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Deployment Optimization of Pressure Sensors in Pipeline Network Via Fusing Shortest Path Planning and Monte Carlo Tree Search

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Abstract
The branched topology of thermal pipeline networks creates multiple propagation paths for leak-induced negative pressure waves (NPWs), causing leak localization algorithms to potentially output "multiple matching solutions," resulting in erroneous localization. To address this challenge, this paper proposes a novel method that combines shortest path planning (SPP) and Monte Carlo tree search (MCTS) to optimize pressure sensor deployment. Unlike conventional approaches relying on historical network information or simulation software, this method optimizes sensor placement based on actual NPW transmission paths. First, the method discretizes the pipeline network and employs the sum of inter-sensor shortest path lengths as the optimization objective. Then, it utilizes MCTS to iteratively update sensor deployment schemes, ultimately improving the uniqueness of leak localization results obtained through NPW arrival delay matching. In a 12 km×12 km network with 10 sensors, the optimization method increased the total SPP length from 26.1 km to 68.6 km. Across 1,000 simulated leak scenarios, points with unique NPW arrival delay signatures increased from 54.8 to 79.0%, while points located on the SPP rose from 8.6 to 20.3%. We further examined sensor deployment optimization by increasing sensor quantities. Increasing sensors from 10 to 20 led to significant performance improvements in the optimization algorithm. Further increasing sensors to 30, however, yielded negligible performance gains, indicating algorithm saturation. Considering cost constraints, deployment optimization is essential with limited pressure sensors but becomes optional once sensor density reaches sufficient levels. The proposed SPP-MCTS synergistic approach offers practical guidelines for thermal network monitoring system design, especially for cost-constrained leak detection implementations.

Keywords Pipeline network · Shortest path planning · Monte Carlo tree search · Sensor deployment optimization

Yupei Yan and Longyu Chen contributed equally to this work.

Extended author information available on the last page of the article

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1 Introduction

Pipeline transportation, one of the five fundamental modes of transportation, has gained increasing attention due to its high efficiency, low cost, and adaptability (Tan and Que 2022). Pressurized pipeline networks for water and heat supply play a crucial role in both industrial production and daily life. Long-term operation of these pipelines leads to continuous corrosion and aging, resulting in more frequent leakage incidents (Wang et al. 2022a, b). Failure to promptly detect and locate leaks results in significant economic losses, resource waste, and potential threats to public safety.

Sensor technology, often referred to as "electronic sensory organs," provides reliable methods for monitoring and managing complex pipeline networks. By deploying devices such as pressure sensors, flow meters, and ultrasonic sensors at critical nodes throughout the network and connecting them to Internet of Things (IoT) platforms, researchers have achieved comprehensive real-time monitoring of pipeline operations (Dhulavvagol et al. 2018; Kumar and Jagadeep 2022). Numerous recent studies have investigated pipeline leak detection and localization using artificial intelligence (AI) with multi-source sensor data. Ma et al. (2019) applied Kalman filtering to flow sequences to generate accumulated residual series and implemented a triple standard deviation threshold, successfully identifying burst leaks while minimizing false alarms. Wu and Zhang (2022) employed a Fuzzy C-Means Clustering Flow (FCMCF) algorithm to select limited monitoring points based on node similarities, then identified leakage points by analyzing pressure data 24 h before and after leakage events using an integrated neural network combining Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM). Liu et al. (2023) proposed a Convolutional Neural Network-based Transfer Learning (CNN-TL) method and collected pipeline leakage datasets under various working conditions, transport media, and fluid pressures for training. Compared to traditional CNN models, the CNN-TL model exhibits superior adaptability. Zhou et al. (2019) and Chen et al. (2021) used hydraulic models to simulate leakage scenarios, generating pressure distributions and residual maps that served as training data for machine learning algorithms to classify and predict leak locations. These AI-based detection methods typically can only determine whether a leak has occurred in the pipeline network, with very few methods capable of identifying the specific district or pipe section where the leak has occurred, and no one achieving precise leak localization.

Therefore, our laboratory developed a pressurized pipeline leak detection method based on shortest path planning (Huang et al. 2023). The method involves three steps: (1) discretizing the pipeline network into nodes, (2) creating a reference database of negative pressure wave (NPW) arrival times using acoustic velocity formulas, and (3) comparing measured time delay combinations from pressure sensors during actual leaks against the reference database to determine leak locations. Although this approach minimizes sensor requirements, complex networks may produce "multiple solutions" when different points generate identical NPW propagation patterns. Optimal sensor placement is essential to ensure unique time delay signatures and enhance leak localization accuracy.

Researchers have conducted extensive studies on pipeline network sensor deployment optimization. Zhang et al. (2022) developed optimal sensor deployment strategies by analyzing cross-correlations of historical hydraulic characteristics at network nodes. Chen et al. (2024) analyzed historical leakage data across network areas to optimize sensor coverage in high-risk zones. Yang and Wang (2023) evaluated sensor deployment schemes by simulating leakage events to assess coverage rates and sensitivity. Du et al. (2024) estimated maximum potential burst flow rates through simulation to develop deployment schemes that minimize leakage volumes. Rayaroth and Sivaradje (2019) used simulation data to calculate node fitness values based on water flow rate, performing local exploration and memeplex shuffling to achieve optimal sensor positions with higher accuracy and minimal error rate. However, existing methods — whether based on historical data or simulations — inadequately address how NPW transmission paths impact leak localization accuracy.

