i njegova precizna lokalizacija ključni su za smanjenje količine neprihodovane vode te očuvanje učinkovitosti mreže. U ovome radu predlaže se modelski okvir utemeljen na strojnome učenju koji objedinjuje statičke hidrauličke simulacije generirane programom EPANET i umjetnu neuronsku mrežu (engl. Artificial Neural Network – ANN) optimiranu algoritmom optimizacije roja čestica radi učinkovitog izdvajanja pojedinih pogonskih svojstava. Simulirani su podaci o tlaku za različite scenarije s curenjem i bez njega, pri čemu su pažljivo odabrani osjetljivi senzorski čvorovi kako bi se povećala točnost modela. Povezivanjem simulacijskih modela sa stvarnim radnim uvjetima vodoopskrbnog sustava predložena metoda uspješno integrira hidrauličko modeliranje i podatkovno utemeljeno učenje te potvrđuje velik potencijal hibridnog okvira za skalabilno i precizno otkrivanje, lokalizaciju i procjenu veličine curenja u vodoopskrbnim mrežama.

Ključne riječi:

vodoopskrbna mreža, hibridno strojno učenje, optimizacija rojem čestica (PSO), lokalizacija curenja, procjena veličine curenja

1. Introduction

Water loss in urban water distribution networks (WDNs) poses a significant challenge to sustainable water management, particularly in developing countries where resource scarcity and infrastructure limitations exacerbate the issue. The International Water Association (IWA) has established comprehensive frameworks for understanding and quantifying these losses, revealing alarming statistics that underscore the urgency of addressing this issue [1]. The economic implications are equally concerning, as noted in [2] with the total cost of non-revenue water is conservatively estimated at \$141 billion annually for water utilities worldwide, with developing countries accounting for approximately one-third of these losses. Furthermore, [3] estimated roughly 3,800 damage occurrences in a single water supply network following a seismic event, with repair costs exceeding 28 million HRK, which underscores the economic stakes of inadequate network monitoring. The factors responsible for leaks may be internal or external, including ageing infrastructure, pipe corrosion, defects, inappropriate installation of pipes, excessive traffic loads on buried pipes, and ground movement [4]. The increasing conflict amongst water scarcity, ageing infrastructure, and growing urban populations has made efficient leak detection in WDNs a compelling concern.

Contemporary approaches to leak detection and localisation in urban WDNs encompass a diverse array of methods, each offering distinct advantages and operational characteristics. Based on the technique adopted for leakage detection, these methods can be classified as either hardware- or software-based. Hardware-based leakage detection typically involves the installation of physical sensors and devices throughout a water network. A common approach is acoustic detection, in which piezoelectric sensors are deployed to capture the vibrations and sound waves produced by leaking water [5]. These sensors are highly sensitive and, when paired with modern signal processing techniques, such as logarithmic spectrograms and convolutional neural networks (CNNs), can achieve detection accuracies above 99 % [6]. Techniques such as acoustic vibration detection using contact microphones or vibro-acoustic sensors can achieve high sensitivity, particularly when paired with real-time monitoring [7]. Other tools include flow meters and pressure sensors, which track sudden drops or anomalies indicating possible leaks. Electromagnetic flowmeters offer ± 0.2 % accuracy and can detect background leaks as low as 0.2 l/s [8]. However, these methods have distinct limitations: installation is often intrusive, sensor placement is labour-intensive, and detection performance may degrade over time or under environmental noise [9]. These drawbacks, along with associated cost and scalability issues, render them less adaptable to large or ageing infrastructures.

By contrast, software methods, including model-based, statistical, and data-driven approaches, avoid these limitations. Software-based leak detection uses hydraulic modelling and machine learning (ML) to identify anomalies in pressure, flow, and velocity data. Hydraulic model simulations provide pressure and flow residuals at junctions and pipes under different leak scenarios, identifying deviations from the baseline (no-leak) conditions to detect leaks with high accuracy [11]. When paired with ML algorithms such as artificial neural network (ANN), CNN, support vector machines (SVM), or ensemble learning (EL), these systems can classify leak events and localise them effectively [10]. High detection and localisation accuracies can be achieved using well-calibrated network models [6]. Moreover, contrastive learning [11] and time-frequency CNNs [12] improve performance under noisy conditions. Deep learning frameworks, such as CNNs, applied to pressure imaging using sensor data achieve true positive rates of up to 98 % and significantly outperform traditional manual or purely acoustic survey methods [13]. CNN-driven signal analysis and data fusion [6, 11] offer scalable, non-invasive, and continuously improving solutions with higher adaptability and automation potential. Hardware deployment strategies, such as localised vibration sensors or wireless sensor networks, further enhance the coverage in both metallic and non-metallic pipes, making sensor-driven solutions broadly applicable and indispensable for modern leak detection. Sensor networks not only reduce the leak response time and minimise water loss, but also improve operational efficiency and cost-effectiveness [14]. Unlike hardware methods, software-based approaches are nonintrusive, cost-efficient, and scalable, making them ideal for real-time monitoring and future smart water systems. Recent advancements in ML for WDN leak detection demonstrate diverse algorithmic applications yet reveal significant gaps in neural network architecture optimisation [11, 15, 16]. SVM, including hybrid SVM–CNN and maximum entropy-enhanced MLT-KSVC (Maximum Entropy version of Least Square Twin K-Class Support Vector Machine) approaches, show promising accuracy for classification, but often lack systematic hyperparameter tuning, limiting their full potential [17].

Graph Neural Networks (GNNs), has an ability to leverage WDN topological structures for enhanced generalisation and dynamic partitioning, thereby improving resilience. However, GNN studies have largely neglected leakage magnitude estimation, primarily focusing on detection and localisation. Software-based methodologies for leak detection are predominantly motivated by data-driven approaches that utilise statistical and signal processing analyses to identify leaks by comparing abnormal data values with normal patterns in pipeline systems. ML techniques, including CNNs and Long Short-Term Memory

