Topology-Based Resilience Metrics for Seismic Performance Evaluation and Recovery Analysis of Water Distribution Systems

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Abstract: Water distribution systems (WDSs) need to be resilient against seismic hazards to ensure rapid recovery of the community following an earthquake. Topology-based resilience metrics are often used to determine the system-level performance of WDSs. However, existing topology-based resilience metrics are unable to estimate seismic performance of WDSs accurately because they do not account for the vulnerability of pipelines in the metrics. This study tailored an existing topological metric and developed a new edge-betweenness-based topological metric for evaluating the seismic resilience of a complex water distribution network. System-level performance of WDSs is compared using four performance measures including minimum cut set (MCS)–based system reliability, topological resilience metric (TRM), modified TRM, and the newly developed edge-betweenness-based TRM. These metrics were applied for four WDSs (i.e., Anytown, New York Tunnel, Jilin, and Bellingham WDSs) with unique characteristics to validate their effectiveness in estimating the seismic performance of WDSs against seismic hazards. The outcomes of these applications show that the proposed TRM can be used to determine pipelines' seismic performance and functionality after an earthquake with an acceptable accuracy compared with existing approaches. While the topology-based resilience analysis provides information about system-level functionality, it is also vital to determine an optimal recovery sequence for damaged WDSs to maximize the functionality during the recovery process. Therefore, an easy-to-use recovery strategy is proposed to determine the optimal recovery sequence based on a repair index. The optimal recovery strategy was tested for the recovery procedure for the damaged Anytown WDS due to an earthquake, and outcomes show the system functionality is restored quickest using the proposed optimal recovery strategy. **DOI: 10.1061/JPSEA2.PSENG-1303.**

Introduction

Water distribution systems (WDSs) are regarded as critical infrastructure systems because their operational conditions directly affect the economic prosperity and human health of a society (Mazumder et al. 2018). WDSs are typically complex interconnected networks consisting of a large set of pipelines, tanks, pumps, reservoirs, valves, storage tanks, and other hydraulic control components. During the designed operational lifetime, the functionality of a WDS is often interrupted due to moderate to large earthquakes, particularly in regions of high seismicity. Past earthquakes have caused severe damage to WDSs. For instance, 2,311 water pipelines failed (i.e., leaks and breaks) due to the 2011 Christchurch earthquake (Bagriacik et al. 2018). After the 1995 Hyogoken-Nanbu earthquake, 1,610 failures were reported and 71,235 repair tasks were conducted by the local water supply department (Kitaura and Miyajima 1996). Hence, system-level seismic performance analysis is crucial for existing WDSs in their asset management plans. A WDS is typically modeled by a network graph, with links representing pipelines and nodes representing water consumers, water sources, and hydraulic control components. While previous research highly focused on evaluating the system-level performance of WDS using topology-based approaches, most of the topology-based resilience evaluation metrics lack evaluation of the seismic performance of pipelines.

Conventionally, system-level performance can be measured by risk and reliability assessments (e.g., Hosseini and Moshirvaziri 2008; Karamouz et al. 2010). However, their effectiveness is often hampered by the system's complexity and time-dependent performance (Balaei et al. 2020). To develop a better tool for the assessment of system-level behavior, Bruneau et al. (2003) introduced the concept of system-level resilience to estimate system-level residual functionality and recovery time after earthquakes. System resilience is defined as a system's ability to overcome disruptive events, keep functioning, and recover quickly (Bruneau et al. 2003). Previous studies focused on modeling the resilience of infrastructure systems, including water networks (e.g., Candelieri et al. 2017; Sitzenfrei et al. 2020; Giudicianni et al. 2021), transportation networks (e.g., Zio and Sansavini 2007; Masucci et al. 2009), electrical power networks (e.g., Crucitti et al. 2005; Holmgren 2006; Bompard et al. 2009), and buildings (e.g., Olshesky 2012; Comber and Poland 2013). More specifically, Olshesky (2012) studied several methods to improve the resilience of buildings against wind, tornados, and harsh sunlight; Zio and Sansavini (2007) analyzed the reliability of a tramway system; Masucci et al. (2009) studied the performance of a road network; and Crucitti et al. (2005), Holmgren (2006), and Bompard et al. (2009) analyzed the performance of electrical power system. For water systems, Candelieri et al. (2017) presented a framework to estimate WDS resilience to save hydraulic energy of water sources. Sitzenfrei et al. (2019) investigated system characteristics and identified the optimal WDS

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patterns using complex network theory, then Sitzenfrei et al. (2020) proposed a methodology to optimize large WDS design in which the trade-off between cost and resilience was obtained. Giudicianni et al. (2021) presented a method to find the shortest paths of WDSs quickly and precisely, helping management and operation of WDSs.

The resilience of a WDS is defined as its ability to keep functioning at the desired level and speedy recovery to its minimum functionality level when subjected to earthquakes or other disasters. Natural disasters such as earthquakes, floods, tornados, and wildfires can disrupt smooth functionality and contaminate water quality of a WDS. The approaches for resilience assessments of a WDS due to different natural disasters are varied because different natural disasters have different impacts on the water network. For instance, strong earthquakes can damage water pipelines and hydraulic control facilities. Floods may contaminate supplied water, causing consumers to become sick. To ensure firefighting after an earthquake, excessive water supply is required at the fire location, which may cause a shortage of water supply in other parts of the network. Tornados may lead to a power outage, pipe failure, and damage to other components. This study focuses on estimating the resilience of WDSs due to an earthquake. The resilience of WDSs can be classified into two types: (1) topological, and (2) hydraulic (Farahmandfar and Piratla 2018; Mazumder et al. 2019). Topology-based resilience evaluates the system-level connectivity between demand and source nodes. On the other hand, hydraulic resilience evaluates the percentage of customers whose water demands are satisfied. Topologic resilience metrics need to be investigated in priority because it is impractical to consider hydraulic resilience if the system is not connected (Gheisi et al. 2016; Mazumder et al. 2018). Topological connectivity is reflected by the mechanical reliability of WDSs, providing the probability that every demand node is connected to a water source. There are several approaches to calculate the mechanical reliability of WDS, including minimum cut set (MCS) and graph decomposition.

Researchers developed resilience metrics to study the performance of WDSs under stressed conditions. Several performance indicators such as robustness, redundancy, and vulnerability are selected in the resilience metrics. Todini (2000) proposed a resilience index for WDSs to determine the system's intrinsic ability to overcome pipelines' sudden failures. However, Todini's (2000) resilience cannot capture hydraulic resilience when multiple water sources exist in a WDS (Jayaram and Srinivasan 2008). Prasad and Park (2004) modified Todini's resilience by incorporating surplus energy and reliable network loops to address pipe diameter uniformity. Yazdani and Jeffrey (2012) critically reviewed the effectiveness of several existing robustness and vulnerability measurements, and then presented a network-based method to determine the relationship between system functionality and its network layout. Farahmandfar et al. (2017) proposed a metric for computing topology-based resilience of WDSs against seismic hazards. Further, Farahmandfar and Piratla (2018) proposed a flow-based resilience metric and compared topology-based and flow-based resilience metrics for rehabilitating a water network subject to an earthquake. However, redundancy is not appropriately considered in the resilience metrics proposed by Farahmandfar et al. (2017), which is discussed subsequently in this paper. Herrera et al. (2016) proposed a graph-based resilience measure based on system redundancy and paths between demand and source nodes. However, this measure cannot take seismic impact into consideration directly. Di Nardo et al. (2017) studied redundancy of water networks, then Di Nardo et al. (2018) investigated the relationship between topological characteristics and network resilience and presented an approach to estimate WDS resilience using geometrical and topological metrics. However, they did not consider seismic performance of pipelines. Santonastaso et al. (2018) utilized flow entropy as the metric of system robustness after investigating the relationship between flow entropy and network topological features. Matthews (2016) quantified the resilience of WDSs by four critical aspects: redundancy, storage capacity, structural integrity, and backup power. Balaei et al. (2020) proposed a metric for measuring system-level robustness based on vulnerability, redundancy, and criticality of WDS. However, Matthews (2016) and Balaei et al. (2020) used engineering judgment to determine the performance indicators, lowering the accuracy of the proposed methods. Mazumder et al. (2020a) developed a renewal strategy to identify the pipeline's vulnerability by combining topological characteristics, condition index, and failure impact index.