Moreover, large-scale pipeline networks with complex topologies necessitate analysis of NPW transmission paths between all potential leak points and sensors, creating an exponentially expanding search space for optimal sensor deployment. Traditional optimization approaches—including genetic algorithms (GA) (Owoade et al. 2023), greedy algorithms (Mamaghan et al. 2023), and particle swarm optimization (PSO) (Bhandari et al. 2023; Zhao and Hao 2022; Wang et al. 2022a, b)—face significant challenges in this context: high computational complexity and susceptibility to local optima. While GAs can expand the search range through crossover and mutation operations, they exhibit slow convergence in large-scale networks; greedy algorithms are computationally simple and efficient, but their locally optimal choices cannot guarantee global optimality; PSO algorithms offer good parallelism but suffer from complex parameters tuning and susceptibility to local optima. These algorithmic limitations make it difficult to effectively address large-scale pipeline network sensor deployment optimization problems that consider NPW transmission paths.

This paper proposes an integrated approach for optimizing pressure sensor deployment in pipeline networks, combining shortest path planning (SPP) with Monte Carlo Tree Search (MCTS) to maximize leak localization uniqueness based on NPW arrival time delay matching. To address the complex NPW transmission paths in large-scale networks, shortest path planning algorithms are employed to optimize routes from leak points to sensors; facing exponentially growing search spaces, the combined breadth-depth characteristics of MCTS effectively avoid local optima while improving search efficiency (Rong 2022). Three evaluation methods were developed: maximum total shortest path length, maximum number of uniquely solvable leak points, and maximum number of shortest path endpoints. The first evaluation method was utilized to implement the sensor deployment optimization algorithm, while the latter two methods validated the correctness and effectiveness of the optimization results. Finally, optimization was performed for additional pressure sensor deployments, demonstrating the improved effectiveness of the deployment optimization algorithm with increasing sensor quantities.

2 Presentation of Questions

As shown in Fig. 1, the pipeline network leak location methodology comprises four main components: pipeline network segmentation, shortest path search, standard time delay library establishment, and time delay comparison. First, the pipeline network is subdivided into discrete points with equal propagation time using linear interpolation formulas; next, a breadth-first search algorithm determines the shortest path of NPWs from each discrete point to every pressure sensor; subsequently, the propagation time for each shortest path is calculated using NPW velocity formulas to establish a comparative time delay database.

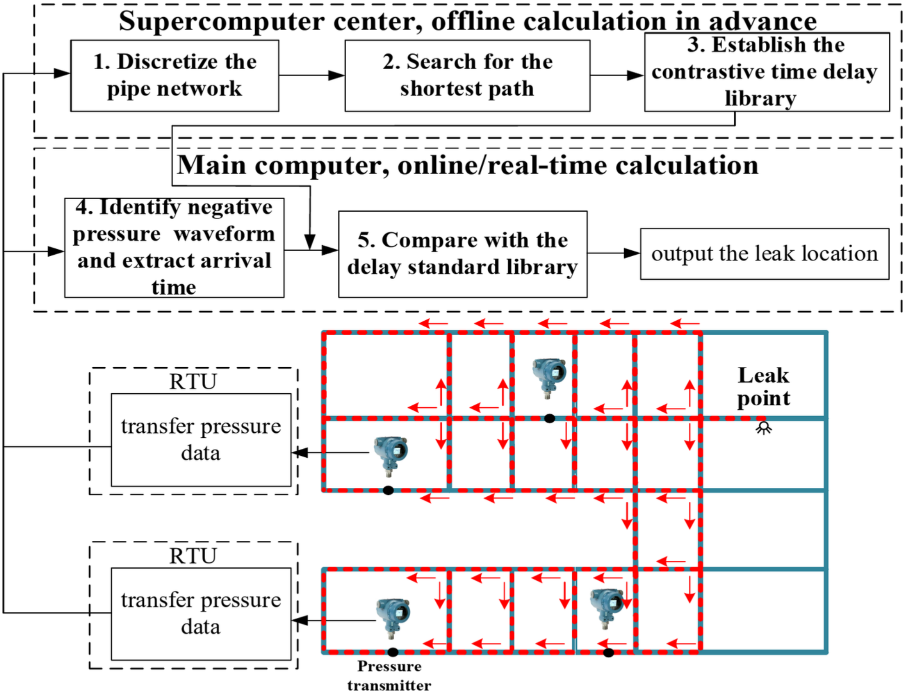
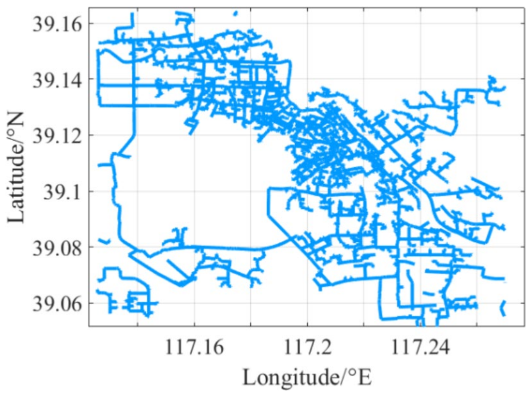


Fig. 1 Block diagram of pipeline network leak localization system

Fig. 2 Pipeline network map



During real-time monitoring, our system matches observed signal timing sequences from the deployed sensors against this pre-computed database to precisely locate the fault positions.