(LSTM), have shown considerable effectiveness in analysing complex patterns within WDNs [18–20]. These ML models leverage historical data to recognise patterns, significantly reducing the need for extensive information, which is typically required in model-based approaches [21]. With the capability of distinguishing between leaked and non-leaked datasets, ML algorithms create predictive models from input data. The accuracy and efficiency of leak detection have been supported by the utilisation of large volumes of sensor and operational data, particularly using pressure and flow values at monitoring stations to train ML models. Studies [22, 23] indicated that leak detection accuracies could reach between 90.56 % and 98.23 % using CNN and LSTM models, thereby outperforming traditional statistical methods. Advanced encoder–decoder models, such as LSTM-autoencoders, excel at processing time-series pressure data with lower false-positive rates [13]. Furthermore, the integration of various data types, including acoustic signatures and hydraulic parameters, enables real-time and adaptive leak detection, making ML models suitable for contemporary smart infrastructure applications [20]. Hybrid models, combining hydraulic simulations with ML, offer robustness through error correction but face challenges in computational complexity and scalability for large networks [24, 25]. ML automates sensor data analysis, reducing the time and cost of leak management while improving detection precision [14, 20, 26, 27]. Although its effectiveness depends on high-quality data and model tuning, the evolving role of ML in optimising WDN operations supports sustainable water management. Pressure plays an important role in leak detection in WDNs, as a small leak can cause a noticeable pressure difference, whereas flow or demand often varies due to natural diurnal consumption patterns [28]. The accurate assessment of WDN performance requires the simultaneous consideration of hydraulic parameters and component failure probabilities, which motivates data-driven approaches capable of capturing pressure–flow relationships across network nodes [29]. Pressure indicates the hydraulic state of the entire network, as it responds to the sensitivity of the leak when the sensor is distant [30], and node pressures thereby provide a more stable, continuous, and spatially distributed signal. This is effective in indicating the presence of a leak at an approximate location [31]. Leakage is pressure-dependent; thus, pressure-dependent analysis (PDA) offers a more realistic hydraulic modelling approach for WDNs under pressure-deficient conditions than traditional demand-driven analysis (DDA) [32]. The PDA dynamically adjusts outflows based on the actual pressure, accurately simulating conditions such as leaks, pipe failures, or sudden demand spikes [33], and aids in leak detection by reflecting pressure-induced demand reduction. PDA also prevents unrealistic flow predictions, including the negative

pressures commonly produced by DDA during network stress [34, 35]; improves water quality modelling during low-pressure events; and delivers more accurate outflows at distant nodes when pressure drops occur [36, 37]. Furthermore, PDA forms a physically consistent foundation for ML approaches, outperforming DDA-based datasets by providing valid hydraulic conditions. This significantly improves the accuracy and generalisability of models such as ANNs in leak magnitude estimation and localisation under variable pressure [38, 39].

This paper discusses a classification model for identifying leaky nodes in a WDN using a hybrid ANN–SVM model. This highlights the strengths of both prediction methods, focusing on aspects such as the activation functions, learning algorithms, and data scaling. The proposed hybrid learning framework utilises feature learning using an ANN and classification using an SVM. This approach accounts for the complexities of leak signatures, thereby improving leak detection efficiency. By leveraging the ANN's ability to recognise intricate pressure patterns and the SVM's capability to differentiate similar classes, the model ensures better localisation accuracy and enhanced predictive stability, resulting in a more robust decision-making process despite individual model imperfections.

ANNs are computational models inspired by the structure and function of the human brain. An ANN is composed of interconnected processing units called neurones arranged in input, hidden, and output layers. Each neuron computes the weighted sum of its inputs, adds a bias term, and applies an activation function, such as a sigmoid, hyperbolic tangent, or ReLU, to introduce nonlinearity. They were developed to recognise patterns, learn from data, and generate predictions or decisions [40]. ANNs have been widely adopted because they can model complex and nonlinear relationships between inputs and outputs without requiring explicit mathematical formulations [41, 42].

Artificial Neural Networks are typically applied to classification and regression problems. In classification, the model assigns inputs to predefined categories using activation functions such as sigmoid or softmax and loss functions such as cross-entropy [43], where the network predicts continuous values and is typically trained using the mean squared error or mean absolute error. Learning occurs through the forward transfer of the processed data by each layer and backpropagation with gradient descent optimisation [44]. Over successive epochs, the weights are iteratively updated to minimise prediction error. An SVM is a supervised ML algorithm applied to classification and regression problems, with strong foundations in statistical learning theory. It is particularly effective in high-dimensional feature spaces, and is most commonly used as a binary classifier, although it can also be extended to multi-class tasks [45].

The core principle of the SVM is to determine an optimal decision boundary or hyperplane that separates the data points belonging to different classes. Among all candidate hyperplanes, the SVM selects the one that maximises the margin, defined as the distance between the boundary and the nearest data points from each class [46]. These points, known as support vectors, define the classifier and contribute to an improved generalisation with reduced overfitting.

Following feature extraction by ANN, the SVM operates on numerical feature vectors rather than raw data. If the features are linearly separable, then a linear hyperplane is sufficient. However, real-world data are often nonlinear. In such cases, SVM applies the kernel trick, which implicitly maps the input data into a higher-dimensional space in which linear separation becomes possible. Common kernels include the radial basis function and polynomial kernel [27]. For multiclass classification, the one-against-one strategy has been shown to provide a strong recognition performance with lower complexity [47].

Among the various hybrid ML models applied for leak detection in WDNs, the hybrid ANN-SVM approach is particularly effective. Unlike other hybrid models, such as ANN and Random Forest or ANN and Naïve Bayes, the ANN - SVM combination effectively merges the two complementary strengths of the ANN's capability to model complex nonlinear relationships in pressure data and the SVM's superior generalisation and decision boundary precision. The hybrid ANN-SVM model synergistically integrates the strengths of both learning paradigms, offering improved leak detection performance in WDNs compared to standalone models.

By training the known WDN framework on historical or simulated data, the hybrid learning framework helps the system identify leak locations when presented with new realistic static datasets. This hybrid approach effectively combines pattern recognition with classification, making it a feasible and scalable solution for leak monitoring in operational water networks.

A critical limitation of current WDN research is the widespread use of fixed ANN architectures without systematic hyperparameter optimisation. Many studies employ predetermined network configurations, which are often arbitrary, constraining performance given the data-dependent nature of optimal architectures [24, 48, 49]. Despite the proven benefits of systematic optimisation techniques such as Response Surface Methodology (RSM) in other engineering fields, their application in water systems is minimal [50]. ANN optimisation for leak detection in WDNs often uses techniques such as particle swarm optimisation (PSO), genetic algorithms (GA), and Levenberg-Marquardt (LM) for hyperparameter tuning and improved accuracy [51-53].

However, the use of PSO for ANN hyperparameter tuning remains underexplored in this domain. Although PSO-optimised ANNs have demonstrated superior convergence and accuracy in various applications [54], comprehensive PSO-ANN implementations for WDN leakage detection are lacking. This significant research gap highlights a substantial opportunity to enhance leak detection methodologies through systematic neural network architecture optimisation, leveraging PSO's global search capabilities and robustness. PSO is often preferred over GAs and Bayesian optimisation (BO) for tuning the ANN parameters because of its faster convergence and simpler implementation. PSO efficiently handles continuous hyperparameters such as the learning rate and neuron numbers by dynamically adjusting particle positions based on individual and global best solutions [54]. Unlike GAs, PSO requires fewer parameters and avoids complex operations such as crossover and mutation. Compared with BO, PSO performs better in high-dimensional search spaces and does not rely on surrogate modelling [55]. The balance between exploration and exploitation makes it robust and computationally efficient for ANN architecture optimisation. It is often faster to converge, has a low computational cost, and exhibits superior performance in continuous parameter spaces, such as learning rates and neuron counts. As mentioned in Table 1, where GAs require intensive computation for crossover and mutation operations, PSO efficiently explores the solution space with fewer evaluations. While BO excels in small, expensive search spaces through surrogate models, PSO provides better local refinement with fewer iterations [55-57].

