Full Length Article

Digital twin-based resilience evaluation and intelligent strategies of smart urban water distribution networks for emergency management

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A R T I C L E   I N F O

A B S T R A C T

Resilient smart urban water distribution networks are essential to ensure smooth urban operation and maintain daily water services. However, the dynamics and complexity of smart water distribution networks make its resilience study face many challenges. The introduction of digital twin technology provides an innovative solution for the resilience study of smart water distribution networks, which can more effectively support the network's real-time monitoring and intelligent control. This paper proposes a digital twin architecture of smart water distribution networks, laying the foundation for the resilience assessment of water distribution networks. Based on this, a performance evaluation model based on user satisfaction is proposed, which can more intuitively and effectively reflect the performance of urban water supply services. Meanwhile, we propose a method to quantify the importance of water distribution pipes' residual resilience, considering the time value to optimize the recovery sequence of failed pipes and develop targeted preventive maintenance strategies. Finally, to validate the effectiveness of the proposed method, this paper applies it to a water distribution network. The results show that the proposed method can significantly improve the resilience and enhance the overall resilience of smart urban water distribution networks.

1. Introduction

In recent years, building resilient and safe cities, enhancing urban resilience, and improving risk resistance have become key themes in contemporary urban construction and management [1]. The water distribution networks (WDNs), as one of the basic lifeline systems of a city, are a vital cornerstone of a resilient city [2]. The WDNs are pivotal in providing essential water services to residents, industries, and businesses, with their regular operation being directly linked to the quality of life for urban residents and the seamless functioning of economic activities. With the rapid development of sensor technology and Internet of Things (IoT) technology, smart WDNs are gradually being constructed to provide a new guarantee for urban water supply services. However, the complexity and dynamics of smart WDNs make its resilience study face many challenges, especially when facing various emergencies and system failures. To cope with these challenges, applying digital twin (DT) technology in smart WDNs has become a promising solution [3]. By creating real-time digital replicas of the physical WDNs, DT technology enables continuous monitoring of key components, facilitates intelligent anomaly detection, and supports predictive maintenance. This allows water companies and city administrators to proactively manage disruptions, optimize the resilience of WDNs, and ensure quick recovery

in case of failures, ultimately enhancing the overall reliability and efficiency of the water distribution system. Therefore, city administrators and water companies must integrate DT technology into their strategies to reinforce the resilience of WDNs and ensure their sustained operation.

DT technology builds a "digital model" by integrating and analyzing data from real systems, such as WDNs [4]. This digital model allows for realistic simulation and analysis based on real-time data acquired from physical systems to support decision-making and help achieve more accurate and efficient management [5]. DT technology has become an important and emerging research topic in urban water supply services [6]. Singh et al. [7] proposed a DT framework for applying leakage detection technology for leakage detection in large-scale WDNs. Sergi et al. [8] implemented two DT prototypes to effectively predict failures of pumping stations in WDNs and monitor water quality, which significantly improved the networks' operational efficiency and management quality, highlighting the great potential of DT technology in WDNs management innovation. Dodanwala and Ruparathna [9] created a service level assessment framework based on DT technology for monitoring and managing the service level of drinking water infrastructure systems.

The concept of "resilience" was first introduced by Holling [10] and applied to ecosystem studies. Subsequently, it was gradually applied to various fields, including social, economic, power, transportation, and

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water systems [11–13]. The resilience of WDNs is primarily evaluated through energy-based and topology-based approaches. Todini [14] was the first to introduce the concept of "resilience" into WDN research, defining it as the network's energy redundancy, or its capacity to withstand destructive events, from an energy standpoint. Subsequently, numerous studies have investigated WDN resilience using energy-related indicators [15–18]. However, while focusing on the network's overall performance, this energy-based approach may overlook individual consumers' particular requirements. In contrast, Yazdani et al. [19] have applied graph theory to model WDNs, quantifying their redundancy and failure tolerance. Similarly, Herrera et al. [20] have employed graph-based parameters to assess resilience. Archetti et al. [21] propose that algebraic connectivity and spectral gap are the most relevant graph-theory-based metrics, especially for assessing the overall resilience of WDNs in the face of physical disconnections caused by pipe bursts. Li et al. [22] have introduced a novel edge-betweenness topological metric for evaluating the seismic resilience of WDNs. Topology-based methods do not rely on complex flow analyses and are, therefore, more suitable for assessing the resilience of large WDNs. However, topology-based methods may not accurately reflect the actual operation of WDNs. In addition, the resilience of WDNs is a dynamic process, and network characteristics (such as topology and flow direction) may change. Therefore, a resilience assessment index based only on topological indicators may not fully reflect the changes that occur in the WDN during the recovery process [23].

Rapid recovery of system performance is a key focus in resilience optimization. For example, Mazumder [24] proposed a recovery decision method based on maximizing cumulative recoverability, which guides the maintenance sequencing of failed pipes to recover system performance and improve system resilience quickly. Li et al. [22] further proposed an evaluation method that combines performance recovery and node importance to guide the repair of failed pipes. It can be seen that the key to rapid recovery of system performance is ensuring the rapid recovery and maintenance of critical system components after a failure, especially when resources are limited. Therefore, developing efficient recovery strategies and preventive measures for critical components has become indispensable to resilience management [25,26]. Many studies have focused on resilience optimization methods based on component importance, which aim to identify critical components and potential weaknesses in the system. Barker et al. [27] proposed two measures of component importance to assess the criticality of system components in terms of fragility and recoverability. Similarly, Wu et al. researchers [28] developed an importance metric for prioritizing preventive maintenance to optimize the maintenance strategy of components.

In view of the above literature review and existing deficiencies, this study proposes a resilience evaluation model for WDNs based on DT technology to open up new perspectives for resilience research. Firstly, this study constructs a digital twin architecture of smart WDNs to realize real-time monitoring and intelligent control of WDNs. This provides the basis for studying large-scale WDN resilience. Next, a model for assessing the performance of WDNs based on user satisfaction is proposed, which can show the level of urban water supply services more intuitively and effectively. Finally, this study develops a quantitative method that considers the time value for assessing the residual resilience importance of water distribution pipes to determine the optimal recovery sequence of failed pipes and the implementation targets of preventive strategies.

The rest of this paper is organized as follows. Section 2 details the construction of the digital twin architecture of smart WDNs and describes the problems and pipe failures of the WDNs. Section 3 establishes the resilience assessment model of WDNs. Section 4 proposes a resilience importance measure for water distribution pipes and then gives the resilience optimization strategies. Section 5 investigates the changes in the performance and resilience of the WDN under different recovery and preventive strategies through a case study. Finally, the conclusion is summarized in Section 6.

2. DT architecture and description of smart WDNs

2.1. DT architecture of smart WDNs

Digital twin WDNs leverage digital technologies to create a real-time virtual model of water systems for simulating, monitoring, analyzing, and optimizing WDN operations. Integrating sensor data, IoT, big data analytics, AI, and other technologies reflects the real-time state and behaviour of the actual network. The DT model enables dynamic management, predicts future trends, detects potential issues, and optimizes operational efficiency. A typical architecture consists of four layers: the perception layer, data layer, platform layer, and application layer, as shown in Fig. 1.

As the digital twin WDNs' foundation layer, the perception layer collects data from the actual WDNs. By deploying sensors, meters, and other sensing devices, this layer can collect key data such as water flow, pressure, temperature, pipe status, valve position, and water quality in real-time and monitor the status of the WDNs in real time to detect problems such as pipe leakage and burst. In addition, the perception layer can also collect external environmental information, such as weather data and changes in water demand, thus providing comprehensive data support and environmental perception capabilities for the operation of the WDNs.

The data layer plays a central role in the digital twin WDNs and is responsible for storing, managing, and processing the raw data collected from the perception layer. It stores real-time data such as flow rate, pressure, and equipment status in a database while performing data integration and cleansing to guarantee data consistency and acritical accuracy. In addition, the data layer provides a solid data foundation for subsequent data analysis, modelling, and machine learning to support deeper data processing and decision-making.

