Identification of Critical Pipes for Proactive Resource-Constrained Seismic Rehabilitation of Water Pipe Networks

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Abstract: Utility managers in charge of water pipe networks that are exposed to high seismicity make difficult decisions regarding the allocation of a limited rehabilitation budget to be most effective in enhancing a network's postearthquake serviceability. Seismic vulnerability models are typically integrated with simple prioritization methods to identify the critical pipes subjected to earthquakes. These methods do not distribute resources at the system level and may not provide an economical solution. The objective of this paper is to develop an approach to identify the critical pipes for proactive seismic rehabilitation that will enhance a network's postearthquake serviceability when only a finite length of pipes can be rehabilitated. To achieve this objective, a proper stochastic combinatorial optimization was formulated and then solved, using a genetic algorithm that was integrated with a network-level seismic vulnerability model. The approach was implemented to identify critical links for proactive seismic rehabilitation of two benchmark networks. The results showed that this approach outperforms the simple length-based prioritization methods used by the utilities, as well as the latest proposed methodology in the literature, in identifying the critical pipes in a water pipe network subjected to an earthquake. **DOI: 10.1061/(ASCE)IS.1943-555X.0000439.**

Introduction

Past earthquakes such as the 1906 San Francisco, the 1994 Northridge, the 1995 Hyogoken-Nanbu (Kobe), and more recent earthquakes such as the 2007 Niigata Chuetsu-Oki, the 2011 Christchurch, the 2011 East Japan, and the 2015 Gorkha have demonstrated that water pipe networks are extremely vulnerable to earthquakes (Cubrinovski et al. 2011; Hwang et al. 1998; Maruyama et al. 2011; Thapa et al. 2016; Yasuda et al. 2012). Earthquake impacts on water supply networks can result in enormous direct losses such as the cost of repair and indirect losses such as a disruption in water distribution (Yerri et al. 2017), and can severely limit the capacity to control conflagrations following earthquakes (Selina et al. 2008). These facts highlight the significance of seismic vulnerability assessment of water pipe networks and mitigation of such vulnerabilities. A seismic vulnerability assessment of water supply networks estimates the likelihood of damage to pipelines and degradation of service after seismic events. The probabilistic nature of losses following earthquakes, a complex network topology, a wide range of pipe materials, and different pipe and soil characteristics make seismic vulnerability assessment challenging. Several seismic vulnerability assessment models have been proposed to address these challenges. Despite all these models and technological advancements, water utility managers are often limited in what they can do, even when their budget allows additional maintenance. For example, if their budget covers only the cost of inspecting or rehabilitating 1000 m (3280.84 ft) of large-diameter pipes, the water utility management must decide which pipe sections should be selected for rehabilitation. To address this, a methodology is required that can identify the critical pipes in water pipe networks by considering the criticality of the pipes along with the limited rehabilitation resources of the utilities.

Research Background

In this section, we initially discuss the current literature dealing with vulnerability assessment of networked infrastructure systems and methodologies with synergistic applications. Then, we discuss the literature dealing with vulnerability assessment of water pipe networks considering nonseismic/generic hazards. Last, we focus on the works dealing particularly with the seismic vulnerability of buried pipe networks.

Pipe network is one of the lifeline networks that perform the critical function of providing access to drinking water, transportation, electric power, and transportation services (Reed et al. 2009). Despite their critical function, such networks are vulnerable to an array of natural and human-caused threats such as earthquakes, flooding, hurricanes, accidents, and manufactured threats (Bonneau and O'Rourke 2009). Extensive research has been conducted to quantify the vulnerabilities of infrastructure systems to these threats and to mitigate them. Due to the complexity and the interdependence of these infrastructure systems, the synergistic application of multidisciplinary ideas is usually needed to model these systems. Infrastructure systems are typically modeled as networks composed of nodes and links (Eusgeld et al. 2009; Ouyang 2014) and analyzed primarily using topological analysis and flow-based analysis. Topological analysis uses graph theory and topological measures to study the vulnerability of a wide variety of infrastructure systems such as electrical power systems (Crucitti et al. 2005; Rokneddin et al. 2009) and transportation systems (Angeloudis and Fisk 2006; Berche et al. 2009; Chen et al. 2007). In contrast, flow-based analyses use physics-based equations to quantify the vulnerabilities of

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Note. This manuscript was submitted on May 30, 2017; approved on April 16, 2018; published online on August 14, 2018. Discussion period open until January 14, 2019; separate discussions must be submitted for individual papers. This paper is part of the ***Journal of Infrastructure Systems***, © ASCE, ISSN 1076-0342.

transportation networks (Sullivan et al. 2010), natural gas distribution systems (Han and Weng 2010), and wireless networks (Huang et al. 2007).

Topological and flow-based approaches are used to assess the vulnerability of water pipe networks, as well. Grigg (2003) and Haimes et al. (1998) reviewed various threats, natural and human-caused, and identified various vulnerabilities of water pipe networks. Apostolakis and Lemon (2005) used graph theory and value tree analysis to yield a prioritized list of scenarios induced by a terrorist attack on a water supply system. Yazdani and Jeffrey (2011) used several topological metrics to formulate resilience-enhancing expansion strategies for water pipe networks. Gutiérrez-Pérez et al. (2013) used the page rank and the hyperlink-induced topic search (HITS) algorithms combined with graph theory to identify the critical zones in a water supply network. These topology-based methods are economical in terms of computational resources in solving a relatively large network. However, these models are inferior to flow-based models in predicting the system-level serviceability of the network (Cavalieri et al. 2014). Hence, many other researchers used flow-based network models to assess the vulnerability of water network systems. Murray et al. (2004) discussed the development of a probabilistic flow-based model by the USEPA to assess the vulnerability of water distribution systems to a broad range of contamination attacks. Shuang et al. (2014) used hydraulic simulation to study the nodal vulnerability of water pipe networks subjected to cascading failure due to intentional attacks.