To validate our methodology, we examined an urban heating infrastructure in northeastern China, depicted in Fig. 2. This network spans approximately 12.5×12.7 km, comprising nearly 5000 interconnected segments with a combined length exceeding 465 km. Although the leak location method based on time delay matching developed by our laboratory effectively eliminates the need for pressure sensors on each path of this extensive network, the network complexity presents a fundamental challenge: geographically distinct discrete points can generate identical transmission delays. Therefore, optimizing pressure sensor deployment becomes necessary to ensure that, with a limited number of sensors, the standard time delay database contains maximum time delay information, thereby minimizing the "multiple solutions" effect.

After discretization, the pipeline network contains tens of thousands of discrete points. Randomly selecting dozens of positions as sensor deployment points generates an immeasurable number of combinations, far beyond the capabilities of exhaustive evaluation methods. To efficiently navigate this vast solution space, we implement a stochastic tree-based search algorithm that balances exploration and exploitation while avoiding computational intractability.

3 Deployment Optimization Method of Pressure Sensors

3.1 Optimization Principle

Monte Carlo Tree Search is a heuristic search algorithm applied to decision-making processes, particularly in scenarios with extensive search spaces. Its primary function is to identify the optimal next action for a given node state. The algorithm operates through four sequential steps: Selection, Expansion, Simulation, and Backpropagation.

In Monte Carlo Tree Search, each node requires a calculated *Score* value, which directly determines the optimization algorithm's update direction, making the selection of this *Score* metric critically important. With fixed sensor deployment, a leak occurring anywhere along the shortest path between two sensors creates negative pressure waves (NPWs) that propagate along segments of this same path. This configuration enables leak localization through time delay measurements between these two sensors. Consequently, the sum of shortest path lengths serves as the optimization value parameter in Monte Carlo Tree Search, maximizing network coverage while minimizing localization ambiguity.

Therefore, the relationship between the Monte Carlo Tree Search algorithm and the shortest path planning algorithm in this paper is as follows: Monte Carlo Tree Search traverses discrete locations within the pipeline network to identify optimal sensor deployment positions. Meanwhile, the shortest path planning algorithm calculates paths between selected discrete points, with path lengths serving as *Score* values for nodes in the Monte Carlo Tree Search.

This paper proposes three evaluation methods for sensor deployment optimization: (1) maximum total shortest path length, (2) maximum number of unique solution leak points, and (3) maximum number of shortest path drop points. The first method drives the sensor deployment optimization algorithm, while the latter two methods serve to verify the optimization results.

(1) The method of maximum total length of shortest path
When using the Monte Carlo tree to optimize the deployment, the total length of the shortest path between the sensors is selected as the gain *Score* of the sensor combination. As established in the previous analysis, leaks occurring at any point along the shortest path between sensors can be precisely located using the methods described in this paper. Optimal sensor deployment should maximize shortest path coverage throughout

the network. Therefore, the total length of shortest path can be used to evaluate the deployment effect of sensors. The higher the length value, the better the deployment effect of the sensor.

(2) The method of maximum number of unique solution leak points
The complex pipeline network structure creates numerous NPW propagation paths, potentially causing different locations to exhibit identical NPW delay combinations—a "multiple solution" effect that compromises leak localization accuracy. To evaluate sensor deployment effectiveness, 1000 discrete points are randomly selected as potential leak points throughout the pipeline network. For each deployment configuration, we calculate the number of points among these 1000 that produce unique delay combinations—specifically, points that avoid the "multiple solutions" problem. Higher values indicate more effective sensor deployment configurations.

(3) The method of maximum number of the shortest path drop points
1000 discrete points are randomly selected as potential leak points. For each sensor position combination, the number of points on the shortest path between any two of the deployed sensors is calculated. The higher the value is, the more reasonable the sensor deployment becomes.

3.2 Algorithm Design

The algorithm of pressure sensor deployment optimization includes three parts: preprocessing, additional constraints and algorithm design.

Firstly, the pipeline map information is pre-processed. There are many short branches in the pipeline network, such as the burr section shown in Fig. 2. To reduce computational complexity, these short branches are eliminated prior to optimal sensor deployment for the network shown in Fig. 2. This pruning operation preserves both the shortest path solutions for the remaining network points and the integrity of Monte Carlo Tree Search results. After pruning, the pipeline network has a total length of 337,466.61 m and consists of 1,361 branches.

Secondly, additional operational constraints are incorporated into the model. The detection method proposed in this paper relies on sensor-measured time delays for leak localization. Greater measured time delay differences increase localization success probability, necessitating maximized inter-sensor distances. Consequently, deploying pressure sensors at pipeline endpoints enables monitoring of longer pipe sections. The pipeline network contains 503 endpoints, which constitute the candidate pool for sensor deployment locations. In addition, considering that the actual NPW attenuates as the propagation distance increases, which make it difficult for the pressure sensor at the far end to monitor the corresponding waveform, the node values are not counted for paths longer than 10 km.

