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Mixed Reality-Based Inspection Method for Underground Water Supply Network with Multi-Source Information Integration

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Abstract: Regular on-site inspection is crucial for promptly detecting faults in water supply networks (WSNs) and auxiliary facilities, significantly reducing leakage risks. However, the fragmentation of information and the separation between virtual and physical networks pose challenges, increasing the cognitive load on inspectors. Furthermore, due to the lack of real-time computation in current research, the effectiveness in detecting anomalies, such as leaks, is limited, hindering its ability to provide immediate and direct-decision support for inspectors. To address these issues, this research proposes a mixed reality (MR) inspection method that integrates multi-source information, combining building information modeling (BIM), Internet of Things (IoT), monitoring data, and numerical simulation technologies. This approach aims to achieve in situ visualization and real-time computational capabilities. The effectiveness of the proposed method is demonstrated through case studies, with user feedback confirming its feasibility. The results indicate improvements in inspection task performance, work efficiency, and standardization compared to traditional mobile terminal-based methods.

Keywords: information integration; mixed reality (MR); water supply network (WSN); building information modeling (BIM); internet of things (IoT); numerical simulation

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1. Introduction

The safety and stable operation of underground pipeline systems are critical for the normal functioning and development of cities, serving as their lifelines [1,2]. However, long-term usage and environmental impacts have led to frequent aging, corrosion, and ruptures, endangering water supply systems and urban residents' lives [3,4].

On-site inspection is widely regarded as the most direct method for promptly identifying issues within WSNs [5,6]. It plays an indispensable role in diagnosing problems, such as leaks, but depends on various types of information to support decision-making. However, the cognitive load on inspectors is increased due to the fragmentation of multi-source information and the inherent separation between virtual information and the physical pipeline network [7]. Current research based on augmented reality (AR)/mixed reality (MR) offers an approach to address the issue of information fragmentation in on-site visual inspection [8]. However, due to the lack of real-time computation in current research, the effectiveness in detecting anomalies, such as leaks, is limited, hindering its ability to provide immediate and direct decision support for inspectors [9]. Furthermore, although theoretical research on leak detection mechanisms in WSNs has been advancing, the accuracy of leak detection remains inherently limited, making it necessary to integrate other types of information to assist in verifying the accuracy of leak detection during on-site inspections [10,11].

Given the above issues, it is essential to further identify the types of integrated information required for the AR/MR-based pipeline visualization inspection method and to

explore how to embed the leak detection mechanism to enhance the capability of on-site decision-making. From another perspective, existing research on AR/MR-based on-site visualization inspection of pipeline networks also lacks a focus on specific types of pipeline networks, limiting their practical application and effectiveness in real-world scenarios [9,12]. Analysis reports on underground pipeline accidents in China from 2020 to 2023 reveal that inherent structural hazards are the primary factor contributing to leakage accidents in WSNs. Therefore, this research focuses on WSNs, with particular emphasis on on-site inspection and the detection of anomalies such as leaks. The research proposes a mixed reality-based inspection method for underground water supply networks with multi-source information integration. This method combines MR, BIM, IoT, and numerical simulation technologies, focusing on information processing and integration for on-site inspection of WSNs. It also considers how this information maps onto the physical entities of the pipeline network, aiming to achieve immediate, direct, and user-friendly interactive inspection in situ. The main contributions are as follows:

(1) Development of MR-Based Inspection Method for WSN: Proposed an MR-based non-destructive on-site inspection method specifically for WSNs. Developed a human–computer interaction system that provides in situ information presentation and independent real-time computation, thereby enabling effective penetrative operation and maintenance (O&M) of underground WSNs.
(2) Integration of Multi-Source Information for Clearer Information Types: Utilized MR as the integration medium to combine the advantages of various technologies, achieving a more precise and clearer in situ integration of multi-source heterogeneous information within WSNs. This integration reduces the cognitive load on inspectors by providing clearer and more actionable information.
(3) First-Time Embedding of the Leak Detection Mechanism in MR-Based WSN Inspection: Innovatively embedded the leak detection mechanism into the MR-based inspection method for underground WSNs, marking the first instance of such integration. This advancement enhances decision support by integrating real-time leak detection with interactive inspection, providing a novel contribution to the field of WSN O&M.
(4) Application of the Genetic Algorithm for Visual Leak Detection On-Site: Combined monitoring information with numerical simulation data of WSNs. Applied a genetic algorithm to visually locate and present leak nodes in situ, integrating numerical simulation information into on-site O&M scenarios and enabling real-time computation and visualization of network anomalies.

2. Literature Review

2.1. Multi-Source Information Integration in Infrastructure O&M

In the field of infrastructure O&M, the integration of multi-source information is crucial for enhancing management efficiency and decision-making support. The effective integration of multi-source information has brought significant benefits to infrastructure O&M, including improved decision accuracy, reduced response times, and lower O&M costs [13,14]. However, the integration of multi-source information in the WSN O&M still faces significant challenges, such as inconsistencies in data formats, inadequate real-time performance, and weak spatial correlation. Although the existing WSN O&M research aggregate multi-source information, the research predominantly focuses on desktop or mobile platforms within purely virtual environments. The lack of on-site virtual information overlay capabilities often necessitates that inspectors rely on their imagination to map various types of information onto the actual site, thereby neglecting the direct connection with the inspection scene [15].

2.2. Application of AR/MR in Infrastructure O&M

In addressing the challenges of on-site visualization of integrated multi-source data in infrastructure O&M, AR has been increasingly adopted to aid visual O&M tasks, integrated with diverse intelligent analysis techniques to enhance effectiveness [16–18]. However, the

current application of AR technology in O&M still presents several limitations, such as equipment performance constraints, and poor environmental adaptability.

MR, as a further development of AR [19,20], leverages the technical characteristics of merging virtual and real spaces, enabling seamless integration of multiple sources of information in real operational environments. It facilitates natural behavioral interaction and meets requirements for operational and maintenance collaborative management [21–23]. Research on O&M related to MR has been conducted in various fields, including structural health diagnosis [24,25], auxiliary equipment maintenance [26], energy infrastructure inspection [27,28] and more. The most prominent feature of using MR in O&M is its ability to reduce maintenance operational time and enhance efficiency through visual interfaces [29,30]. Secondly, MR can integrate various information and incorporate it into interactive O&M systems, providing reliable decision-making foundations [31,32]. Furthermore, to address the shortcomings of passive maintenance and enhance the accessibility of professional support for O&M, combining predictive maintenance and remote assistance with MR can achieve data and knowledge-driven operational management [33].

In the area of MR-based O&M of underground pipeline networks, a distributed MR-IoT method was proposed that utilizes an IoT cloud platform to collect and manage data, achieving multi-dimensional dynamic information exchange between on-site workers and backend managers [9]. However, the absence of real-time computational capabilities on-site will limit its capacity to furnish immediate and direct decision support to inspectors.