Significant literature exists in the field of seismic vulnerability of buried water pipe networks and can be broadly classified in two categories: component-level seismic vulnerability assessment models and system-level seismic vulnerability assessment models. Component-level seismic vulnerability assessment models evaluate the seismic performance of individual components of water pipe networks such as a single pipe or a single joint. System-level seismic vulnerability assessment models evaluate the seismic performance of the entire water pipe network, and the performance metrics of the entire network are monitored in such an assessment. Early seismic vulnerability assessment methods were mostly component-level vulnerability assessment methods that focused on the seismic performance of individual water pipes. Many analytical component-level seismic vulnerability assessment models of buried pipes were developed. These models are summarized in Datta (1999). However, empirically derived seismic vulnerability relations for buried pipes (ALA 2001; Honegger and Eguchi 1992; Jeon and O'Rourke 2005; O'Rourke and Ayala 1993) are typically used in system-level vulnerability assessment.

During the past two decades, advances in computational engineering, probabilistic modeling, and network simulation have motivated researchers to go beyond component-level assessments and create seismic vulnerability assessments of water pipe networks, that is, system-level seismic vulnerability assessment models. These existing component-level and system-level seismic vulnerability assessment methods for water pipe networks are reviewed here. Markov et al. (1994) developed the software graphical interactive serviceability analysis of lifelines subjected to earthquake (GISALLE) to evaluate the seismic performance of the auxiliary water supply system of San Francisco. Markov et al. (1994) considered only pipe breaks in their model and ignored pipe leaks. However, that is not realistic, as most of the damage (80%) due to seismic ground shaking is realized as leaks (Ballantyne and Taylor 1990). Hwang et al. (1998) proposed a GIS-based method to study the postearthquake serviceability of water supply systems considering probabilistic leaks and breaks. Shi (2006) built on the work of Markov et al. (1994) and created a computer program called the graphical iterative response analysis for flow following earthquakes (GIRAFFE). GIRAFFE uses empirical seismic vulnerability functions proposed by Jeon and O'Rourke (2005) and Monte Carlo simulation in order to simulate random, earthquake-induced pipe damage in the network. Shi (2006) also refined the hydraulic models of leaks and breaks proposed by Ballantyne and Taylor (1990), Markov et al. (1994), and Hwang et al. (1998). He then incorporated it into GIRAFFE to perform accurate hydraulic analysis of a water pipe network damaged by an earthquake. GIRAFFE was then used to study the seismic response of the pipe network managed by the Los Angeles Department of Water and Power (LADWP) during the Northridge earthquake of 1994. However, Shi (2006) did not propose any method of identifying proper rehabilitation measures to reduce the seismic vulnerability of the system and was focused solely on the seismic vulnerability assessment of water supply systems. Takao Adachi (2007) and Adachi and Ellingwood (2008) proposed a method to analyze the postearthquake serviceability of a water supply system considering its interdependence with the electrical power distribution system, using fault tree analysis and the shortest path algorithm. Their work also highlighted the need to consider spatial correlation and scenario earthquake in analyzing the seismic vulnerability of spatially distributed systems. However, their work ignored the hydraulics (flows and pressures) of the water pipe systems and considered only the postearthquake connectivity of the system to evaluate the seismic vulnerability of a water pipe network. Wang et al. (2010) introduced the system serviceability index (SSI) for a water pipe network subjected to earthquakes. These indices combined with the efficient frontier approach were used to identify and rank the network's critical pipes. The system serviceability index (SSI), as defined by Wang et al. (2010), is the ratio of water demand fulfilled after an earthquake to the inherent (original) demand of the water pipe network. Zohra et al. (2012) proposed an index for prioritizing pipes in a water supply network. The index is based on the pipe diameter, seismic intensity, and soil conditions. However, hydraulics and network topology are not considered in this index.

Due to budget limitations, water utilities cannot perform seismic rehabilitation of an entire network. They must instead identify a few critical pipes and invest in their seismic rehabilitation to enhance the network's postearthquake serviceability (Klise et al. 2015). Currently, utility managers are struggling to find a comprehensive model that can identify critical pipes for seismic rehabilitation. However, most of the models (Adachi 2007; Hwang et al. 1998; Shi 2006; Zolfaghari and Niari 2009) propose approaches only for the seismic vulnerability assessment of water pipe networks and do not consider the seismic rehabilitation of water pipes. A few simple prioritization models (Fragiadakis and Christodoulou 2014; Wang et al. 2010; Zohra et al. 2012), based on seismic vulnerability, were proposed in the literature to identify critical pipes for seismic rehabilitation. Fragiadakis and Christodoulou (2014) and Zohra et al. (2012) ignored the hydraulics of the problem in recommending critical pipes. Wang et al. (2010) oversimplified the seismic vulnerability assessment by using a uniform peak ground velocity for the entire network in identifying critical links. This led to an underestimation of seismic hazard, especially for spatially distributed systems such as water pipe networks (Adachi 2007; Weatherill et al. 2013; Zanini et al. 2016). Furthermore, none of the discussed models has considered the limited rehabilitation resource constraint and system level distribution of this limited resources and therefore cannot find an economical solution. For example, suppose that there is a long pipe that has the highest priority for rehabilitation, and the cost of rehabilitating this pipe is equal to the cost of rehabilitating several short pipes that have a lower priority. It is possible that the rehabilitation of the short pipes would result in much greater enhancement of the postearthquake serviceability. Hence, departing from current priority-based models (Fragiadakis and Christodoulou 2014; Wang et al. 2010; Zohra et al. 2012), a proper stochastic combinatorial optimization was formulated and then solved, using a genetic algorithm integrated with a network-level seismic vulnerability assessment model to identify critical pipes for proactive seismic rehabilitation of the water pipe network. The probabilistic nature of the objective function, along with the combinatorial nature of pipe selection for seismic rehabilitation, makes the problem a stochastic combinatorial optimization. Hence, a stochastic combinatorial optimization was formulated, with the following advantages:

- This is the first attempt to integrate a metaheuristic-based optimization algorithm with a system-level seismic vulnerability assessment model of pipe networks, which is a novel contribution to the body of knowledge.
- This method also facilitates seismic rehabilitation of water pipe networks by identifying critical pipes for rehabilitation when only a limited length of pipe can be rehabilitated, which is a novel contribution to the state of practice.

