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A Robust Multi-Objective Pressure Sensor Placement Method for Burst Detection in Water Distribution Systems

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Key Points:

- The proposed method deals with issues of low robustness and inconsistency within pressure sensor placements
- Five metrics and three case studies are used for comparison between the proposed method and three existing approaches
- Placements with a larger average shortest-path distance outperform those with an average geographic-plane distance in detection performance

Supporting Information:

Supporting Information may be found in the online version of this article.

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Abstract Bursts in water distribution systems (WDSs) lead to water wastage and negative environmental impacts. Optimizing pressure sensor placement (PSP) for effective burst detection is crucial for prompt response and adverse event mitigation. While many optimization methods are available for this purpose, their resulting PSP strategies often exhibit large variability caused by background noise or metering accuracy, representing low robustness. This consequently hinders the wide application of existing PSP methods for burst detection in WDSs. This study proposes a novel multi-objective PSP method aimed at maximizing burst detection while minimizing the number of sensors. Within this method, a new threshold metric is introduced to quantify the minimum detectable burst outflow across all pipes. The metric has the key advantage of taking into account the fact that the relative magnitude of the detectable threshold for different pipes is independent of noise, thereby addressing the low robustness issue. The proposed method is applied to three WDSs, and results show that it can consistently achieve robust optimal PSP strategies across diverse noise conditions. Comprehensive comparisons between the proposed method and the other benchmark approaches are conducted using five metrics, including detection performance and layout characteristics. These comparisons reveal the properties of each optimization method and show how detection performance is affected by various placement features. It is anticipated that the proposed method can be useful in engineering practice due to its great robustness in determining the optimal PSP strategies for burst detection in WDSs compared to other alternatives.

Plain Language Summary In water distribution systems (WDSs), bursts can cause water wastage and environmental harm. Strategic pressure sensor placement (PSP) is crucial for prompt burst detection and mitigation. However, existing PSP methods often lack robustness due to background noise or metering inaccuracies, hindering their widespread use. This study introduces a novel multi-objective PSP method aiming to maximize burst detection while minimizing sensor count. It includes a new threshold metric to quantify minimum detectable burst outflow, independent of noise, addressing the robustness issue. Based on results from three case studies, the proposed method consistently achieves optimal PSP strategies across diverse noise conditions. Comparative analyses with benchmark approaches demonstrate its robustness and effectiveness in detecting bursts. This method can be very useful in engineering as it can provide reliable PSP strategies for WDS burst detection.

1. Introduction

A water distribution system (WDS) plays a vital role in conveying clean water from sources to end-users. However, bursts are inevitable due to factors like aging pipes and high operational pressures (Qi, Zheng, Guo, Maier, et al., 2018; Qi, Zheng, Guo, Zhang, et al., 2018), causing significant water wastage and posing environmental and health threats, including ground collapse and contaminant infiltration into WDSs (Giustolisi et al., 2023). Advances in sensor and information communication technologies offer the potential for real-time burst detection (Wang et al., 2022), which is a critical aspect for promptly preventing adverse consequences arising from pipe bursts (Henriques-Silva et al., 2023). Leveraging real-time hydraulic data, especially from budget-friendly pressure sensors (PSs), allows for the prompt detection of bursts through data-driven analysis of abnormal pressure drops (Fallahi et al., 2021; Wu et al., 2022). Hence, this underscores the need for a cost-effective pressure sensor placement (PSP) to efficiently detect pipe bursts, given the impracticality of installing PSs at every node in a WDS.

Optimizing PSP presents challenges given the complexity of real WDSs and the inherent tradeoff between desired performance and economic considerations. Therefore, extensive research has been conducted, with developed approaches broadly classified into two types based on their specific objectives: model calibration-oriented methods and burst detection-oriented methods (BDOM). The method proposed in this paper, classified under BDOM, seeks to optimize PSP for enhanced burst detection. Notably, it focuses on steady-state hydraulic simulations, excluding transient analysis as did in Zhang et al. (2019) and Duan and Keramat (2022).

MCOMs aim to enhance hydraulic model accuracy through strategic PSP for improved parameter calibration. For example, Kapelan et al. (2005) framed a two-objective optimization problem, seeking to maximize calibrated model accuracy while minimizing relevant uncertainties and overall costs. Morosini et al. (2014) developed a sensitivity matrix-based model to guide PSP for network model calibration, and Wéber and Hős, 2020 proposed an iteration-free algorithm for optimizing PSP and calibrating individual pipe roughness coefficients. Although the mentioned studies improved PSP for model calibration, they do not account for burst detection. Recently, Ferreira et al. (2022) presented a multi-objective optimization for PSP, simultaneously calibrating hydraulic models and detecting bursts. However, their proposed PSP did not undergo a comparative analysis with alternative methods, and hence its utility has not been well demonstrated.

In contrast to MCOMs, BDOMs focus on optimizing PSP for better burst or leakage detection, often neglecting the impact of PS on model calibration. This oversight may be attributed to the valuable assistance offered by temporary on-site loggers, as demonstrated in fire flow tests (Walski, 1983). BDOMs can roughly categorize methods into sensitivity matrix-based and event simulation-based approaches. For instance, Farley et al. (2010) and Pérez et al. (2011) employed GA and a binary sensitivity matrix for PSP optimization; Steffelbauer and Fuchs-Hanusch (2016) optimized PSP for leakage detection, utilizing a sensitivity matrix-based approach that considers uncertainties. Subsequently, Forconi et al. (2017) introduced three risk-based functions to determine PSP for burst/leak detection, assisting system managers in addressing various requirements in the Harrogate network. More recently, Li et al. (2023) introduced an embedding graph auto-encoder clustering algorithm for PSP optimization, integrating topology and hydraulic characteristics effectively. Boatwright et al. (2023) presented an efficient leak/burst detection framework in district meter areas, leveraging geospatial techniques to reduce dependency on calibration efforts. Additionally, metrics or concepts like sampling-oriented modularity (Simone et al., 2016), trans-information entropy (Taravatrooy et al., 2020), and value of information (Edgar & Alfonso, 2022) are proposed to optimize PSP for enhanced leakage or burst detection.

The mentioned methods contribute significantly to PSP optimization by utilizing metrics such as sensitivities, modularity, and entropy. However, these metrics do not directly indicate improved detection of random burst or leakage events. In contrast, the event simulation-based method optimizes PSP to maximize coverage rates of randomly generated leakage or burst events, likely resulting in improved detection performance. The involved process typically consists of two steps: firstly, simulating events through a hydraulic model, and secondly, solving an optimization problem to optimize PSP by maximizing either the leakage coverage rate (LCR) or burst coverage rate (BCR).

In particular, Wu and Song (2012) pioneered the event simulation-based method in realistic networks, achieving greater leakage coverage with fewer PSs than designs by experienced engineers. Building on the intuitive advantage of the event simulation-based method, Wu et al. (2015) integrated it into a software prototype for optimizing monitoring and data logging in WDSs. Similarly, Hagos et al. (2016) optimize meter placement to maximize detection effectiveness for a specified number and type of meters. More recently, Zhao et al. (2020) introduced the "net cost" economic indicator to determine optimal PS number. They deemed smaller leakages as detectable when their resulting pressure drop exceeds sensor accuracy, aligning with Wu and Song (2012). In contrast, Cheng et al. (2020) introduced an innovative PSP optimization method to detect severe pipe bursts under a realistic background noise environment. Specifically, background noise encompasses legitimate pressure variations linked to normal water consumption changes, variability between monitoring devices, and pump or valve operations. This results in a larger pressure drop being necessary to trigger burst warnings.

While previous studies have achieved notable progress, challenges persist in the practical application of event simulation-based methods for PSP optimization. A primary issue involves the variability in optimal placements, caused by uncertainties related to background noise, metering accuracy, and simulated burst magnitudes. Specifically, Cheng et al. (2020) showed that optimal PSPs are highly sensitive to changes in simulated burst intensity and background noise levels. Additionally, Zhao et al. (2020) observed significant variations in optimal PS number based on different metering accuracies and simulated burst magnitudes. The variability observed in the optimal PSPs gives rise to a low robustness issue for practitioners intending to apply these methods in practical applications.

The second issue involves the inconsistency observed in PSPs that have been optimized with different objective functions. In particular, Cheng et al. (2020), focusing on large burst detection, achieved the optimal PSP differing significantly from Zhao et al. (2020), who aimed to maximize small leakages coverage rate. This implies that the effectiveness of achieved PSP may be context-specific; for instance, an optimized placement for detecting larger bursts in high background noise could face challenges in detecting smaller leakages during periods of reduced background noise, like in the late-night hours with low water consumption (Wu et al., 2010). Unfortunately, the lack of comparative studies between optimal methods and the scarcity of research on how various PSP features affect detection performance leave practitioners without clear guidance for implementing these methods in real-world scenarios. Lastly, a significant limitation in event simulation-based approaches is formulating PSP optimization as a single-objective problem, leading to tedious and repetitive solving for different sensor number.