Finally, the algorithm is designed. In this paper, the Monte Carlo Tree Search algorithm for optimal sensor placement is implemented in Python 3.6.8 and the overall steps of the algorithm are as follows:

Step 1: An array board _ 1 is defined containing the 503 pipeline endpoint indices representing all potential sensor deployment locations. A transition array board and a deployed sensor array board_2 are defined to track algorithm state. Upon initialization, both board and board_2 are set as empty arrays. The number of iterations for a single search is set to 100 and the total number of deployed sensors is 10.

Step 2: A selection operation is performed. According to Formula (1), the *UCB* (Upper Confidence Limit) value of each node in **board_1** is calculated:

$$UCB\left(S_i\right) = Score_i + c\sqrt{\frac{\log N}{n_i}} \tag{1}$$

Where $Score_i$ is the average size of the node. Initially, the value of each node is 0; c is the weighting constant of the formula, which is usually taken as 2; N is the total number of times the nodes have been searched; n_i is the number of times the current node S_i has been searched.

The node with the maximum *UCB* value is selected as the root node, and the search count of this node is added by one.

Step 3: An expansion operation is performed on the root node, generating new child nodes that are then added to the transition array **board**. The visit count for each newly added node is incremented by one. If the number of elements in the **board** reaches 10, perform **Step 4**, otherwise, continue the expansion process.

Step 4: A simulation operation is performed. For each sensor pair in **board**, a breadth-first search algorithm calculates the shortest path between them. The gain *Score* for the sensor configuration in **board** is then calculated as the total length of all valid shortest paths. Only shortest paths less than 10 km in length are included in the benefit calculation, as longer paths exceed the effective NPW detection range.

Step 5: A backpropagation operation is performed. The *Score* value is returned to all nodes in **board** and the number of searches of the nodes is added by one.

Step 6: The algorithm tracks the current iteration count against the defined threshold. When the maximum iteration count (100) is reached, the algorithm recalculates the *UCB* value for each node in **board_1** and adds the node with the highest *UCB* value to **board_2**. The procedure then advances to **Step 7**; otherwise, the **board** will be cleared and the algorithm returns to **Step 2** for another iteration cycle.

Step 7: Determine whether the value of **board_2** is 10, if so, the search is ended and the solution result **board_2** is output, otherwise, the elements in **board** are cleared and **Step 2** will be repeatedly executed. The flow chart of the above algorithm is shown in Fig. 3.

4 Validation of Optimization Results

Optimization verification was conducted on the heating pipeline network described previously. The total length of the pipeline network is 337466.61 m, with a total of 1361 pipeline branches. A total of three experiments are conducted this time. Firstly, the calculation results of 10 sensors are verified. Subsequently, to comprehensively evaluate scalability, the sensor count was increased to 20 and 30 in separate trials, with resulting performance changes analyzed. All computations were performed on a system with an Intel(R) E5-2680 24-core processor running a 64-bit operating system. Computational requirements were relatively high: the 10-sensor optimization required 7 days, 4 h, and 35 min; the 20-sensor configuration took 15 days, 18 h, and 2 min; while the 30-sensor scenario needed 27 days, 17 h, and 6 min.

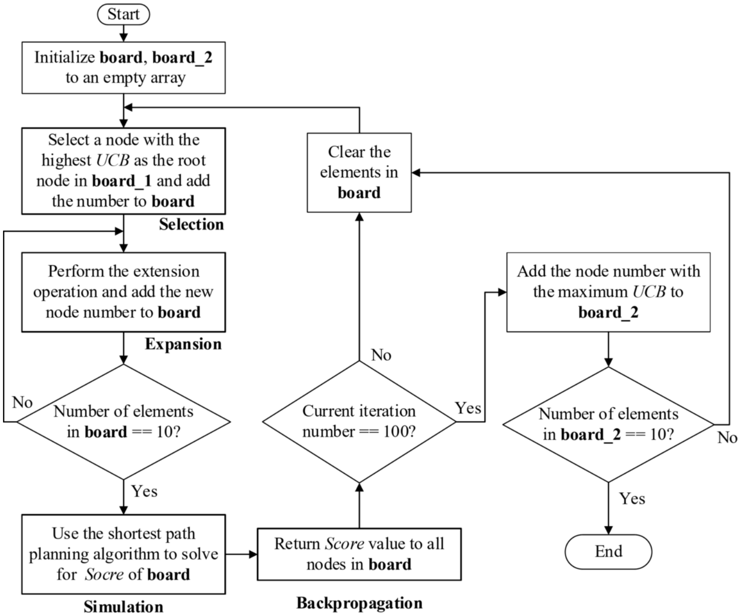


Fig. 3 Flow chart of sensor deployment optimization algorithm

4.1 Optimization Results

By running the pressure sensor deployment optimization program based on Monte Carlo Tree Search and shortest path planning, the optimal deployment locations numbers are solved, which is [16741, 3871, 19687, 9614, 11272, 18276, 16897, 2283, 7027, 22110]. To demonstrate the algorithm's effectiveness, four intermediate deployment schemes were extracted from sequential outputs during the calculation process. Figure 4a-e illustrates the progressive optimization of sensor deployment schemes arranged chronologically, with each diagram showing discrete point serial numbers at the selected locations and the shortest path coverage between all sensors. The final deployment (Scheme 5) shown in Fig. 4e demonstrates an optimal distribution of 10 sensors across all directions of the pipeline network. Figure 4f presents both the cumulative program iterations (bar chart) and maximum path sum values (line graph) for each scheme. As shown in the figure, the total inter-sensor path length increases progressively through successive iterations, validating both the algorithm's correctness and the reasonableness of the final optimization result.