The objective of this paper is to develop an approach for identifying pipes that are most critical to the proactive seismic rehabilitation of water pipe networks for enhancing postearthquake serviceability. The methodology adopted to achieve this objective is explained in the following sections. Application of the proposed methodology is demonstrated using two benchmark water pipe networks. Subsequently, the results are validated by comparison with the results obtained by implementing a simple length-based prioritization scheme and the latest methodology available in the literature. Then, the limitations of the model and the potential of the model to be applied to other infrastructure systems are discussed. Finally, the conclusions are presented.

Methodology

The methodology adopted to achieve the objective can be divided into two steps:

1. Formulating a stochastic combinatorial optimization to maximize the postearthquake serviceability of water pipe networks for which rehabilitation is constrained by the ability of the utilities to rehabilitate only a limited length of pipes; and
2. Solving the stochastic combinatorial optimization by integrating a genetic algorithm with the network-level seismic vulnerability assessment to identify critical pipes for proactive seismic rehabilitation.

Formulation of Stochastic Combinatorial Optimization

The problem was defined as the maximization of the expected value of the SSI of a water pipe network if the water agencies can rehabilitate only a limited length of pipes (l_{rehab}) due to budget limitations. Eq. (1) presents the objective function

$$\mathbf{max}_{\boldsymbol{x}\in\mathbf{X}} \boldsymbol{E}[\boldsymbol{SSI}(\boldsymbol{x})] \tag{1}$$

where $\mathbf{X}$ represents the set of all the rehabilitation policies ($\boldsymbol{x}$). Here, a rehabilitation policy ($\boldsymbol{x}$) is created by choosing two outcomes, rehabilitation or no rehabilitation, for each pipe in the network. Let us consider a network with two pipes. A rehabilitation policy for this network can be represented by a set $\{x_1, x_2\}$, where $x_i = 1$ represents that the i^{th} pipe is rehabilitated and $x_i = 0$ means i^{th} pipe is not rehabilitated. Based on this, the set of all rehabilitation policy for this network would be $\mathbf{X} = \{\{0,0\}, \{0,1\}, \{1,0\}, \{1,1\}\}$. As such, without any feasibility constraints, $\mathbf{X}\epsilon\mathbf{B}^{2^{\mathrm{N_p}}\mathrm{xN_p}}$, which is a combinatorial decision space where N_p is the total number of pipes in the network. However, the size of $\mathbf{X}$ is reduced by the feasibility constraint imposed by the condition that any rehabilitation policy ($\boldsymbol{x} \in \mathbf{X}$) cannot suggest rehabilitating pipes longer than l_{rehab}. As a proof of concept, we have used the rehabilitation length constraint as the only constraint in this paper. However, the proposed model is flexible enough to accommodate any other constraints, such as prioritizing the rehabilitation of a subset of pipes.

The calculation of the SSI involves solving a large number of nonlinear hydraulic equations that require knowledge of the location and magnitude of earthquake-induced damage (pipe leaks and pipe breaks). The properties of earthquake-induced damage are probabilistic, due to aleatory uncertainties, making the SSI a probabilistic quantity. Thus, the probabilistic nature of the SSI, along with the combinatorial nature of the pipe selection for seismic rehabilitation, makes the problem a stochastic combinatorial optimization. Hence, a solution of the formulated problem will entail a solution of a stochastic combinatorial optimization.

Solution Methodology

Solving the stochastic combinatorial optimization problem is extremely challenging due to the nonconvex and noncontinuous objective function and the lack of closed-form representation for the objective function. Because the objective function does not necessarily have a closed-form representation, conventional algorithms for solving combinatorial stochastic optimization problems, such as deterministic reformulation, are not applicable. Therefore, a genetic algorithm (Holland 1975) was devised and integrated with the seismic vulnerability assessment of water pipe networks. The integrated genetic algorithm identifies which pipes in a water pipe network are critical for proactive seismic rehabilitation to maximize the postearthquake serviceability of water pipe networks. The maximization is constrained by the water agencies' inability to rehabilitate all the pipes due to infrastructure funding gaps (USEPA 2002). Fig. 1 shows how the genetic algorithm is integrated with the seismic vulnerability assessment of water pipe networks.

Binary encoding was adopted to represent rehabilitation policies, that is, chromosomes of the genetic algorithm. Each rehabilitation policy (x) was represented by a binary vector, so that each element of the binary vector represented a rehabilitation decision for a specific pipe (0 and 1 indicate no rehabilitation and rehabilitation, respectively, for a pipe). For example, assume a water pipe network with five pipes. A rehabilitation policy of rehabilitating the first and last pipe for this network would be represented by the binary vector [10001]. In this paper, these vectors are referred to as solution vectors.

In generating solution vectors, the following constraint was used to discard solutions:

$$\sum_{k=1}^{N_p} a_k l_k \le l_{rehab} \tag{2}$$

where a_k is 1 if pipe k is rehabilitated; a_k is 0 if pipe k is not rehabilitated; N_p is the number of pipes in the network; and l_k is the length of pipe k.

The algorithm begins with an initial population generation, which involves the creation of five random solution vectors that represent five random rehabilitation policies. This initial population acts as the current generation at the start of the genetic algorithm. The mutation rate of the genetic algorithm is initialized at 0.9 at the start of the algorithm.