2.3. Research on Leak Detection in WSN

Therefore, to enhance decision support for inspectors during on-site inspections of WSNs and improve the convenience of on-site decision-making, current research has embedded leak detection mechanisms into pipeline decision support systems [34,35]. However, this research lacks in situ mapping of information.

From another perspective, current research on leak detection lacks integration with on-site visualization. This research integrates a leak detection mechanism into the on-site inspection system based on the MR-based penetrative inspection method discussed in Section 2.2, providing rapid, real-time decision support.

In the selection of leak detection methods, traditional approaches often suffer from low detection accuracy and poor efficiency [36,37]. Data-driven leak detection algorithms show great potential in improving detection accuracy and real-time performance. However, these methods require high data quality and quantity, posing challenges in practical applications [38,39]. In recent years, leak detection methods based on numerical simulation have been widely studied. By establishing hydraulic models of pipeline networks and combining them with real-time monitoring data, these methods can quickly locate leak points [10,40]. This approach is particularly effective in areas where sensor deployment is relatively sparse. Therefore, this research employs a numerical model-based leak detection method, supplemented by monitoring information and other information, to assist in verifying the accuracy of leak detection during on-site inspection. This approach aims to mitigate the inherent limitations in the accuracy of leak detection.

2.4. Summary

As shown in Figure 1, on-site inspection of WSNs face issues such as weak temporal and spatial correlation and inadequate real-time performance. AR/MR technologies can effectively address these problems, but current methods for the AR/MR-based WSN inspection lack real-time computational capability, thereby limiting their ability to provide timely and rapid decision support for inspectors. Therefore, this research proposes a mixed reality-based inspection method for underground WSNs with multi-source information integration, incorporating monitoring information and numerical simulation for on-site leak detection. This method aims to achieve complementary multi-source information, in situ visualized information integration, and real-time computational capability in on-site inspection, providing inspectors with immediate and direct decision support.

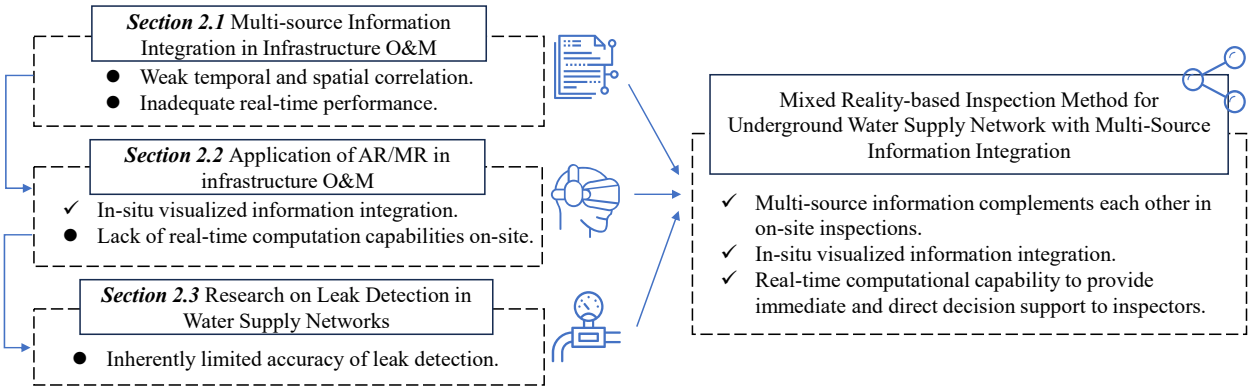


Figure 1. Flowchart of literature review.

3. Research Framework

The concept of Milgram's reality–virtuality continuum was proposed in 1994 to describe the relationship between virtual reality, augmented reality, and mixed reality [41,42]. As shown in Figure 2, this framework is based on the reality–virtuality continuum theory and consists of three steps: In Step 1, the virtual object of WSNs is created based on geometric information as the foundation for information integration and visualization. In Step 2, the necessary related information for on-site inspection of WSNs, including attribute information, real-time monitoring information, numerical simulation information, and inspection process information, is combined and mapped onto the virtual 3D model. Step 3 involves aligning virtual object with the physical object to achieve seamless in situ integration of both static and dynamic multi-source information within WSNs in the real environment.