Although studies have used topology-based metrics to analyze the system-level performance of WDSs, application of these metrics is often limited to specific network characteristics. Limited research has been performed to validate the overall effectiveness of the topology-based resilience metrics in assessing the seismic performance of the WDS and their applicability to different network configurations (e.g., Farahmandfar et al. 2017; Farahmandfar and Piratla 2018). Hence, there is a need to investigate the applicability of the topology-based resilience measures in seismic performance evaluation of WDSs with various network configurations. Hence, this study aimed to extend an existing topology-based resilience metric and develop a new topology-based resilience metric to quantify the seismic resilience of WDSs that can be applied to evaluate network performance with any characteristics.

Another aspect of seismic resilience is the system's capability of repairing damaged components immediately after an earthquake. The rapidity of a system refers to the recovery speed to restore a damaged system to its pre-earthquake state. It is desirable to restore the system's functionality as quickly as possible; however, because of limited resources and budgets, it is often impractical to repair failed components simultaneously. Therefore, an optimal recovery strategy is required. Different infrastructure systems have different repair plans. For example, the repair plan for an electrical power system needs to set up the repair sequence for failed gate stations and substations, and the repair plan for natural gas systems sets up repair priorities for failed gas pipes and gas stations (Lin and El-Tawil 2020). For WDSs, earthquakes can cause damage to water pipes, tanks, and pumps. Because WDSs contain only a few tanks and pumps, these facilities can be monitored frequently and repaired quickly (Tabucchi et al. 2010). The restoration speed for a damaged WDS is controlled by the repair sequence of failed pipelines.

Researchers have investigated restoration procedures and provided several restoration strategies for WDSs. For instance, Davis (2014) defined five water network service categories, distinguished system operability and functionality, and then provided restoration procedures for each service category and investigated the effects of interactions between the categories on restoration procedures. Choi et al. (2018) compared six restoration scenarios, and the restoration priorities for different scenarios were determined based on various rules: pipe's flow, pipe's closeness to a water source, pipe's distance to the current repair location, and whether to create repair zones. Mazumder et al. (2020b) proposed postdisaster recovery plans for water networks in terms of topological efficiency, hydraulic resilience, and hydraulic availability. Cimellaro et al. (2016) explained the advantages and disadvantages of three restoration plans: closing tanks until full recovery of their reserve capacity, using the maximum amount of flow from the pump stations, and a combination of the first two plans. Paez et al. (2020) compared the efficiency of restoration plans based on three types of restoration algorithms: general-purpose metaheuristic algorithms, greedy algorithms, and rank-based prioritizations. Although the strategies in previously mentioned studies are effective, these recovery strategies are either event or case specific and may not be applied for a different network configuration. The applicability of existing strategies can be validated when they are applied to different network configurations and physical conditions. Hence, in addition to developing topology-based resilience metrics, this study also develops an optimal post-earthquake recovery strategy for WDSs.

The first part of this study analyzes and develops the topology-based resilience metrics for WDSs. After tailoring the topology-based resilience metric, a new topology-based resilience metric is introduced to estimate the system-level seismic performance of WDSs. Then the effectiveness of the proposed resilience metrics is evaluated by applying them to four WDSs (Anytown, New York Tunnel, Jilin, and Bellingham WDSs) with different network characteristics. In the second part of this study, an optimal recovery analysis strategy is proposed to guide postdisaster recovery planning of damaged WDSs. The proposed optimal recovery strategy is illustrated for the Anytown WDS.

Framework of Resilience Analysis and Recovery Strategy

The proposed research framework is illustrated in Fig. 1. The framework is composed of two parts: (1) developing a topology-based seismic resilience matric to analyze the system-level performance of WDSs, and (2) formulating a post-earthquake recovery strategy for a damaged WDS to find a recovery path that optimizes the functionality of the WDS during the recovery process. In the first part, a system-level reliability–based topological resilience metric (TRM) is developed in which reliability of the WDS is calculated using the MCS approach. Thereafter, an existing TRM is analyzed and modified to evaluate seismic resilience of the WDS. To evaluate the robustness of the newly modified metric, an edge betweenness centrality (EBC)–based resilience measure is developed and analyzed for WDS. The seismic failure probability of pipelines measured as a function of the repair rate of pipelines is used in determining these resilience metrics. In the second part, a recovery strategy is developed to determine the optimal recovery sequence for damaged WDS using pipeline repair index. System-level resilience measures estimated from the first part of this study are used in computing the repair index for the WDS.

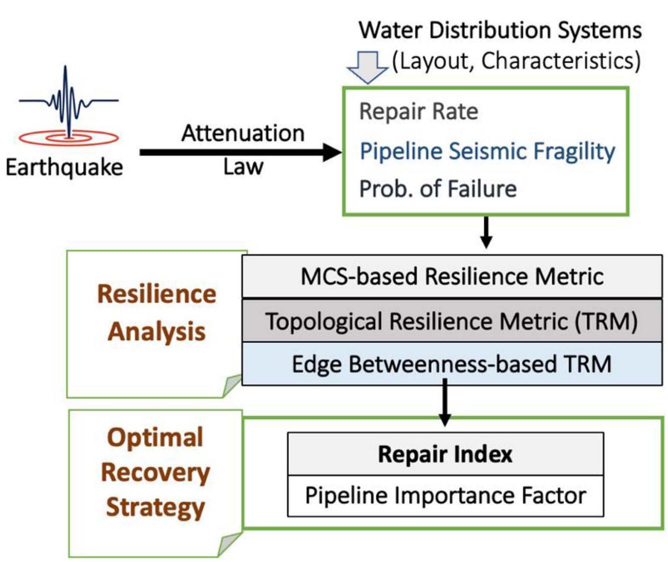

Fig. 1. Proposed methodology.

Seismic Performance Analysis of Pipeline

The seismic performance of a WDS was investigated based on a scenario earthquake event. A scenario earthquake represents one realization of a potential earthquake, where earthquake characteristics are defined by magnitude, epicentral depth, epicentral location, and fault geometry. For analyzing the potential earthquake risk on a particular WDS, a scenario earthquake event is typically selected according to the maximum probable earthquake that can be generated from the nearest fault. Seismic intensities at any site due to the earthquake are estimated using the ground motion prediction equation (GMPE). Earthquake characteristics such as magnitude, epicenter, location, and depth are required to determine seismic intensities using GMPE. Scenario-based seismic analysis is able to overcome practical difficulties in seismic hazard research for distributed systems, and results of scenario-based seismic research can be easily interpreted by decision makers (Mazumder et al. 2020c). Past studies investigated pipeline damages from past earthquakes to develop empirical fragility curves in which pipeline seismic damage is represented as a function of seismic intensities (e.g., permanent ground displacement, peak ground velocity) for pipelines, including Eguchi (1983), Barenberg (1988), O'Rourke and Ayala (1993), and Eidinger (1998). Because water pipelines are buried underground, seismic wave propagation causes severe damage to water pipelines. During an earthquake, seismic wave propagation covers larger areas of the distributed water network (Fragiadakis and Christodoulou 2014; Mazumder et al. 2020c). Hence, the current study utilizes peak ground velocity (PGV) as seismic intensity in analyzing pipeline seismic failure probability. The seismic failure probability of pipelines is estimated as per the American Lifelines Alliance (ALA) (2001) guideline.