As the core of the digital twin WDNs, the platform layer is responsible for in-depth analysis, modelling, simulation, and intelligent decision-making optimization. It simulates the operation status of the WDNs in different scenarios by constructing a DT model, conducts in-depth analysis and processing of the data collected in the perception layer and the data layer, and provides intelligent decision-making support for water supply scheduling, resource allocation, and failure early warning by applying techniques such as machine learning and data mining, to ensure the optimal operation and efficient management of the WDNs.

The application layer is indeed the key endpoint of the digital twin WDNs, which translates the complex analytics of the platform layer into concrete operations and strategies covering a wide range of aspects such as decision support, resource scheduling, WDNs resilience optimization, emergency management, and intelligent control. This layer provides data insights through decision support to help managers optimize system operations based on real-time monitoring and analysis. The resource scheduling function dynamically allocates pumps, pipes, and other resources to ensure efficient system operation and respond to fluctuations in demand or equipment failures. Using DT technology, the WDN resilience optimization function evaluates and improves system design and operation and maintenance strategies to enhance the ability to respond to emergencies. The emergency management function monitors the status of the network in real-time, quickly identifies risks, and implements contingency plans to mitigate the impact of disasters. Intelligent control ensures the system operates optimally based on real-time data by automatically adjusting equipment to provide stability and reliability.

In short, using DT technology to build a digital twin WDNs can achieve real-time monitoring of critical pipes, failure prevention, and targeted maintenance to enhance the WDNs' resilience. It can also optimize the decision-making and emergency response capabilities through visual management to ensure system stability is quickly recovered in the face of unforeseen events.
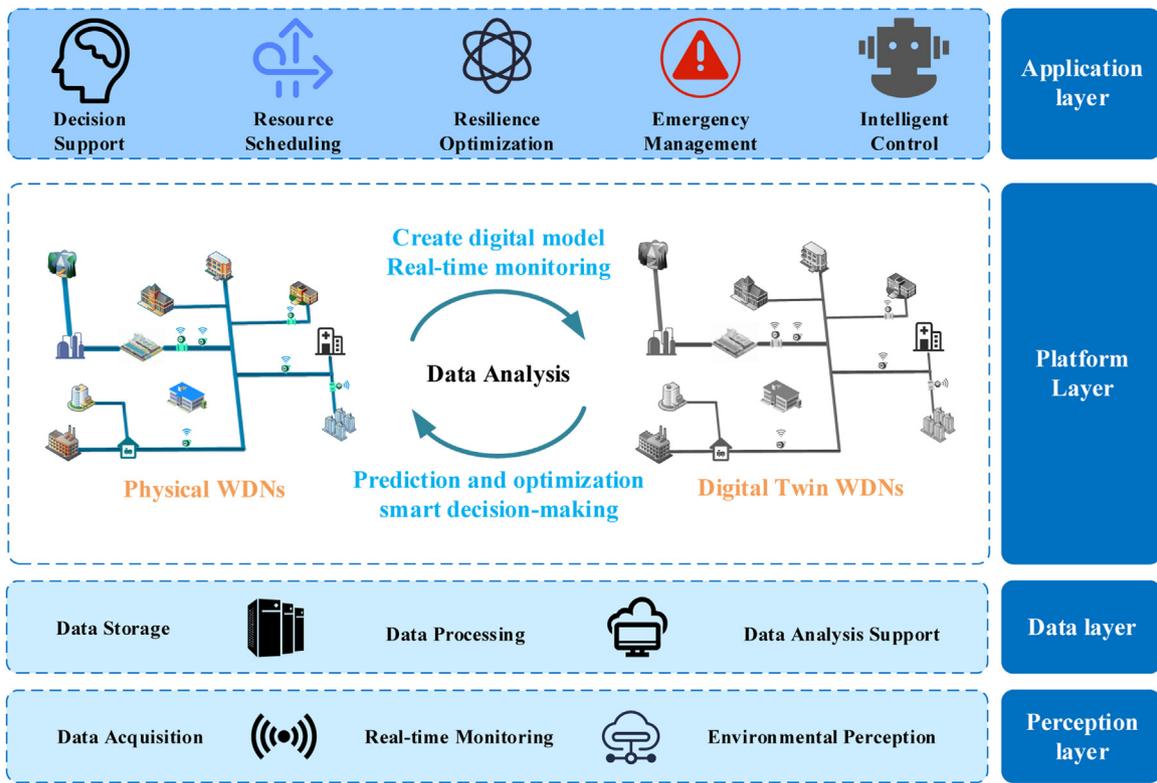
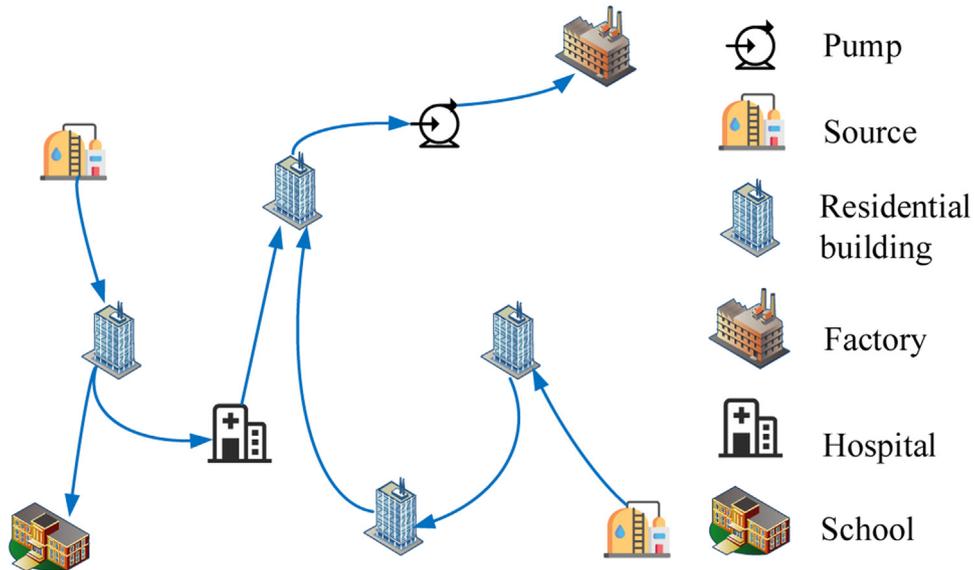**Fig. 1.** The digital twin architecture of smart WDNs.

Fig. 2. Schematic diagram of WDNs.

2.2. Smart WDNs description

WDNs distribute water from limited sources to different areas. These networks have a complex topology and extensive coverage, forming a complex network of numerous nodes and edges. In WDNs, nodes include supply nodes and demand nodes. The supply nodes, which provide water, typically consist of reservoirs, water treatment plants, and similar network facilities. The demand nodes are primarily water-intensive areas such as residential districts, factories, and hospitals. These nodes receive water input and function as water output, distributing water to downstream nodes. The pipes connecting these nodes form the edges of WDNs. Fig. 2 shows a schematic diagram of WDNs.