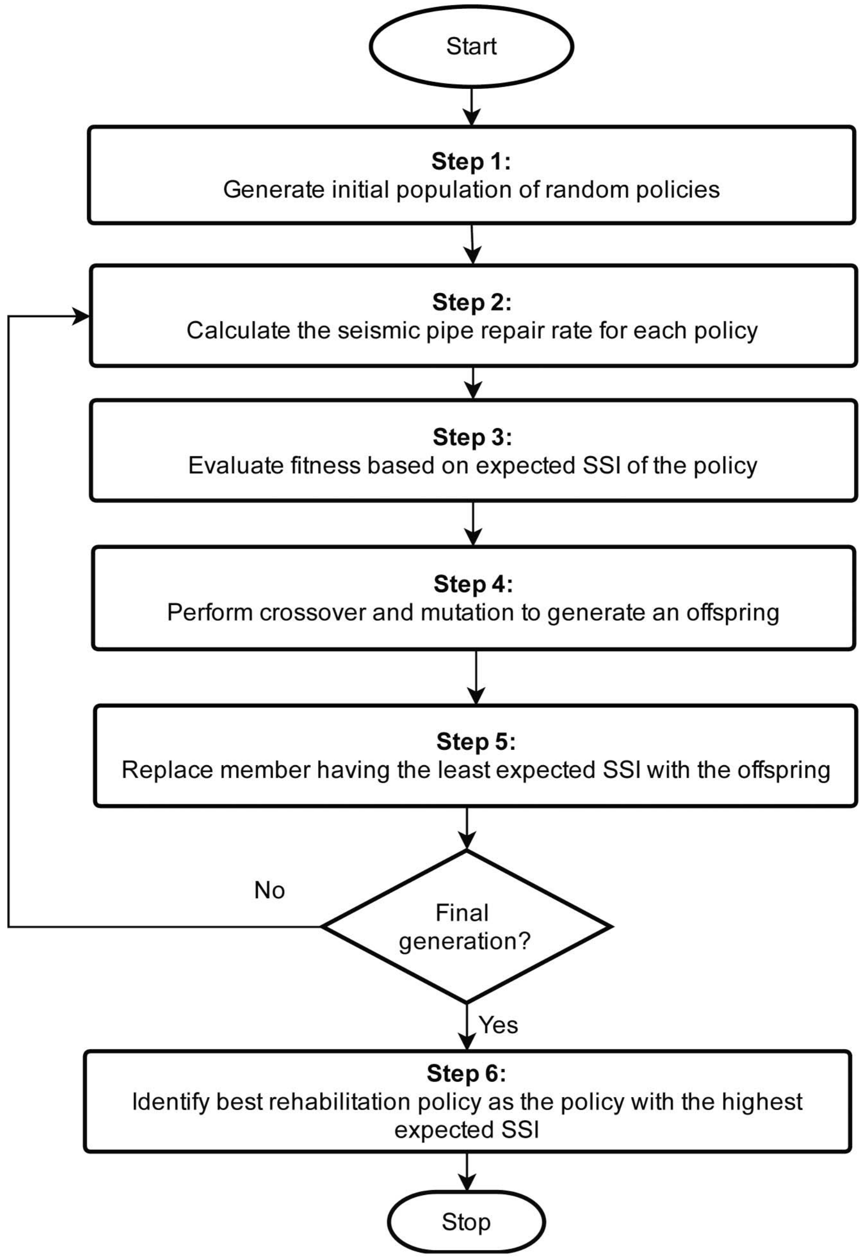

Fig. 1. Genetic algorithm integrated with seismic vulnerability assessment of water pipe networks.

Following the initialization of parameters of the genetic algorithm, seismic pipe repair rates were calculated. ALA defines seismic pipe repair rate as the expected pipe repairs per 304.8 m (1,000 ft) of pipe following an earthquake. Thus, the seismic pipe repair rate indicates the number of expected leaks and breaks in a pipe following an earthquake and is determined on the basis of the peak ground velocity at the location of the pipe, the structural properties of the pipes, and the corrosivity of the soil. Fig. 2 shows the method of calculating the seismic pipe repair rate.

The calculation of the seismic pipe repair rate starts with the selection of a scenario earthquake subjected to which the expected SSI of a water pipe network should be maximized. Scenario earthquakes are typically used for seismic analysis of utilities because modeling earthquakes as scenarios allows consideration of spatial correlations between seismic intensities, which cannot be ignored for spatially distributed infrastructure systems such as water pipe networks, transportation networks, and spatially distributed portfolios of structures (Adachi 2007; Weatherill et al. 2013; Zanini et al. 2016, 2017). Moreover, results from scenario earthquakes are easier to use in communicating with nonspecialist decision makers (Adachi 2007). Hence, for this paper, we use a scenario earthquake selected on the basis of deaggregation analysis proposed by Adachi (2007). In accordance with this method, a return period is selected on the basis of the utility's resources and risk tolerance. The selected return period is then used to generate deaggregation maps for 1.0-s spectral acceleration maps using a deaggregation tool developed by the USGS (2018b). Then, an earthquake with the highest contribution ratio is selected from the list of characteristic earthquakes obtained from deaggregation analysis to be the scenario earthquake for the analysis.

Next, the peak ground velocity and permanent ground deformation should be calculated for the selected earthquake. The peak ground velocity quantifies the maximum level of transient seismic

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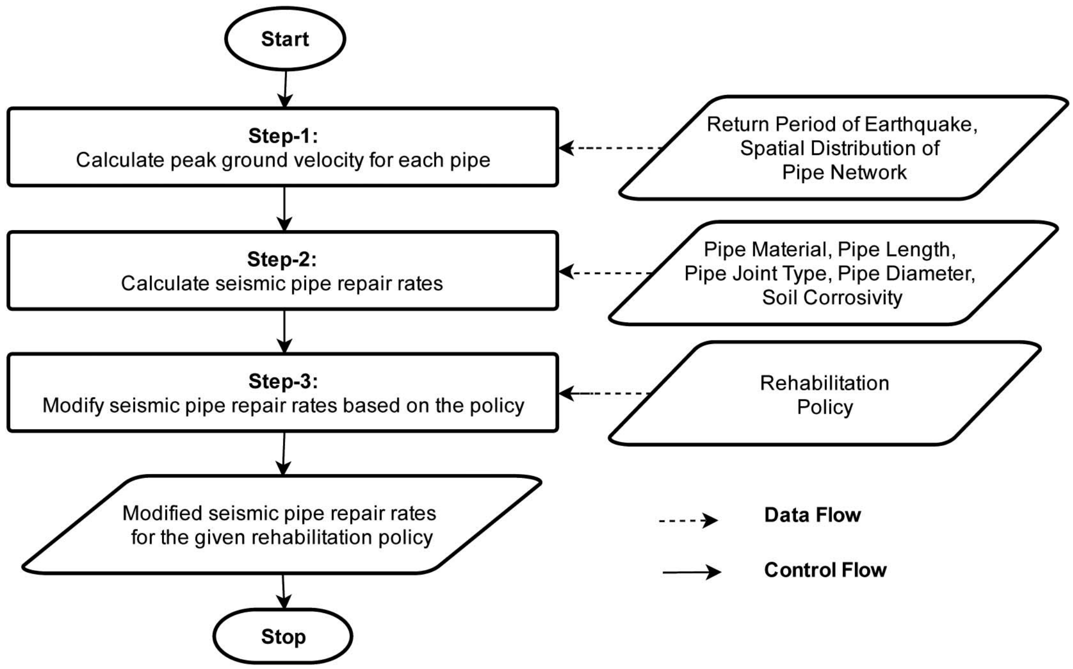

Fig. 2. Seismic pipe repair rate calculation.

ground shaking experienced at a given location during an earthquake. We selected peak ground velocity as the seismic intensity parameter because peak ground velocity is directly related to the transient strains induced in the soil during an earthquake, which are the primary causes of failures of buried pipes, due to seismic ground shaking (Pineda-Porras and Najafi 2010).