4.2 Validation of Optimization Results

4.2.1 Verification Using the Maximum Number of Unique Solution Leak Points Method

Following the methodology described in Sect. 3.1.(2), 1000 discrete points were randomly selected throughout the pipeline network to calculate the number of points with unique delay combinations (denoted as λ). Table 1 presents the calculated λ values for each deployment scheme along with their corresponding test results. The rightmost column displays the

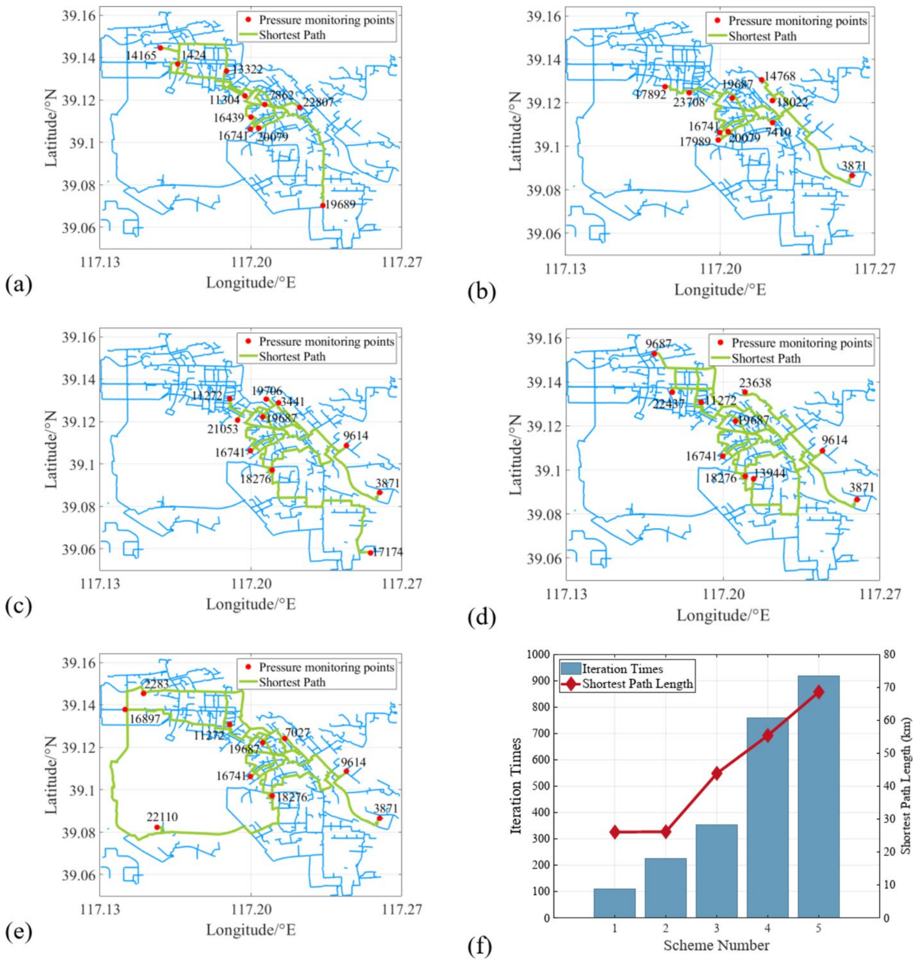


Fig. 4 Different sensor deployment schemes output by the algorithm at different iteration times: (**a**) Scheme 1 (**b**) Scheme 2 (**c**) Scheme 3 (**d**) Scheme 4 (**e**) Scheme 5 (final optimization result); (**f**) Performance metrics showing iteration count (bar chart) and shortest path length (line graph) for each scheme

Table 1 Evaluation results of the method of maximum number of unique solution leak points

Scheme number	Total length of the shortest path(km)	λ	Proportion
1	26.1	548	54.8%
2	26.2	697	69.7%
3	43.9	739	73.9%
4	55.4	755	75.5%
5	68.6	790	79.0%

percentage of points with unique delay signatures (λ/1000). In Table 1, Schemes 1 through 5 represent sequential intermediate results from the optimization process, with Scheme 5 representing the final deployment solution. The last two columns of Table 1 reveal a steady increase in the number of potential leak points with unique delay signatures as optimization progresses. The optimal deployment solution (Scheme 5) achieves a λ value of 790, enabling accurate detection of the maximum number of potential leak locations. This progressive improvement demonstrates convergence toward the optimal sensor deployment configuration.

4.2.2 Verification Using the Method of Maximum Number of the Shortest Path Drop Points

As in Section 3.1.(3), 1000 discrete points are randomly selected as potential leak test points. For each combination of sensor locations, the percentage of test points located on the shortest paths of deployed sensors is calculated. The test results for the five deployment schemes are shown in Fig. 5. The blue scatter points represent 1,000 test points, while red scatter points indicate test points located on the shortest paths.