For a scenario earthquake, seismic intensities are estimated using GMPE. The GMPE developed by Yu and Jin (2008) was utilized for determining PGV:

$$\mathrm{PGV} = 10^{-0.848+0.775M+1.834\log(R+17)} \tag{1}$$

where M = earthquake magnitude; and R = distance to epicenter.

ALA (2001) estimates pipeline vulnerability by a repair rate, which is estimated as a function of PGV:

$$\mathrm{rr} = K_1 \times (0.00187) \times \mathrm{PGV} \tag{2}$$

where rr = repair rate representing the number of repairs required per 304.8 m (1,000 ft) of pipe length exposed to a specific PGV; PGV = peak ground velocity (in./s); and K_1 = modification factor depending on pipe material, pipe joinery, pipe diameter, and soil corrosivity; K_1 values are given in ALA (2001).

Pipeline failure probability, provided by the ALA (2001) guideline, is expressed as follows:

$$P_f = 1 - e^{-\mathrm{rr}\times L} \tag{3}$$

where P_f = pipeline failure probability; and L = length of the pipeline.

Topologic Resilience Metrics for WDSs

The resilience of a WDS is defined as the ability to maintain acceptable function and recover quickly when subjected to earthquakes. Resilience metrics are utilized to quantify a system's residual functionality after earthquakes. Topologic resilience metrics are used to measure the system's mechanical connectivity. However, there are no unanimously agreed resilience metrics for the following reasons. Developing resilience metrics requires translating abstract concepts and definitions into quantitative indicators (Balaei et al. 2020). Moreover, engineering judgments are often used to select performance indicators for a WDS. Several topologic resilience metrics are discussed next, and the comparisons of these metrics are shown in case studies.

MCS-Based TRM

System topologic connectivity can be represented by the mechanical reliability of a network graph. System mechanical reliability of a WDS is estimated by the probability that all demand nodes are physically connected to source nodes (Ostfeld et al. 2002; Li et al. 2021); in contrast, the system fails as long as at least one demand node is disconnected from the source nodes. Therefore, system mechanical reliability is a complement of the failure probability of the system. Among the existing approaches, the MCS approach is utilized to compute the system-level connectivity of a WDS. The MCS is a well-defined approach in network probability calculation (Mazumder et al. 2019). For large and complex networks, it is time-consuming to calculate system mechanical reliability by theoretical probability equations because there are too many failure cases. The MCS method is proven to be the most efficient (Tung 1985). A minimum cut set may have one or a few pipes, and a cut set is regarded as an MCS when the system loses the connection only if all components in the cut set fail. The number of MCSs depends on system complexity and system size. For small systems, all MCSs can be quickly found by visual inspection. For large systems, however, an adjacency matrix algorithm can be applied to determine the number of MCSs in a WDS. It is assumed that pipelines in a WDS are statistically independent; therefore, the failure of one pipeline did not affect the operational status of other pipelines. The failure probability of an MCS can be calculated as Eq. (4) (Shinstine et al. 2002)

$$P(\mathrm{MCS}_i) = \prod_{l=1}^{n_p} P_{fl} \tag{4}$$

where $P(\mathrm{MCS}_i)$ = failure probability of the ith MCS that contains n_p pipelines; and P_{fl} = failure probability of pipeline l.

The system failure probability is the summation of failure probabilities of all MCSs (Yannopoulos and Spiliotis 2013; Mazumder et al. 2019). The system topologic resilience metric, represented by system mechanical reliability, is the complement of system failure probability, as shown in Eq. (5)

$$\mathrm{TR}_{\mathrm{con}} = 1 - \sum_{i=1}^{S} P(\mathrm{MCS}_i) \tag{5}$$

where S = number of significant MCSs in the system; and $\mathrm{TR}_{\mathrm{con}}$ = MCS-based topologic resilience metric.

Topologic Resilience Metric

A majority of existing resilience metrics deal with hydraulic or energy resilience of WDSs, and only a few topology-based metrics studied the system topological connectivity condition of WDSs, particularly for determining the seismic performance of WDSs. The TRM proposed by Farahmandfar et al. (2017), integrating robustness and redundancy dimensions, is investigated herein. Because robustness refers to residual functionality after earthquakes, pipeline robustness is the complement of its failure probability. Farahmandfar et al. (2017) considered the system redundancy by its nodal degree because system redundancy increases as nodal degree increases. In this metric, nodal degree is the summation of reliabilities of all pipelines connected to the node, and nodal demand is used as weight to prioritize nodes. They defined TRM as follows:

$$\mathrm{TR}_{\mathrm{Far}} = \frac{\sum_{i=1}^{N_n}\{[\sum_{l=1}^{N_i}(1-P_{fl})] \times Q_i\}}{4 \times \sum_{i=1}^{N_n} Q_i} \tag{6}$$

where N_n = number of nodes in the WDS; N_i = number of pipelines connected to node i; Q_i = demand of node i; and $\mathrm{TR}_{\mathrm{Far}}$ = TRM.

Modified TRM

Although TRM is easy to use, there is a limitation that TRM may overestimate or underestimate system resilience depending on different system configurations because of its denominator $4 \times \sum_{i=1}^{N_n} Q_i$. Farahmandfar et al. (2017) explained in their paper that in real WDSs few nodes have a degree greater than or equal to 4, therefore using $4 \times \sum_{i=1}^{N_n} Q_i$ as the denominator of TRM is able to provide the upper bound of the seismic resilience. In other words, TRM is developed using $\sum_{i=1}^{N_n} N_i \times Q_i$ as the denominator in which all N_i values are assumed equal to 4. However, the value of average nodal degree changes according to the configuration of a WDS, and it can be normally varied between 2 and 5. If a system's average nodal degree is less than 4, then 4 in the denominator reduces their resilience metric values significantly, which is discussed in the case studies. Moreover, using $\sum_{i=1}^{N_n} N_i \times Q_i$ as the denominator of TRM, the magnitude of the metric varies in a closed interval [0, 1]. Thus, the metric can be compared with other probabilistic-based resilience metrics easily. TRM can be further modified as

$$\mathrm{TR}_{\mathrm{Mod}} = \frac{\sum_{i=1}^{N_n}\{[\sum_{l=1}^{N_i}(1-P_{fl})] \times Q_i\}}{\sum_{i=1}^{N_n} N_i \times Q_i} \tag{7}$$

where $\mathrm{TR}_{\mathrm{Mod}}$ = modified TRM.