Permanent ground deformation quantifies the expected level of earthquake-induced geotechnical instability such as liquefaction, landslide, and lateral spreading at a given location following an earthquake. In this paper, to focus on the effects of seismic ground shaking alone, it was assumed that the site was not susceptible to earthquake-induced geotechnical instability; hence, the peak ground displacement was assumed to be 0.

Following the selection of an earthquake scenario, we chose the ground motion prediction equation (GMPE) proposed by Abrahamson and Silva (2007) along with the Zanini et al. (2016, 2017) approach to generate a spatially correlated peak ground velocity field. The general expression for calculating peak ground velocity is

$$\boldsymbol{log}_{10}(\boldsymbol{PGV_{ij}}) = \boldsymbol{f}(\boldsymbol{M_i}, \boldsymbol{R_{ij}}, \boldsymbol{\theta_i}) + \boldsymbol{\sigma_B \nu_i} + \boldsymbol{\sigma_W \varepsilon_{ij}} \tag{3}$$

where PGV_{ij} is the peak ground velocity for a site j, at a distance of R_{ij} from the source i during an earthquake event of magnitude M_i; θ_i is the geological parameters defining the fault at source i; $\sigma_B \nu_i$ represents the residual interevent variability, whereas $\sigma_W \varepsilon_{ij}$ represents the intraevent residual. A peak ground velocity map for the selected earthquake, without interevent and intraevent variability, that is, $f(M_i, R_{ij}, \theta_i)$, was generated on the basis of Abrahamson and Silva (2007) using the scenario shake map calculator by Field et al. (2005). To incorporate the interevent and intraevent variabilities in this map, ν_i and ε_{ij} were generated, where ν_i and ε_{ij} are normally distributed random variables with mean ($\mu = 0$) and standard deviations σ_B and σ_W. However, ε_{ij} is spatially correlated, as well. To consider this, we used the following equation based on Weatherill et al. (2013) and Zanini et al. (2016) to generate $\boldsymbol{\varepsilon}$

$$\boldsymbol{\varepsilon} = \boldsymbol{\mu} + \boldsymbol{LZ} \tag{4}$$

where $\boldsymbol{\mu}$ is taken as [0]; $\boldsymbol{Z}$ is the vector of random variables with standard normal distribution; and $\boldsymbol{L}$ is the lower triangular matrix, obtained using the Cholesky decomposition method, such that $\boldsymbol{LL^T} = \boldsymbol{C}$, where C is a positive-definite covariance matrix

$$\boldsymbol{C} = \begin{bmatrix} \mathbf{1} & \boldsymbol{\sigma}(\boldsymbol{h}_{\mathbf{1,2}}) & \dots & \boldsymbol{\sigma}(\boldsymbol{h}_{\mathbf{1},N}) \\ & 1 & \dots & \boldsymbol{\sigma}(\boldsymbol{h}_{\mathbf{2},N}) \\ & & \ddots & \vdots \\ \boldsymbol{sym} & & & \mathbf{1} \end{bmatrix} \tag{5}$$

where $\sigma(h_{j,k})$ is a correlation coefficient between intraevent residuals calculated for sites j, k, among total N sites, where $\sigma(h_{j,k})$ is calculated, based on Zanini et al. (2016)

$$\boldsymbol{\sigma}(\boldsymbol{h_{j,k}}) = \boldsymbol{e}^{\left(\frac{-3h_{j,k}}{b}\right)} \tag{6}$$

where $h_{j,k}$ is the intersite distance between sites j and k; and b is the intersite distance between which spatial correlation is negligible. Wang and Takada (2005) recommends the value of b within a range of 20–40 km when the spatial correlation is calculated for peak ground velocity. Hence, for this study, $b = 30$ km was used. By repeating this process m times, m random peak ground velocity fields were generated as per Zanini et al. (2017). For each of these m fields, average peak ground velocity was calculated for each pipe. The average peak ground velocity was used because Adachi (2007) concluded that using average peak ground velocity for each water pipe leads to a lower bound estimate of network serviceability, which is conservative from a disaster planning perspective.

After the average peak ground velocity was calculated for each pipe, the seismic repair rate was calculated by using the empirical seismic vulnerability relationship proposed by ALA (2001)

$$\boldsymbol{RR_{k,m}} = \boldsymbol{K1} * \mathbf{0.00187} * \boldsymbol{PGV_m} \text{ (For seismic ground shaking)} \tag{7}$$

where $RR_{k,m}$ is seismic repair rate per 304.8 m (1,000 ft) of pipe k for mth peak ground velocity field; PGV_m (measured in inches/second) is the average peak ground velocity for the pipe based on mth peak ground velocity field; and $K1$ is the modification factor that adjusts the repair rate based on pipe material, diameter, pipe joint characteristics, and soil corrosivity. The values of $K1$ are tabulated in ALA (2001).

Seismic pipe repair rates thus calculated are referred to as unmodified repair rates. Modified seismic pipe repair rates are calculated using Eq. (8) for each rehabilitation policy in the current generation of the genetic algorithm

$$RR_k^{x,j} = RR_{k,j} * (1 - a_k^x) \tag{8}$$

where $RR_k^{x,j}$ is the modified seismic pipe repair rate for pipe k based on rehabilitation policy x and jth peak ground velocity field; $RR_{k,j}$ is the seismic pipe repair rate for pipe k and jth peak ground velocity field; a_k^x is 0 if the pipe is unrehabilitated based on policy x; and a_k^x is 1 if the pipe is rehabilitated based on policy x.