The escalating challenge of water loss in urban WDNs demands accurate and computationally efficient leakage detection strategies. This study addresses this problem by proposing an embedded two-stage leakage localisation framework that integrates an ANN and an SVM. The ANN model is optimised using PSO to enhance learning accuracy through systematic network parameter tuning. The mean absolute difference (MAD) is employed to identify the most sensitive monitoring nodes (sensor nodes) for effective leak detection. As an ANN captures complex nonlinear pressure-flow dynamics effectively, whereas an SVM generalises well on noisy or small datasets, assigning higher weights to ANN predictions ensures better decision making under real-world variability [58, 59].

In the first stage, the trained hybrid ANN-SVM model determines the precise leak location (i.e. node), whereas in the second stage, the leak magnitude is estimated using the pressure and flow data obtained using the PDA. The proposed methodology aims to improve the detection accuracy, localisation reliability, and magnitude estimation, thereby supporting efficient leak mitigation and management in water distribution systems.

Table 1. Comparison of different optimization methods

Aspect	PSO (particle swarm optimization)	GA (genetic algorithm)	Bayesian optimization
Convergence speed	Fast	Moderate	Moderate
Local refinement	Good	Moderate	Strong
Computational cost	Low to moderate	High	Moderate
Best use case	Continuous tuning	Discrete parameters	Small search space

Leak-magnitude estimation in networks employs several established methodologies tailored to different operational contexts. Model-based hydraulic simulation approaches, pioneered by [60], utilise Bayesian reasoning combined with pressure residual analysis to calibrate all possible offline leak scenarios. This concurrently estimates leak size and location while accounting for measurement uncertainties and demand variability. Sensor fusion techniques demonstrated in [61] integrate inlet flow measurements with real-time sensor data and demand forecasting models to identify the presence of leaks. The integration of AI for pattern recognition, state-space modelling for leak identification, and an extended Kalman filter for accurate leak location estimation was proposed by [62]. Conversely, [1] identified a pipeline leak through inverse mathematics, which analysed the changes in the pressure response magnitude under resonant conditions using a measured frequency response diagram for transient pressure to ascertain the leak location and size.

When a leak occurs in a WDN, it causes a localised pressure drop that affects both the surrounding demand nodes and the leaky node. The PDA captures this behaviour by adjusting the outflow from both legitimate consumer demands and leaks based on the available pressure at each node. This reflects the pressure-discharge relationship typically modelled by an orifice equation, in which a larger leak induces a greater pressure reduction. This limits the flow rate from the leak and the connected demands. Additionally, PDA-generated data, which incorporate nonlinear pressure–flow dynamics during leak events, serve as superior training inputs for ML models, such as ANNs, improving their accuracy and generalisability when detecting and quantifying leaks in real-world systems.

2. Methodology

The primary goal of this study is to identify a single leak in a WDN. Figure 1 presents a flowchart of the methodology. The sequential steps comprise:

- I. Leak and hydraulic simulation: For a given network, an EPANET input file was fed to the model, the leak is simulated randomly by selecting the emitter coefficient, and a hydraulic analysis of the network is executed.

- II. Fixing of relevant number of sensor nodes.
- III. Optimising the ANN architecture and executing its embedded hybridisation with the SVM.
- IV. Identifying the leaky node and assessing the leak magnitude.

The data simulation was developed in MATLAB which was linked to EPANET for hydraulic analysis. A hybrid ANN–SVM code was developed using Python. A detailed stepwise description is presented in the following section.

3. Application of methodology to Hanoi network

3.1. Data generation

The Extended Hanoi WDN is a benchmark network first presented in [63], based on the planned trunk network of Hanoi, Vietnam. A total of 34 pipes are connected to the reservoir alongside 31 demand nodes. The layout of the Hanoi WDN is shown in Figure 2.

The MATLAB code simulates different single-leak scenarios in a network modelled using EPANET 2.2. Leaks are assumed to occur at the nodes. For each of 10,000 samples, a junction node is randomly selected to apply a leak by assigning it a random emitter coefficient (between 0.2 and 0.7) simulating a leak. The simulated results (nodal pressures) for the no-leak and leakage scenarios were stored in a data matrix. The pressure values at all junctions, the leak node index, and the corresponding emitter coefficient were used to generate labelled datasets for training the leak detection model.

A node with a randomly selected emitter coefficient represents a leakage scenario. This approach preserves the pressure–flow relationship through the emitter equation (1), ensuring realistic leakage behaviour:

$$Q_{\text{Leak}} = C \cdot P^{\gamma} \quad (1)$$

Node-based leaks also simplify the data generation for ML, reporting the volume of water discharged from the emitter per unit time as Q_{Leak} . C is the emitter coefficient, and P as the available pressure at the selected node.