In a recent study, Qi, Zheng, Guo, Zhang, et al. (2018), Qi, Zheng, Guo, Maier, et al. (2018) introduced a detectable threshold among five metrics to assess the burst detection performance of an existing pressure sensor system (PSS) by revealing the minimum detectable burst flow. Determining this threshold involves incrementally increasing nodal outflow until the induced pressure drop triggers the burst alarm threshold. Unlike metrics BCR or LCR, which solely assess the coverage rate of PSSs for randomly generated leaks or bursts (Cheng et al., 2020; Wu & Song, 2012; Zhao et al., 2020), the detectable threshold can precisely quantify the minimum burst outflow that a newly designed PSS can detect, thus offering a more accurate assessment of its detection performance. Importantly, the relative magnitude of the detectable threshold for different pipes remains consistent despite variations in background noise or metering accuracy, thereby addressing concerns about low robustness.

Inspired by that, the paper introduces an innovative framework for PSP optimization within WDSs, focusing on minimizing the detectable threshold through a multi-objective optimization approach. It should be noted that the proposed optimization method aims to ensure consistent sensor placement under varying noise conditions, but it does not address the PSP's capability to detect various leakage types, such as incipient leaks with minimal initial outflow, which depends on the sensor's metering accuracy and legitimate pressure fluctuations in a given WDS. The key novelties and contributions are as follows:

1. The formulation of a new PSP optimization approach that minimizes the newly developed average detectable threshold (ADT) across all pipes and an efficient method for ADT computation. Among other things this new approach helps address the issue of low robustness for PSP optimization, a concern prevalent in current event simulation-based methods.
2. New insights for enhancing the practical design of a PSP generated by a comprehensive comparison of placement strategies optimized by different state-of-the-art PSP methods, integrating evaluation metrics for burst and leakage detection, as well as metrics to characterize PSP features. The comparison improves the understanding of how different PSPs impact detection performance.
3. The introduction of the non-dominated differential evolution (NSDE) algorithm as the multi-objective framework enables various optimal placements to be obtained in a single optimization run, enhancing application convenience.

2. Methodology

Figure 1 outlines the overall investigation schematic and research objectives of this study. As seen from this figure, the proposed method and the three benchmark methods are introduced for comparisons across three WDSs. Five metrics are employed for a comprehensive PSP assessment, where three of them (ADT, BCR, and LCR) are used to assess burst or leakage detection performance, while the remaining (ASPD and AGPD) are used to characterize PS layouts. Specifically, our study uses one of the ADT, BCR, or LCR as the optimization objective, while the remaining four metrics are employed for evaluating performance and analyzing sensor layout characteristics. In addition, robustness tests are conducted to emphasize the variability issue in other methods and demonstrate the robustness and practical utility of the proposed method when faced with noise conditions. The study also explores the optimal PS number identification that incorporates detection performance, economic considerations and PSP extensibility. To improve readability, Table 1 presents a comprehensive list of acronyms used throughout this paper.

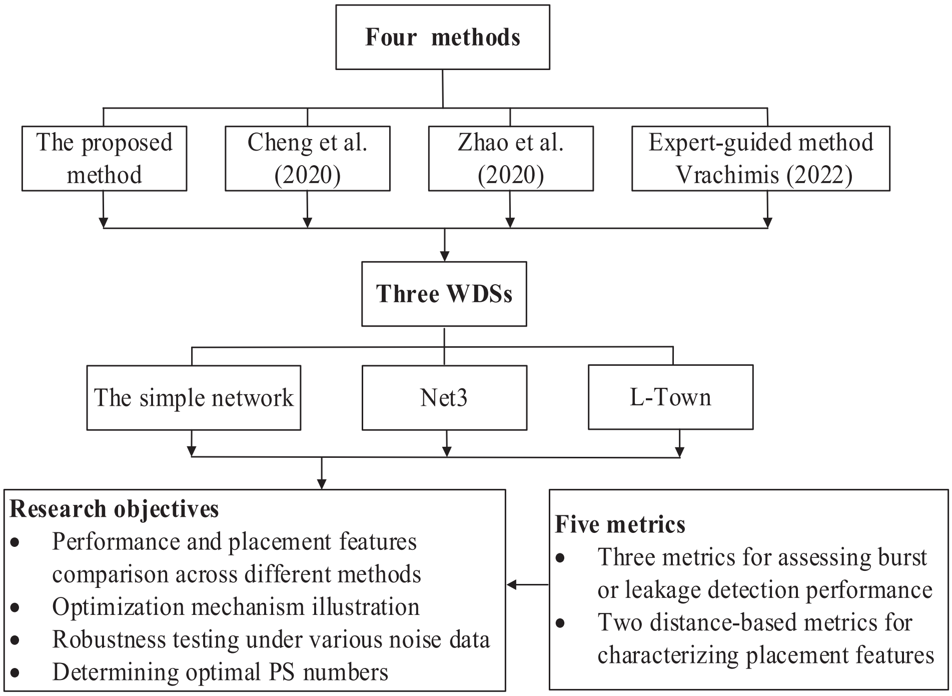

Figure 1. Overall investigation schematic and research objectives.

2.1. Burst Detection With Pressure Measurements and Robust Sensor Placement

Despite some randomness, daily water consumption generally follows predictable cyclic patterns, peaking in the mornings and evenings, and tapering off during late-night hours. This inherent predictability enables burst detection by comparing pressure measurements with either historical data-derived predictions (Qi, Zheng, Guo, Maier, et al., 2018; Qi, Zheng, Guo, Zhang, et al., 2018) or simulated values generated from a base diurnal water consumption pattern (Zhao et al., 2020). Specifically, bursts are deemed detectable (regardless of the detection method used) if the difference between pressure measurements and predictions (e.g., the burst-induced pressure drop) exceeds a predefined threshold, described as follows:

$$\Delta P^{threshold} = \delta_{sensor} + \delta_{noise} \tag{1}$$

where $\Delta P^{threshold}$ represents the pressure threshold to generate a burst alarm, its value combines metering accuracy (δ_{sensor}) and background noise (δ_{noise}) associated with system operations or normal demand changes. Clearly, $\Delta P^{threshold}$ can exhibit substantial uncertainty, driven not only by sensor performance but more crucially by legitimate pressure fluctuations. However, in traditional PSP optimization to maximize BCR or LCR, Cheng et al. (2020) and Zhao et al. (2020) reported that an uncertain $\Delta P^{threshold}$ leads to varying optimal PSPs and

Table 1
List of Acronyms Used in the Paper

Water distribution systems = WDSs	Burst coverage rate = BCR
Pressure sensor = PS	Average detectable threshold = ADT
Pressure sensor placement = PSP	Non-dominated differential evolution = NSDE
Pressure sensor system = PSS	Pressure-driven analysis = PDA
Model calibration-oriented methods = MCOM	Average Shortest-Path Distance = ASPD
Burst detection-oriented methods = BDOM.	Average Geographic-Plane Distance = AGPD
Leakage coverage rate = LCR	Cost-Benefit Analysis = CBA

number. As a result, concerns about low robustness arise, particularly regarding the variability of the optimal PSP under noise conditions.

This issue stems from less robust evaluation when utilizing the BCR or LCR metric to assess PSP detection performance. In particular, these metrics rely on a binary assessment, determined by whether a PSP detects burst-induced pressure drops surpassing a given threshold, disregarding the degree of burst outflow. Consequently, different PSPs may yield identical BCR or LCR values, posing challenges in assessing their relative detection performance, despite notable variations in layout and sensor count.

To address this challenge, our study introduces the ADT metric-based optimization method aimed at achieving robust sensor placement even in the presence of noise. In our method, in line with prior studies (Cheng et al., 2020; Qi, Zheng, Guo, Maier, et al., 2018; Qi, Zheng, Guo, Zhang, et al., 2018; Zhao et al., 2020), bursts are considered detectable when their induced pressure drop exceeds a threshold. In contrast to binary pressure drop detection, our method utilizes ADT to accurately measure the average minimum detectable burst outflow across all pipes, enabling precise assessment of PSP performance. More importantly, the relative magnitudes of ADT values remain consistent across different thresholds for various PSPs, ensuring robust sensor placement optimization even amidst uncertain thresholds commonly encountered in practical applications.

It is crucial to clarify that this study solely focuses on robust sensor placement, rather than the robustness to detect various leakage types, such as incipient leaks with minimal initial outflow. In other words, this paper introduces a novel optimization method to ensure consistent sensor placement under varying noise conditions, but it does not address the PSP's capability to detect bursts or leaks, which depends on the sensor's metering accuracy and legitimate pressure fluctuations in a given WDS. In fact, pressure sensors often lack sensitivity to minor leaks due to their small induced pressure drops, which may fall below the sensor's accuracy or be masked by legitimate pressure fluctuations. Therefore, in our study, "leakage" specifically denotes "small bursts" characterized by relatively large outflows, excluding the detection of minor leaks from our scope. While alternative methods such as acoustic hydrophones, ground-penetrating radar, transients, and ultrasonic sounding equipment may be required for detecting minor leaks, their investigation falls beyond the scope of our study.