In the study of WDNs, supply nodes can be considered as special "demand nodes" with a negative demand. Therefore, the directed graph $G(V, E)$ can represent the demand nodes, water distribution pipes, and flow direction in the WDNs, which V denotes the set of all nodes in the graph, $V = \{1, 2, \cdots, N\}$, which N represents the number of nodes. E denotes the set of edges between nodes, $E = \{e_{ij} | i \in V, j \in V, ij\}$, which e_{ij} represents the flow of water from node i to node j through pipe l. The state of any two nodes in the WDN can be represented by the adjacency
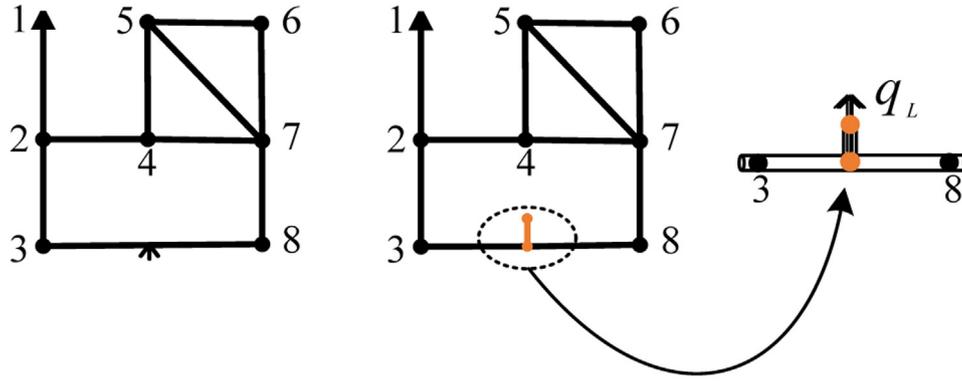
Fig. 3. Pipe leakage failure.

matrix as shown in Eq. (1).

$$A = \left[a_{ij}\right]_{N \times N} = \begin{bmatrix} a_{1,1} & a_{1,2} & & a_{1,N-1} & a_{1,N} \\ a_{2,1} & a_{2,2} & & a_{2,N-1} & a_{2,N} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ a_{N-1,1} & a_{N-1,2} & & a_{N-1,N-1} & a_{N-1,N} \\ a_{N,1} & a_{N,2} & & a_{N,N-1} & a_{N,N} \end{bmatrix} \quad (1)$$

If water flows from node i to node j, $a_{ij} = 1$, if water flows from node j to node i, $a_{ij} = -1$, otherwise, $a_{ij} = 0$.

Water distribution pipes are one of the most essential water distribution system components. It connects supply nodes with demand nodes, as well as demand nodes with each other, ensuring that WDNs can effectively satisfy the water demand of urban residents. As China's urbanization process continues to accelerate, the mileage of water distribution pipes is increasing year by year, the coverage is expanding, and the complexity of the network structure is growing exponentially. Additionally, some areas' water distribution pipes face issues such as long service life, outdated materials, and severe aging and corrosion of the pipes. Consequently, failures in the water distribution pipes are unavoidable in the daily operation of the WDNs. These failures significantly affect users' satisfaction with their daily water supply. Among them, leakage and burst are the two most common types of pipe failure.

When leakage occurs in the water distribution pipes, the delivery capacity of the pipes decreases, resulting in a reduced actual water supply to downstream nodes. In the analysis of leakage in water distribution pipes, the leakage scenario can be simulated by adding virtual nodes and virtual pipes to the pipe with the leakage, as shown in Fig. 3.

The virtual node is located at the midpoint of the failed pipe, with its elevation being the average of the elevations of the two end nodes of the pipe. The node flow of the virtual node is equal to the leakage flow of the failed pipe. The length and roughness coefficient of the virtual pipe are set to 1 m and 10^6, respectively, and the cross-sectional area of the virtual pipe is equal to the leakage area of the failed pipe. Finally, the virtual flow is substituted into the node flow balance equation, and the modified node flow balance equation is shown in Eq. (2) [29]:

$$\sum_{i \in \phi} q_{ij} - \left(\sum_{k \in \varphi} q_{jk} + q_j + q_L \right) = 0 \quad (2)$$

where ϕ denotes the set of upstream nodes connected to node j, φ denotes the set of downstream nodes connected to node j, q_{ij} denotes the flow from node i to node j, q_{jk} denotes the flow from node j to node k, q_j is the flow at node j, and q_L is the leakage flow, which can be quantified through a modified leakage model, as shown in Eq. (3) [30]:

$$q_L = 0.6 C_L A_L \sqrt{2g H_L} \quad (3)$$

where C_L is the leakage coefficient, which ranges from 0.1 to 0.3 (in this paper, it is set to 0.3), A_L is the leakage area, g is the acceleration due to gravity, and H_L is the head at the virtual node.
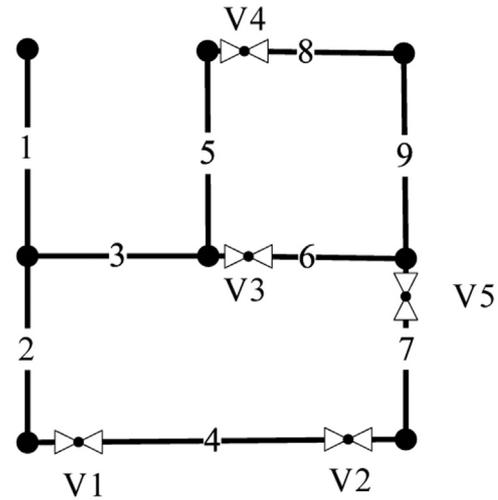

Fig. 4. Typical valve installation in WDNs.

Compared to water distribution pipe leakage, pipe burst occurs less frequently. However, a pipe burst can cause a water supply interruption at nearby nodes, which causes significant losses to the performance of the WDNs. Therefore, swift action should be taken in an emergency involving a pipe burst to isolate the failed pipe to prevent more severe consequences. Compared with traditional WDNs, smart WDNs use advanced DT technologies and IoT technologies to achieve real-time data collection, status monitoring, and automated control of the WDNs [31–33]. Using these technologies, the smart WDNs can sense information about pipe burst failures in real-time and remotely close automated valves to isolate the burst pipe [34]. In practice, the number of valves in WDNs is limited, typically installed only on critical pipes. When a section of pipe bursts, it may not have enough valves for direct isolation. In other words, the burst pipe might lack sufficient valves to isolate the failure, necessitating the closure of valves on adjacent pipes to isolate the failure. This requires a valve closure strategy based on the depth-first search to isolate the failed pipe, aiming to reduce pipe bursts' impact on the WDNs' performance. The typical valve installation methods in WDNs are illustrated in Fig. 4.

As shown in Fig. 4, valve installation in the WDNs mainly falls into three types: valves installed at both ends of the pipe, valves installed at only one end, and no valves installed on the pipe. For these three different valve installation methods, corresponding valve closure strategies are required to address pipe failures:

(1) Valves installed at both ends of the burst pipe: The valves at both ends of the failed pipe should be closed immediately to isolate

the pipe. For example, in Fig. 4, pipe 4 bursts can be isolated by closing V1 and V2.

(2) Valves installed at only one end of the burst pipe: The valve at the end of the burst pipe should be closed first. Then, a depth-first search should be performed on all pipes connected to the node at the other end of the burst pipe. Start the search with one adjacent pipe until all valves are found and closed. Then, proceed to the next adjoining pipe. The search continues until all adjacent pipes have been searched and the failed pipe is isolated. For example, if pipe 6 bursts, first close V3. Then, close the V5 on pipe 7, which is adjacent to the node at the other end of pipe 6. Next, search the adjacent pipe 9, which has no valve, and continue to search pipe 8. Close V4 on pipe 8 to complete the isolation of the failed pipe 6.

(3) No valves installed on the burst pipe: Perform a depth-first search on the pipes connected to both ends of the failed pipe until all adjacent pipes have been searched and the failed pipe is isolated. For example, if pipe 9 bursts, search all adjacent pipes, pipe 6, pipe 7, and pipe 8, and close their respective V3, V5, and V4 to isolate the failed pipe.

After isolating the failed pipe, all affected pipes and nodes are removed from WDNs. Subsequently, the hydraulic analysis is conducted again to determine the flow rates and heads at each demand node.