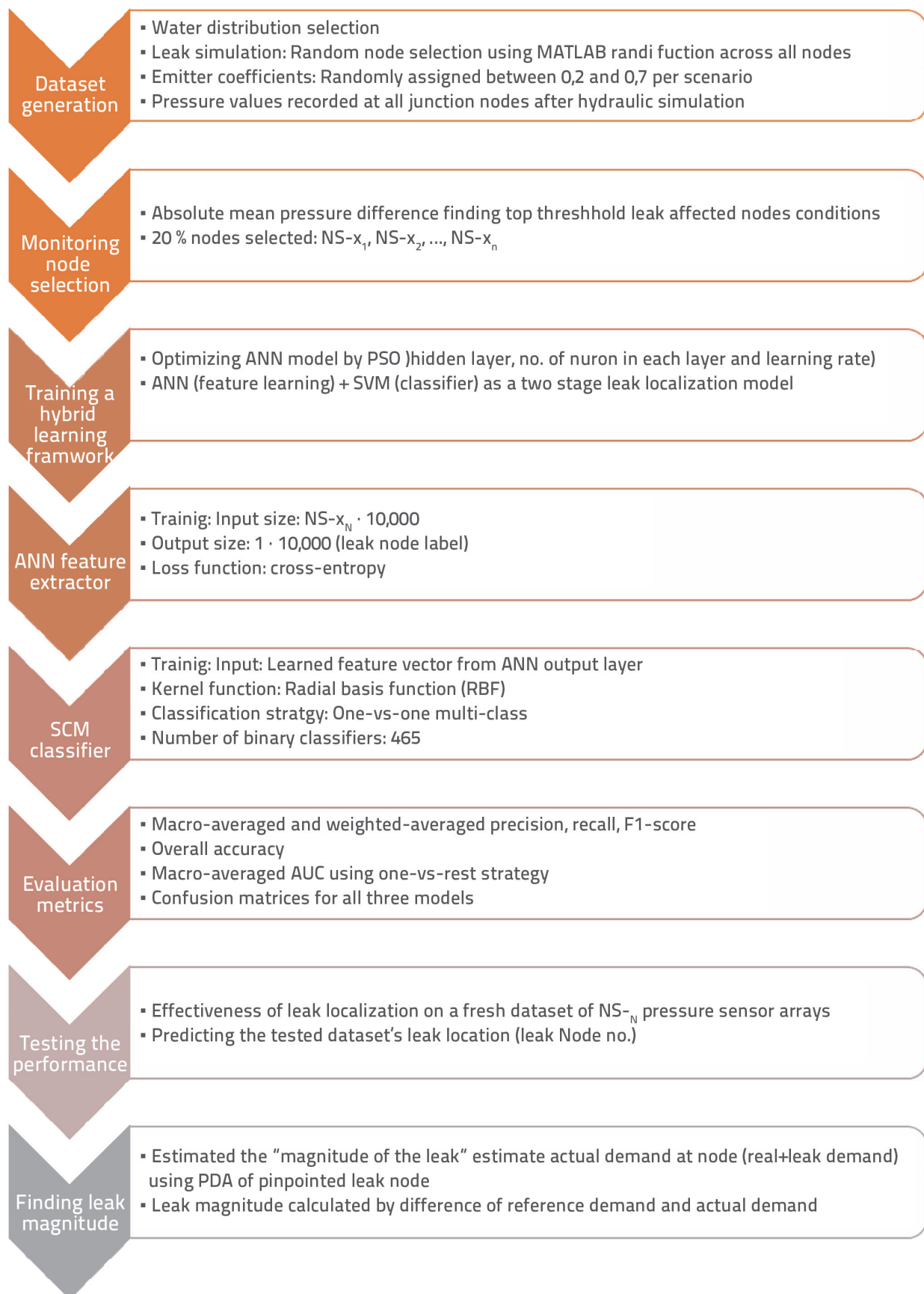


Figure 1. Flowchart of methodology

3.2. Sensor placement

Sensors are essential for effective leak detection and localisation in WDNs, enabling the real-time monitoring and the rapid identification of leakage events. Optimally placed pressure sensors provide distributed measurements across the network, allowing for the statistical analysis of nodal pressure data to detect and localise leaks with high accuracy. The developed MATLAB pseudocode performs a series of operations to identify the most sensitive nodes in a water distribution networks for leakage detection using differential pressure data, Figure 3. The number of pressure sensors for the network is selected in accordance with [64]. The code reads the pressure data from two Excel files, the initial pressure

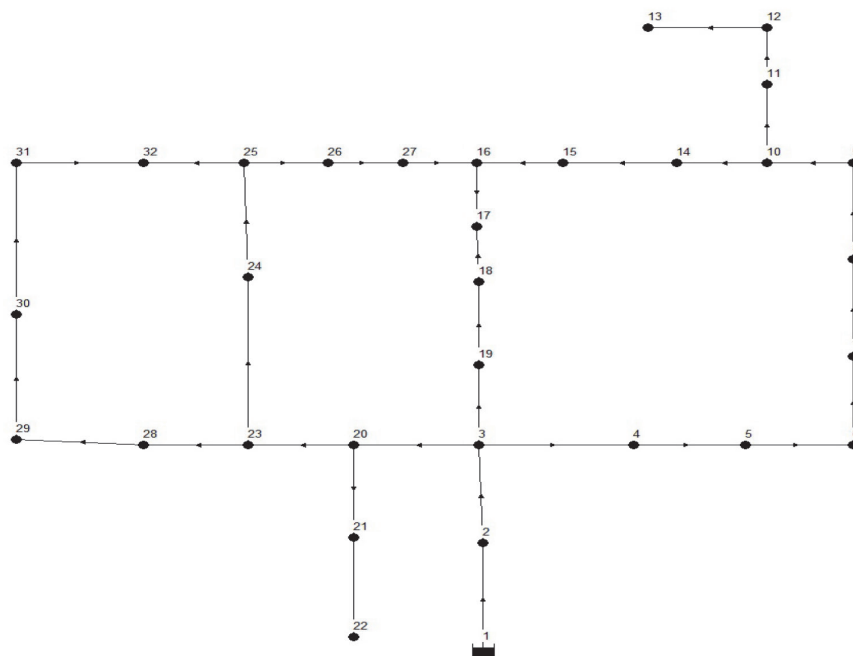


Figure 2. Water distribution network of the extended Hanoi network

```
STORE in "difference_result.xlsx" = leak_pressure - no_leak_pressure"
READ data from file "difference_result.xlsx"
STORE it in RESULT_MATRIX
(Rows = leak scenarios, Columns = nodes)

FOR each node (each column in RESULT_MATRIX)
  CALCULATE absolute value of all differences
  COMPUTE mean of those absolute values
  STORE this in MEAN_DIFF for that node
END FOR
SORT MEAN_DIFF in descending order
STORE sorted values in SORTED_DIFF
STORE corresponding node numbers in SORTED_NODES

SET TOTAL_NODES = number of columns in RESULT_MATRIX

CALCULATE N = 20% of TOTAL_NODES
ROUND N up to nearest whole number

SELECT first N elements from SORTED_NODES → TOP_NODES
SELECT first N elements from SORTED_DIFF → TOP_DIFF_VALUES

PRINT "Top N nodes (20% of total) with highest average differential pressure"

FOR i = 1 to N
  PRINT TOP_NODES[i], TOP_DIFF_VALUES[i]
END FOR
```

Figure 3. MATLAB pseudocode for identify the most sensitive nodes in a water distribution networks for leakage detection

(no-leak) and different leak scenarios, and subtracts each row to create a differential pressure matrix, saving the output.

To quantify the average pressure change per node across all the leak scenarios, the algorithm reads the differential pressure data from this new file and computes the MAD for each node (i.e. each column in the matrix).

The sensitivity of the nodes was then ranked by sorting them in descending order according to their mean values. A sensor placement rate of 20 % (seven nodes) is selected to achieve adequate spatial coverage without excessive installation costs.