The proportions of test points located on the shortest paths for the five deployment schemes were calculated and are shown in Fig. 5f. The proportion of potential leaks located on the shortest path increases as the optimization progresses. The final deployment result (Scheme 5) demonstrates the highest proportion of test points on shortest paths at approximately 20.3%. Therefore, the "total path length" metric can be used to select the optimal sensor locations. This confirms that the pressure sensor deployment scheme solved in this paper is both correct and effective.

4.3 Deployment Optimization Results of More Sensors

4.3.1 Optimization Results

The number of pressure sensors further increases to 20 and 30, and the deployment of sensors are optimized. By running the optimization program, the optimal deployment position numbers for the 20 sensor points are [10265, 10342, 4463, 2782, 6190, 22727, 16439, 14454, 3770, 6329, 11778, 17283, 1439, 13693, 11063, 24621, 24602, 14726, 17707, 1932]. The optimal deployment position numbers for the 30 sensor points are [22761, 3347, 20027, 12560, 23638, 21198, 12257, 24681, 19706, 23976, 4479, 497, 16185, 14366, 13300, 12537, 11062, 19246, 16439, 23088, 18763, 20970, 15907, 6190, 12931, 21037, 8237, 13895, 7410, 10447]. The deployment diagrams for both optimization and random selection methods are shown in Fig. 6a-e, where the labeled numbers represent discrete point locations, and the green polylines indicate the shortest paths between sensors.

Figure 6f presents a comparative analysis of total shortest path lengths between sensor pairs for both optimization-based and manually randomized deployment schemes across three sensor quantities (10, 20, and 30). For each fixed sensor quantity, the optimization program consistently generated greater total shortest path lengths compared to manually randomized deployment schemes.

When the number of sensors increases from 10 to 20, the total length increases significantly. This indicates that increasing the number of sensors can improve sensor deployment

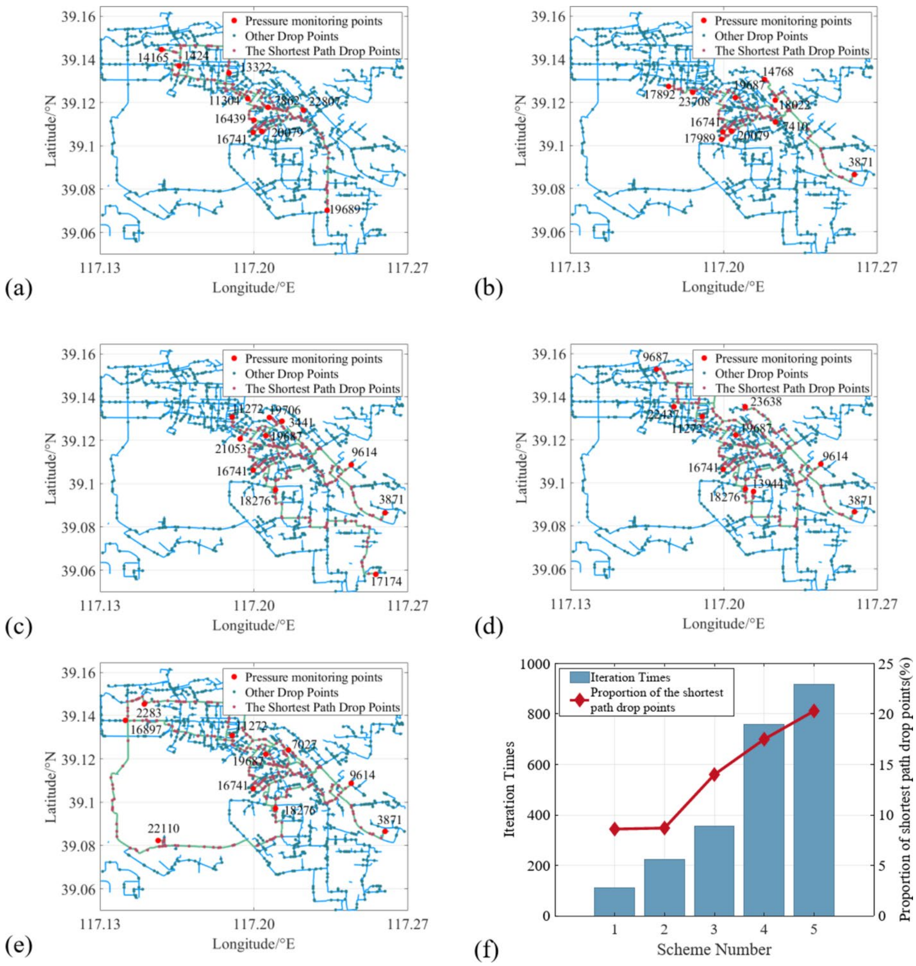


Fig. 5 Verification results using the method of maximum number of the shortest path drop points (**a**) Scheme 1 (**b**) Scheme 2 (**c**) Scheme 3 (**d**) Scheme 4 (**e**) Scheme 5 (final optimization result); (**f**) Performance metrics showing iteration count (bar chart) and proportion of shortest path drop points (line graph) for each scheme

performance, which is consistent with the expected results. However, when the number of sensors increases from 20 to 30, the total length of the shortest paths does not increase significantly. Furthermore, when there are 30 sensors, the results of manual selection and program solving are similar. Therefore, when the number of pressure sensors is small due to cost limitation, deployment optimization is necessary, but when the number of sensors is sufficient, optimization can be omitted.