3. Resilience evaluation of smart WDNs

WDNs are a crucial component of urban infrastructure and are vital to ensuring residents' quality of life and public safety. Their core objectives are to ensure the continuity, safety, and reliability of water supply services and to satisfy the daily water demand of residents. When evaluating the performance of WDNs, it is essential not to focus solely on economic profit. Instead, assessments should be based on the number of satisfied users and the network's capacity to satisfy daily water demand. Residents' water supply satisfaction is a crucial indicator of system performance. In the evaluation process, a residential building or an entire residential area is typically simplified to a single demand node, each representing a certain number of users. This article assumes that q_i^{nor} denotes the normal water demand at node i, and q_i^{act} denotes the actual water supply at node i in WDNs. The actual water supply of the nodes is simulated using pressure-driven analysis. This method assumes that the water flow is static or simplified based only on the pressure field, which is challenging to adapt to dynamic and complex hydraulic systems. However, with DT technology, the pressure-driven analysis can be dynamically adjusted to reflect real-time network conditions through real-time sensor data (such as pressure, flow rate, and pipe status), thereby overcoming the static assumptions and providing more accurate hydraulic simulations. Therefore, the actual water supply at node i is shown in Eq. (4) [35].

$$q_i^{act}(t) = \begin{cases} 0, & P_i^{act}(t) \le P_i^{\min} \\ q_i^{nor}\sqrt{\dfrac{P_i^{act}-P_i^{\min}}{P_i^{nor}-P_i^{\min}}}, & P_i^{\min} < P_i^{act}(t) < P_i^{nor} \\ 1, & P_i^{nor} \le P_i^{act}(t) \end{cases} \tag{4}$$

where P_i^{min} denotes the minimum pressure at node i that satisfies the water supply, and when the water pressure at the node is less than P_i^{min}, no water supply is provided at node i; P_i^{nor} denotes the water pressure that satisfies the normal water demand at node i; $q_i^{act}(t)$ denotes the actual water pressure at node i.

Under normal operating conditions, WDNs are designed to satisfy users' demands at each node. However, in the event of pipe failures, the reduction in hydraulic head diminishes the actual supply flow, affecting users' water demand and leading to a significant decline in user satisfaction at the affected demand nodes. Usually, users are highly dissatisfied with the lack of water supply, and this paper assumes that when the

ratio of actual water supply to normal water demand at a node is below a certain threshold, the user experience of water use at that node is considered to have suffered a serious negative impact. In this case, the user satisfaction of the node is 0. Therefore, the node satisfaction degree (NSD) of any demand node can be expressed as Eq. (5):

$$NSD_i(t) = \begin{cases} 1, & 1 \le \dfrac{q_i^{act}}{q_i^{nor}} \\ \dfrac{q_i^{act}-\mu q_i^{nor}}{(1-\mu)q_i^{nor}}, & \mu \le \dfrac{q_i^{act}}{q_i^{nor}} < 1 \\ 0, & \dfrac{q_i^{act}}{q_i^{nor}} < \mu \end{cases} \tag{5}$$

where $NSD_i(t)$ is the node satisfaction degree at node i at time t. Based on Klise's research [36] and industry experience, the threshold value μ is set to 0.5.

In this paper, the performance of WDNs is defined as the weighted sum of the node satisfaction degree at each demand node within the network, which can be expressed as Eq. (6):

$$P(t) = \sum_{i=1}^{N} \omega_i NSD_i(t) \tag{6}$$

where $P(t)$ represents the performance of the WDNs at time t, ω_i is the weight coefficient for node i, which takes a value between [0, 1] and satisfies $\sum \omega_i = 1$. In this paper, the weight of each demand node is determined by the population it serves. Nodes that cater to critical infrastructure, such as hospitals, schools, and factories, are assigned a higher weight than general demand nodes, effectively considering them as nodes with a larger population. Consequently, the weight of each node can be calculated as shown in Eq. (7):

$$\omega_i = \dfrac{pop_i}{\sum_{i=1}^{N} pop_i} \tag{7}$$

where pop_i denotes the population at node i.

In practical scenarios, the performance of WDNs fluctuates over time, providing the foundation for resilience assessment. Under normal operating conditions, where there are no disruptions due to pipe failures, the performance of WDNs tends to remain relatively stable. However, in the event of pipe failures, the network's performance will deteriorate to a certain degree. After the failure, recovery strategies are implemented to repair it, leading to a gradual recovery of the network's performance until it achieves the desired performance level. Fig. 5 depicts the changes in network performance before, during, and after the occurrence of pipe failures.

In Fig. 5, there are three key points: t_1 (failure occurs), t_3 (recoveries begins), and t_4 (recovery completes). Therefore, the performance changes of WDNs can be broadly categorized into the following stages:

Stage 1: Normal Operation. During the period $t \in (0, t_1)$, WDNs function normally, maintaining a stable state. The flow at each node satisfies the user demand, and the system performance of the network is P_0.

Stage 2: Performance Degradation. Pipe failures occur at the time t_1. With the help of DT and IoT technologies, it is possible to quickly locate the failed pipe and close the valves around the burst pipe. The performance of the WDNs drops dramatically after the valves are shut down. Subsequently, the WDNs will be re-distributed hydraulically. During this process, the network's performance will gradually decrease and is expected to stabilize at the lowest performance level, $P_{\min}$, at time t_2. During the period $t \in (t_2, t_3)$, it is considered recovery response times, which refer to the period from the time the water utility receives a report of a failure to the time a repair crew is dispatched to arrive at the site and complete the preparations before recovery.

Stage 3: Performance Recovery. During the period $t \in (t_3, t_4)$, the performance of WDNs progressively improves as the failed pipes are repaired. By the time t_4, when the recovery is fully completed, the performance of the WDNs has returned to its initial level.
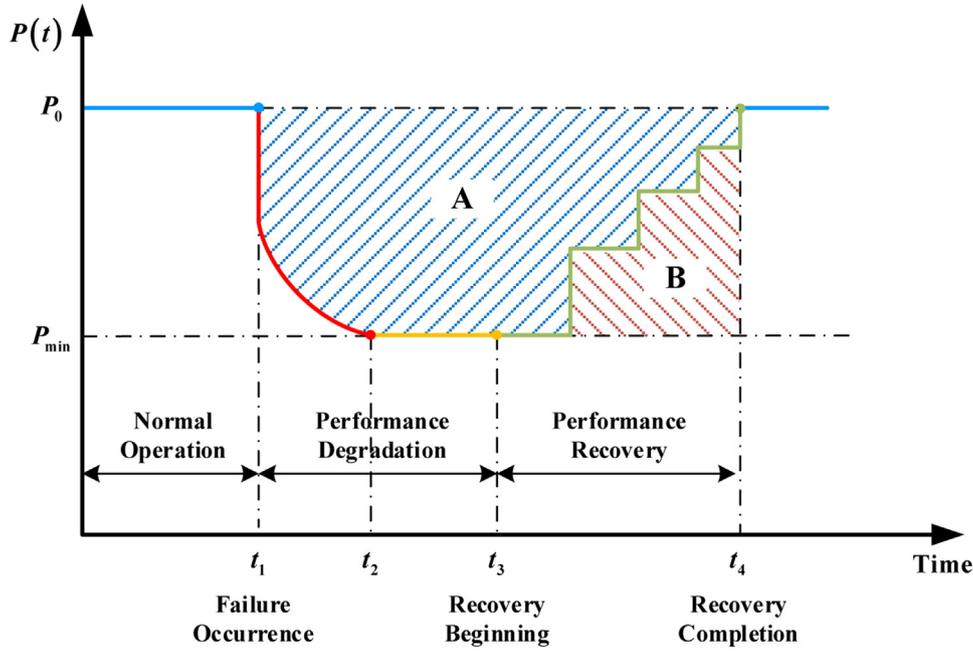
Fig. 5. Performance changes of WDNs.