2.2. The Proposed Multi-Objective Framework for PSP Optimization

A well-designed PSP aims for superior performance in leak or burst event detection while minimizing the number of PSs. Therefore, this task can be framed as a multi-objective optimization, simultaneously minimizing sensor number and maximizing detection performance. The proposed PSP optimization framework involves three main steps. Initially, simulations of leakage and burst events are conducted to establish a basis for evaluation (Step 1). Using the evaluation data, the NSDE algorithm is then applied to solve the multi-objective optimization problem (Step 2). Subsequently, the optimal number of PS is determined based on the Pareto front obtained from the optimization (Step 3). Additionally, five metrics are introduced to compare and analyze PSP features optimized using different methods, providing insights into their respective optimization mechanisms and aiding in practical decision-making for real-world PSP applications. The following offers detailed elaboration on these steps, complemented by a visual representation in Figure S1 in Supporting Information S1, which enhances clarity on the proposed method.

2.2.1. Burst Simulation and Evaluation Data Generation

Two literature-documented methods for burst or leakage simulation include (a) utilizing the emitter function in EPANET (Hagos et al., 2016), and (b) directly adding extra demand (Zhao et al., 2020). The emitter-based method considers emitter coefficients and nodal pressure, enabling simulated changes in leakage or burst outflow with pressure variations. However, accurately quantifying leakage outflow from emitters necessitates solving network hydraulics, presenting a challenge in the immediate assessment of its proportion to overall demand. In contrast, the demand-adding method addresses this limitation by specifying extra demand as the expected leakage or burst outflow, enabling a direct evaluation of PS detection performance. Furthermore, PSP optimization typically involves steady-state simulations, such as minimum or maximum demand conditions, where the advantages of the emitter-based method in reflecting changes in leakage or burst outflow with pressure become less significant. Consequently, this paper employs the demand-adding method, introducing extra demand in the middle of a pipe, to simulate leakages and bursts. This choice aligns with Zhao et al. (2020) and Cheng et al. (2020), ensuring consistency for meaningful comparisons.

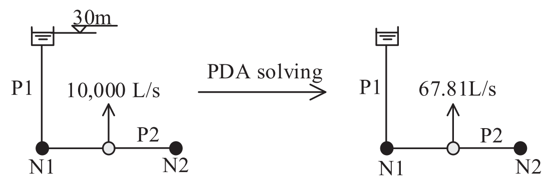

Figure 2. Estimating maximum burst flow through PDA solving the network.

Furthermore, to determine leakage and burst outflow, we follow Zhao et al.'s (2020) recommendation, specifying leakage outflows within the range of 0.46%–0.92% of the total mean demand. For major pipe bursts, following Cheng et al.'s (2020) method, outflows are simulated with a pipe velocity increase ranging from 0.8 m/s to 1.2 m/s. Cheng et al. (2020) justify their method by emphasizing its convenience relative to the challenges of measuring burst outflow from a crack. This method involves directly observing the increase in pipe flow velocities during burst occurrences, offering a practical and straightforward alternative. For a detailed comparison of burst simulation methods, refer to Cheng et al. (2020). Additionally, to accurately simulate hydraulic conditions under pressure deficiency, we employ the pressure-driven analysis (PDA) method using the latest built-in function in EPANET 2.2 (Qi, Zheng, Guo, Maier, et al., 2018; Qi, Zheng, Guo, Zhang, et al., 2018), as it offers improved accuracy compared to traditional demand-driven analysis.

Evaluation data, derived from simulating pressure drop and outflow related to leakage and burst events, assesses the detection performance of a PSP. In addition to the detectable threshold matrix, the leakage and burst coverage matrices function as evaluation data for comparative analysis. Specifically, the leakage or burst coverage matrix is a binary representation, with 0 and 1 indicating undetected or detected simulated burst or leakage events by the PSS (Cheng et al., 2020; Zhao et al., 2020). In contrast, the detectable threshold matrix is a matrix of real number, where each value signifies the minimum leakage flow that the PSS can detect for the corresponding pipe.

For detectable threshold identification, Qi, Zheng, Guo, Zhang, et al. (2018), Qi, Zheng, Guo, Maier, et al. (2018) proposed an incremental procedure, but its computational complexity hinders its practical use. It involves iteratively increasing burst flow until the pressure drop at each node reaches a specified value, and hence it requires adjustments for convergence particularly for large systems. To overcome this, a three-step method is developed to efficiently compute the detectable threshold matrix as illustrated below.

Step 1: Estimating maximum burst outflow

Figure 2 demonstrates the estimation of maximum burst outflow using the PDA function in EPANET 2.2, involving an initial demand guess of 10,000 L/s to trigger pressure-driven simulation and automatically estimate burst outflow. The choice of 10,000 L/s, as recommended by Qi, Zheng, Guo, Zhang, et al. (2018), Qi, Zheng, Guo, Maier, et al. (2018), ensures accurate estimation of maximum burst flow across diverse network scales. This value should be sufficiently large to initiate pressure-driven simulations without affecting the final results. The obtained results use 200 mm diameter pipes, 500m length, Hazen-Williams coefficient of 100, and nodes with 5 L/s demand and 0m elevation. Note that selecting a different coefficient value does not alter the method's demonstration, despite a Hazen-Williams coefficient of 150 being more suitable for systems with new plastic pipes.

Step 2: Identifying pressure drops corresponding to various burst outflows

In this step, nodal pressure drops for any given burst outflow are estimated as follows: First, an arithmetic progression range from 0 L/s to the maximum burst outflow is generated. For example, Figure 3 employs 20 intervals, while larger networks with higher burst outflows may employ 100 or 500 intervals to minimize estimation errors. Second, these values are input into the hydraulic network model to compute corresponding pressure drops, as shown in Figure 2. Finally, the pressure drop for any burst flow is estimated using linear interpolation. For example, with a burst outflow of 40 L/s in Figure 3, the linear interpolation predicts a pressure drop of 4.96 m, closely matching the hydraulic calculation's 4.95 m. The negligible 0.2% error is due to the weak nonlinear velocity-head loss relationship, underscoring the method's effectiveness in estimating pressure drops for various burst outflows.

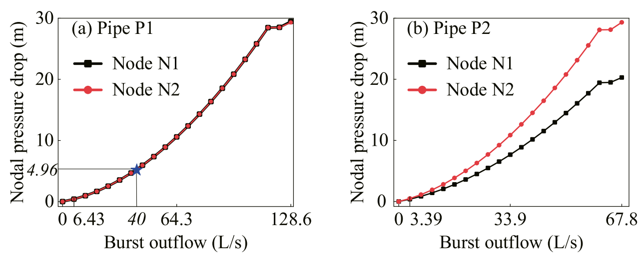

Figure 3. Pressure drop at nodes N1 (red lines) and N2 (black lines) due to varying burst outflows of pipes P1 (Figure 2a) and P2 (Figure 2b).

Step 3: Identifying detectable thresholds based on linear interpolation

This step constructs the detectable threshold matrix (m×n) for a specified noise level using linear interpolation based on the correlations established in step 2. The matrix has m rows (pipes) and n columns (nodes), where each element represents the minimum detectable threshold when pressure sensors are located at the respective nodes. Table 2 shows detectable thresholds at

Table 2
Three Detectable Threshold Matrices for Noise Levels of 0.3, 0.6 and 1.2 m, Where Each Element Denotes the Minimum Burst Outflow Detectable by Placing PSs at Respective Nodes

	Detectable thresholds under noise level of 0.3 m		Detectable thresholds under noise level of 0.6 m		Detectable thresholds under noise level of 1.2 m	
	Node N1	Node N2	Node N1	Node N2	Node N1	Node N2
Pipe P1	4.82 L/s	4.82 L/s	8.72 L/s	8.72 L/s	15.02 L/s	15.02 L/s
Pipe P2	2.68 L/s	2.05 L/s	4.98 L/s	3.92 L/s	8.90 L/s	7.04 L/s

noise levels of 0.3 m, 0.6 m, and 1.2 m, calculated using linear interpolation from Figure 2's correlation.

For example, the value of 4.82 L/s in the first row and first column denotes the minimum detectable burst flow for pipe 1 under a 0.3 m noise level, with a PS at Node 1. This value increases to 8.72 L/s and 15.02 L/s at noise levels of 0.6 and 1.2 m, respectively, as higher noise levels require larger outflows to trigger the burst alarm. Furthermore, installing pressure sensors at nodes N1 and N2 results in identical detection thresholds for pipe 1, as both nodes experience equivalent pressure drops upon P1 bursts. Conversely, for pipe P2, differing thresholds emerge when pressure sensors are placed at N1 and N2, visible in the second row of Table 2, due to the varied pressure drops at nodes 1 and 2 during P2 bursts.