EBC-Based TRM

TRM uses nodal demand as weight to prioritize nodes; however, nodal demand is more related to hydraulic characteristics. Additionally, nodal demand may have different hourly multipliers, and hourly multipliers of nodal demand also refer more to hydraulic condition than the system's mechanical connectivity condition. To develop a topology-based resilience metric independent of hydraulic condition, indicators of the metric should not be affected by hydraulic status. Therefore, a new topologic resilience metric is proposed that integrates robustness, the vulnerability and redundancy aspects, to predict the system's topological condition. Vulnerability and redundancy of WDS are considered by using EBC herein. The EBC of an edge is defined as the summation of the fraction of shortest paths between all pairs of nodes that pass through the edge, and it is expressed as follows (Brandes 2008; Giustolisi et al. 2019; Mazumder et al. 2021):

$$C_l^B = \sum_{\substack{p \neq q \in V \\ l \in E}} \frac{\sigma_{u,o}(l)}{\sigma_{u,o}} \tag{8}$$

where C_l^B = edge betweenness centrality of edge l; $\sigma_{u,o}(l)$ = number of shortest paths between node u and node o that pass through the edge l; $\sigma_{u,o}$ = total number of shortest paths between node u and node o; and V and E = sets of nodes and edges in the system, respectively.

This approach uses the EBC instead of betweenness centrality for nodes because pipelines are the most vulnerable components of the WDS against earthquake loading. As motioned previously, the reliability of the network, estimated based on the MCS approach, only considers the vulnerability of the pipelines of a WDS. To account for the relative importance of pipelines within a network

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graph, the EBC is used in the proposed resilience metric. The EBC provides information on the vulnerability of pipelines in a network. A failed pipeline with a greater EBC value is likely to have more severe flow path disruption (Mazumder et al. 2021). Moreover, redundancy of a pipe can be determined by evaluating the number of shortest paths between source nodes and demand nodes that pass through the pipe. Therefore, a pipeline's vulnerability and redundancy can be determined by its EBC. Hence, the following resilience metric is proposed based on the EBC:

$$\mathrm{TR}_{\mathrm{EBC}} = \frac{\sum_{i=1}^{N_m}(1 - P_{fi}) \times C_i^B}{\sum_{i=1}^{N_m} C_i^B} \tag{9}$$

where N_m = total number of pipelines in the system; and $\mathrm{TR}_{\mathrm{EBC}}$ = topologic resilience metric based on the EBC.

Optimal Recovery Strategy

The ideal restoration plan is repairing all failure pipes simultaneously to recover system functionality as quickly as possible; however, it is hampered by resource limitations such as monetary and repair crew. Therefore, the restoration process needs to be optimized to minimize adverse impact due to earthquakes. System functionality is represented by the topologic resilience metric herein, as discussed previously. Fig. 2 shows that system functionality drops significantly after earthquakes and then it recovers to normal operational condition when all of the damaged components are fully repaired. The vertical axis presents the topologic resilience metric and the horizontal axis presents elapsed time. The system is in normal operation status until time t_1, when the earthquake occurs. Following that, the system functionality drops drastically and reaches the minimum value $\mathrm{TR}_{\min}$ at time t_2, then the restoration process begins and the system is fully recovered at time t_3. From Bruneau et al.'s (2003) definition, the resilience obtained between t_2 and t_3 can be calculated as follows:

$$\mathrm{RO} = \int_{t_2}^{t_3} \mathrm{TR}(t)dt \tag{10}$$

where RO = resilience obtained.

The most effective restoration process has two requirements: (1) maximizing the value of resilience obtained, and (2) taking the pipeline's importance into consideration. Fig. 3 shows a recovery sample having four restoration strategies. The repair strategies are determined by various rules such as system functionality enhancement, downtime, budget, and available repair crews. This study proposes a recovery strategy to restore system functionality in the shortest time possible. System functionality restores at various speeds because of different repair sequences, and it restores more quickly if an important pipeline (i.e., carrying higher water flow, closer to water source) is repaired first. Strategy 1 is the best option because the area under its functionality curve has the highest value. To obtain a higher resilience obtained value, the repair sequence for failure components needs to be prioritized. Moreover, the criticality of the two end nodes of the pipeline needs to be considered in the restoration strategy. For example, if the end nodes of a pipeline supply water resources to critical facilities (i.e., hospital, fire station), the repair task of this pipeline should be prioritized even though it does not significantly increase system overall performance. This paper proposes a new restoration strategy, in which the repair prioritization is determined based on three factors: system functionality enhancement upon reparation of the pipeline, required time to repair the pipeline, and pipeline's importance factor. The enhancement of system functionality upon reparation of pipeline i is given as follows:

$$\mathrm{FE}_i = \mathrm{TR}_{r,i} - \mathrm{TR}_{0,i} \tag{11}$$

where FE_i = system functionality enhancement if pipeline i is repaired; $\mathrm{TR}_{0,i}$ and $\mathrm{TR}_{r,i}$ = topological resilience metric before after pipeline i is repaired, respectively.

Repairing the pipelines with higher FE values will restore greater system functionality; however, required time to complete the tasks and pipeline's importance factor are also important for developing an effective recovery strategy. Individually, two similar breaks may need the same repair time, but their contribution to system-level functionality gain could be different. Hence, the repair time is not the dominant factor in determining the repair sequence. In the proposed approach, the repair sequence is determined by the largest area under the repair sequence curves presented in Fig. 2. The repair index for pipeline i is developed based on following rules: system functionality enhancement has a positive relationship with resilience obtained, required time to complete reparation has a negative relationship with resilience obtained, and pipeline's importance factor is utilized as the modification factor

$$\mathrm{RI}_i = \frac{\mathrm{FE}_i}{t_i} \times \mathrm{IMF}_i \tag{12}$$

$$\mathrm{IMF}_i = \begin{cases} 1.0 \text{ serving nodes are residential} \\ 1.5 \text{ serving nodes are essential (e.g., school, government)} \\ 2.0 \text{ serving nodes are critical (e.g., hospital, fire station)} \end{cases} \tag{13}$$

where RI_i = repair index of pipeline i; t_i = required time to repair pipeline i; and IMF_i = importance factor of pipeline i, and it is assumed based on engineering judgment in this study. The

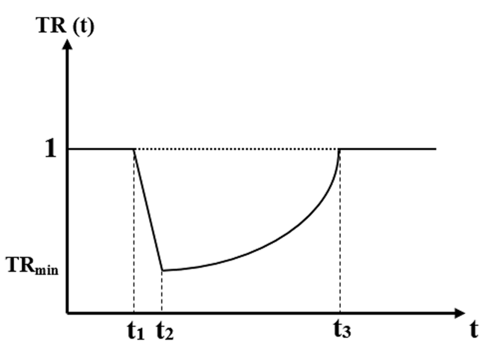

Fig. 2. Measure of topologic resilience obtained.

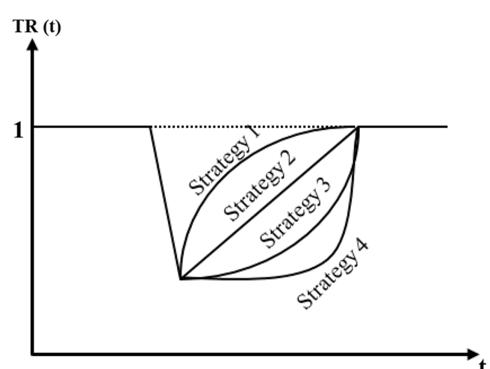

Fig. 3. Restoration processes based on different restoration strategies.

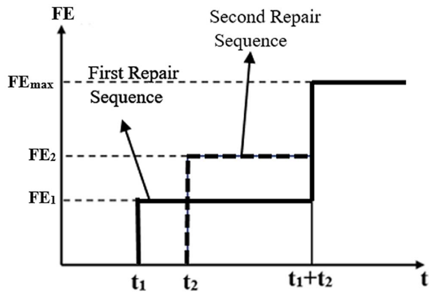

Fig. 4. Topologic resilience curves for two recovery strategies.

pipeline with the highest RI value should be prioritized in the repair process.