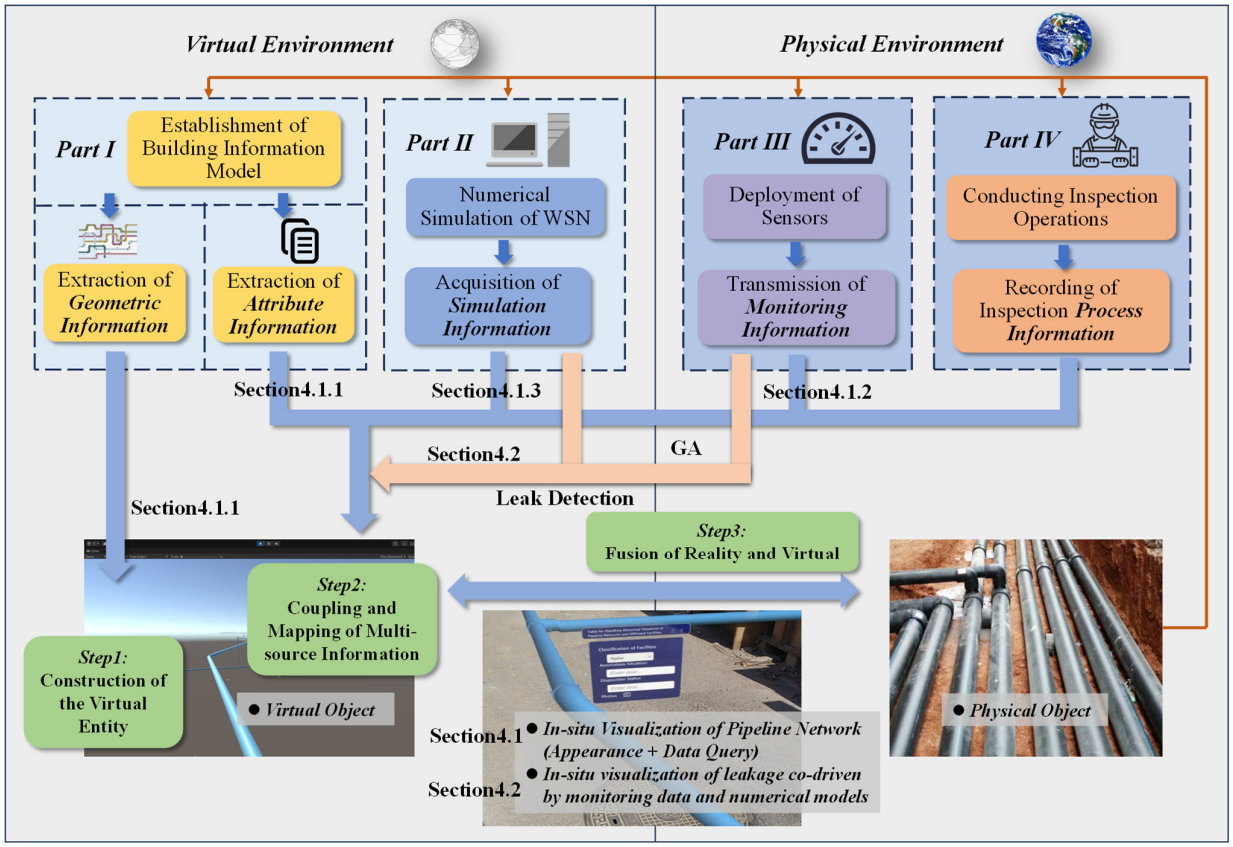


Figure 2. Research framework.

(1) Step1: Construction of the Virtual Object

In projects, BIM is often employed to guide construction and O&M. Therefore, BIM, which encompasses a wealth of information from various stages such as design, construction, and maintenance, serves as an excellent data source for achieving virtual mapping. By extracting geometric information from the building information model, the virtual object in the framework is constructed. This establishes a linkage with tangible inspection targets, forming the foundation for subsequent information integration and the fusion of virtual and physical environments.

(2) Step2: Combining and Mapping of Multi-source Information

The primary objective of the WSNs' on-site inspection is to assess operational status and diagnose issues through various measures. This focuses on static data and operational status data. The research emphasizes basic information, numerical simulations, real-time monitoring, and inspection process data from both virtual and physical environments.

Data from the virtual environment include basic information and numerical simulations. Basic information covers geometric and attribute data acquired in the design phase and refined during construction and operation. Real-time monitoring and inspection process data are collected during the network operation from the physical environment. These four information types support on-site WSN inspection, enabling mapping to the physical object via integration into the virtual object. Combining simulation data from the virtual environment with real monitoring data facilitates data and model-driven in situ visualization of leaks.

(3) Step3: Fusion of Reality and Virtual

To achieve in situ visualization of information in the real environment, the virtual model of the network must be aligned with its physical object, enabling seamless integration of the virtual and the real. This process involves extracting features for camera pose estimation, performing coordinate transformations to align the virtual WSNs with the real one (including mapping real-world coordinates to the camera coordinate system and vice versa), and rendering the virtual WSNs onto the image to blend virtual objects with the physical scene.

4. Implementation Path

In the implementation of the research framework outlined in Section 3, the primary approach involves separating and re-associating BIM information, embedding and combining real-time monitoring information and numerical simulation information for the MR-based inspection method for WSNs (as shown in Figure 3).

4.1. Information Integration and Mapping for Inspection

4.1.1. The Processing and Integration of Information from BIM in WSNs

The essential information required in the WSN model comprises geometric and attribute information. BIM, which contains a wealth of information, emerges as an excellent source of virtual information for MR-based inspection of WSNs, serving as the primary object for visualizing the network and integrating information [43,44]. Parametric modeling offers highly flexible model adjustment capabilities for underground water system networks, enhancing data visualization in MR environments [45,46]. In this study, parametric data within BIM, facilitated through Autodesk Revit, allows precise control over geometric shapes and component attributes, enabling adaptable WSN modeling under varying environmental conditions.

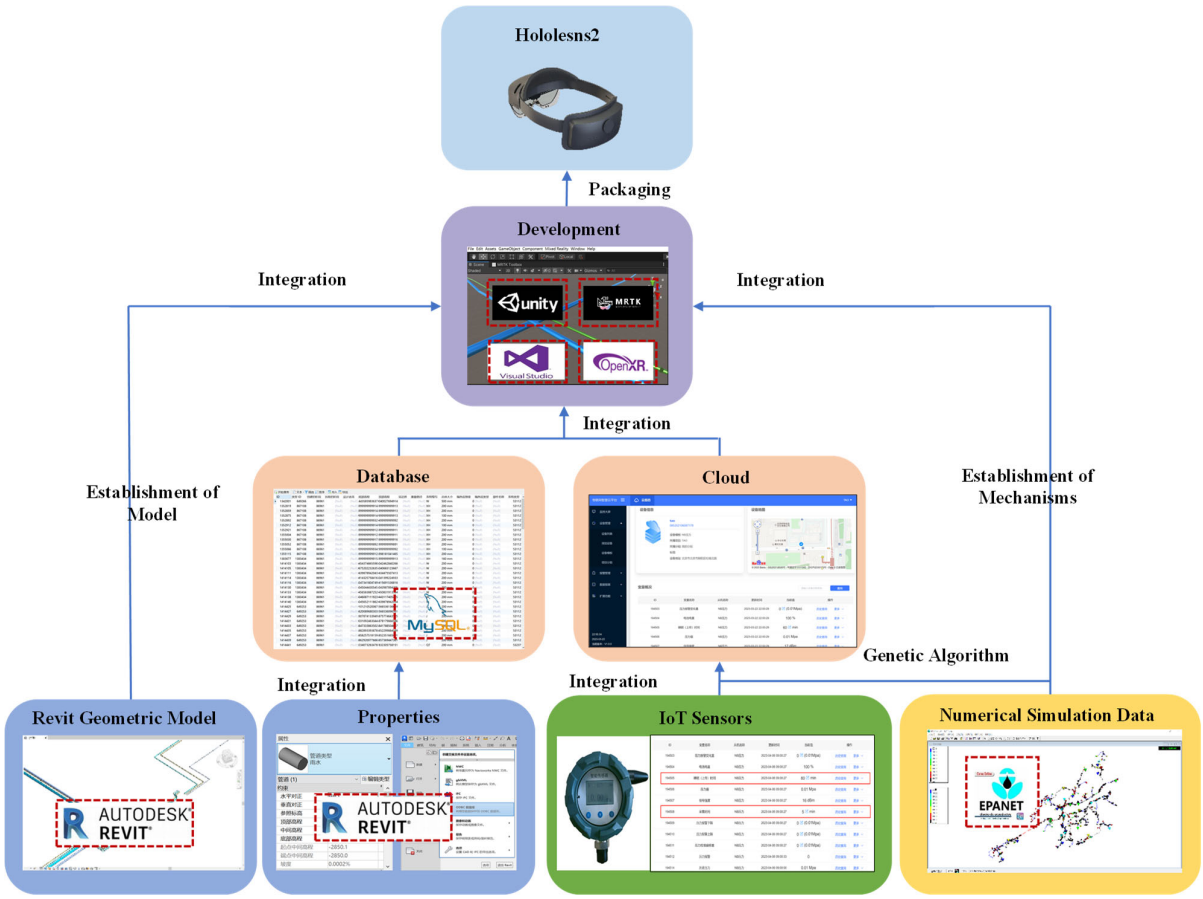


Figure 3. Implementation path.