Table 2 shows that placing one PS at Node N2 consistently yields the smallest detectable thresholds for both Pipe P1 and Pipe P2, regardless of the noise level. This consistency arises because detectable thresholds adjust proportionally across pipes with varying noise levels. As a result, the relative magnitude of detectable thresholds remains consistent across different pipes, independent of noise, ensuring that PSP optimization based on detectable thresholds is robust against noise effects. In contrast, PSP optimization using the leakage and burst events coverage matrix (Cheng et al., 2020; Zhao et al., 2020) may yield varied optimization results influenced differently by noise. Further discussion will be presented in the Results and Discussion section.

2.2.2. Multi-Objective Optimization Framework

Determining sensor placement in a WDS involves binary decision-making, transforming PSP optimization into a 0–1 integer optimization problem. In a network with n nodes (i.e., n candidate placement locations), the optimization variables can be concisely represented as a binary vector $\mathbf{X}$, with $\mathbf{X}[\mathrm{i}] = 1$ if node i has a PS, and $\mathbf{X}[\mathrm{i}] = 0$ otherwise. Using this representation, the objective functions for PSP optimization can be formulated as follows:

$$\{Minimize \qquad \mathrm{N} = \textstyle\sum_{i=1}^{n} X_i \tag{2}$$

$$\{Minimize \qquad \mathrm{ADT} = \frac{\sum_{j=1}^{m} l_j d_j DT_j^{\min}}{\sum_{j=1}^{m} l_j d_j} \tag{3}$$

In objective function (2), the summation over the binary vector X calculates the total number of PSs. In objective function (3), $DT_j^{\min}$ represents the minimum detectable threshold for pipe j under the PSP strategy defined by X, identifiable conveniently based on the constructed detectable threshold matrices (see Table 2). Furthermore, l_j and d_j denote pipe length and diameter, acting as weighting coefficients that consider both diameter and lengths of the pipes.

Note that objective function (2) minimizes the number of PS for cost-effective placement, while objective function (3) enhances burst or leakage detection by minimizing ADT. Therefore, balancing these goals creates a conflict: fewer PSs may increase ADT. Thus, solving this multi-objective optimization yields a Pareto front of optimal placements with minimized ADT for varying number of PS. This study applies the NSDE algorithm to solve the formulated multi-objective optimization problem, selected for its proven superior performance in experiments. It prioritizes practical application over extensive algorithm comparisons and directs readers to comprehensive NSDE information (Moosavian & Lence, 2016).

Based on the Pareto Front derived from solving the aforementioned multi-objective optimization problem, two methods proposed by Cheng et al. (2020) and Zhao et al. (2020) were employed to determine the optimal PS number. Cheng et al. (2020) employed a criterion where the marginal gain of adding an additional sensor contributed less than 1% to the objective value increase. In contrast, Zhao et al. (2020) introduced an economic evaluation indicator, the net cost, through Cost-Benefit Analysis (CBA) for the determination of optimal PS number. For further details on CBA implementation, please refer to Zhao et al. (2020). These two methods were selected for their state-of-the-art approach and demonstrated effectiveness in determining the optimal number of PS in practical applications.

2.2.3. Placement Feature Analysis and Robustness Testing

The study introduces five metrics: three (ADT, LCR, and BCR) for evaluating leakage and burst detection performance, and two (AGPD, ASPD) for characterizing placement features. The ADT, as in defined Equation 3 above, represents the average minimum detectable burst outflow across all pipes, with smaller values indicating superior detection performance. LCR and BCR, as defined in Equations 4 and 5 respectively, measure a PSP's success rates in detecting randomly generated burst and leakage events, with higher values indicating better detection performance. Average Geographic-Plane Distance (AGPD) and Average Shortest-Path Distance (ASPD) are two newly introduced distance metrics for characterizing placement features. AGPD measures the 2D spatial dispersion of PSs, while ASPD assesses PS dispersion considering network topology, as shown in Equations 6 and 7.

$$\left\{ LCR = \frac{N_{DL}}{N_{TL}} \right. \tag{4}$$

$$\left\{ BCR = \frac{N_{DB}}{N_{TB}} \right. \tag{5}$$

$$\left\{ AGPD = \frac{\sum_i^k GD_i^{\min}}{k} \right. \tag{6}$$

$$\left\{ ASPD = \frac{\sum_i^k SD_i^{\min}}{k} \right. \tag{7}$$

N_{TL} and N_{TB} represent the total number of randomly generated leakage and burst events, while N_{DL} and N_{DB} denote the number of detected burst or leakage events; k is the total number of pressure sensors; $GD^{\min}$ and $SD^{\min}$ represent the distance between each pressure sensor and its nearest neighbor, with $GD^{\min}$ determined geographically in 2D space and $SD^{\min}$ via the shortest path across the network graph.

The process to compute AGPD and ASPD involve: (a) Identifying the nearest neighboring PS in 2D space or determining the shortest path across the network graph for each PS; (b) Calculating the distance between each PS and its nearest neighbor; (c) Collecting all the nearest neighbor distances and computing the average. Introduction of these two metrics is driven by the absence of reported methods to rigorously quantify the uniform dispersion of a PSP, despite the acknowledged significance of evenly dispersing PSs throughout a WDS for effective leakage and burst detection (Cheng et al., 2020). These metrics enable a comparative analysis to understand how placement features affect detection performance, thereby offering insights for enhancing placement strategies in practical applications.

Robustness, crucial for practical considerations, is indicated by reduced variability in optimal placement strategies under changing noise data. When using traditional BCR and LCR metrics for PSP optimization, factors affecting PSP robustness include background noise, metering accuracy, simulated leakage or burst intensity, and varied demand conditions. Consequently, robustness testing follows the steps below: (a) Optimizing the PSP under a given background noise level or metering accuracy and a demand multiple, and using this optimized PSP as a reference; (b) Change background noise, metering accuracy, or demand multiples, and re-optimize the PSP; (c) Compare two optimized PSPs in terms of PS positions and optimal PS number changes. The fewer changes in positions and number, the better the robustness of the corresponding method, indicating greater practical applicability in engineering.

3. Case Studies

3.1. Case Description

Figure 4 shows network layouts of three WDSs, serving as case studies to demonstrate the proposed method. The simple network (Figure 4a) is intentionally designed with only five nodes and six pipes to illustrate the proposed method and the Net3 network (Figure 4b) is chosen for direct comparison of optimized placements between our method and others (Cheng et al., 2020; Zhao et al., 2020). L-Town (Figure 4c), a new benchmark WDS for the Battle of the Leakage Detection and Isolation Methods (BattLeDIM) competition, is a realistic and complex WDS

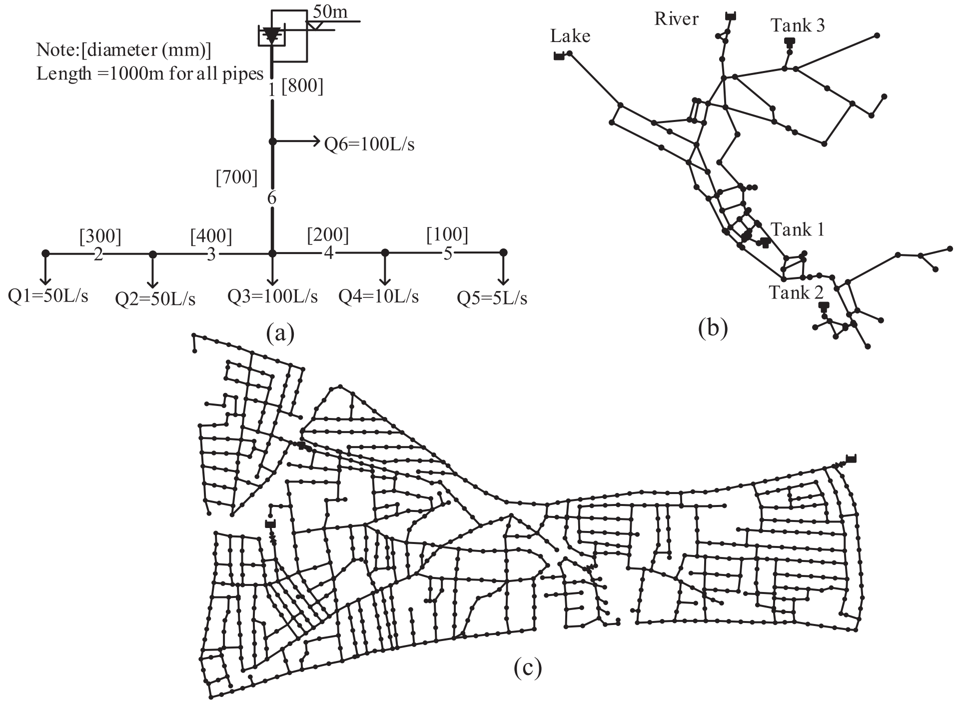

Figure 4. Layouts for (a) Simple network; (b) Net3 network; (c) L-Town network.

inspired by a coastal city in Cyprus (Vrachimis et al., 2022). Its intricacy network topology makes it as an ideal candidate for assessing algorithm feasibility. More importantly, BattLeDIM organizers have developed a PSP strategy for burst localization based on their experience, serving as an expert-guided placement strategy. This enables a direct comparison between placement strategies obtained by different methods and those guided by experts.