An example is used to theoretically prove the proposed recovery strategy. Two pipelines (Pipe 1 and Pipe 2) in a WDS fail, and it is assumed that both of their importance factors are equal to 1 and $\mathrm{RI}_1 > \mathrm{RI}_2$ ($\mathrm{FE}_1/t_1 > \mathrm{FE}_2/t_2$). The curves of system functionality enhancement are shown in Fig. 4. The first repair sequence is to repair Pipe 1 at first, and the system functionality gains FE_1 after time period t_1, and then the system functionality regains $\mathrm{FE}_{\max}$ at time $t_1 + t_2$ upon repair of Pipe 2. Therefore, system resilience obtained (RO_1) between time duration $t_1 + t_2$ is $\mathrm{FE}_1 \times t_2$ for the first repair sequence. The second repair sequence is to repair Pipe 2 at first, and the system functionality gains FE_2 after time period t_2, and then the system functionality regains $\mathrm{FE}_{\max}$ at time $t_1 + t_2$ upon repair of Pipe 1. Therefore, system resilience obtained (RO_2) between time duration $t_1 + t_2$ is $\mathrm{FE}_2 \times t_1$ for the second repair sequence. Because $\mathrm{FE}_1/t_1 > \mathrm{FE}_2/t_2$, $FE_1 \times t_2 > FE_2 \times t_1$; therefore, repairing Pipe 1 first is more effective than repairing Pipe 2 first. This example proves that repairing the pipeline with the highest repair index value in priority is the optimal two-component recovery plan. The recovery strategy can be applied to recovery plans containing any number of pipelines, and it is validated in the following five recovery case studies (four three-pipeline failure cases and one four-pipeline failure case).

Case Studies

Four case studies are analyzed to illustrate proposed concepts and methods. Fig. 5 shows layouts of four illustrative water distribution systems: Anytown, New York Tunnel, Jilin, and Bellingham WDSs. All data files for Anytown and New York Tunnel WDSs were obtained from the University of Exeter Centre for Water Systems (Mazumder et al. 2020c), and data files for Jilin and Bellingham WDSs were obtained from the University of Kentucky Water Distribution System Operation (Hernadez et al. 2016). The Anytown WDS consists of three source nodes, 19 demand nodes, and 41 pipelines. The New York Tunnel WDS is composed of one source node, 19 demand nodes, and 21 pipelines. The Jilin WDS has one source node, 27 demand nodes, and 34 pipelines. The Bellingham WDS contains two sources, 118 demand nodes, and 164 pipelines.

Topological Resilience Analysis

Table 1 provides basic topological characteristics of sample WDSs. In the analysis, nodal degree refers to numbers of pipelines connected to the node. Meshedness coefficient is defined as the fraction of actual number of existing loops to the number of maximum possible loops (Yazdani and Jeffrey 2012), and it is an approximate quantifier in estimating system redundancy. Based on various definitions, common water systems can be defined as tree, grid, and arterial-loop systems or grid iron, ring, radial, and dead-end systems. However, these well-defined common systems are quite simple networks. Only the New York Tunnel system can be defined clearly as a ring system. The other three networks are combinations of the common network layouts, and it is hard to explain the categories of the other three systems. Therefore, this study used the meshedness coefficient to represent network redundancy. Buhl et al. (2006) proposed the equation for computing meshedness coefficient of a system as follows:

$$\mathrm{MC} = \frac{N_m - N_n + 1}{2N_n - 5} \tag{14}$$

where MC = system meshedness coefficient.

A majority of previous studies determined seismic resilience of WDSs using a scenario-based approach, and past studies often ignored evaluating the effectiveness of the resilience metrics when the system is subjected to different levels of earthquake intensities. To determine how system-level performance varies with seismic intensity changes, this paper calculates the values of existing topology-based resilience metrics when a WDS is subjected to different levels of seismic intensities. Pipeline failure probabilities were calculated using Eq. (3) due to a scenario earthquake, and then MCS-based TRM, TRM, modified TRM, and EBC-based TRM were determined by Eqs. (5)–(7), and (9), respectively. As an example, Table 2 lists the PGV for pipelines of the New York Tunnel system due to a 5.0 magnitude earthquake scenario where the earthquake epicenter is located 2.3 km east of Node 6 with epicentral depth of 10 km. For this earthquake scenario, the PGV intensities for the pipelines were estimated using the GMPE presented in Eq. (1), and the average PGV for the pipelines was 6 cm/s. This earthquake resulted in MCS-based TRM, TRM, modified TRM, and EBC-based TRM of 0.49, 0.51, 0.92, and 0.93, respectively.

There are several approaches to increase average PGV value at pipelines to consider various seismic intensities such as increasing magnitude, reducing epicenter depth, and relocating seismic epicenter. The decreasing trends of the topologic resilience metrics as seismic intensity increases for the four sample systems are provided in Figs. 6–9. The horizontal axes are the average PGV value at pipes of the WDSs, and the values of the TRMs are shown on the vertical axes.

Fig. 6 compares four TRMs for Anytown WDS. It is seen that modified TRM and EBC-based TRM provide similar results, and these two metrics decrease almost linearly with PGV. For example, modified TRM values are 0.85, 0.73, 0.62, and 0.53 at PGVs of 5, 10, 15, and 20 cm/s, respectively; EBC-based TRM values are 0.84, 0.71, 0.60, and 0.51 at PGVs of 5, 10, 15, and 20 cm/s, respectively. TRM provides relatively higher values compared to modified TRM and EBC-based TRM for Anytown system. This is because 8 of 19 nodes in the Anytown WDS have nodal degree 5 and the average nodal degree is 4.16; therefore, TRM that uses $4 \times \sum_{i=1}^{N_n} Q_i$ as the denominator overpredicts network resilience. The minimum value of TRM is 0, and there is no limit to the maximum value of TRM. Hence, TRM is 1.09 when there is no ground shaking for the Anytown WDS, as shown in Fig. 6. Because these metrics are probability-based measures, TRM needs to be modified to make sure the estimated resilience value is within the closed interval [0, 1]. MCS-based TRM provides higher values compared to modified TRM and EBC-based TRM up to 7 cm/s of PGV, and then it decreases more quickly, as shown in Fig. 6. This is because MCS-based TRM provides the probability that all nodes are