This proportion allows for strategic placement at hydraulically sensitive and high-impact nodes, providing reliable leak or anomaly detection while maintaining computational and operational efficiency [64]. The associated mean differences of the top nodes are then extracted, assisting the user in determining the nodes that are most sensitive to pressure fluctuations caused by leaks.

3.3. Hybrid ML model

The proposed hybrid ANN-SVM model combines the ANN's nonlinear feature extraction with the SVM's precise classification. This two-stage leak localisation model enhances accuracy, generalisability, and robustness, effectively handling complex hydraulic patterns, and improves leak identification in large nonlinear water distribution networks.

3.3.1. Optimization of ANN model

In ANNs, the configuration and key hyperparameters, including the number of hidden layers, number of neurones in each layer, and learning rate, are often determined using a trial-and-error approach [40, 54, 65], which is time-consuming and inefficient. Optimisation is crucial for ANNs because of the complexity of adjusting numerous weights in a nonconvex, high-dimensional loss landscape that features multiple local minima and saddle points. This requires iterative optimisation methods such as gradient descent to update the weights via backpropagation for effective convergence and generalisation. Conversely, SVM training is a convex optimisation problem that ensures a unique global minimum and eliminates the need for intricate iterative weight adjustments typical of ANNs.

A custom PSO algorithm was implemented to optimise the ANN architecture. The PSO was configured with a population of 20 particles and run for 30 iterations. Each particle represents a potential ANN configuration defined by three hyperparameters: the number of hidden layers (bounded between 1 and 3), the number of neurones in each layer (ranging from 5 to 100), and learning rate (ranging from 0.001 to 0.1). During each iteration, the particles were evaluated based on their mean squared error, and the best configuration is selected for final model training.

3.3.2. Hybrid model

ANNs are highly effective at modelling complex nonlinear relationships, such as pressure–flow interactions, particularly with large datasets [40]. However, these methods are prone to overfitting and require careful hyperparameter tuning. In

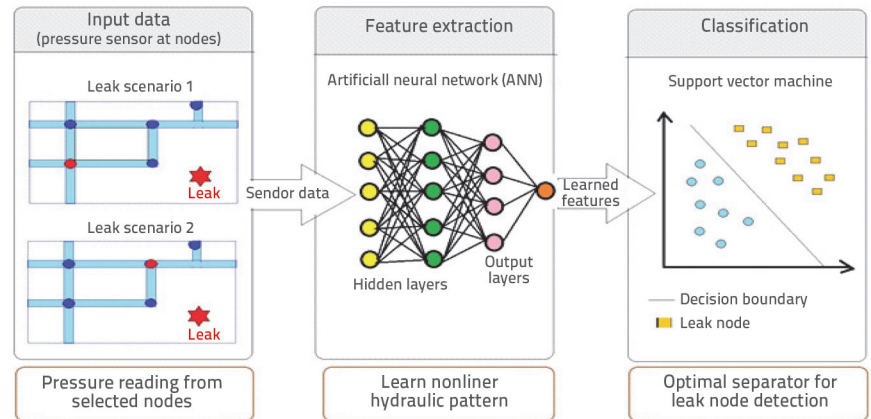


Figure 4. Two-stage leak localization model

contrast, SVMs exhibit a strong generalisability and perform robustly on smaller datasets by optimising the margin between classes using statistical learning theory [66, 67]. However, SVMs struggle to learn intricate nonlinear dependencies when feature representations are insufficient. The hybrid ANN–SVM framework mitigates these weaknesses by using an ANN for feature extraction and an SVM for final classification, enhancing accuracy and stability across diverse operational scenarios [68]. Figure 4 shows the proposed hybrid model.

The proposed hybrid framework uses a two-stage sequential process. An ANN was first trained on pressure readings from selected monitoring nodes to learn the nonlinear hydraulic patterns associated with different leak scenarios. Its output layer produces a feature representation of the pressure–flow relationships in the network. These features are fed directly into an SVM that fits a hyperplane boundary to classify the leak location among the 31 possible junction nodes. To prepare the data for training, min–max normalisation was applied to the input pressure values to scale them between 0 and 1, ensuring that all features contributed equally during the ANN training process.

Table 2. Details of the hybrid learning framework

Parameters	ANN	SVM	
Network type	Feed-forward pattern recognition	Kernel function	Radial basis function (RBF)
	Broj skrivenih slojeva: 3	Number of binary	Classifiers: 465 (31×30/2)
	1. Relu – 34	Strategy	One-versus-One
	2. Relu – 50	Bias:	-0.197
	3. Softmax – 85		
Size of input	7 x 310000		
Size of output	1 x 310000		
Loss function	Cross-entropy		
Trainning: validation test	70 : 10 : 20		
Nodes selected	(NS-8, NS-12, NS-15, NS-21, NS-24, NS-28 i NS-31)		
Learning rate	0.04	Scaling factor	0.1

The dataset is divided into three subsets: 70 % for training, 10 % for validation, and 20 % for testing, enabling a robust model evaluation.

The simulation and training are conducted using MATLAB R2023b on a system running Windows 11 with an Intel Core i7 processor, 16 GB of RAM, and the MATLAB neural network, and global optimisation toolboxes. Finally, the trained and validated hybrid model is tested on the new data, and its classification accuracy is reported for performance evaluation.

Table 2 presents an overview of the parameters governing the hybrid ANN-SVM model. This two-stage leak localisation model is adaptive to a performance-driven approach. This reduces the number of false positives and supported scalable deployment, rendering it a compelling strategy for real-time data-driven WDN monitoring and fault diagnosis.

3.4. Magnitude of leak

PDA evaluates the hydraulic behaviour of the network based on the actual pressure available at each node. When the node pressure is less than the required pressure, the nodal demand is not fully satisfied and becomes a function of the pressure rather than being fixed. By establishing Q_{req} (demand at reference pressure under normal conditions without leakage), P_{req} (reference pressure at that node under a no-leak scenario), P_{act} (current pressure at the predicted leak node), and Q_{act} (actual demand at the node, accounting for both real demand and leakage), they can be evaluated by a mathematical relationship:

$$Q_{\text{act}} = Q_{\text{req}} (P_{\text{act}}/P_{\text{req}})^{\alpha} \quad (2)$$

Equation (2) ensures that the demand and leakage rates adjust proportionally to the pressure changes, enabling a more accurate estimation of the leak magnitude. The pressure exponent, α , is set to a universal value of 0.5 [38]. This dynamic relationship is particularly vital for analysing leaks because the discharge from a leak is directly dependent on the pressure head at the leakage point.

This dynamic interaction between the pressure and flow provides a more realistic depiction of the hydraulic state of a network under leakage conditions. As a result, the PDA enables a more accurate estimation of the leak magnitude by accounting for the pressure-dependent nature of water loss. It also enhances leak localisation by simulating the propagation of pressure changes throughout the network, creating pressure contours that support more effective inverse modelling.