Resilience assesses a system's capacity to resist disturbances from natural or human-induced events [37]. Resilience can be conceptualized regarding system attributes such as reliability, robustness, recoverability, and redundancy. Balut et al. [38] defined the resilience of WDNs as the capability to restore all operational functions and promptly deliver safe drinking water in the aftermath of a significant disruption. This paper introduces the notion of residual resilience by examining the residual loss performance of WDNs. It defines the resilience of WDNs as the ability of WDNs to resist, adapt to, and swiftly revert to normal and stable operations following a catastrophe. The residual resilience $R(t)$ is described as the ratio of residual loss value to loss value, as depicted in Eq. (8).

$$R(t) = \frac{loss(t) - recovery(t)}{loss(t)} = 1 - \frac{\int_{t_1}^{t_4} (P(t) - P_{\min}) dt}{\int_{t_1}^{t_4} (1 - P_{\min}) dt} \quad (8)$$

where $R(t)$ represents the residual resilience of WDNs, with a value range of $[0, 1]$, $loss(t)$ represents the loss value of WDNs, with the area A in Fig. 5 quantifying the cumulative loss value, $recovery(t)$ represents the recovery value of WDNs, with the area B in Fig. 5 quantifying the cumulative recovery value, and $P(t)$ is the performance function of WDNs. A smaller residual resilience value indicates better network performance, and the closer $R(t)$ is to 0, the more effective the performance recovery of WDNs.

4. Intelligent strategies of WDNs based on resilience importance

Determining the relative importance of various water distribution pipes and prioritizing resource allocation to those of higher importance is paramount for enhancing the robustness and resilience of WDNs. Consequently, evaluating the importance of pipes constitutes a critical step in optimizing the resilience of WDNs and is essential for guaranteeing stable operation and optimizing the performance of these networks.

4.1. The resilience importance of WDNs

Dui et al. [39] applied the minimum residual resilience model across various importance measures. Then, they introduced the OPT residual resilience importance measure, the Birnbaum residual resilience importance measure, the RRW residual resilience importance measure, and

the RAW residual resilience importance measure. These measures assess the potential impact of system component recovery on residual resilience from different perspectives. Building upon this, this paper introduces a method for quantifying the residual resilience importance of water distribution pipes. The proposed method considers the time value based on the Birnbaum residual resilience importance to measure the influence of alterations in the state of water distribution pipes on the residual resilience of WDNs.

The state τ_l of the water distribution pipe l within WDNs is defined as Eq. (9):

$$\tau_l = \begin{cases} 0, & Normal\ operation \\ 1, & Leakage \\ 2, & Burst \end{cases} \quad (9)$$

When the state of water distribution pipes undergoes a change, the loss and recovery values of WDNs respond differently. The residual resilience importance of the pipe can be quantified as the rate of change in residual resilience per unit time before and after the repair of the pipe within the recovery time T, that is Eq. (10):

$$I_l^{RR}(t) = \frac{\min R\left(T \mid \sum_{t=1}^{T} \tau_l(t)0\right) - \min R\left(T \mid \sum_{t=1}^{T} \tau_l(t)=0\right)}{T_l} \quad (10)$$

where $I_l^{RR}(t)$ represents the residual resilience importance value of the failed pipe l within the networks, $\min R(T \mid \sum_{t=1}^{T} \tau_l(t)0)$ represents the minimum residual resilience value of WDNs within the recovery time T when none of the failed pipes have been repaired, $\min R(T \mid \sum_{t=1}^{T} \tau_l(t) = 0)$ represents the minimum residual resilience value of WDNs within the recovery time T when only the failed pipe l is successfully repaired, and T_l represents the time required to repair the failed pipe l.

Therefore, the residual resilience importance of the leakage pipes is expressed as Eq. (11):

$$I_l^{RR}(t) = \frac{\min R\left(T \mid \sum_{t=1}^{T} \tau_l(t)=1\right) - \min R\left(T \mid \sum_{t=1}^{T} \tau_l(t)=0\right)}{T_l} \quad (11)$$

where $\min R(T \mid \sum_{t=1}^{T} \tau_l(t) = 1)$ represents the minimum residual resilience of WDNs when pipe l is in a state of leakage, and no failed pipes have been repaired within the recovery time T.

The residual resilience importance of the burst pipes is expressed as Eq. (12):

$$I_l^{RR}(t) = \frac{\min R\left(T \mid \sum_{t=1}^{T} \tau_l(t)=2\right) - \min R\left(T \mid \sum_{t=1}^{T} \tau_l(t)=0\right)}{T_l} \tag{12}$$

where $\min R(T \mid \sum_{t=1}^{T} \tau_l(t) = 2)$ represents the minimum residual resilience of WDNs when pipe l is in a state of burst, and no failed pipes have been repaired within the recovery time T.

4.2. intelligent strategies

The strategies for optimizing system resilience can be roughly divided into three categories based on the timing of their implementation: preventive strategies before disturbances occur, response strategies during disturbances, and recovery strategies after disturbances. Given the intricate network topology, extensive coverage, and subterranean nature of WDNs, it is often challenging to swiftly implement effective resilience optimization strategies when disturbances occur. Therefore, this paper concentrates on resilience optimization strategies for WDNs before and after disturbances occur.

4.2.1. Preventive strategies

Implementing an effective preventive strategy can significantly enhance the resistance of WDNs against pipe failures, mitigating the detrimental effects on network performance and maintaining a higher level of overall performance even in the aftermath of failures. Nevertheless, comprehensive preventive strategies across the entire water distribution system can be costly and logistically challenging. Therefore, it is advisable to prioritize preventive strategies for critical pipes that substantially influence the network's performance. The prevalent preventive strategies for water distribution pipes encompass two primary types:

(1) Adding valves

During the routine operation of WDNs, a pipe burst necessitates the immediate isolation of the affected pipe. This is typically achieved by closing the valve on the failed pipe. However, in large-scale WDNs, there may be insufficient valves directly on the pipes to isolate the burst effectively. In such cases, valves on adjacent or more distantly located pipes must be closed, leading to disruptions in water distribution to neighbouring water demand nodes and a subsequent decrease in the performance of WDNs. Therefore, strategically adding valves to water distribution pipes with high residual resilience importance within WDNs can effectively reduce the isolation range of bursts, thereby diminishing their adverse impact on the residual resilience of the WDNs.

(2) Adding redundant pipes

Establishing redundant pipes for the demand nodes located downstream of water supply pipes with high residual resilience importance diminishes the probability of service interruptions in the WDNs due to a single pipe failure. In scenarios where the WDNs are exposed to attacks or natural disasters that lead to pipe leakage or burst, the redundant pipes can seamlessly assume the functions of the damaged pipes, thereby maintaining water distribution to critical areas. This strategy enhances the system's redundancy, ensuring that the water demands of residents and essential infrastructure can be satisfied even during emergencies.

4.2.2. Recovery strategies

In the event of multiple water distribution pipes failing within WDNs, the performance of WDNs is compromised, and it becomes challenging to fulfil the normal water demands of users. Therefore, establishing an efficient recovery sequence is imperative to allocate available repair resources to the failed pipes that significantly influence the network's performance. This approach facilitates the swift recovery of network functionality, enhancing the networks' performance while minimizing the residual resilience.
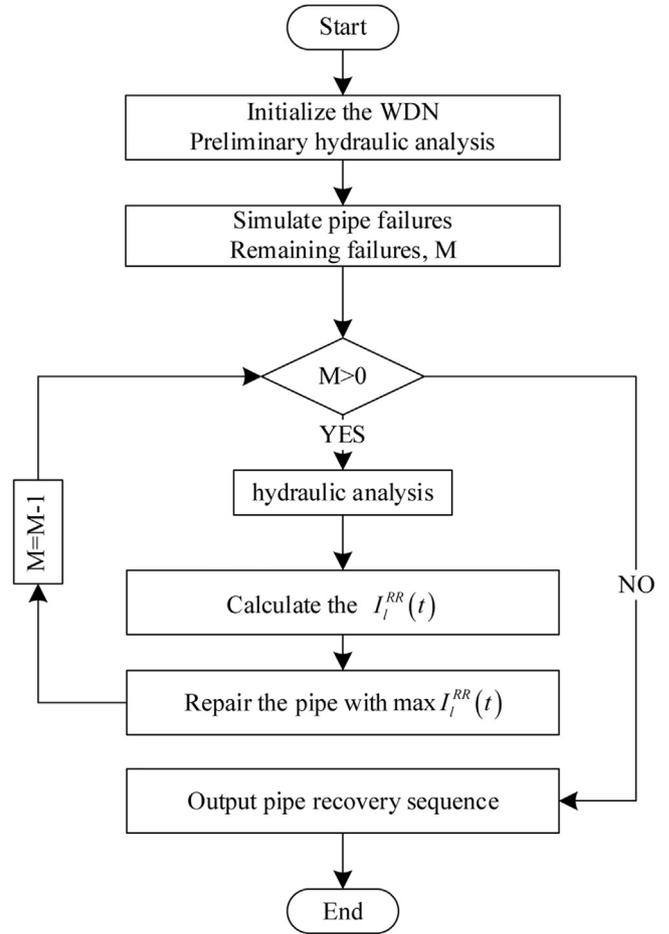

Fig. 6. Dynamic recovery process.