3.2. Parameterization

When applying the NSDE algorithm, the population size of 100 and 500 evaluation generations are used for the simple network, while the Net3 and L-Town networks employ a larger population size of 5,000 with 1,000 evaluation generations. The mutation rate is consistently set at 0.7, and the crossover rate is 0.5 for all three networks. Notably, sensitivity analysis shows minimal impact on final optimization results from variations in mutation and crossover rates, highlighting NSDE's robustness for the formulated multi-objective optimization problems. During the PDA analysis, a cutoff pressure of 20 m is applied for the simple and L-Town networks, while the Net3 network uses a cutoff pressure of approximately 10psi.

4. Results and Discussion

4.1. Application Results for Three Networks

4.1.1. Results for the Simple Network

The proposed method establishes the Pareto front by minimizing both the ADT and the PS count for the simple network. In contrast, Cheng et al. (2020) and Zhao et al. (2020) derived their Pareto fronts by maximizing the BCR or LCR, while minimizing the PS count. Besides, the noise level was set at 1.3 m for both the proposed method and Cheng et al. (2020), following Cheng et al. (2020)'s recommendation. Zhao et al. (2020) considered a metering accuracy of 0.035 m (≈0.05 psi), as specified in their work. Figure 5 summarizes the application results of the three methods for straightforward comparison.

Figure 5 shows that all three methods converge to an optimal number of PSs of two as indicated by red points on their respective Pareto fronts. This convergence indicates that additional PSs do not lead to further enhancement in burst detection effectiveness. However, despite reaching the same optimal number, the generated placement

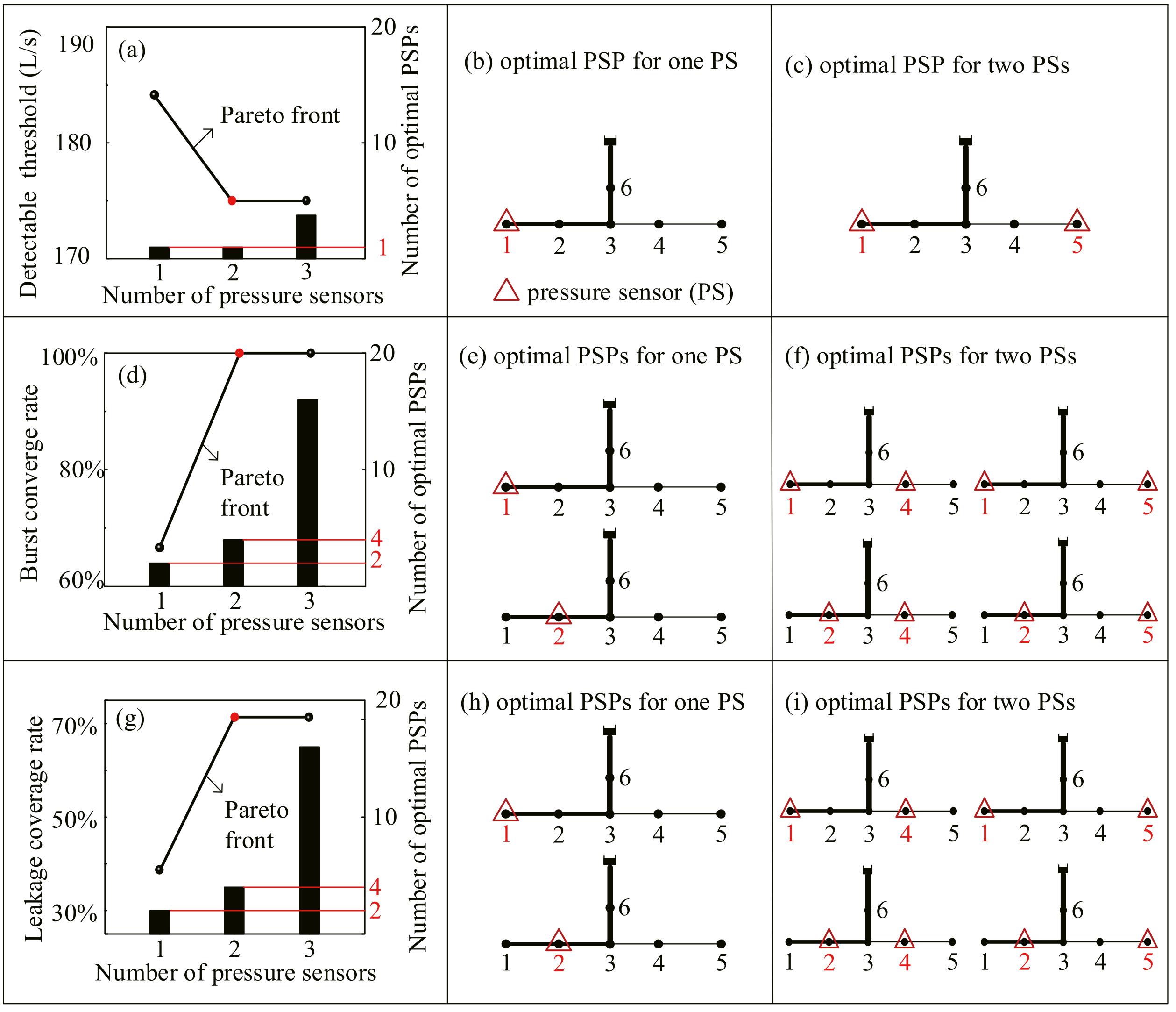

Figure 5. Optimization results of three methods applied to simple network; the proposed method (a–c); Cheng et al. (2020) (d–f); Zhao et al. (2020) (g–i).

strategies are different. Notably, Figures 5b and 5c demonstrate that the proposed method establishes a unique optimal placement for both one and two PSs. For a single PS, the sensor is strategically placed at the terminal node of the larger-diameter pipeline on the left, enhancing burst detection in that section.

For the two PSs, sensors are positioned at the terminal nodes of both the left and right pipelines, ensuring comprehensive perimeter coverage and maximizing sensor dispersion across the network, aligned with engineering best practices (Walski, 1983). In contrast, methodologies by Cheng et al. (2020) and Zhao et al. (2020) yield two and four equivalent placement strategies, respectively, for optimizing the placement of one and two PSs (Figures 5e, 5f, 5h, and 5i). These multiple equivalent strategies introduce decision-making challenges that could potentially affect the robustness of PSPs in practical applications.

To further reveal the placement differences among these three methods, their optimization mechanisms are examined. In particular, Table 3 summarizes: (a) the detectable threshold matrix from the proposed method; (b) the burst coverage matrix from Cheng et al. (2020) method, employing a pipe velocity increase of 0.8 m/s for burst simulation; and (c) the leakage detection matrix from Zhao et al. (2020) based on simulations of 1,000 leakage events. Noting that the simulation parameters for leakage and burst outflow may vary across studies, but these differences do not affect the conclusions.

Table 3
Detectable Threshold Matrix and the Burst Coverage Matrix Under a 1.3 m Noise Level, and Leakage Detection Matrix Using 0.035 m Metering Accuracy

(a) Detectable threshold matrix (L/s)

	Node ID					
Pipe ID	1	2	3	4	5	6
1	397.33	397.33	397.33	397.33	397.33	397.33
2	10.93	20.80	106.79	106.79	106.79	243.16
3	34.08	34.08	106.79	106.79	106.79	230.62
4	113.13	113.13	113.13	7.34	7.34	113.13
5	17.07	17.07	17.07	4.08	0.66	17.07
6	144.65	144.65	144.65	144.65	144.65	230.62

(b) Burst coverage matrix

	Node ID					
Pipe ID	1	2	3	4	5	6
1	1	1	1	1	1	1
2	1	1	0	0	0	0
3	1	1	0	0	0	0
4	0	0	0	1	1	0
5	0	0	0	1	1	0
6	1	1	1	1	1	1

(c) Leakage detection matrix

	Node ID					
Pipe ID	1	2	3	4	5	6
1	0	0	0	0	0	0
2	171	171	0	0	0	0
3	167	167	0	0	0	0
4	0	0	0	164	164	0
5	0	0	0	162	162	0
6	0	0	0	0	0	0

Table 3a shows the effectiveness of the proposed placement strategy with PSs at nodes 1 and 5, minimizing burst detectable thresholds for each pipe: 397.33 L/s, 10.93 L/s, 34.08 L/s, 7.34 L/s, 0.66 L/s, and 144.65 L/s. Conversely, Tables 3b and 3c reveal that placing PSs at nodes 1 or 2, and nodes 4 or 5, yields identical effectiveness in burst coverage or leakage detection. This occurs because BCR or LCR maximum-based methods utilize a binary assessment that does not take into account the magnitude of leakage or burst outflow, resulting in equivalent placement strategies.