The development of the digital twin model focused on balancing accuracy and performance within the constraints of the HoloLens 2. Higher resolution models improve leak detection and structural accuracy but impose greater demands on device processing power. The digital twin model for WSNs was constructed with a Level of Development (LOD) 300, providing a balanced representation of essential geometric and attribute data to support leak detection and structural assessments within the processing limits of the HoloLens 2 [47,48]. This medium-level LOD allows accurate visualization of key components without overloading device capacity. For critical network areas, such as potential leak zones, higher LODs (350 or 400) could be selectively applied to capture finer details of pipes, joints, and valves, enhancing spatial accuracy where it is most needed. This targeted approach maintains overall model performance while optimizing MR interactions in key inspection areas. As MR device capabilities evolve, full-network high-resolution modeling may become feasible, allowing comprehensive use of higher LODs across the WSNs. For now, the medium-level LOD combined with efficient data handling in Unity optimizes rendering efficiency and supports effective MR-based inspections.

Due to the different information expressions of the two platforms and the limited performance of the MR device (HoloLens 2), this research utilizes the method of separating data and model to extract pertinent information and then reassociate them in Unity, aiming to enhance the efficiency of graphic rendering and the effectiveness of data transmission. Exporting component attribute information from Revit to the database via the ODBC data source, concurrently exporting the 3D model of WSNs from Revit as an initial FBX file, and further optimizing it through software such as Pixyz Studio 2022.1 and MeshLab 2022.02 allows for direct accessing in Unity, thus completing the reconstruction of geometric information including component ID identifiers.

4.1.2. The Processing and Integration of Real-Time Monitoring Information in WSNs

This research focuses on the collection and communication research of real-time monitoring information in pipelines using wireless pressure sensor devices as an example. Firstly, configuration and acquisition of sensor data are performed within the data collection devices, followed by the utilization of communication protocols such as HTTP and MQTT to transmit data to the cloud platform, implementing timed or event-triggered mechanisms for data upload to ensure continuous data updating. Data are then stored in databases within the cloud platform, with encryption and access permissions set to ensure data security. Finally, the obtained monitoring data are used in Unity to visualize.

4.1.3. The Integration of Numerical Simulation Information in WSNs

Embedding numerical simulation information of WSNs as a basis for assessing the network's status using the MR-based inspection method is a crucial aspect of this research. In this research, the open-source software EPANET2.2, developed by the United States Environmental Protection Agency (USEPA), was chosen as the numerical simulation software [49]. The integration process of numerical simulation information of the WSNs in Unity involves first establishing the topological structure of the WSNs in EPANET and determining the parameters and initial conditions. Then, the EPANET Dynamic Link Library (DLL) for ×86 architecture is called in Unity to perform the hydraulic simulations.

In the physical system of a WSN, a node represents a user node where pipes connect. A segment refers to a pipe section between two nodes, representing the physical pipeline through which water flows. The hydraulic simulation of WSNs is based on the network continuity equation (Equation (1)), and the head loss equation (Equation (2)).

(1) Network Continuity Equation:

$$\sum_{j \in S_i} Q_{ij} - q_i = 0 \tag{1}$$

where:

Q_{ij} is the flow rate in the pipeline segment from node i to node j.

q_i is the external demand or supply at node i.

S_i is the set of nodes adjacent to node i.

This equation ensures mass conservation at each node, indicating that the sum of flows into and out of a node, including any external demands or supplies, must be zero.

(2) Head Loss Equation:

$$h_{ij} = H_i - H_j = A{Q_{ij}}^B \tag{2}$$

where:

H_i and H_j are the heads at nodes i and j, respectively.

A is a friction factor dependent on pipe characteristics.

Q_{ij} is the flow rate in the pipeline segment between nodes i and j.

B is the flow exponent, characterizing the relationship between flow rate and head loss due to friction.

This equation calculates the head loss due to friction in each pipe segment, essential for determining the pressure distribution throughout the network.

Due to the inconsistency between component IDs in the EPANET model and the 3D model exported from Revit, it is necessary to establish a mapping relationship table for the critical nodes and pipe sections. Utilizing the mapping relationship, the corresponding Revit model IDs can be identified for the 3D model in Unity, thereby enabling the matching of EPANET simulation results with the 3D model. Finally, the colors of the corresponding nodes and segments in the model are set to represent the simulated pressure and flow results.

4.2. Combination of Monitoring Information and Simulation Information for Inspection

In the assessment of WSN conditions, the lack of real-time on-site computation will reduce efficiency. This research employs a method where monitoring data and numerical simulations jointly drive computations on the MR device, aiming to efficiently identify and highlight potential leak points, thereby improving effectiveness of leak detection.

The monitoring data are obtained through the wireless transmission method described in Section 4.1.2, and the leakage numerical simulation, using the EPANET DLL in Unity as detailed in Section 4.1.3, is embedded in an optimization algorithm—a genetic algorithm in this case. The leakage modeling is based on the leakage flow equation (Equation (3)), and the optimization process uses the fitness function (Equation (4)) to evaluate candidate solutions.

(3) Leakage Flow Equation:

$$Q = K \cdot P^n \tag{3}$$

where:

Q is the leakage flow rate at the node.

P is the pressure at the node.

K is the leakage coefficient, depending on the specific characteristics of the network.

n is the leakage exponent, reflecting the non-linear relationship between pressure and leakage flow rate.

The leakage exponent n varies due to factors such as the type of leak, pipe material, and pipeline condition. This exponent reflects the non-linear relationship between pressure and leakage flow rate. It is typically determined through empirical studies, with common values ranging from 0.5 to 2 [50,51]. In this research, we adopted a commonly used value of n = 0.5 based on similar pipeline conditions [52]. In the hydraulic simulation under leakage conditions, Equations (1) and (2) are used to solve for the flow rates and pressures throughout the network, incorporating the leakage flow Q calculated using Equation (3).

(4) Fitness Function:

$$\min f = \sum_1^N (p_{1,n} - p_{2,n})^2 \tag{4}$$

where:

N is the number of pressure monitoring points.

$p_{1,n}$ is the simulated pressure value at monitoring point n.

$p_{2,n}$ is the observed pressure value at monitoring point n.

This function quantifies the discrepancy between simulated and observed pressures, guiding the optimization process to find the leakage parameters that best explain the observed data.