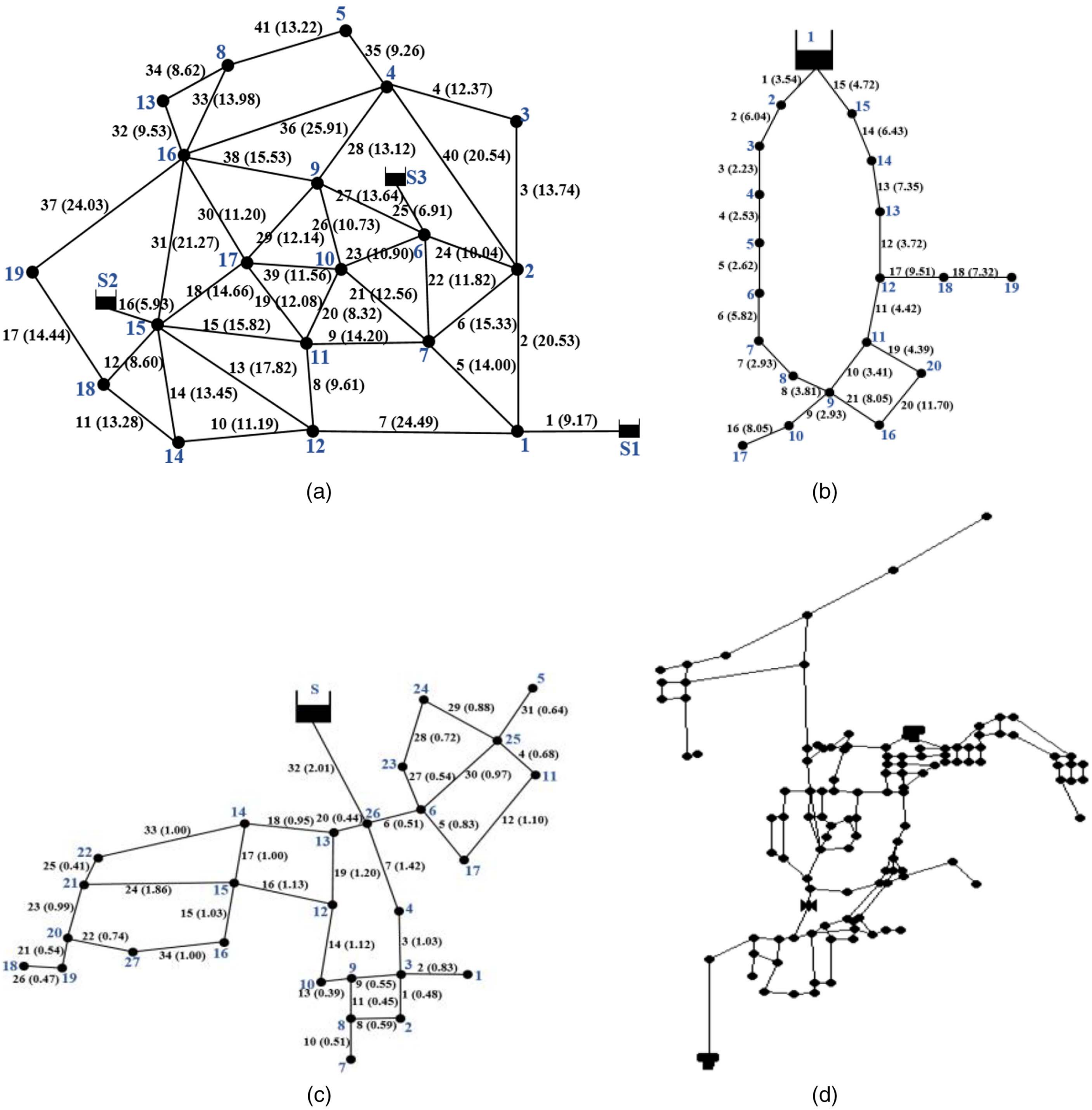

Fig. 5. WDS layout: (a) Anytown; (b) New York Tunnel; (c) Jilin; and (d) Bellingham.

Table 1. Basic topological characteristics of illustrative WDSs

Water distribution system	Number of nodes	Number of pipelines	Average nodal degree	Average pipeline length (km)	Meshedness coefficient
Anytown	19	41	4.16	13.55	0.69
New York Tunnel	19	21	2.11	5.31	0.09
Jilin	27	34	2.33	0.85	0.16
Bellingham	118	164	2.72	0.29	0.20

physically connected. As the failure probability of pipeline increases, the probability that the system loses the connection increases quickly. For example, MCS-based TRM values are 0.89, 0.56, and 0.03 at PGVs of 5, 10, and 15 cm/s, respectively.

Fig. 7 compares four TRMs for the New York Tunnel WDS. Similar to the Anytown system, modified TRM and EBC-based TRM predict close outcomes. However, TRM exhibits much smaller values compared with the two previously mentioned TRMs. The reason for this phenomenon is that the majority of nodes in the New York Tunnel have nodal degree 2, and the average nodal degree is 2.11, which is almost half of the denominator coefficient (i.e., 4) of TRM, thus leading to underestimation of network resilience. MCS-based TRM for the New York Tunnel system decreases even more quickly as PGV increases compared with the Anytown system because the New York Tunnel is a less redundant system, with only 0.09 of meshedness coefficient. Because of a lack

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Table 2. PGV for pipelines of the New York Tunnel WDS due to scenario earthquake

Pipe ID	PGV (cm/s)
1	5.24
2	5.44
3	5.68
4	5.94
5	6.15
6	6.26
7	6.29
8	6.38
9	6.19
10	6.49
11	6.55
12	6.62
13	6.36
14	5.78
15	5.31
16	5.76
17	6.22
18	5.62
19	6.16
20	5.86
21	6.13

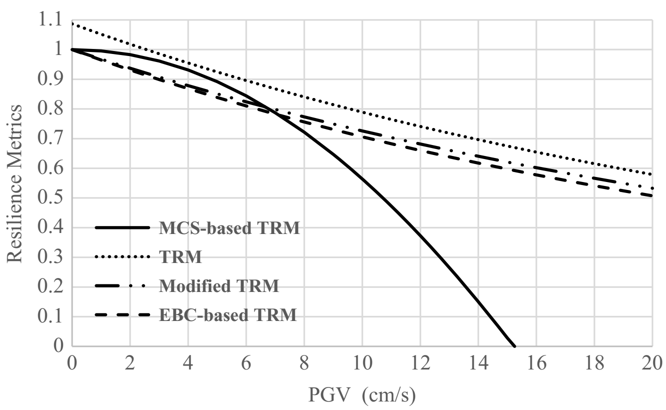

Fig. 6. TRMs for Anytown WDS.

of alternative paths between source nodes and demand nodes, the probability of nodal isolation increases drastically as pipeline failure probability increases, thus leading to rapid decrease of MCS-based TRM.

Fig. 8 compares four TRMs for the Jilin WDS. TRM predicts much smaller values compared with modified TRM and EBC-based TRM for the same reason as the New York Tunnel system. Modified TRM and EBC-based TRM are in close proximity, and MCS-based TRM drops quickly because it lacks redundancy. To evaluate the effectiveness of the previously mentioned TRMs, these TRMs are applied to a larger network, the Bellingham WDS, and the results are shown in Fig. 9. Results predicted by modified TRM and EBC-based TRM match perfectly. Because the network average nodal degree is 2.72, which is less than 4, TRM predicts lower resilience values in comparison. Because it is not a redundant network with meshedness coefficient of 0.2, the resilience curve predicted by MCS-based TRM decreases rapidly. Although the network size of the Bellingham WDS is much larger than the Anytown, New York Tunnel, and Jilin WDSs, the reasons for similarities and differences between the four TRMs are nothing more

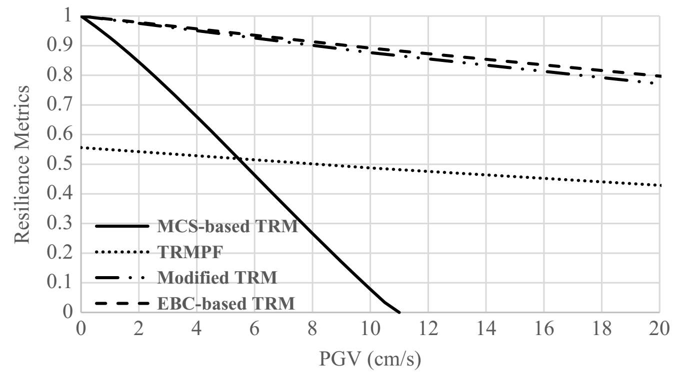

Fig. 7. Comparison of topologic resilience metrics of New York Tunnel WDS.