4. Results and discussion

By analysing the real-time pressure or flow data collected from sensors throughout the network, it is possible to infer the presence, magnitude, and location of leaks. The hydraulic response of the system to pressure drops or flow anomalies was used to determine where and how the leak occurred. This approach forms the basis for many modern leakage-detection methods [40, 69, 70] and sets the context for the discussion presented in this study.

4.1. Optimal ANN configuration obtained using PSO

The optimal network architecture was obtained through PSO, which was applied to tune the number of hidden layers, number of neurones in each layer, and the learning rate. The variation of mean squared error (MSE) with respect to training epochs for the optimal ANN architecture is presented in Figure 5. The MSE decreased from approximately 0.0012 to 0.0009 within ten iterations and stabilised thereafter, indicating that the model achieved convergence (minimised its loss function) with minimal further improvement.

4.2. Hybrid ANN- SVM model Vs Individual models

The ANN was designed to identify and learn pressure patterns for leak localisation. The Pressure data collected from the seven sensor nodes were used as the input variables. A feedforward neural network trained using gradient descent backpropagation was implemented for pattern recognition. Figure 6 shows the ANN feature-extraction training curve. The ANN training curve showed stable convergence over 50 epochs with no overfitting. The training and validation accuracy both converged to approximately 0.97 and

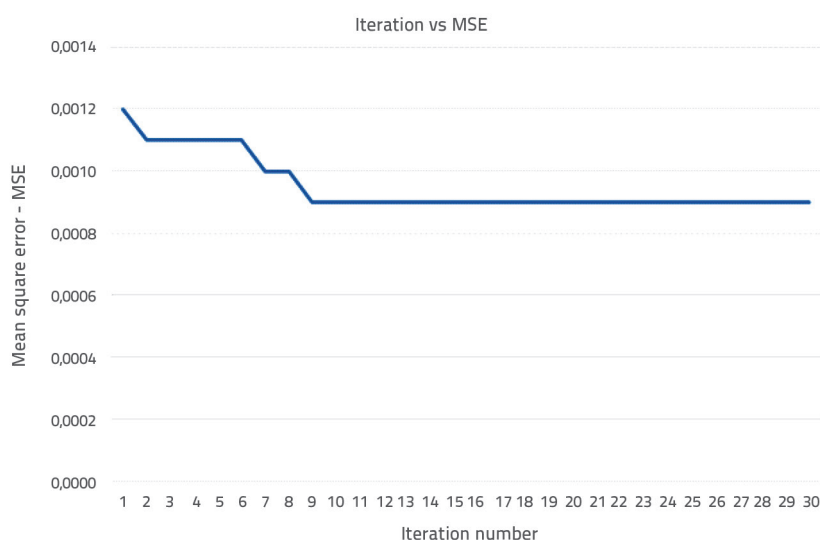


Figure 5. MSE versus the number of epochs for the optimal architecture in ANN architecture

remained tightly aligned across all epochs. Overfitting was not observed. All results were obtained by running the full pipeline with a fixed random seed for reproducibility. The close alignment between the training and validation accuracy curves confirmed that the model successfully learned the generalisable hydraulic pressure patterns rather than memorising the training samples. The ANN model was validated using an independent dataset to prevent overfitting.

The features extracted by the ANN model were then passed through a supervised multiclass SVM classification model (number of classes = 31) which accurately identifies the leaky node. The performance of the developed hybrid

model was evaluated using the Precision, Recall and F1 score values listed in Table 3. To compare the efficacy of the developed model, the same network was solved using the individual ANN and SVM models.

Table 3 shows a clear comparative evaluation of the classification performance of the three models, reporting consistently high performance over the single models.

Confusion matrices were used to evaluate and compare the classification performances of all three models, as shown in Figure 7.a to 7.c. A confusion matrix is an essential tool in classification analysis because it provides a comprehensive visualisation of model performance, displaying how accurately each class is identified. Each cell in the matrix represents the number of predictions made for a particular class, whereas the diagonal elements indicate correctly classified instances.

To evaluate the classification capabilities of all three models against a single leak, a receiver operating characteristic (ROC) curve was drawn, as shown in Figure 8. The ROC curve plots the true positive rate (TPR) against the false positive rate (FPR) for various classification thresholds. The area under the curve (AUC) serves as a scalar summary of model quality; a higher AUC denotes a superior ability to distinguish between the leak and no-leak classes. The



Figure 6. ANN feature extractor training curve over 50 epochs

diagonal line represents random classification, whereas the curves above indicate better performance. The improved performance of the hybrid ANN–SVM model arises from its complementary structure, in which the ANN efficiently extracts nonlinear pressure patterns while the SVM provides robust boundary-based classification. This synergy explains the superior ROC performance and sharper TPR response compared with those of the standalone ANN and SVM.

The AUC was computed using a macro-averaged one-versus-rest strategy across all 31 node classes on a sample test set. The ROC curve of the hybrid model rose sharply to near-perfect TPR at an FPR of approximately 0.01, demonstrating the highest class separability of the three frameworks. The hybrid model's AUC of 0.9983 and macro-recall of 0.9662 were independently strong.

Figure 9 shows the loss per epoch of the hybrid model, complementing the accuracy plot by showing the error minimisation process of the model. The loss function measures the deviation of model predictions from the actual output, where lower loss values indicate better performance. In this case, both training and validation losses were relatively high initially but decreased sharply within the first 10 epochs, reaching low (near-zero) levels as the training progressed. This steep decline indicates an efficient weight optimisation through

Table 3. Overall performance metrics of ANN, SVM and hybrid ANN–SVM

Model	Macro precision	Macro recall	Macro F1	Weighted precision	Weighted recall	Weighted F1
ANN	0.812	0.673	0.775	0.944	0.918	0.926
SVM	0.694	0.548	0.673	0.875	0.842	0.851
ANN+SVM	0.950	0.966	0.956	0.951	0.967	0.957