The recovery process of the failed pipes in the WDNs is dynamic. As each failed pipe is repaired, the WDNs undergo hydraulic redistribution, leading to fluctuations in the residual resilience importance of the remaining failed pipes. In response to these dynamic changes, this paper proposes a dynamic recovery strategy based on the residual resilience importance of water distribution pipes. The illustration of this dynamic recovery process is depicted in Fig. 6.

Step 1: Initialize the WDN, input the initial parameters of each component in the network, construct the water distribution network model, and perform a preliminary hydraulic analysis.

Step 2: Simulate water distribution pipe failures and identify the types and quantities of failures.

Step 3: Perform a hydraulic analysis simulation of the WDN after the pipe failures and calculate the residual resilience importance of the failed pipes.

Step 4: Identify and repair the pipe with the highest residual resilience importance, then return to step 3 until all the failed pipes have been repaired.

Step 5: Output the recovery sequence of the failed pipes based on the order of repairs determined in Step 4.

Fig. 6 shows the dynamic recovery process based on residual resilience importance. In each iteration, the decision-making step consists of identifying the pipe with the highest residual resilience importance based on hydraulic analysis and failure simulation, which can involve significant computational effort. In order to address the data processing needs of large WDNs, the introduction of digital twin technology is crucial. This technology is used in conjunction with automated optimization tools such as genetic algorithms, particle swarm optimization

Table 1
Node data.

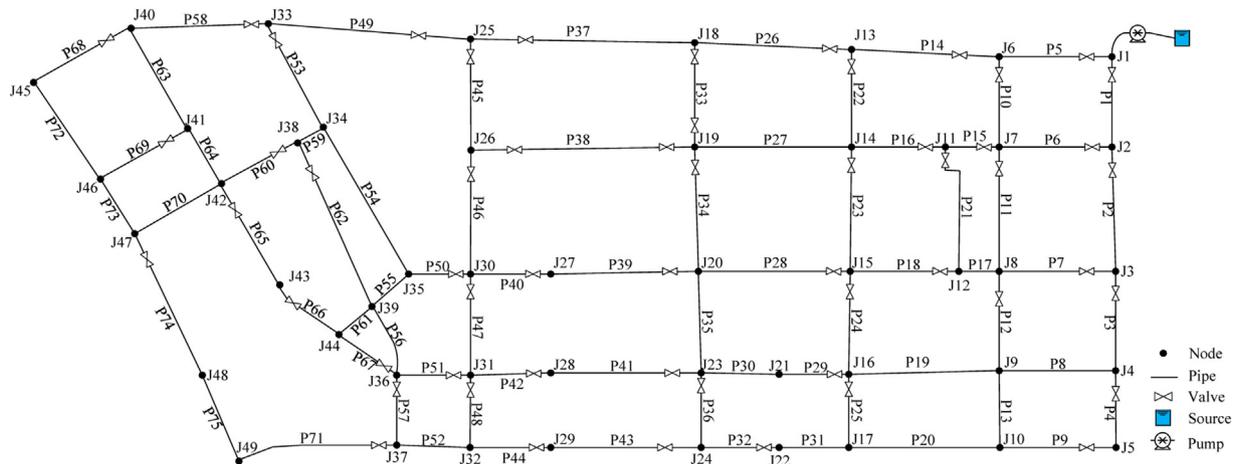| Node ID	Elevation (m)	BaseDemand (L/s)	Node ID	Elevation (m)	BaseDemand (L/s)
J1	84	9.4	J26	90.6	8.95
J2	84	9.4	J27	91	65
J3	84.5	5.17	J28	91.5	7.52
J4	85	8.93	J29	92	122.2
J5	85	12.22	J30	92.5	7.99
J6	84.6	9.4	J31	93	11.75
J7	84.9	11.28	J32	93.5	6.58
J8	85	9.44	J33	93.8	10.34
J9	85.3	8.46	J34	94	13.15
J10	85.6	20.04	J35	94.6	11.28
J11	87	7.52	J36	94.5	8.46
J12	87.1	10.34	J37	94.9	32.2
J13	87.3	8.93	J38	94.8	12.22
J14	88	7.52	J39	95	7.55
J15	88.1	8.95	J40	95.6	10.26
J16	88.6	10.85	J41	95.7	7.95
J17	88.9	9.87	J42	96	11.76
J18	88.9	24.65	J43	96.1	6.58
J19	89	150.4	J44	96.2	7.05
J20	89.3	9.4	J45	97	9.4
J21	89.6	10.81	J46	97.6	12.7
J22	90	11.5	J47	98	9.4
J23	90.2	22.92	J48	97.5	9.4
J24	90.4	10.34	J49	98.8	10.34
J25	91	8			

Fig. 7. Layout of the WDN.

algorithms, and machine learning models, thereby automatically identifying the critical pipes most in need of repair, reducing the computational burden and providing a more scalable solution for large-scale networks.

5. Case study

In this section, a case study is carried out using the WDN shown in Fig. 7, which consists of a water source node, 49 water demand nodes, 75 distribution pipes, and 56 valves. This study simulates and analyzes this network using EPANET 2.2 software. The simulation data is derived from the public data released by Zhengzhou Water Supply Company and combined with the network information collected in real-time by the DT model. On this basis, the data were rationalized and extrapolated to simulate the performance changes of the WDN.

In this WDN, the pipes located in the east (P1-P25) are sections upgraded within the last five years with good hydraulic performance, and the Hazen-Williams coefficient is 130. The other pipes in the WDN have been in use for about 30 years, and due to deterioration, the Hazen-Williams coefficients have been reduced to 90. The node data includes

the node IDs, the demanded amount of water, and the node elevation (see Table 1), and the pipeline data includes the pipe IDs, pipe length, and flow (see Table 2). In addition, the demand water pressure at the node is set to 20 meters.

In this paper, we set different failure probabilities for the old and new pipes and simulate the pipe failures using the Monte Carlo simulation method. In this simulation, we assume the set of failed pipes E_f comprises P9, P20, P32, P36, P41, P46, P51, P54, P65 and P71. Within this set, the subset of burst pipes includes P9, P32, P51, and P71, while the subset of leakage pipes consists of P20, P36, P41, P46, P54, and P65. The detailed data of these failed pipes are shown in Table 3.

According to Eqs. (10)-(12), and following the steps outlined for the residual resilience analysis of water distribution pipes depicted in Fig. 6, the residual resilience importance values for the failed pipes were calculated. The importance values for each failed pipe are shown in Table 4.

As shown in Fig. 8, the residual resilience importance of the failed pipe P9 is the highest, indicating that it exerts the most significant influence on the residual resilience of the WDN. In contrast, the residual resilience importance of the failed pipes P32, P51, and P71 is negative. This anomaly arises due to the hydraulic redistribution within the WDN

Table 2

Pipe data.