The detailed process is outlined in Algorithm 1. First, the 3D model of the WSNs is loaded and configured in the Unity environment (line 1), providing a foundation for subsequent visualization. The algorithm then initializes the population with random combinations of leakage node indices *LNi* and corresponding leakage coefficients *Ki* (line 2). During the main optimization loop, the genetic algorithm performs evolutionary operations on the population. For each individual (candidate solution), crossover and mutation operations are applied according to their respective probabilities (lines 4–7), generating new potential solutions. The fitness evaluation process integrates hydraulic simulation, where for each individual, the algorithm extracts the leakage node index and coefficient (lines 9–10) and performs hydraulic calculations based on Equations (1)–(3). These hydraulic calculations (line 11) generate simulated pressures which are then compared to the observed pressures using the fitness function defined in Equation (4). This fitness function (line 12) guides the optimization process by quantifying how well each candidate solution explains the observed pressure data.

In the genetic algorithm's selection phase, individuals are chosen for the next generation based on their fitness values (line 14). Specifically, we employ a tournament selection method, where a subset of individuals is randomly selected from the population, and the individual with the best fitness within this subset is chosen to be part of the next generation. This method balances exploration and exploitation, maintaining genetic diversity while promoting convergence toward the optimal solution. The population is then updated with the selected individuals (line 15), and the algorithm parameters are adjusted if necessary (line 16). The optimization process continues until the termination condition is met, which could be a maximum number of iterations. Finally, the best chromosome is identified (line 18), and the corresponding leakage node index and injection coefficient are extracted (lines 19 and 20). These results are then visualized in the 3D model through relational mapping (line 21), aiding inspectors in decision-making through in situ visualization of the leakage.

Algorithm 1. Leak detection using the genetic algorithm and hydraulic simulation in Unity

Input: RealTimeMonitoringData, GeneticAlgorithmParameters [Population size, Iterations, Crossover probability, Mutation probability], 3D model data
Output: NodeIndexNumber LNi, InjectionCoefficient Ki, VisualizationData
//Initialization Phase
1: Initialize3DModel(ModelData)
2: Population = InitializePopulation (GeneticAlgorithmParameters.PopulationSize)
//Main Optimization Loop
3: While Not TerminationCondition Do
    //Genetic Operations
4: For Individual in Population Do
5: PerformCrossover (Individual, GeneticAlgorithmParameters.CrossoverProbability)
6: PerformMutation (Individual, GeneticAlgorithmParameters.MutationProbability)
7: End For
    //Fitness Evaluation with Hydraulic Simulation
8: For Individual in Population Do
9: NodeIndex = GetNodeIndex (Individual)
10: LeakCoefficient = GetLeakCoefficient (Individual)
11: SimulationResults = SimulateHydraulics (NodeIndex, LeakCoefficient)
12: Individual.Fitness = EvaluateFitness (SimulationResults, RealTimeMonitoringData)
13: End For
    //Selection and Population Update
14: SelectedIndividuals = SelectBestIndividuals (Population)
15: Population = UpdatePopulation (SelectedIndividuals)
    //Update Parameters if needed
16: UpdateParameters()
17: End While
//Extract and Visualize Results
18: BestChromosome = FindBestChromosome (Population)
19: LNi = ExtractNodeIndex (BestChromosome)
20: Ki = ExtractInjectionCoefficient (BestChromosome)
21: VisualizeBestSolution (LNi, Ki, ModelData)
22: Return LNi, Ki, VisualizationData

5. Application and Analysis

5.1. System Development and Functional Implementation

Given that the current research is in the laboratory verification phase, we use two cases to verify the availability of our aforementioned methodology in this section. The part of information integration and mapping for inspection is elucidated by employing a real-case scenario from a specific area, while the combination of monitoring information and simulation information for inspection is addressed by employing a hypothetical network, referred to as Anytown, for the analysis and discussion.

Given the complex inspection procedures, there is a need for portable inspection tools. Head-mounted displays are selected for their mobility, with HoloLens 2 chosen for its MR display capabilities. Unity is selected for MR functionality development due to its advanced graphics and interactive design features, which, with toolkits, allow for immersive MR experiences. Since HoloLens 2 apps require the Universal Windows Platform (UWP), adjustments are made for packaging. The mixed reality toolkit (MRTK) by Microsoft is used for streamlined MR app development, integrating essential components like input methods and gestures for cohesive operation with Unity.

This research has established a building information model and a hydraulic model of WSNs based on the CAD drawings and the actual conditions of the specific area's main WSN. Within the hydraulic model, the WSN is abstracted and simplified to include a water source, 12 nodes, and 13 pipe sections (as shown in Figure 4), with detailed information provided in Table 1. The time step for hydraulic simulation is set to 3 h; the simulation is conducted on a daily cycle. The simulation results are shown in Tables 2 and 3, which serve as the basis for visualizing numerical simulation information. In response to the integration and mapping of attribute information, real-time monitoring information, numerical simulation information, and inspection process information for inspection, the system's operational interface is depicted as shown in Figure 5. Firstly, by aligning the virtual model with the physical object using on-site markers, the spatial disconnection between information and the pipeline network is resolved. This directly enhances the readability and comprehensibility of the information (Figure 5a). Secondly, on-site inspectors can interact with the pipeline model through multimodal inputs, such as manual dragging, rotating, moving, and voice-controlled resetting, significantly improving the observation, familiarity, and understanding of WSNs by inspectors, reducing misinterpretations of the pipeline network, and enhancing work efficiency during inspection (Figure 5b). Simultaneously, the integration of multiple sources of information through the model allows for in situ querying of dynamic and static information related to WSNs in the human–machine interaction system developed in this research. This querying utilizes ray-casting, where inspectors point at components in the MR environment to retrieve information, effectively reducing errors caused by miscommunication and manual data entry in traditional systems; therefore, achieving in situ visualization of information in time and space (Figure 5c). Embedding the maintenance guidance process into the system assists inspectors in conducting repair operations using MR devices, effectively freeing their hands, and improving work efficiency (Figure 5d–g). The hydraulic simulation results and the in situ presentation effect are illustrated in Figure 5h.

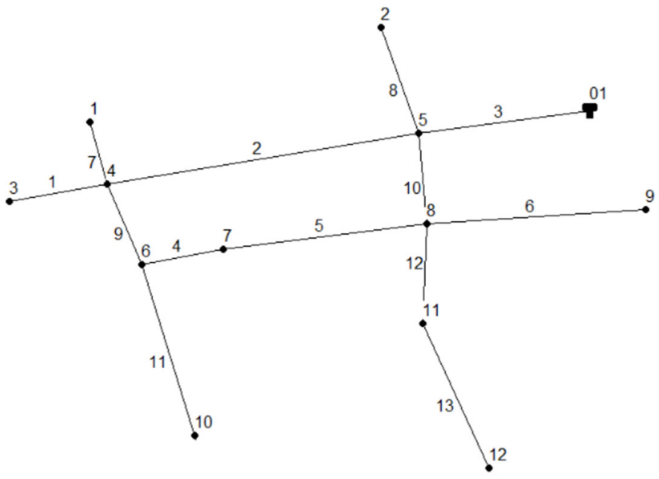


Figure 4. Schematic diagram of WSN nodes and pipeline sections.