4.3.2 Result Analysis

Firstly, the maximum number of unique solution leak points method is used to verify the results. After calculating the six schemes in Table 2, it can be found that when the number

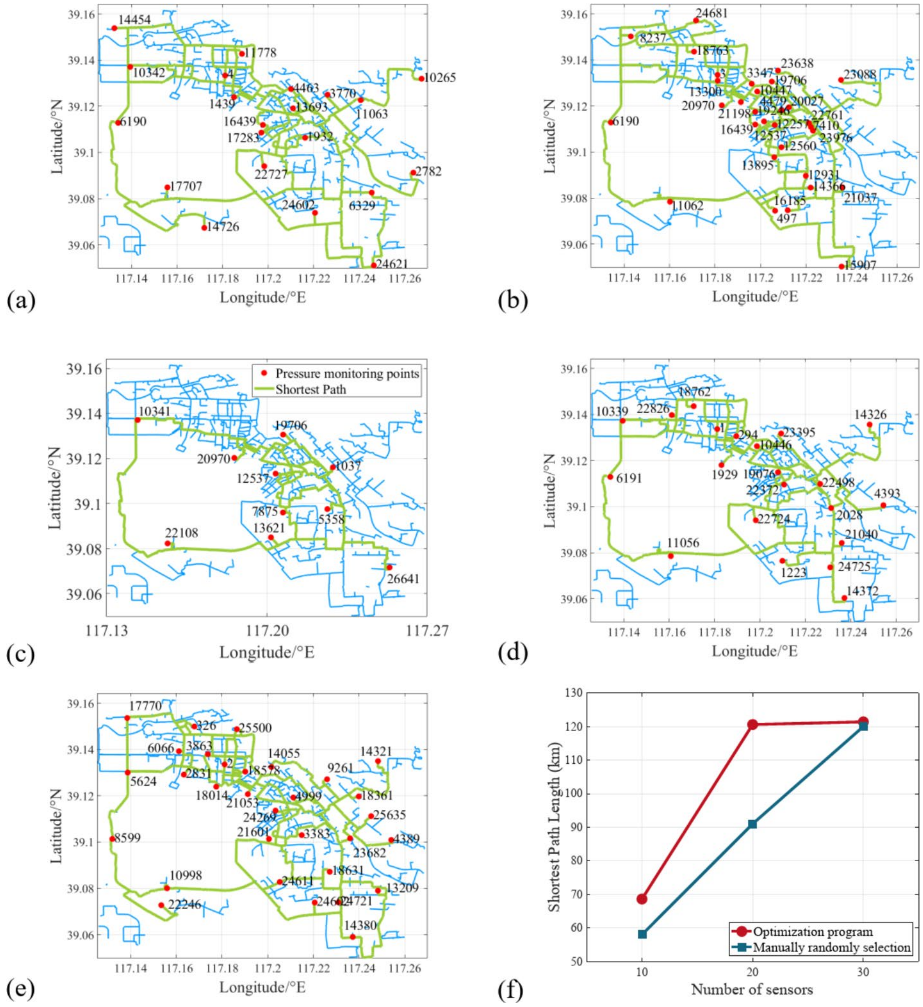


Fig. 6 Sensor deployment results of optimization program: (**a**) 20 sensors, (**b**) 30 sensors; Sensor deployment via manual random selection: (**c**) 10 sensors, (**d**) 20 sensors, (**e**) 30 sensors; (**f**) Performance metrics showing shortest path lengths for optimization program and manual random selection at different sensor quantities

Table 2 Evaluation results of the method of maximum number of unique solution leak points

Number of sensors	Solution method	λ	Proportion
10	Optimization program	790	79.0%
20	Optimization program	1000	100%
30	Optimization program	1000	100%
10	Manually randomly selection	768	76.8%
20	Manually randomly selection	1000	100%
30	Manually randomly selection	1000	100%