Pipe ID	Length (m)	Flow (L/s)	Pipe ID	Length (m)	Flow (L/s)	Pipe ID	Length (m)	Flow (L/s)
P1	300	425.49	P26	540	141.83	P51	250	31.26
P2	400	273.59	P27	520	139.73	P52	260	37.53
P3	300	174.16	P28	520	131.24	P53	390	10.01
P4	300	64.56	P29	240	126.63	P54	590	22.75
P5	380	400.88	P30	270	115.82	P55	170	27.28
P6	380	142.5	P31	240	128.62	P56	240	5.13
P7	380	94.26	P32	250	117.12	P57	250	13.42
P8	380	100.67	P33	370	71.37	P58	450	39.59
P9	380	52.34	P34	430	1.17	P59	100	19.61
P10	300	133.53	P35	330	9.28	P60	300	14.72
P11	400	80.16	P36	250	28.16	P61	150	17.53
P12	300	63.41	P37	760	45.81	P62	630	7.34
P13	300	28.38	P38	750	59.53	P63	390	13.59
P14	520	257.95	P39	500	113.73	P64	230	2.22
P15	180	184.59	P40	250	48.73	P65	400	8.15
P16	340	153.95	P41	500	74.03	P66	270	14.73
P17	150	101.57	P42	250	66.51	P67	200	4.25
P18	380	114.36	P43	520	134.94	P68	380	15.75
P19	500	127.24	P44	260	12.74	P69	340	7.85
P20	500	60.68	P45	400	22.13	P70	330	8.89
P21	500	23.13	P46	430	28.45	P71	540	18.75
P22	360	107.19	P47	340	7.88	P72	425	6.35
P23	400	113.88	P48	250	31.37	P73	210	1.5
P24	340	88.05	P49	700	59.94	P74	530	0.99
P25	250	77.81	P50	200	61.31	P75	310	8.41

Table 3

Detailed data of failed pipes.

Failed Pipe ID	Failed Type	Leakage Area (10^{-4}m^2)	Water Distribution Priority	Repair time(h)
P9	Burst	-	5	7.04
P32	Burst	-	8	8.27
P51	Burst	-	8	7.04
P71	Burst	-	10	8.27
P20	Leakage	16.62	6	4.74
P36	Leakage	18.86	7	4.74
P41	Leakage	27.34	7	6.55
P46	Leakage	19.63	6	5.39
P54	Leakage	15.21	8	5.99
P65	Leakage	13.20	11	4.74

Fig. 8. Resilience importance of each failed pipe during the first repair operation.

following the repair of these pipes and the subsequent opening of the isolation valve. This redistribution leads to an overall increase in network flow, yet the actual flow at the demand nodes near these pipes diminishes. However, the ratio of the actual flow to the normal demand at these nodes falls below the threshold μ, leading to a degradation in the performance of the entire water distribution network. Notably, the residual resilience importance values for pipes P20, P36, and P54 are 0, indicating that repairing these pipes did not enhance the WDN's performance or decrease the network's residual resilience.

Therefore, the initial repair operation is directed towards the failed pipe P9. Following its repair completion, the WDN's performance is elevated to 0.7423, and its minimum residual resilience is established at 0.6714.

By iteratively repeating the above steps until all failed pipes have been repaired, the dynamic recovery sequence based on residual resilience importance is determined to be {P9, P32, P51, P36, P41, P65, P46, P71, P54, P20}.

To substantiate the efficacy of the proposed dynamic recovery strategy, which is contingent upon the residual resilience importance value of failed pipes (recovery strategy 1), a comparative analysis is conducted against alternative approaches. This comparative study includes a static recovery strategy based on the residual resilience importance values of failed pipes (recovery strategy 2), a recovery strategy based on performance enhancement (recovery strategy 3), and a recovery strategy based on the betweenness centrality of failed pipes (recovery strategy 4). Among them:

(1) The static recovery strategy based on the residual resilience importance of failed pipes arranges the pipes in descending order of
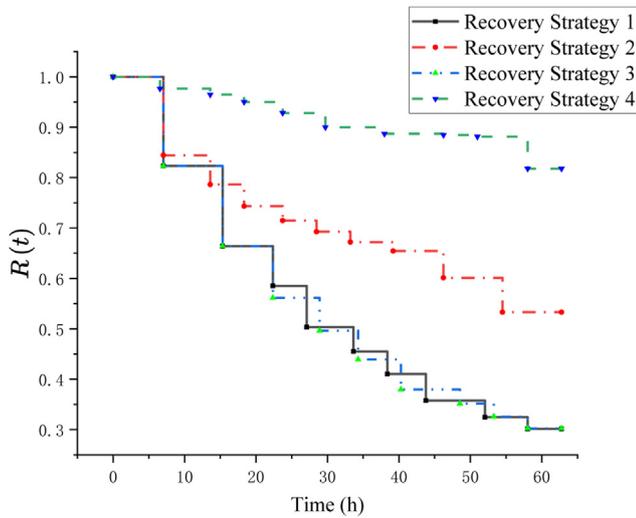
Table 4

Resilience importance of each failed pipe during the first repair operation.

Failed Pipe ID	P9	P32	P51	P71	P20	P36	P41	P46	P54	P65
$I_l^{RR}(t) \times 10^{-3}$	46.67	-1.24	-0.27	-1.78	0	0	7.17	5.79	0	6.28

Fig. 9. The changes in the residual resilience of the WDN.

Table 5
Residual resilience of the WDN under different recovery strategies.

Recovery Strategy	$R(t)$	Reduction ratio(%)
Recovery strategy 1	0.3013	63.15
Recovery strategy 2	0.5331	34.81
Recovery strategy 3	0.3024	63.02
Recovery strategy 4	0.8117	0.00

Table 6
Performance and resilience of the WDN under different preventive strategies.

Preventive strategy	$P(t)$	Improvement ratio(%)	$R(t)$	Reduction ratio(%)
No preventive strategy	0.5910	0.00	0.3013	0.00
Preventive strategy 1	0.7783	31.69	0.1803	40.20
Preventive strategy 2	0.8519	44.15	0.1223	59.41

their initial residual resilience value. Therefore, the recovery sequence for the failed pipes is {P9, P41, P65, P46, P20, P36, P54, P51, P32, P71}.

(2) The recovery strategy based on performance enhancement is to prioritize the restoration of the failed pipes that have the greatest performance enhancement to the WDN. Therefore, the recovery sequence for the failed pipes is {P9, P32, P51, P41, P46, P54, P71, P36, P65, P20}.

(3) The recovery strategy based on the betweenness centrality of failed pipes arranges the pipes in descending order of their betweenness centrality. Therefore, the recovery sequence for the failed pipes is {P41, P51, P65, P46, P54, P71, P32, P20, P9, P36}.

The changes in the residual resilience $R(t)$ of the WDN under different recovery strategies are shown in Fig. 9, and the residual resilience values post-repair are shown in Table 5.

As shown in Fig. 9, following the repair operation, the residual resilience values of the WDN exhibit gradually decrease as the failed pipes are progressively repaired. Among the four recovery strategies, recovery strategy 1 is the most effective. Specifically, Recovery strategy 1 is significantly better than recovery strategy 2 and recovery strategy 4. According to Table 5, after repairing the failed pipes, recovery strategy 1 reduces the residual resilience of the WDN from 1 to 0.3013, which is 43.47% and 63.15% lower than that of recovery strategies 2 and 4,

respectively. Whereas the overall advantage of recovery strategy 1 over recovery strategy 3 is less significant, it reduces the residual resilience of WDN more rapidly. When applying recovery strategy 1 to large networks, recovery strategy 1 will show a more significant advantage and can reduce the residual resilience of the network more efficiently.

To substantiate that preventive strategies taken before accidents can effectively mitigate the impact of pipe failures on the performance of the WDN, this paper compares the changes in the performance and the residual resilience during the recovery process of the original WDN against that of the WDN that has incorporated preventive strategies, as in Table 6. The preventive strategies encompass adding valves to the failed pipes that are prioritized for repair under the proposed recovery strategy, ensuring that there is a valve at both ends of the pipe (preventive strategy 1), and based on preventive strategy 1, adding redundant pipes to the downstream nodes connected to the failed pipes (preventive strategy 2).

This paper mainly implements preventive strategies for the four failed pipes with the highest repair priority: P9, P32, P51, and P71. The layout of WDN with these preventive strategies is shown in Fig. 10. In this figure, the red valves represent the newly installed valves, and the red pipes represent the newly added redundant pipes.