Table 1. Basic information of WSNs.

Water Sources and Nodes			Pipeline Sections			
Number	**Elevation(m)**	**Water Demand (LPS)**	**Number**	**Pipe Diameter(mm)**	**Length(m)**	**Roughness Coefficient**
Source 1	10.0961	—	Section 1	800	220	120
Node 1	10.848	0.081	Section 2	200	900	141
Node 2	10.5128	0.073	Section 3	200	525	141
Node 3	4.4417	0.064	Section 4	200	245	141
Node 4	6.3457	0.076	Section 5	300	615	130
Node 5	9.5944	0.053	Section 6	300	570	130
Node 6	5.8553	0.066	Section 7	200	50	141
Node 7	6.0618	0	Section 8	200	225	141
Node 8	0.4527	0.057	Section 9	200	200	141
Node 9	−3.3290	0.063	Section 10	200	270	141
Node 10	8.9291	0.081	Section 11	200	990	141
Node 11	0.6961	0.076	Section 12	200	400	141
Node 12	−4.7443	0.069	Section 13	200	600	141

Table 2. Pressure results of hydraulic simulation of nodes at different time points (m).

Number	**0:00**	**3:00**	**6:00**	**9:00**	**12:00**	**15:00**	**18:00**	**21:00**	**24:00**
Node 1	9.25	9.24	9.24	9.22	9.21	9.2	9.19	9.19	9.19
Node 2	9.58	9.58	9.57	9.56	9.54	9.53	9.53	9.53	9.52
Node 3	15.65	15.65	15.64	15.63	15.61	15.61	15.6	15.6	15.59
Node 4	13.75	13.74	13.74	13.73	13.71	13.7	13.7	13.69	13.69
Node 5	10.5	10.5	10.49	10.48	10.46	10.45	10.45	10.44	10.44
Node 6	14.24	14.24	14.23	14.22	14.2	14.19	14.19	14.18	14.18
Node 7	14.03	14.03	14.02	14.01	13.99	13.99	13.98	13.98	13.97
Node 8	19.64	19.64	19.63	19.62	19.6	19.6	19.59	19.59	19.58
Node 9	23.42	23.42	23.41	23.4	23.38	23.38	23.37	23.37	23.36
Node 10	11.16	11.16	11.15	11.14	11.13	11.12	11.11	11.11	11.11
Node 11	19.4	19.39	19.39	19.38	19.36	19.35	19.35	19.34	19.34
Node 12	24.84	24.83	24.83	24.82	24.8	24.79	24.79	24.78	24.78

Table 3. Flow results of the hydraulic simulation of sections at different time points (LPS).

Number	**0:00**	**3:00**	**6:00**	**9:00**	**12:00**	**15:00**	**18:00**	**21:00**	**24:00**
Section 1	0.03	0.03	0.05	0.08	0.1	0.08	0.07	0.04	0.03
Section 2	0.11	0.09	0.18	0.28	0.34	0.3	0.25	0.16	0.11
Section 3	0.71	0.57	1.13	1.7	2.12	1.84	1.56	0.99	0.71
Section 4	0.07	0.06	0.11	0.17	0.21	0.18	0.15	0.1	0.07
Section 5	0.07	0.06	0.11	0.17	0.21	0.18	0.15	0.1	0.07
Section 6	0.03	0.03	0.05	0.08	0.09	0.08	0.07	0.04	0.03
Section 7	0.04	0.03	0.06	0.1	0.12	0.11	0.09	0.06	0.04
Section 8	0.37	0.29	0.58	0.88	1.1	0.95	0.8	0.51	0.37
Section 9	0	0	0.01	0.01	0.01	0.01	0.01	0.01	0
Section 10	0.2	0.16	0.32	0.48	0.6	0.52	0.44	0.28	0.2
Section 11	0.04	0.03	0.06	0.1	0.12	0.11	0.09	0.06	0.04
Section 12	0.07	0.06	0.12	0.17	0.22	0.19	0.16	0.1	0.07
Section 13	0.03	0.03	0.06	0.08	0.1	0.09	0.08	0.05	0.03



Figure 5. Operation interfaces: (**a**) alignment between model and physical objects, (**b**) multimodal inputs, (**c**) information inquiry, (**d**) detailed information display, (**e**) route guidance, (**f**) maintenance guidelines, (**g**) handling of abnormal situations, and (**h**) visualization of hydraulic simulation information.

Due to the current stage of our research and laboratory conditions, verification is conducted using the Anytown case network to simulate leakage scenarios and validate the proposed method's effectiveness. Real-world deployment for detecting and locating actual leaks is planned for future work. In this research, the Anytown network—a standard hypothetical network widely used in water distribution system studies—is utilized for the analysis and discussion of the combination of monitoring information and simulation information for inspection. As shown in Figure 6, the Anytown network includes 19 user nodes, 40 pipes, 3 reservoirs, and 1 pump. To validate our method, we pre-set leak nodes and leakage coefficients in the Anytown network and utilize the genetic algorithm to identify these leaks. This approach allows us to test the effectiveness of our method in a controlled environment, thereby circumventing the situation where insufficient precision of real sensor data leads to an inability to locate the leak position at this stage.

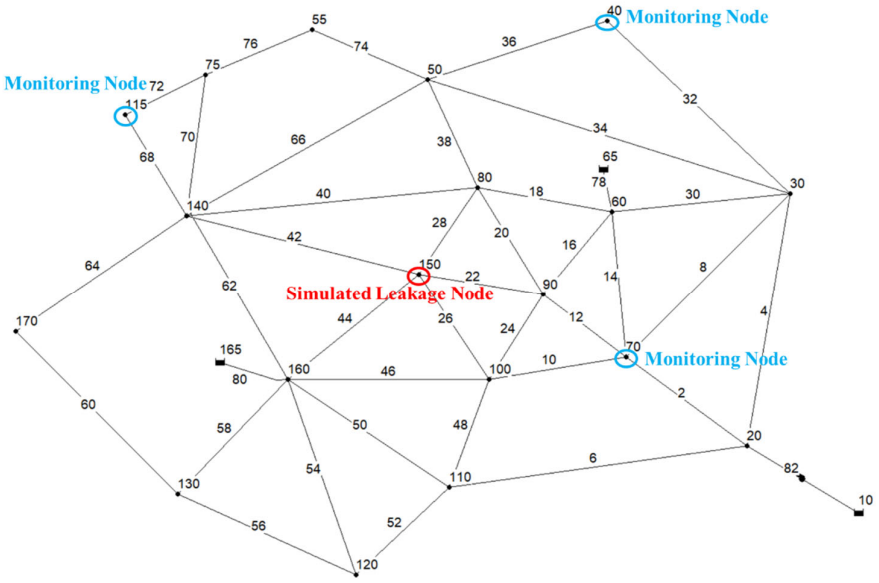


Figure 6. The monitoring nodes and the simulated leakage node in the case network Anytown.