In conclusion, these results underscore a fundamental difference in optimization approaches between the proposed method, Cheng et al. (2020), and Zhao et al. (2020). The proposed method prioritizes minimizing ADT and achieves a unique optimal PSP placement, making it more suitable for robust optimal placements in practical applications.

4.1.2. Results for Net3

This subsection comprehensively compares three methods applied to the Net3 with the aid of three performance metrics (ADT, BCR, and LCR). Specifically, ADT quantifies average detectable thresholds across all pipes. BCR evaluates detection of larger bursts (32.43–456.04 L/s) at a 0.6 m noise level, while LCR assesses the detection performance for 1,000 random leakages (3.15–6.30 L/s) with a metering accuracy of 0.035 m (≈0.05 psi). Results in Table 4 for Cheng et al. (2020) and Zhao et al. (2020) use their original placement strategies, employing real-number encoding and GA for optimization.

As can be seen from Table 4, the proposed method outperformed others across all metrics. It achieved the lowest ADT at 36.56 L/s, along with the highest BCR and LCR values at 88.28% and 90.40%, respectively. In contrast, Zhao et al. (2020) achieved a BCR nearly 10% lower than the proposed method, while Cheng et al. (2020) exhibited slightly inferior BCR and LCR but substantially poorer ADT performance, despite using one more PS. These results underscore the effectiveness of the proposed method in detecting both large bursts and small leakages, even with ADT minimization as its primary objective.

It is noteworthy that despite Cheng et al. (2020) and Zhao et al. (2020) adopting BCR and LCR as their objective functions, their results are inferior to those achieved by the proposed method. This can be attributed to two factors in their optimization processes. Firstly, their utilization of a real-number encoding scheme increase exponentially solution space complexity with the enhanced number of PSs, while the proposed method employed a 0–1 binary encoding, maintaining constant solution space size regardless of PS number. Secondly, the proposed method utilized the NSDE algorithm, which possesses superior exploration in high-dimensional optimization problems compared to the GA used in their studies. Therefore, it is recommended to employ a 0–1 binary encoding scheme combined with the NSDE algorithm for PSP optimization, especially in large-scale realistic networks.

Table 4
Metric Values for Three Methods Applied to Net 3

Metric values	This study	Cheng et al. (2020)	Zhao et al. (2020)
Number of PSs	11	12	11
ADT	36.56 L/s	69.56 L/s	47.90 L/s
BCR	88.28%	88.17%	80.08%
LCR	90.40%	90.10%	90.00%

Figure 6 compares placement strategies across three methods, evaluating their impact on the detectable thresholds for each individual pipe. In Figures 6c and 6d, pipes exceeding a detectable threshold of 20 L/s in the other two methods in contrast to the proposed method are highlighted in red. Additionally, ASPD among PSs indicates their scattering degree, offering insight into how placement features affect detection performance.

A notable observation from Figure 6 is that a more scattered placement of PSs enhances the burst and leakage detection performance. In particular, the

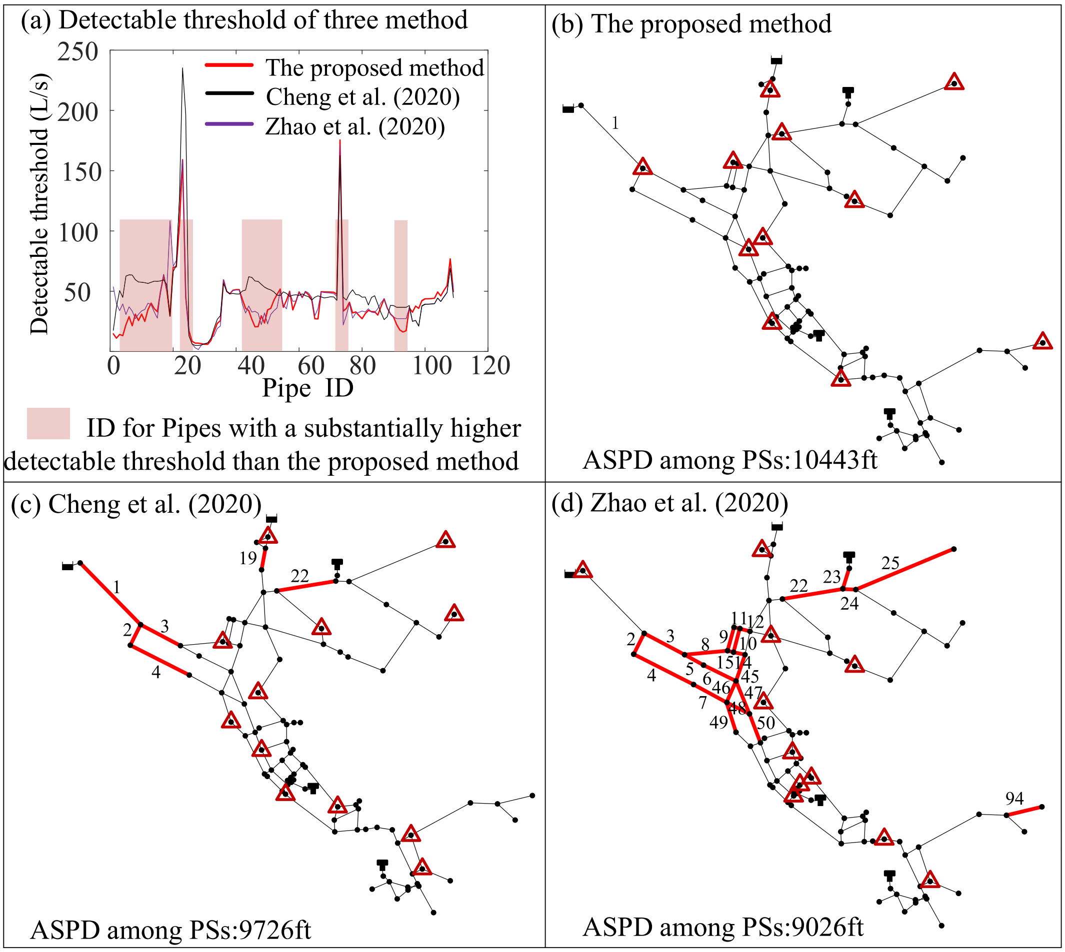

Figure 6. Impact of different PSP features on detectable thresholds.

proposed strategy (Figure 6b) features ASPD of 10,443 feet, showcasing superior ADT, BCR, and LCR compared to Zhao et al. (2020) strategy (Figure 6d) with an ASPD of 9,026 feet. Moreover, Zhao et al. (2020) strategy covers 23 pipes with detection thresholds that are 20 L/s higher than those achieved by the proposed strategy (Figure 6d). This discrepancy arises because PSs are not placed near these pipes, leading to increased detection thresholds.

Comparing Figures 6b and 6c reveals that strategically placing a PS downstream of a long pipe effectively reduces detection thresholds for both the main pipe and its downstream pipes. Specifically, the proposed placement (Figure 6b), with a downstream PS at the end of pipe 1, markedly reduces detection thresholds for pipes 1, 2, 3, and 4 compared to placement using the method in Cheng et al. (2020) (Figure 6c). This enhancement enables a wide scope of burst event detection, but the placement in Cheng et al. (2020) only detects large bursts for the pipe with a velocity increase of 1.0 m/s.

4.1.3. Results for L-Town

For the L-Town, the number of PSs and their placement by Vrachimis et al. (2022) are predetermined by BattLeDIM organizers, representing an expert-guided optimal design. In contrast, the proposed placement minimizes ADT under a 0.6 m noise level, while Cheng et al. (2020) maximize BCR for detecting large bursts ranging from 3.74 to 47.71 L/s under similar noise level. Zhao et al. (2020), on the other hand, prioritize maximizing LCR for detecting 5,000 random leakages (0.61–1.02 L/s) with a meter accuracy of 0.035 m (≈0.05 psi). All three optimal PSPs are determined by solving a multi-objective optimization problem using a 0–1 binary encoding scheme and the NSDE algorithm.

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Table 5
Metric Values for Four Methods Applied to L-Town

Metric values	Vrachimis et al. (2022)	This study	Cheng et al. (2020)	Zhao et al. (2020)
Number of PSs	33	33	33	33
ADT	12.34 L/s	10.40 L/s	12.61 L/s	12.51 L/s
BCR	64.27%	70.46%	78.67%	61.45%
LCR	78.56%	79.26%	74.24%	82.34%

As shown in Table 5, the proposed method, Cheng et al. (2020) and Zhao et al. (2020) achieved the top results in ADT, BCR, and LCR, with values of 10.40 L/s, 78.67%, and 82.34%, respectively. This is expected as each method optimizes for ADT, BCR, and LCR, respectively. Nevertheless, it is interesting to note that Cheng et al. (2020) demonstrate the lowest value in LCR at 74.24%, while Zhao et al. (2020) exhibit the lowest value in BCR at 61.45%. This implies a reciprocal constraint between LCR and BCR metrics, suggesting that exclusively maximizing coverage for larger bursts reduces the PSP's capability to detect smaller leakages, and vice versa.