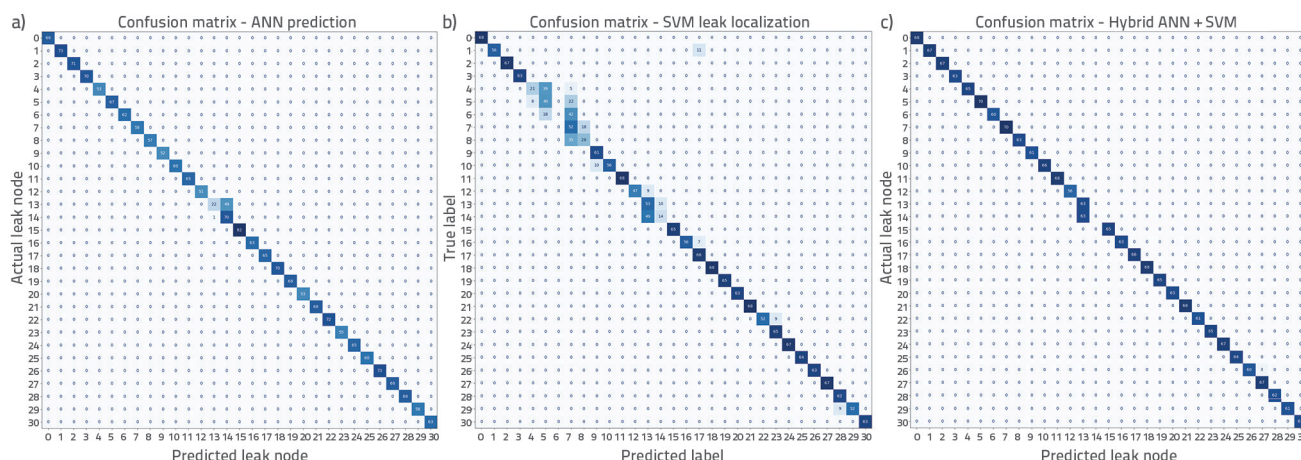


Figure 7. Receiver operating characteristic curve for the ANN, SVM and hybrid models

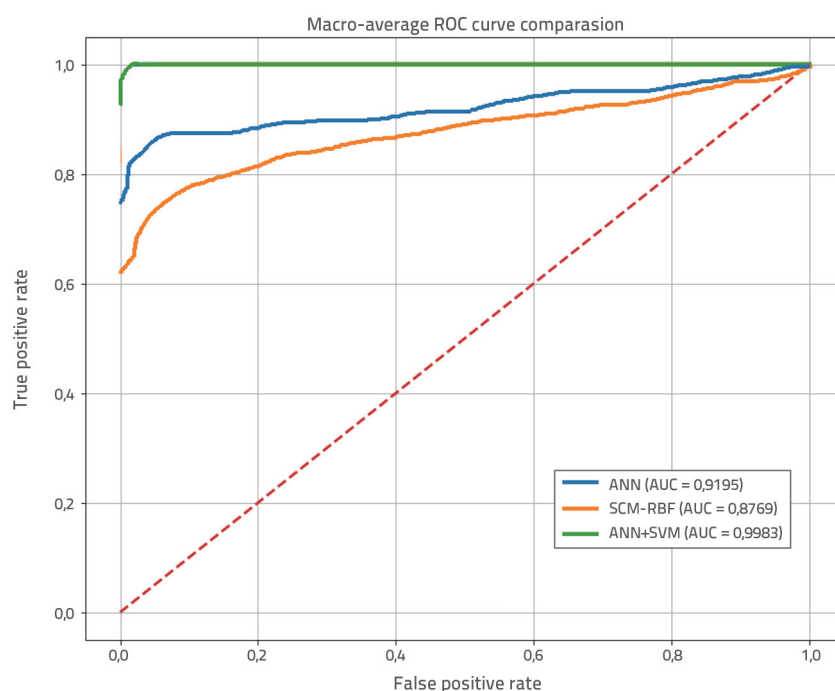


Figure 8. Loss versus number of epochs for the hybrid methodology

backpropagation and adaptive learning rate adjustments. The stabilisation of the loss beyond 40 epochs implies that the model has converged, beyond which any additional training provides minimal improvement. Furthermore, the parallel trends of both loss curves reflect a balanced model free from overfitting or underfitting tendencies. The close alignment of the two curves confirms the consistent learning and robust performance across different data subsets. The above two graphs, accuracy per epoch (Figure 6) and loss per epoch (Figure 10), represent the learning behaviour and convergence performance of the developed hybrid ANN–SVM model during training and validation.

Thus, the steadily decreasing MSE curve confirms the model's learning convergence, whereas the ROC curve validates its classification precision. The combination of low MSE, low loss per epoch, and high AUC signifies a well-trained, stable, and highly discriminative hybrid model capable of differentiating subtle hydraulic variations caused by leakage. These results confirm that the PSO-optimised ANN framework efficiently minimises the prediction errors, while the SVM component enhances the decision confidence and generalisation. The model demonstrated stable generalisation performance consistent with a well-regulated classification framework. Overall, the combination of high accuracy and minimal loss highlights the effectiveness of the ANN–SVM model, its optimised parameter tuning, and its strong predictive performance in identifying leak locations and magnitudes within the

water distribution network. These results validate the reliability and stability of the proposed hybrid approach for real-world leakage detection applications.

4.3. Leak magnitude estimation

The PDA provides a realistic hydraulic representation of WDNs under leakage or low-pressure conditions. Using the available pressure and the actual outflow at the node, the magnitude of the leak was calculated using equation (2). An example shows the leak estimation at Node 30 using the PDA. Once the leak node (e.g. Node 30) is predicted, the current pressure under

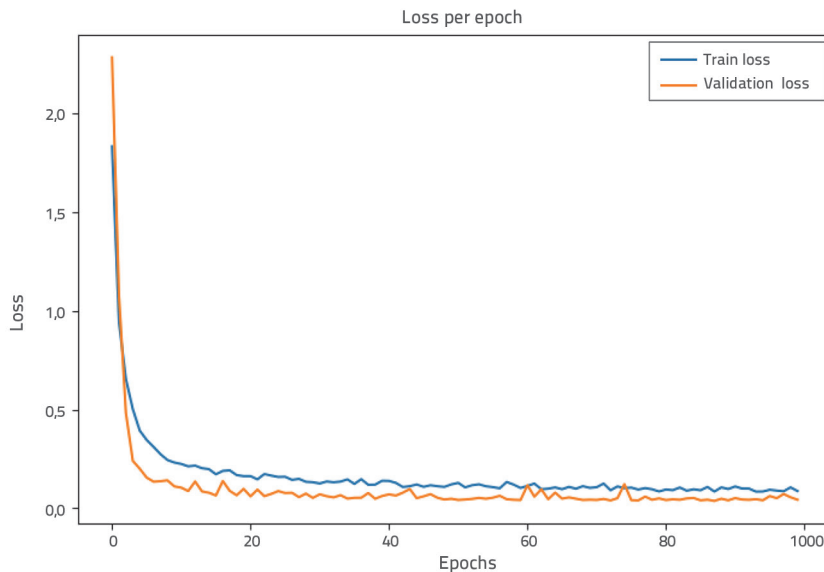


Figure 9. Accuracy of leak prediction with respect to actual leak magnitude

the leak condition and the reference pressure under normal conditions are incorporated into the PDA relationship. Under normal operating conditions, the baseline pressure distribution of the WDN is known and represents the leak-free state. The real-time measured pressures from the field were then compared with the PDA-derived reference pressures to identify the deviations associated with potential leakage events. The reference demand represents the normal flow at full service pressure, whereas the actual demand represents the total outflow, including the real demand and leak discharge. Thus, the leak magnitude is obtained as the difference between the two demands. The estimated leak magnitude closely matched the emitter coefficient applied in the EPANET simulation, validating the accuracy of the PDA-based estimation.