The genetic algorithm parameters were selected based on related research and preliminary testing [53,54]. A population size of 40 and 100 iterations provided a balance between computational efficiency and solution quality. Crossover and mutation probabilities were set to 0.3 and 0.1, respectively. The leakage coefficient $K = 0.8L \cdot s^{-1} \cdot m^{-0.5}$ is assigned to node 150 to simulate the condition of leakage, and nodes 40, 70, and 115 were selected as monitoring points. The pressure values of the three monitoring nodes at various time points under the given leakage simulation conditions are shown in Figure 7. By altering the chromosome individuals and conducting hydraulic simulations under leakage conditions, the pressure values at nodes 40, 70, and 115 are obtained as the input for the simulated values $p_{1,n}$.

Based on the previously established theoretical values for the leakage node, during the 20 computational iterations for locating the leak position, the target location and a leak coefficient close to the set values were identified on 18 occasions, as shown in Figure 8. Among these, the 7th and 13th detections were erroneous. This result preliminarily validates the feasibility of using the genetic algorithm for leak detection in WSNs using the MR-based inspection method proposed in this research. However, due to the need for improvement in the number and placement of monitoring points, as well as the consideration of related parameter settings, and the inherent limitations of the genetic algorithm as a heuristic optimization method, this research only considers the feasibility of the method in the laboratory verification phase.

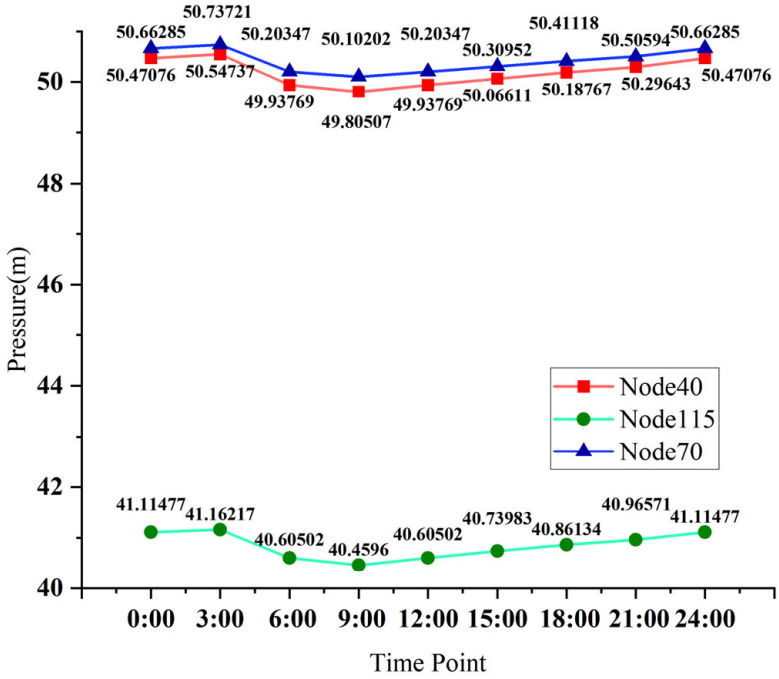


Figure 7. The pressure values of the three monitoring nodes at various time points.

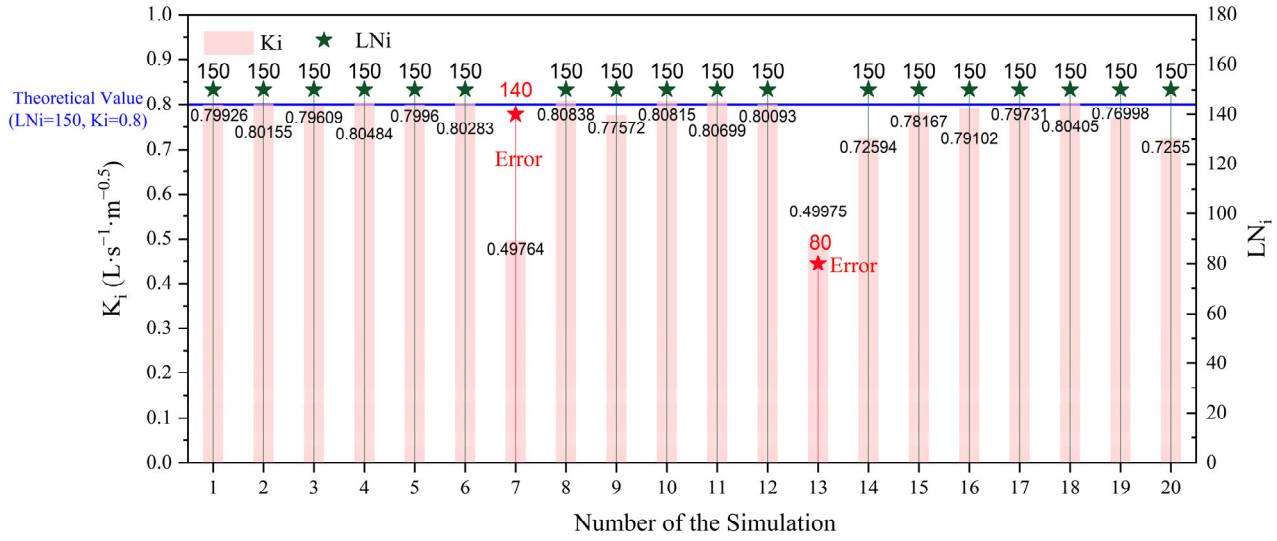


Figure 8. Results of leak detection in 20 trials.