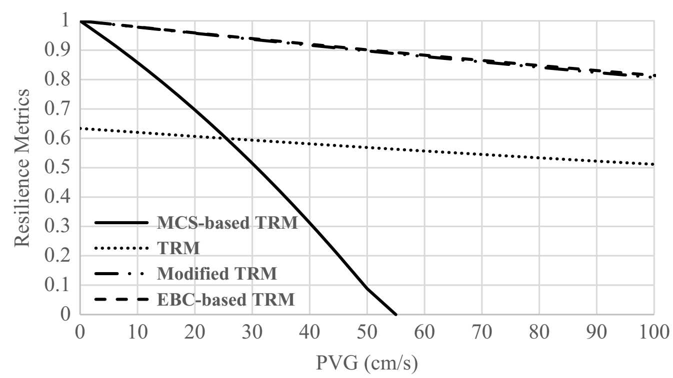

Fig. 8. Comparison of topologic resilience metrics of Jilin WDS.

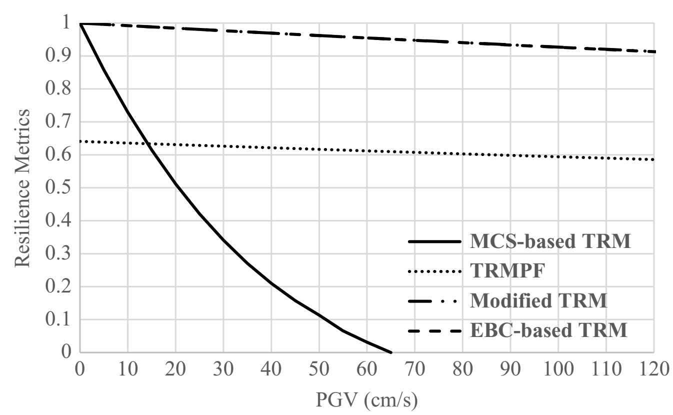

Fig. 9. Comparison of topologic resilience metrics of Bellingham WDS.

than those obtained from the other three systems. It is concluded that system topologic resilience is controlled not by network size but system-level redundancy and average pipeline length. The proposed TRMs can be used to measure system-level connectivity after earthquakes regardless of network size.

Analyzing Figs. 6–9, several conclusions can be obtained. Modified TRM and EBC-based TRM are validated by each other because these two metrics always provide very close values under different system conditions such as number of components, pipeline length, and system-level redundancy. These two metrics provide weighted average residual functionality of the pipelines after earthquakes. The authors recommend using EBC-based TRM because EBC is not a time-dependent and hydraulic-dependent parameter, and EBC-based TRM is easier to use because it is less complicated than modified TRM. TRM cannot provide accurate resilience values because the coefficient of 4 in its denominator may underestimate or overestimate system resilience. The accuracy of TRM depends on how close the system average nodal degree is to 4. If the system's average nodal degree is close to 4, then TRM is able to provide reasonably good results. MCS-based TRM decreases more quickly and provides increasingly smaller values as PGV increases. This is because the definition of system mechanical reliability, calculated by the MCS method, requires that every demand node is connected to source nodes; therefore, the probability of nodal isolation increases rapidly as the failure probability of the pipeline increases. The designer or manager can select the topologic resilience metrics on the basis of different requirements. If the requirement is to determine pipelines' weighted average residual functionality, modified TRM and EBC-based TRM are able to provide accurate results. If the requirement is to check whether every demand node is connected to a water source, MCS-based TRM is a practical metric.

The differences of MCS-based TRMs for four sample WDSs are shown in Fig. 10. It is known from Eq. (3) that pipeline failure probability increases as pipeline length increases. Therefore, systems with longer water pipelines always have less MCS-based TRM than do systems with shorter pipelines. It can be observed by comparing the MCS-based TRMs for the Jilin, New York Tunnel, and Bellingham systems that none of these systems are redundant as shown in Table 1; however, MCS-based TRMs for Jilin and Bellingham are much greater than that for the New York Tunnel because average pipeline lengths are 0.85, 0.29, and 5.31 km for the Jilin, Bellingham, and New York Tunnel systems, respectively. On the other hand, although average pipeline length is greater for Anytown than for the New York Tunnel, the MCS-based TRM for Anytown is still greater than that for the New York Tunnel. This is because the Anytown system is much more redundant than the New York Tunnel system when comparing their meshedness coefficient values. Thus, the systems with higher redundancy have greater MCS-based TRM.

Recovery Strategies

Five recovery cases were performed to verify the effectiveness of the newly proposed optimal recovery strategy. It was assumed that

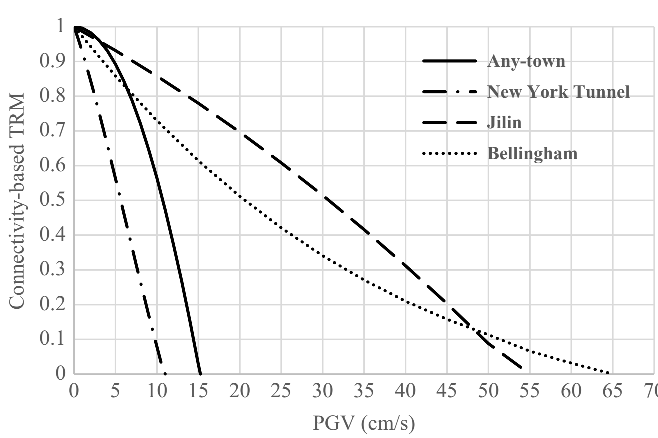

Fig. 10. MCS-based topologic resilience metrics for four WDSs.

all pipelines in the illustrative system were large-diameter pipelines with diameter of 600 mm. The repair time per break is 17 h for large-diameter pipelines (Porter 2016), and thus the repair time for a pipeline is 17 h times the number of breaks for the pipeline. The number of breaks for a pipeline equals the repair rate times the pipeline's length. Because repair time per break depends on diameter of the pipeline, the repair index depends on the diameter. If pipelines in a WDS have various diameters, repair indexes for each pipeline are calculated based on their respective repair time, and then the repair sequence can be updated based on the descending order of the updated repair index values. The Anytown WDS was selected as the sample system, and system functionality was represented by MCS-based TRM. This study selects Anytown as an illustrative system in recovery analysis because Anytown is a more complex network containing more biconnected loops, as shown in average nodal degree and meshedness coefficient. Exactly the same recovery approach can be performed on the New York Tunnel, Jilin, and Bellingham WDSs. When the Anytown WDS is subjected to 14 cm/s PGV, system MCS-based TRM equals 0.1504 calculated using Eq. (5), then the recovery processes begin. It is assumed that the utility has the capacity to repair one pipe break at a time. So, the second reparation task begins immediately after completing the previous repair task. The travel delay in repair phases is ignored. The effect of repair delay can be considered negligible unless significant travel time is required from one pipe break location to another.

In this study, five damage cases, shown in Tables 3–7, were performed. The damage condition for each pipeline was determined stochastically based on the probability of exceedance of the damage condition calculated by Eq. (3) and a random number generated using a uniform distribution U [0, 1]. For each case, only the presented pipelines were in a damaged condition; others were in undamaged condition. It is assumed that the importance factors for all pipelines equal 1.