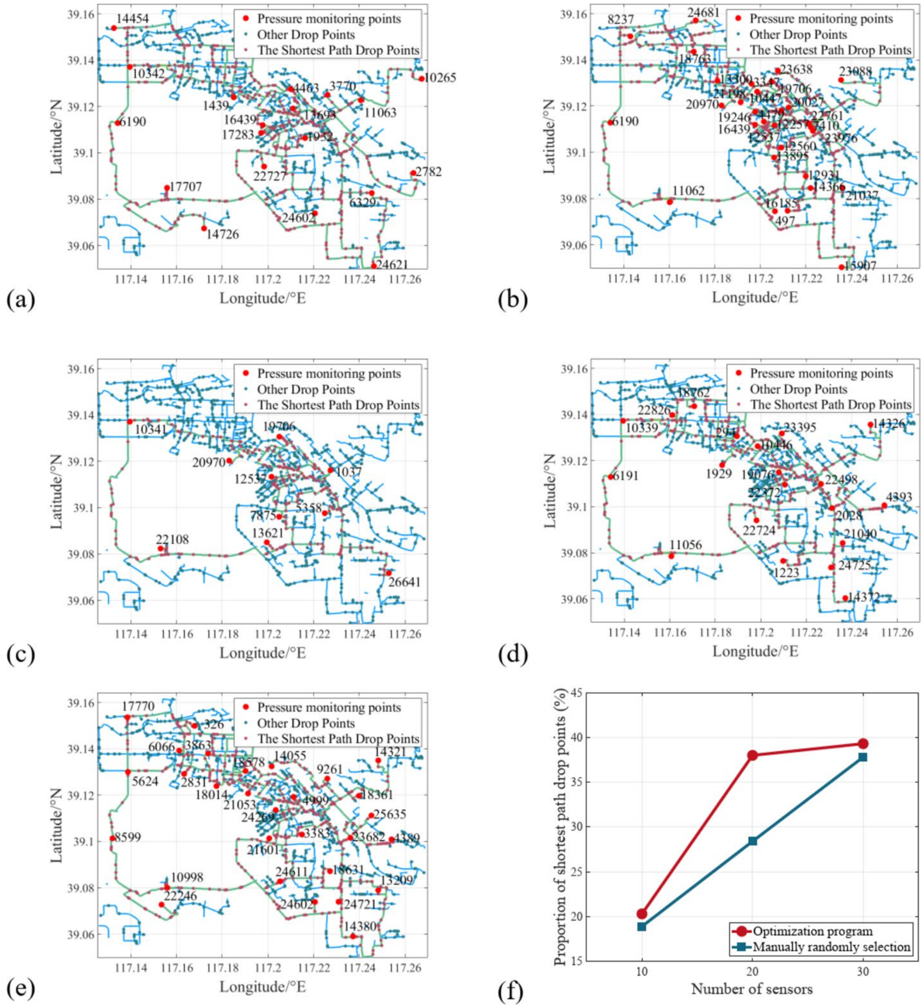


Fig. 7 Verification results using the method of maximum number of the shortest path drop points: optimization program: (**a**) 20 sensors, (**b**) 30 sensors; manual random selection: (**c**) 10 sensors, (**d**) 20 sensors, (**e**) 30 sensors; (**f**) Performance metrics showing proportion of shortest path drop points for optimization program and manual random selection at different sensor quantities

of pressure sensors increases from 10 to 20, the λ value can reach 100% (maximum level). Additionally, the λ value remains at 100% when further increasing sensors from 20 to 30. These results demonstrate that deployment optimization is necessary when cost limitations restrict sensor numbers, but become unnecessary with sufficient sensors.

Then, the maximum number of the shortest path drop points method is used to further verify the results. For each sensor position scheme, the percentage of test points located on the shortest paths was calculated. The test results of the deployment schemes are shown in Fig. 7. The blue scatter points in the figure represent random falling points, while red scatter points indicate test points located on the shortest paths.

Figure 7f compares the program optimization and manual selection approaches under different sensor quantities. The manual selection shows a linear increase in shortest path drop point coverage as sensor numbers grow. The optimization algorithm significantly outperforms random placement when increasing from 10 to 20 sensors. However, when sensor quantities increase from 20 to 30, the improvement in proportion from the program-solving method becomes negligible, indicating that the deployment optimization algorithm has reached saturation. Comparing the shortest path drop point proportions between the program-solving method and manual selection at this level reveals minimal difference, which can be ignored. Therefore, optimization can be omitted when the number of sensors is sufficient.

5 Conclusion

This paper presents a novel pressure sensor deployment optimization method for pipeline networks by integrating shortest path planning with Monte Carlo Tree Search. The Main conclusions are as follows:

(1) The algorithm discretizes pipeline networks and employs Monte Carlo Tree Search to maximize the sum of shortest path lengths between sensors for optimizing sensor deployment. Additionally, by incorporating NPW attenuation constraints and prioritizing sensor placement at pipeline endpoints, the method improves deployment accuracy in complex networks.
(2) When applied to a 12.5 km × 12.7 km pipeline network (337,466.61 m total length), the method optimally positioned 10 pressure sensors, improving three key metrics: the total shortest path length increased from 26.1 km to 68.6 km; the percentage of uniquely identifiable leak points rose from 54.8 to 79.0%; and the proportion of network points covered by the shortest paths increased from 8.6 to 20.3%. These consistent improvements across all evaluation indices validate the effectiveness of the approach.
(3) Scalability analysis revealed that increasing sensor count from 10 to 20 significantly enhanced leak localization capability, achieving 100% unique identification rate. However, further expansion to 30 sensors yielded minimal additional benefits, indicating an optimization saturation point. This finding provides valuable guidance for cost-effective implementation in real-world applications, demonstrating that optimization is crucial when resources are limited but becomes optional with sufficient sensor density.

The proposed SPP-MCTS synergistic optimization method significantly enhances pressure sensor utilization efficiency in pipeline leak detection systems. By minimizing the “multiple solutions” problem without requiring additional sensors, our approach offers a cost-effective strategy for industrial implementation, particularly valuable in resource-constrained thermal pipeline monitoring applications.

Author Contributions Y.P Yan and L.Y Chen: Algorithm design, Data analysis, Writing-original draft. X.J Huang: Project management, Research direction guidance, Writing-review & editing. J.Y Ma, J Li and Z.M Zeng: Resources acquisition, Supporting data collection.

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Data Availability The data that has been used is confidential.

Declarations

Competing Interests The authors have no relevant financial or non-financial interests to disclose.

Ethical Approval All researchers are demonstrating that they have adhered to the accepted ethical standards of a genuine research study.

Consent to Participate All authors have agreed to participate.

Consent to Publish All authors have agreed to publish in this journal.

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