5.2. System Evaluation

Specific inspection tasks were set up to evaluate the method's availability. Twenty participants—ten of whom were graduate students and the remaining ten of whom were professional inspectors—were divided into two control groups, with the graduate students serving as novice inspectors because they had no prior inspection experience. These groups were assigned to perform inspection tasks using either traditional mobile terminals (Method 1) or the MR approach developed in this research (Method 2). The professional inspectors using Method 1 were denoted as 1-P, while those using Method 2 were denoted as 2-P. The graduate students with no inspection experience using Method 1 were denoted as 1-G, and those using Method 2 were denoted as 2-G. The testing scenario assumed a situation in which the pressure monitoring value at a valve in a water supply project exceeded the threshold in a certain area, requiring operators to quickly locate it and accurately identify the specific valve. To achieve this, operators needed to have a thorough understanding of

valve-related information and be able to follow the operational manual to complete specific maintenance tasks. The testing procedure comprises the following steps: (1) Introduction and Demonstration: Initially, the maintenance tasks for this test are introduced, followed by a comprehensive operational demonstration of both traditional mobile terminal operation and the MR device operation developed in this research to all participants involved in the experiment. (2) Training and Practice: The 20 experimental participants are evenly divided into two control groups, receiving detailed training on conducting inspection using handheld mobile terminals and HoloLens 2 for inspection, and engaging in practice sessions within a specified time frame. (3) Task Execution: Participants individually execute the same maintenance task without communicating with each other. (4) Questionnaire Survey: Finally, a five-level Likert scale questionnaire survey was conducted for each experimental participant (as shown in Table 4) to validate the availability of the inspection method proposed in this research. The questionnaire comprises five questions, addressing the overall understanding before formal task execution, performance during task execution, and the overall experience after task completion. Participants are required to rate these five questions on a scale of 1 to 5 ("Strongly Disagree", "Disagree", "Neutral", "Agree", "Strongly Agree"). The final statistical results are represented in a Divergent Stacked Bar chart (as shown in Figure 9), where the bars extend from the center position towards both ends, with the length of each color representing the proportion of respondents selecting that attitude out of the total number of respondents. The numbers within the circles above the bars indicate the average score for each question. It is observed that in terms of advanced understanding of pipeline distribution and multi-source information of the pipeline network, quick comprehension of inspection tasks, improvement in work efficiency and accuracy, as well as standardization, the MR inspection method proposed in this research outperforms the traditional mobile terminal operation method. However, due to the insufficient comfort and battery life of the HoloLens 2, the evaluation of the MR inspection method is lower in terms of comfort.

Table 4. Five-level Likert scal**e.**

Question	Statement	Brief Description
Q1	Before conducting pipeline operations, I can have a good understanding of the distribution and multi-source information of the pipeline network.	current state
Q2	During pipeline operations, I can quickly understand the requirements and purposes of inspection tasks through this method.	inspection tasks
Q3	Using this method, my work efficiency is higher, the likelihood of errors is minimal, and it is easy and intuitive when troubleshooting.	work efficiency and accuracy
Q4	This method exhibits a high level of standardization in the workflow.	standardization
Q5	Working with this method is convenient and comfortable for me.	comfort

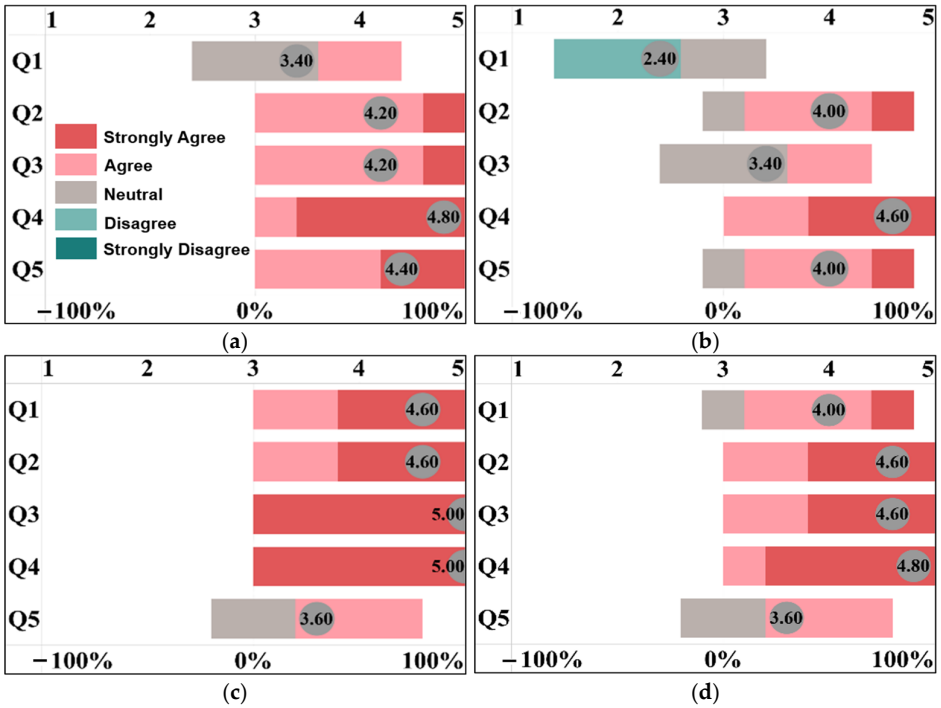


Figure 9. Statistical analysis of survey results using the five-level Likert Scale Questionnaire: (**a**) 1-P (**b**) 1-G, (**c**) 2-P, and (**d**) 2-G.

6. Conclusion and Future Work

6.1. Conclusions

This research developed an MR-based inspection method for underground water supply networks, integrating multi-source information such as BIM, IoT monitoring data, and numerical simulations. The primary conclusions of this study are as follows:

(1) Framework Validation. We proposed a comprehensive MR-based inspection framework and validated its feasibility through two case studies of water supply networks. This framework effectively integrates monitoring information and simulation data, enabling in situ visualization and real-time computational support during the inspection process. By integrating BIM, IoT, and numerical simulations into the MR environment, the framework addresses key challenges in traditional inspection techniques, such as information fragmentation and the spatial disconnect between virtual and physical networks.

(2) Performance Improvements. Preliminary evaluations, combined with user feedback, indicate that compared to traditional mobile terminal-based inspection methods, inspectors can perform tasks more accurately and efficiently, experience reduced cognitive load, and face a lower risk of errors. The capability to visualize information in real time and interact with multi-source data within the MR environment facilitates immediate and direct decision-making, thereby enhancing the overall effectiveness of leak detection and fault identification.

6.2. Future Work

To build upon the findings of this research and address its limitations, future research could focus on the following areas: (1) 3D data acquisition methods. These methods could greatly enhance the creation and updating of MR models, especially in challenging infrastructure contexts, by providing a more efficient and accurate source of data for WSNs model creation and dynamic updating. With the integration of these technologies, digital twins in MR environments would reflect real-world conditions more accurately and in real time, further improving inspection accuracy and reliability. (2) Advanced simulation algorithms. Integrate more sophisticated simulation algorithms and optimize

the placement and density of monitoring sensors to enhance the precision and reliability of leak detection; (3) Field testing and validation. Conduct extensive field testing in various real-world scenarios to validate the system's effectiveness and adaptability across different environments and conditions. By addressing these areas, future work can further improve the practical applicability, user experience, and overall effectiveness of MR-based inspection methods for underground WSNs.

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