On the contrary, the proposed method, focusing on minimizing ADT, demonstrated satisfactory results in both detecting larger bursts and smaller leakages, as evidenced by the second-best performances of 70.46% in BCR and 79.26% in LCR among the four methods considered. This underscores its capability to effectively handle detection across a wide range of burst sizes without prioritizing one over the other. Regarding the expert-guided PSP, it outperforms Cheng et al. (2020) in ADT and LCR, Zhao et al. (2020) in ADT and BCR. However, it falls short in all three metrics compared to the proposed method. For instance, its coverage rate for larger bursts is 64.27%, which is approximately 6% lower than the 70.46% achieved by the proposed method.

Figure 7 compares PSPs from four methods, focusing on ASPD and AGPD metrics among PSs for placement insights. Vrachimis et al.'s (2022) placement strategy (Figure 7a), with a maximum AGPD of 222 m, highlights an expert-guided dispersed spatial arrangement for PSs. In contrast, the proposed PSP (Figure 7b), achieving a maximum ASPD of 441 m, reveals a distinctive mechanism optimizing PSP by considering network topology rather simple spatial distribution. The superior performance of the proposed PSP in detecting bursts and leakages suggests that prioritizing a larger ASPD among PSs, rather than AGPD, enhances PSP effectiveness. This insight can be valuable for improving PS arrangement in engineering applications.

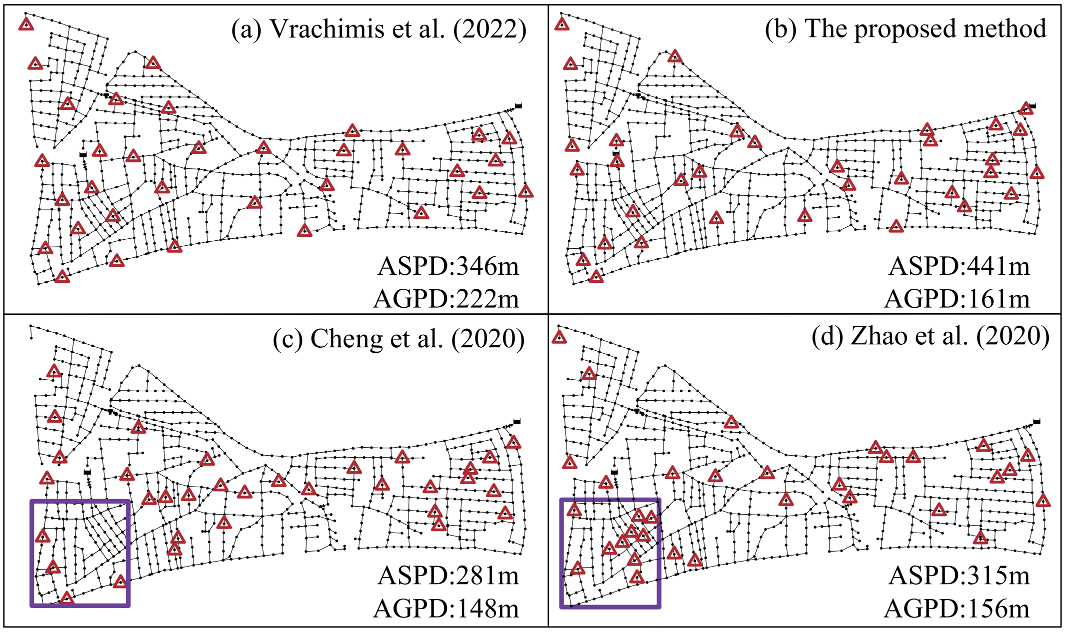

Figure 7. Optimal PSPs from four methods applied to L-town.

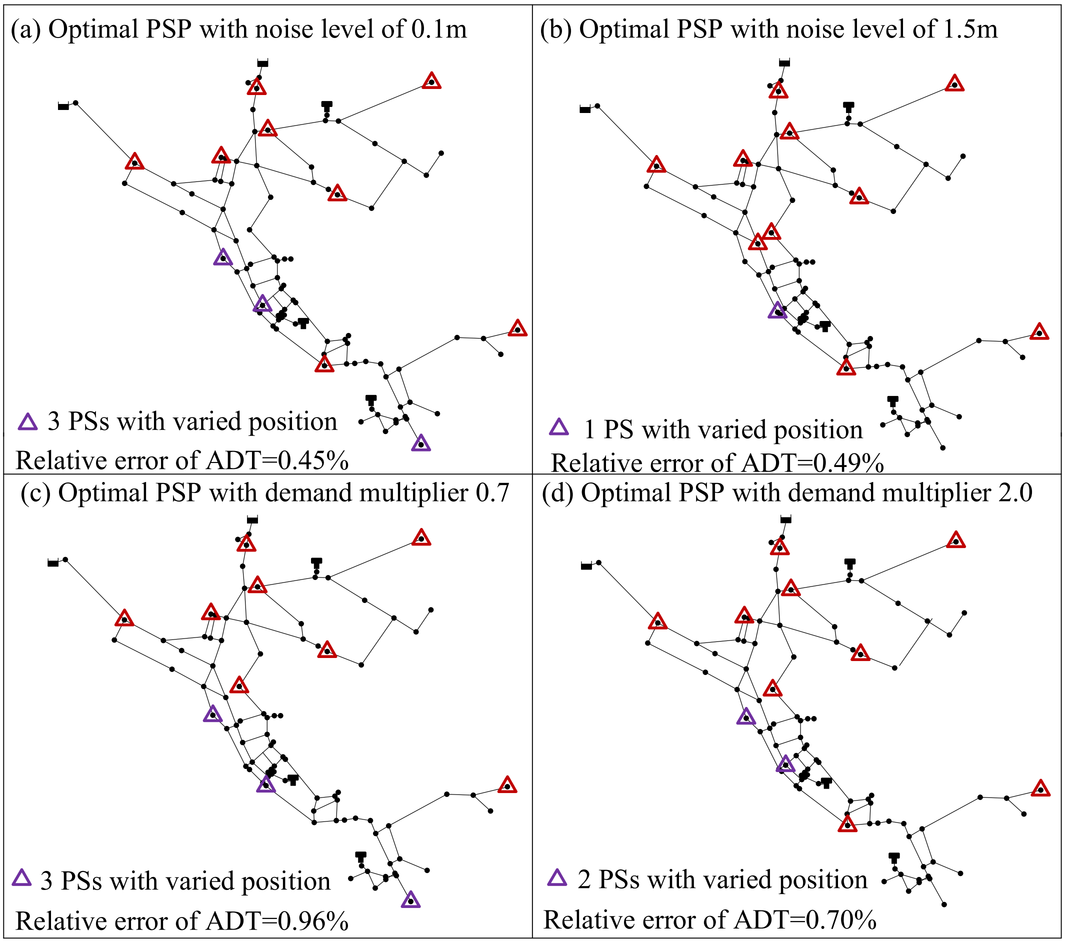

Figure 8. Optimal PSPs under varied noise levels and demand multipliers using the proposed method (reference PSP: Figure 5b).

Comparing Figures 7c and 7d reveals notable differences in placement strategies between Cheng et al. (2020) and Zhao et al. (2020). In the highlighted bottom-left region, Cheng et al. (2020) include 4 PSs, whereas Zhao et al. (2020) deploy 10 PSs, indicating an uneven distribution. In contrast, both the proposed method and Vrachimis et al. (2022) employ 5 PSs, suggesting a more balanced approach. Furthermore, Cheng et al. (2020) and Zhao et al. (2020) demonstrate smaller ASPD and AGPD metrics, potentially deviating from the standard practice of evenly distributing PSs within WDSs.

4.2. Robustness Testing

The robustness of the proposed ADT-minimization method is comprehensively evaluated across nine noise scenarios, encompassing all combinations of two uncertain factors (noise level and demand multiplier) at three levels (maximum, average, minimum), applied to three networks. For the simple network, the results obtained demonstrate that regardless of variations in noise level and demand multiplier, the proposed method consistently identifies the optimal PSP by placing two PSs at nodes 1 and 5. Furthermore, these results show that the detectable thresholds for different pipes adjust proportionally with the noise level, with details provided in Table S1 in Supporting Information S1.