After the modified seismic pipe repair rate is calculated for each pipe in the network, the expected SSI is calculated for the rehabilitation policy x. Calculation of the expected SSI is required for the fitness evaluation of each rehabilitation policy in the current generation of the genetic algorithm. To accomplish this, a Monte Carlo simulation is devised to calculate the expected SSI (Fig. 3).

The expected SSI for a rehabilitation policy T is calculated

$$E[SSI(x = T)] = \frac{\sum_{j=1}^{m} \sum_{r=1}^{NMCS} \sum_{i=1}^{N} x_{ri}^{T,j} D_i}{m * NMCS * \sum_{i=1}^{N} D_i} \tag{9}$$

subject to

$$x_{ri}^{T,j} = 1 \quad \text{if } P_{ri}^{T,j} \geq P_{threshold}$$

$$x_{ri}^{T,j} = 0 \quad \text{if } P_{ri}^{T,j} \leq P_{threshold}$$

where N is the number of nodes in the network; $NMCS$ is the number of Monte Carlo simulation runs adopted for evaluating each rehabilitation policy; D_i is the water demand at node i; $P_{ri}^{T,j}$ is the hydraulic pressure at node i during the rth run of Monte Carlo simulation for rehabilitation policy T for jth peak ground velocity field; and $P_{threshold}$ is the minimum hydraulic pressure required at the node, imposed by the firefighting demand. In this study, a hydraulic pressure of 0.14 MPa (20 psi) was used as the $P_{threshold}$, as suggested by Trautman et al. (1987).

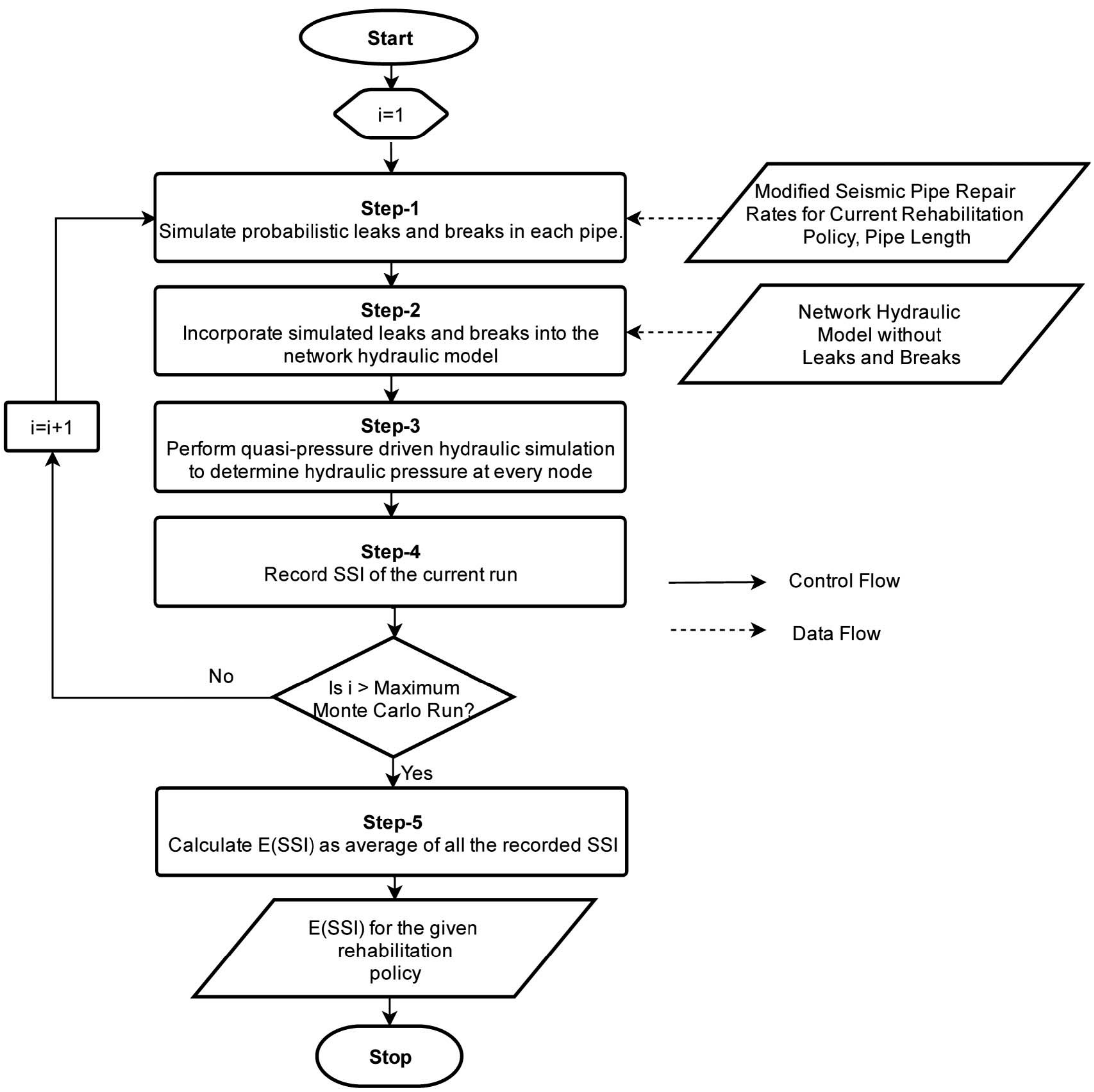

Fig. 3. Expected system serviceability index calculation for a rehabilitation policy.