During the recovery processes of the failed pipes, the changes in the WDN's performance $P(t)$ and the residual resilience $R(t)$ under different preventive strategies are shown in Fig. 11.

Fig. 11 clearly illustrates the significant effect of preventive strategies on optimizing the resilience of WDN. In the event of a pipe failure, WDNs with preventive strategies show better overall performance than WDNs without preventive strategies. After the repair work is completed,
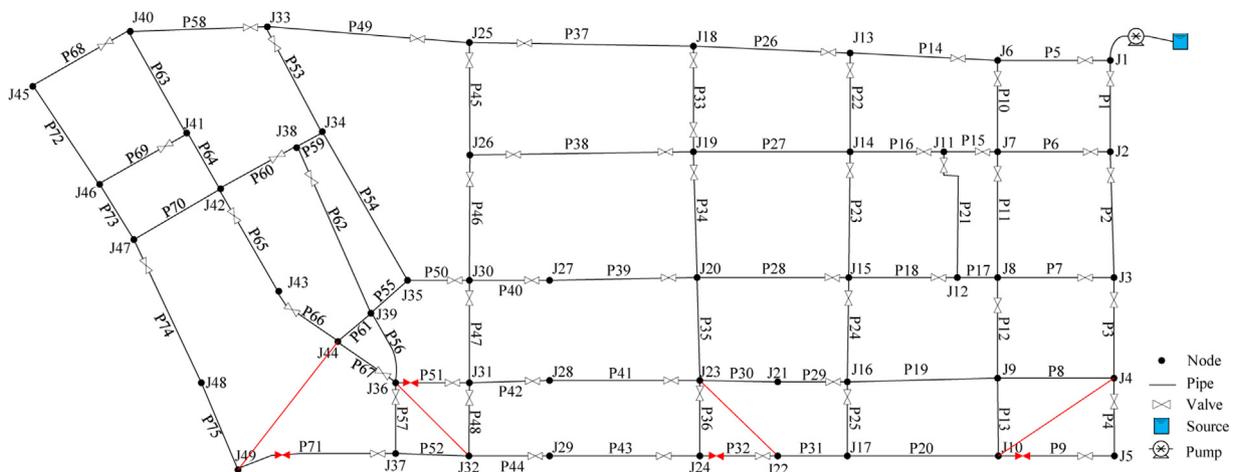

Fig. 10. Layout of the WDN with preventive strategies.

(a) Performance change
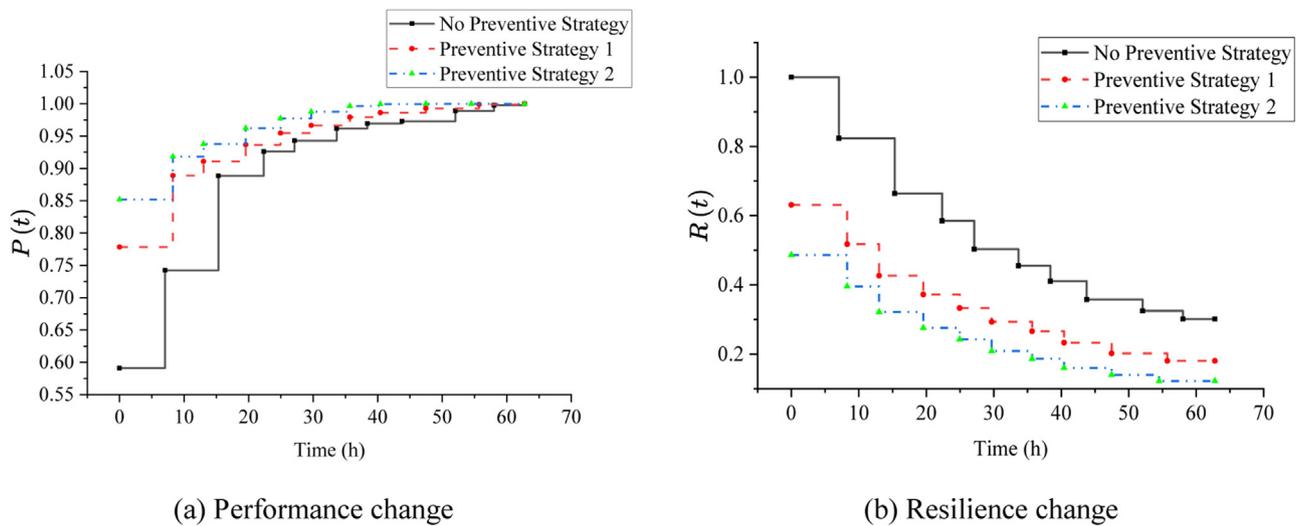
(b) Resilience change

Fig. 11. Performance and Resilience change of the WDN under different preventive strategies.

we can observe that the residual resilience of the WDN with preventive strategies is significantly lower than that of the WDN without preventive strategies. In particular, as shown in part (a) of Fig. 11, even before the failed pipes are completely repaired, the implementation of preventive strategy 2 has already caused the performance of the WDN to quickly return to normal levels, which shows that the WDN has significant performance redundancy in the face of disruptive events.

Specifically, in terms of performance improvement data, as shown in Table 6, we found that under the same pipe failure conditions, the performance of the WDN without preventive strategies was 0.5910. In contrast, the performance after adopting preventive strategies 1 and 2 was improved to 0.7783 and 0.8519, respectively, an increase of 31.69% and 44.15%. After the pipes were repaired, the residual resilience of the WDN without preventive strategies was 0.3013, while the values after preventive measures 1 and 2 reduced to 0.1803 and 0.1223, respectively, a 40.20% and 59.41% reduction. This performance improvement is because preventive strategy 1 only isolates the burst pipes by closing the valves at both ends. Prevent strategy 2 further improves the overall performance by shortening the water distribution distance to the downstream demand nodes.

In summary, this study shows that implementing preventive strategies on critical pipes can effectively mitigate the impact of pipe failures on WDN performance and accelerate the residual resilience of the network during pipe recovery. These strategies not only optimize the residual resilience of the WDN to handle pipe failures during daily operations but also significantly improve the stability and reliability of water supply.

6. Conclusions

This paper proposes a resilience evaluation model for WDNs based on DT technology. It takes user satisfaction with the water supply services as the core performance indicator. It combines it with residual resilience importance analysis to prioritize the maintenance of failed pipes and set the target of implementing preventive strategies. The model's validity is verified through case studies and analysis of WDNs. Compared with other assessment methods, the proposed dynamic recovery strategy outperforms the other three strategies in optimizing the residual resilience of WDNs. Meanwhile, the prevention strategy can effectively improve the performance capability and overall resilience of WDNs after a failure.

Although the research in this paper has certain value, it also has certain limitations. This research primarily concentrates on optimizing the resilience of WDNs under daily operational failures. It does not extend

its analysis to other extreme disaster scenarios like floods and earthquakes. Future endeavours should delve into the resilience optimization strategies for WDNs under these specific disaster events to enhance the practical applicability and thoroughness of the research.

Relevance to Resilience

This paper investigates the resilience of WDNs from a dynamic perspective. A WDNs resilience assessment model was established based on the performance indicators considering the number of users served. Utilizing this residual resilience model, a method for quantifying the residual resilience importance of water distribution pipes considering time value is proposed to determine the optimal recovery sequence for failed pipes and the implementation targets for preventive strategies. The process is dynamic, with WDNs undergoing hydraulic redistribution each time a failed pipe is repaired. The resilience importance of the unrepaired failed pipes is recalculated, ensuring that the resilience of WDNs reaches an optimal state. It can further enrich the research in quantitative assessment and optimization of the resilience of WDNs.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Hongyan Dui: Writing – review & editing, Writing – original draft, Methodology, Investigation. **Taiyu Cao:** Writing – original draft, Methodology. **Fan Wang:** Writing – review & editing, Supervision.

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