Robustness testing of the proposed method applied to Net3 and L-town has also been conducted across nine scenarios. The key results for Net3 are shown in Figure 8, and comprehensive results for both Net3 and L-town can be found in Figures S2 and S3 in Supporting Information S1, respectively. Results reveal that in the Net3 network, only 1 to 3 out of 11 PSs change positions, and in L-town, 3 to 6 out of 33 PSs change positions, with the

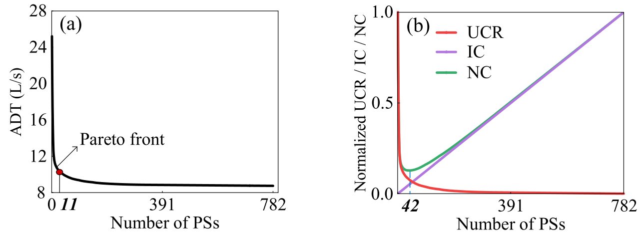

Figure 9. Determining optimal PS number based on (a) the obtained Pareto front using a 1% threshold of improvement proposed by Cheng et al. (2020); and (b) the Cost-Benefit Analysis (CBA) proposed by Zhao et al. (2020).

remaining PSs retaining their positions unchanged. Furthermore, cross-validation (Figure 8) consistently shows relative errors in ADT values due to PS position changes remaining below 1%, highlighting the robustness of the proposed method in determining the optimal PSP.

In contrast, robustness testing of the LCR-maximizing method (Zhao et al., 2020) and the BCR-maximizing method (Cheng et al., 2020) shows significant shifts in optimal PSP positions for both networks, which can be found in Figures S4–S7 in Supporting Information S1. Results also show that optimal number varies as a result of varying noise conditions. For instance, under scenarios with high metering accuracy and low demand multipliers, the LCR-maximizing method fails to produce sensor layout, as shown in Figures S5b and S5c Supporting Information S1. This reflects that LCR-maximizing method has susceptibility to noise interference, where insufficient pressure drop from leakage fails to trigger burst alarms.

4.3. Determination of Optimal PS Number

This section explores the determination of the optimal number of PSs using the Pareto front derived from the proposed NSDE-based multi-objective framework, as depicted in Figure 9. In addition, Figure 10 illustrates four optimal PSPs with varying PS number, highlighting the importance of considering layout extensibility. In this context, extensibility refers to how well the existing placement strategies can accommodate the addition of new PSs without substantially altering the original layout.

As seen from Figure 9, ADT values decrease with the increased number of PSs, indicating improved burst detection using more PSs. However, the improvement is initially significant, and then gradually diminishes, as evident from the flattening tail of the Pareto front. This indicates diminishing returns in burst detection as the number of PSs exceeds a certain limit, emphasizing the need for a trade-off to be considered. Following Cheng et al. (2020) suggestion, with a marginal gain of less than 1% for an additional PS, the optimal number of PSs is identified as 11 (Figure 9a). However, utilizing CBA with $N_{\mathrm{min}} = 1$ and $N_{\mathrm{max}} = 782$ yields an optimal count of 42 (Figure 9b). Therefore, taking into account both detection efficiency and economic considerations, the optimal number of PSs for L-town can be estimated to range between 11 and 42.

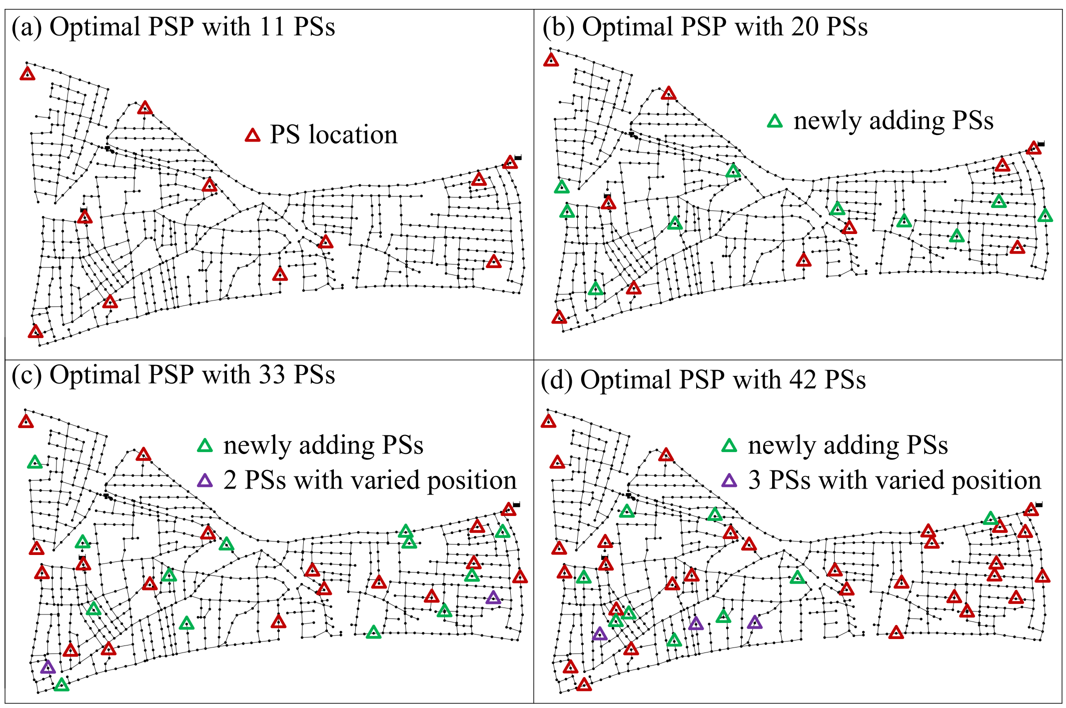

Figure 10. Four optimal PSPs with varying number of PSs obtained from the proposed method.

Figure 10 illustrates stable PS layout as the system scales: 11 to 20 PSs expand without position changes (Figure 10b), 20 to 33 PSs involve 2 changes (Figure 10c), and 33 to 42 PSs, 3 changes (Figure 10d). This highlights the merit of the proposed ADT minimization objective in maintaining consistent layouts and supporting the extensibility of PS systems. Such adaptability is crucial in practical applications where the construction of PS systems may occur incrementally due to financial constraints. Nevertheless, the optimal set for N points may not always include the optimal set for N-1 points, as these results can be case-specific. Therefore, determining the number of PSs in practice should strike a balance between detection performance and economic factors, while also considering layout extensibility.

In summary, results from Figures 9 and 10 demonstrate that the proposed multi-objective optimization method enhances cost-effectiveness analysis, provides insights into layout extensibility, and optimizes sequencing for phased construction scenarios with limited funding, emphasizing its practical value in engineering applications.

5. Conclusions

Bursts in WDSs not only result in substantial water wastage but also pose environmental and health risks. Prompt burst detection can be achieved by analyzing abnormal pressure drops, underscoring the importance of designing a cost-effective PSP for efficient burst detection. While numerous optimization methods have been proposed, the resulting PSP strategies exhibit variability due to background noise or metering accuracy, leading to low robustness. This poses a significant challenge for engineering practitioners applying these methods in real-world applications.

To fill this gap, the study introduces a novel multi-objective optimization framework that maximizes burst detection while minimizing PS count. The core idea introduces the ADT metric for PSP optimization, replacing traditional metrics like BCR or LCR. Its key characteristic lies in considering noise independence to determine the relative magnitude of the detectable threshold for different pipes, effectively resolving the low robustness issue. Three case studies validate the proposed method through comprehensive comparisons with two benchmark optimization approaches, and the main findings are summarized as follows:

1. The proposed ADT-minimization method consistently produces robust optimal PSPs under diverse noise conditions. This occurs because the detectable thresholds adjust proportionally to background noise or metering accuracy, ensuring independence of the resulting placement strategies from noises. In contrast, traditional methods maximizing BCR or LCR yield uncertain optimal PSPs, varying with changes in background noise or metering accuracy (refer to Table 3).
2. Placement strategies optimized based on BCR or LCR metrics fall short of addressing both larger and smaller bursts simultaneously. In contrast, the proposed ADT-optimized placement excels in detecting both, underscoring its superiority, as evidenced by the results in Tables 4 and 5.
3. Compared to the expert-guided placement strategy with a larger AGPD between PSs, the proposed ADT-optimized PSP, characterized by a larger ASPD among PSs, exhibited better performance in detecting both larger bursts and smaller leakages. This insight enhances the understanding of how PSP affect detection performance, offering valuable information for practical engineering improvements in PS arrangements.
4. Determining the optimal number of PS involves balancing detection performance, economics, and layout extensibility. The proposed multi-objective framework efficiently addresses this by generating a Pareto front, offering optimal PSPs for various PS number in a single run, providing utility convenience in real-life applications.

In closing, the aforementioned findings demonstrate three key advantages of the proposed optimization method for PSP optimization: robustness to noise with ADT-minimization, superior detection performance in both small and large bursts, and utility convenience in determining the optimal number. As a result, broad acceptance in practical applications by engineering practitioners is expected.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

The data and codes are available at Du et al. (2024a, 2024b).

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