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For a rehabilitation policy T, each run of the Monte Carlo simulation begins by determining the location of earthquake-induced leaks and breaks in the water pipe network. This is accomplished by modeling the earthquake-induced leaks and breaks as the Poisson process, where the location of the ith leak or break in a pipe P is determined

$$l_{P,i} = l_{P,i-1} - \frac{1}{RR_P^{T,j}} * \ln(1 - U) \quad where\ l_{P,0} = 0 \tag{10}$$

where $l_{P,i}$ is the distance of ith discontinuity (leak or break) in pipe P from its start node; $RR_P^{T,j}$ is the seismic pipe repair rate calculated for the pipe P based on policy T for the jth peak ground velocity field; and U is the uniformly distributed random number between 0 and 1. If the location of the first leak or break lies within the length of the pipe, that is, $l_{P,1}$ is less than the length of pipe P, then a second random number is generated to classify it as either a leak or a break. If the second random number generated is less than or equal to 0.8, the discontinuity at the location $l_{p,1}$ is classified as a leak; otherwise, it is classified as a break (FEMA 2014; Shi 2006). Leaks are further classified, and the diameters of the leaks are calculated on the basis of Shi (2006). This process is repeated for higher values of i until the value of $l_{p,i}$ exceeds the length of the pipe. The same process is repeated for other pipes in the network.

After all the leaks and breaks have been located and the diameters of all the leaks have been determined for the current Monte Carlo run, they are integrated into the network hydraulic model of the undamaged water pipe network. The hydraulic modeling of leaks and breaks proposed by Shi (2006) is used for this integration. The resulting hydraulic model is then analyzed, using a quasi-pressure-driven hydraulic analysis, to determine the hydraulic pressures at each node (P_{ri}^T). This analysis is required because conventional demand-driven hydraulic analysis assumes that the hydraulic demand at each node is always fulfilled, and that may not be a valid assumption for water pipe networks damaged by an earthquake (Cheung et al. 2005; Ozger and Mays 1994; Shi 2006). Hydraulic analysis, with the assumption that nodal water demand is not always fulfilled and that the system can have no negative pressure in the nodes, is more realistic. Therefore, for this study, the quasi-pressure-driven analysis approach was adopted, and the following operations were performed for each run of the Monte Carlo simulation:

1. The hydraulic model with integrated leaks and breaks was analyzed.
2. Nodes with negative pressure were identified and removed from the network.
3. Steps 1 and 2 were repeated until there were no nodes with negative pressure.

Using this approach, the hydraulic pressure at each node (P_{ri}^T) was calculated and recorded for a predefined maximum number of Monte Carlo runs (NMCS) for the rehabilitation policy $(x = T)$. The expected serviceability index of the water pipe network for a rehabilitation policy $(x = T)$ in the current generation of the genetic algorithm was calculated, using Eq. (9). The entire process was repeated for other rehabilitation policies until the expected serviceability index of every rehabilitation policy in the current generation of the genetic algorithm was determined.

Next, to advance to the next generation of the genetic algorithm, genetic operations as proposed by Chen and Shahandashti (2009) were used. All the policies in the current generation were ranked on the basis of their expected SSIs, and the two policies with the highest expected SSIs were selected to produce an offspring policy. A two-point crossover followed by random mutation of 20% of the offspring was performed on the offspring policy. The crossover and mutation operation were repeated until the cumulative rehabilitation length represented by the mutated offspring was less than or equal to l_{rehab}.

Subsequently, the current generation's rehabilitation policy with the least expected SSI was replaced by the offspring. This replacement yielded a new current generation of genetic algorithms. Subsequently, the generation number was increased and checked for exceedance of the maximum generation number. If no exceedance occurred, then for the next generation the mutation rate was decreased by 3%. This process of expected SSI calculation and the genetic operation was repeated for the new current generation until the maximum generation was reached. The rehabilitation policy with the highest expected SSI in the last generation represented the best seismic rehabilitation policy for the selected earthquake, given water pipe network, and given rehabilitation budget constraints. The pipes chosen for seismic rehabilitation were identified as the critical pipes in the water pipe network.

Application

To demonstrate the application of the approach created in this study, we used a benchmark network, the Modena network (Fig. 4), from the Centre for Water Systems (2018). This network was created for resilience study of large-dimensional water pipe networks. The network has 268 junctions, 317 pipes, and four reservoirs with a fixed head within 72.0 to 74.5 m. The total length of the pipes of the entire network is 71806.11 m. For the calculation of the seismic repair rate, pipes with diameters less than 300 mm (12 in.) were considered as cast-iron pipes with lead joints, and pipes with diameters greater than 300 mm (12 in.) were considered as ductile-iron (DI) pipes with rubber-gasketed joints.

For the seismic vulnerability analysis, the location of the centroid of the network was assumed to be Pasadena, California (34.146267° N, 118.144040 W). A deaggregation analysis was performed at 34.146267° N, 118.144040 W for 1.0-s spectral acceleration for the return period of 2475 years using USGS (2018b). From the deaggregation result, an earthquake originating at Raymond fault, 3.25 km from the network's centroid, with a magnitude of 7.12 was identified with a maximum contribution ratio (13.84%). This was selected as the scenario earthquake for this study. Subsequently, a peak ground velocity field due to the scenario earthquake without interevent and intraevent variability was generated on the basis of Abrahamson and Silva (2007) using

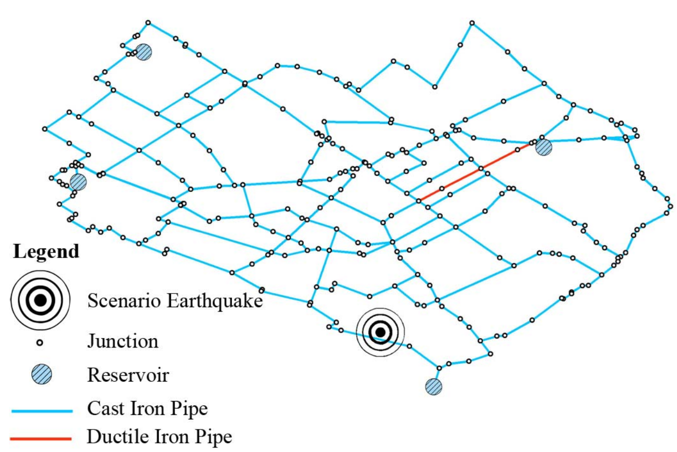

Fig. 4. Modena network.