Predicted leak node number is: 30
 Enter current pressure at node 30 (with leak): 1.28637
 Enter reference pressure at node 30 (no leak): 1.34
 Enter reference demand at node 30 (no leak): 29.17
 Enter pressure exponent 'n' (typical = 0.5): 0.5
 Estimated Actual Demand at Node 30 (Real + Leak):
 29.7719 l/s

Compared with conventional demand-driven models, the PDA accounts for pressure variations more realistically, leading to a precise estimation of leakage magnitudes under reduced-pressure conditions in WDNs. The performance of the leak magnitude estimation model presented in Figure 9 was assessed using the MAE, Root

Mean Square Error (RMSE), and the coefficient of determination (R^2). A comparison between the predicted and actual leak magnitudes, shown in Figure 10, reflects a strong linear relationship with a high R^2 value. The model achieved MAE = 0.0502, RMSE = 0.0544, and $R^2 = 0.9076$, indicating low prediction error and robust explanatory power. The low MAE and RMSE values confirm that the PDA approach provides accurate estimates of the leak magnitudes, which are consistent with the emitter-based leak simulations in EPANET. Overall, these results confirmed the reliability and effectiveness of the proposed model for leak magnitude estimation under PDA conditions.

4.4. Discussion

The proposed hybrid ANN–SVM model demonstrated a notable improvement over standalone ANN and SVM models in leak detection for the Hanoi network. By optimising the key ANN hyperparameters using PSO, the model achieved faster convergence, reduced training errors, and improved generalisation. The hybrid ANN–SVM model produced only three misclassifications across 2,000 test samples. In contrast, the standalone ANN had 22 concentrated between adjacent Nodes 13 and 14, whereas the SVM showed broader confusion across node classes, reflecting the limits of classifying raw pressure values without learned feature representations. The ANN training curve showed an accuracy increase from 0.156 at epoch 1 to 0.970 at epoch 10, with the training and validation curves remaining closely aligned throughout all 50 epochs, offering no evidence of overfitting. The ROC curves yielded an AUC value of 0.9983 for the hybrid model, with lower values for both standalone counterparts.

For leak magnitude estimation, the PDA was employed because it realistically represents the hydraulic behaviour under varying pressure conditions. Unlike DDA, the PDA accounts for pressure-dependent outflows, making it more suitable for accurate leak quantification. Although the model shows high prediction performance, it is limited to a single leak scenario. For a multi-leak scenario, reduced performance, overlapping pressure responses, and a lack of strong inter-node hydraulic interactions may complicate pattern discrimination. This limitation highlights the need for further research to enhance model reliability and extend its applicability to complex multi-leak scenarios.

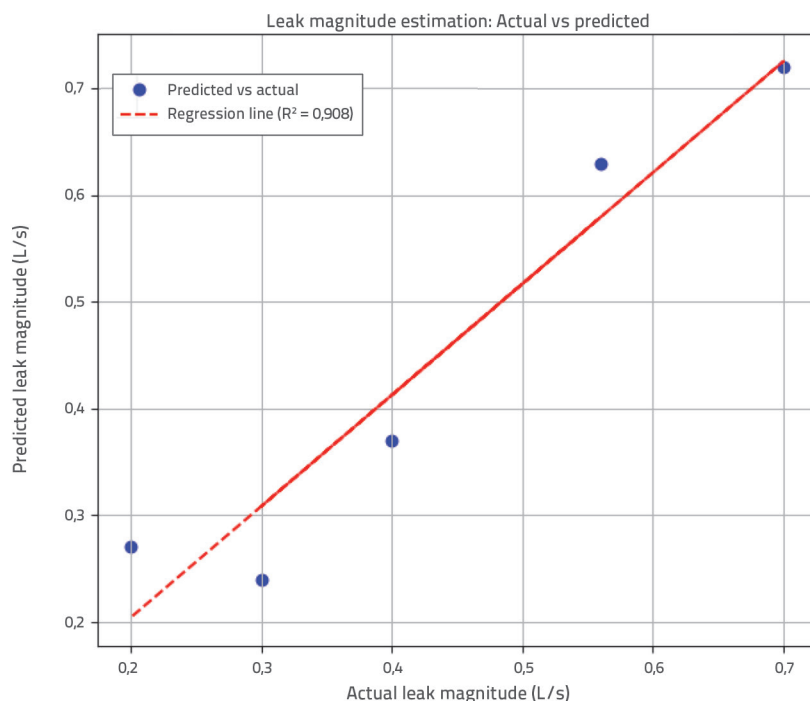


Figure 10. Accuracy of leak prediction with respect to actual leak magnitude

5. Conclusion

Leak detection in WDNs is essential for minimising non-revenue water loss, ensuring system reliability, and maintaining sustainable resource management. The accurate identification of leak locations is crucial, particularly in real-world systems, where limited static pressure sensors are deployed. Effective sensor placement significantly enhanced leak detectability in this study, specifically, seven high-sensitivity nodes were identified using the absolute mean pressure difference method between the leak and no-leak conditions. This data-driven approach proved to be practical for real-world networks

with fixed sensor layouts, ensuring optimal information capture for model training.

The hybrid ANN–SVM–SVM two-stage leak localisation model demonstrated strong classification performance, leveraging the nonlinear mapping capability of the ANN and the decision boundary refinement of the SVM. This integration improved both the robustness and accuracy of the individual models. Furthermore, the PSO-optimized ANN improved the performance by tuning the hyperparameters for faster convergence and improved generalisation. After training, the hybrid model achieved high accuracy in identifying leakage nodes, performing consistently when new single-leak scenario datasets were uploaded, thereby demonstrating its reliability in practical applications where the models were pretrained and tested with real static data. The PDA method

was employed to estimate the leak magnitudes, providing a realistic representation of the pressure-dependent demand. The model exhibited high accuracy and physical consistency in calculating leak magnitudes, with low error metrics and strong agreement between the predicted and actual values. This validated the approach as both computationally efficient and hydraulically meaningful. In leak detection, where data heterogeneity and dynamic operational conditions are common, weighted ensembles improve reliability, reduce false positives, and adapt to network-specific behaviours. Studies on hybrid AI-based detection have confirmed that ensemble frameworks, particularly weighted models, consistently yield higher classification accuracy and robustness.

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