Tables 3–7 provide the basic information for each pipeline for each damage case, including pipe identification number, repair time (t_i), system functionality enhancement (FE_i), and repair index (RI_i). The FE_i for pipeline i is calculated based on the rule: only

Table 3. Repair indexes of the pipelines for Case 1

Pipe ID	Functionality enhancement	Repair time (h)	Repair index
17	0.2614	7.8128	0.0335
35	0.1504	5.0102	0.0300
34	0.1296	4.6639	0.0278

Table 4. Repair indexes of the pipelines for Case 2

Pipe ID	Functionality enhancement	Repair time (h)	Repair index
17	0.2614	7.8128	0.0335
37	0.2819	13.0015	0.0217
7	0.0506	13.2504	0.0038

Table 5. Repair indexes of the pipelines for Case 3

Pipe ID	Functionality enhancement	Repair time (h)	Repair index
25	0.0101	3.7387	0.0027
2	0.0283	11.1078	0.0026
13	0.0223	9.6416	0.0023

Table 6. Repair indexes of the pipelines for Case 4

Pipe ID	Functionality enhancement	Repair time (hour)	Repair index
12	0.1134	4.6531	0.0244
3	0.1270	7.4341	0.0171
33	0.1253	7.5639	0.0166

Table 7. Repair indexes of the pipelines for Case 5

Pipe ID	Functionality enhancement	Repair time (h)	Repair index
17	0.2614	7.8128	0.0335
35	0.1504	5.0102	0.0300
34	0.1296	4.6639	0.0278
32	0.1350	5.1562	0.0262

Table 8. Resilience obtained for Case 1

Repair sequence	Resilience obtained
[17, 35, 34]	9.142
[17, 34, 35]	9.080
[35, 17, 34]	9.007
[35, 34, 17]	8.600
[34, 17, 35]	8.874
[34, 35, 17]	8.539

Table 9. Resilience obtained for Case 2

Restoration sequence	Resilience obtained
[17, 37, 7]	16.457
[17, 7, 37]	16.228
[37, 17, 7]	16.375
[37, 7, 17]	16.155
[7, 17, 37]	13.159
[7, 37, 17]	13.078

pipeline i is repaired and other pipelines are unrepaired. The FE_i is dynamic because system resilience changes corresponding to the recovery process. However, calculating FE_i for all remaining damaged components after each repair task is mathematically intensive. Therefore, FE_i values for all pipelines are calculated based on initial damaged condition in this study, and the repair sequence is determined based on RI_i at initial damaged condition. If this approach is able to provide the most efficient restoration plan as well, it saves a huge amount of computational effort. The first four cases are three-component recovery processes, and the fifth case is a four-component recovery process.

Tables 8–12 give resilience obtained values for every possible recovery sequence for each case. Pipeline identification numbers in the brackets provide the repair sequence. As an example, for repair sequence [17, 35, 34], Pipeline 17 is repaired at first, followed by reparations of Pipelines 35 and 34. Some possible repair sequences for Case 5 were eliminated on basis of the outcomes of Case 1. For example, because the repair sequence [17, 35, 34] is proven to be more effective than the sequence [17, 34, 35] in Case 1, the repair sequence [17, 35, 34, 32] is obviously more effective than the sequence [17, 34, 35, 32]. Fig. 11 presents how system topologic resilience is restored for different repair sequences for Case 5. Results given in Tables 8–12 show that recovery processes in which pipelines are repaired in the sequence of descending order of repair index values always have the highest resilience obtained values.

Table 10. Resilience obtained for Case 3

Repair sequence	Resilience obtained
[25, 2, 13]	4.733
[25, 13, 2]	4.707
[2, 25, 13]	4.727
[2, 13, 25]	4.713
[13, 25, 2]	4.693
[13, 2, 25]	4.687

Table 11. Resilience obtained for Case 4

Restoration sequence	Resilience obtained
[12, 3, 33]	8.038
[12, 33, 3]	8.008
[3, 12, 33]	7.785
[3, 33, 12]	7.510
[33, 12, 3]	7.732
[33, 3, 12]	7.480

Table 12. Resilience obtained for Case 5

Repair sequence	Resilience obtained
[17, 35, 34, 32]	12.769
[32, 17, 35, 34]	12.378
[17, 32, 35, 34]	12.672
[35, 32, 17, 34]	12.121
[34, 32, 17, 35]	11.352

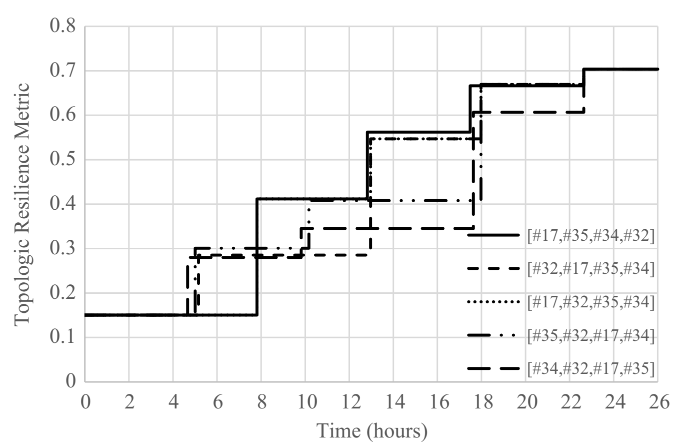

Fig. 11. Topologic resilience metric curves for Case 5.

Although the FE_i for each component is a dynamic value, determining the repair sequence based on FE_i at the initial damaged condition is able to provide the most efficient recovery plan as well and save significant computational time. Therefore, it is concluded that the newly proposed recovery process is the most effective recovery strategy.

Conclusions

WDSs can be severely damaged due to catastrophic earthquakes. It is necessary to measure system residual functionality and apply the best restoration strategy after an earthquake to reduce further losses. This study analyzed existing topologic resilience metrics and proposed a new resilience metric that can be applied to any size and characteristics of WDS. First, system topologic functionality was represented by its mechanical reliability, which was determined by the MCS method. The second and third metrics were TRM and modified TRM, respectively. The newly proposed EBC-based TRM was developed based on pipelines' robustness (reliabilities) and pipelines' EBC values. These four metrics were applied to four water networks (Anytown, New York Tunnel, Jilin, and Bellingham) subjected to various levels of seismic intensities. The outcomes show EBC-based TRM and modified TRM provide similar outcomes. Therefore, these two metrics can be used to determine pipelines' weighted average residual functionality. The newly proposed resilience metric provides more realistic outcomes than modified TRM. The TRM provides conservative estimation of seismic performance of a WDS in which the average nodal degrees are much less than 4. MCS-based TRM drops the most quickly in comparison because it determines the probability that all demand nodes are connected to source nodes. As the seismic intensity increases, the probability of nodal isolation increases quickly. After comparing TRM values for four example networks, it can be concluded that topologic resilience increases with the increase of network redundancy, and it decreases with the increase of pipelines' length.

The proposed recovery strategy helps utilities identify the optimal recovery sequence in which system functionality can be restored quickest. The failure pipelines are repaired in an order of descending repair index, which is defined as a function of functionality enhancement upon reparation of a pipeline, repair time of the pipeline, and pipeline importance factor. The proposed recovery strategy was illustrated using the Anytown WDS. The results show that this recovery strategy is the best plan because it always provides the highest resilience obtained values. Moreover, the optimal recovery model is easy to use as well as computationally efficient. Although the recovery strategy is illustrated for Anytown WDS, the proposed recovery sequence can be applied for other network systems.

This study has some limitations that can be further investigated in future research. This study assumes that only one pipeline is being repaired at a time. The optimal recovery strategy needs to be validated or modified when multiple repair tasks are conducted at the same time. This study evaluates the seismic performance of WDSs using topological measures; seismic hydraulic resilience metrics and water quality metrics require to be studied in future research.

Data Availability Statement

All data, models, and code generated or used during the study appear in the published article.

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