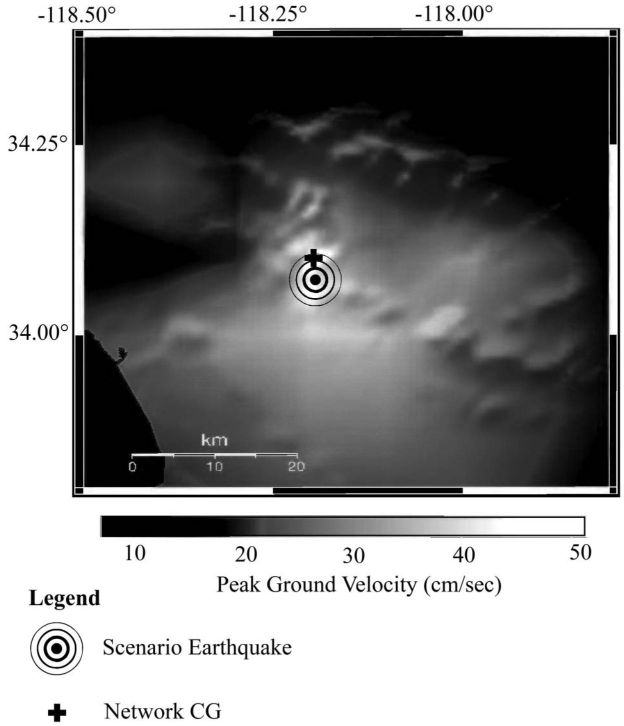

Fig. 5. Peak ground velocity field due to the selected earthquake scenario without intraevent and interevent residuals.

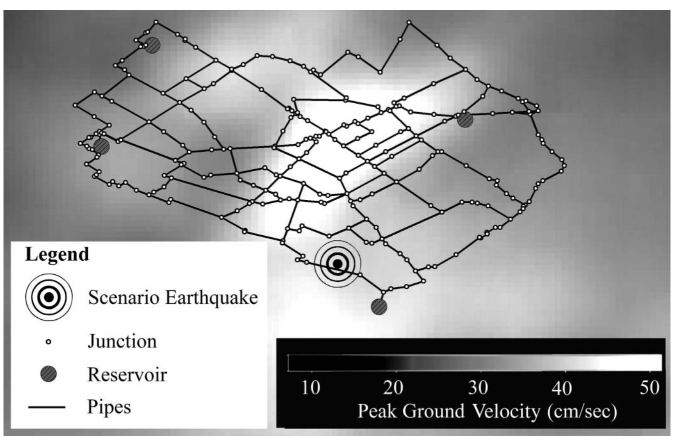

Fig. 6. Peak ground velocity field due to the selected earthquake scenario without intraevent and interevent residuals zoomed to the network's scale.

Field et al. (2005) around the network. A grid of 0.1° was used for generating this field. Fig. 5 shows the generated peak ground velocity field. Fig. 6 shows the same pick ground velocity field, magnified to the scale of the network. The fault parameters used to generate the field were obtained from SCEDC (2018) and USGS (2018a). To generate the interevent residuals and spatially correlated intraevent residuals, every junction in the network and 4 evenly spaced nodes along each pipe were selected. For this problem, $m = 20$ was taken on the basis of Zanini et al. (2017). Hence, 20 interevent and intraevent residuals were generated based on Eqs. (4)–(6) at each junction and 4 evenly spaced nodes along each pipe of the network. These 20 residual vectors were added to the peak ground velocity field shown in Fig. 5, using Eq. (6) to obtain

Table 1. Genetic algorithm parameters

Parameter	Value
Maximum generation	50
Initial mutation rate	90%
Cross over type	2 point cross over
Decrease of mutation rate	3% every generation
Number of bits mutated	20% of chromosome = 24 bits

Table 2. Results based on proposed approach for different rehabilitation length constraints for Modena network

Percentage of total pipe length			
Allowed for rehabilitation (%)	Actually rehabilitated (%)	Expected SSI	Variance
Not more than 15	13.553	0.8377	0.0289
Not more than 20	19.648	0.8557	0.0245
Not more than 25	23.859	0.8669	0.0249
Not more than 30	29.401	0.8864	0.0206
Not more than 35	34.813	0.8997	0.0167
Not more than 40	38.359	0.9103	0.0185
Not more than 45	43.697	0.9293	0.0111
Not more than 50	49.334	0.9313	0.0117

20 random peak ground velocity fields with spatially correlated intraevent residuals. For each of these 20 peak ground velocity fields, an average peak ground velocity was calculated for each pipe. These were then used to calculate the expected SSI of the network using Eq. (9) for each rehabilitation policy. Using the Monte Carlo simulation, the expected SSI of the network without any rehabilitation was calculated as 0.789 for the scenario earthquake. The devised algorithm was then used to calculate the best seismic rehabilitation policy, and consequently the critical pipes, for different rehabilitation constraints. Table 1 provides the parameters of the genetic algorithm, and Table 2 summarizes the results. Fig. 7 shows the critical pipes identified by the devised approach for different rehabilitation constraints as thick lines. Fig. 7 shows the critical pipes for rehabilitation with lengths less than or equal to 15% [Fig. 7(a)], 20% [Fig. 7(b)], 25% [Fig. 7(c)], 30% [Fig. 7(d)], 35% [Fig. 7(e)], 40% [Fig. 7(f)], 45% [Fig. 7(g)], and 50% [Fig. 7(h)] of the total pipe length.

Validation

For validation, a simple rehabilitation scheme was considered, based on pipe length, wherein the longer pipes were identified as the critical pipes. This scheme was combined with different rehabilitation length constraints, provided in Table 3, to identify critical pipes for seismic rehabilitation. Fig. 8 shows the critical pipes identified by this simple prioritization scheme highlighted with thick lines, and Table 3 provides a summary of the results obtained for this scheme. Fig. 8 shows the critical pipes that were identified using this approach, when the length was less than or equal to 15% [Fig. 8(a)], 20% [Fig. 8(b)], 25% [Fig. 8(c)], 30% [Fig. 8(d)], 35% [Fig. 8(e)], 40% [Fig. 8(f)], 45% [Fig. 8(g)], and 50% [Fig. 8(h)] of the total pipe length. When the expected SSI for each of these cases (Table 3) was compared with the expected SSIs obtained by using methodology created in this study for the respective rehabilitation constraint (Table 2), it was clearly shown that the expected SSI of the policy identified by the devised methodology was greater than

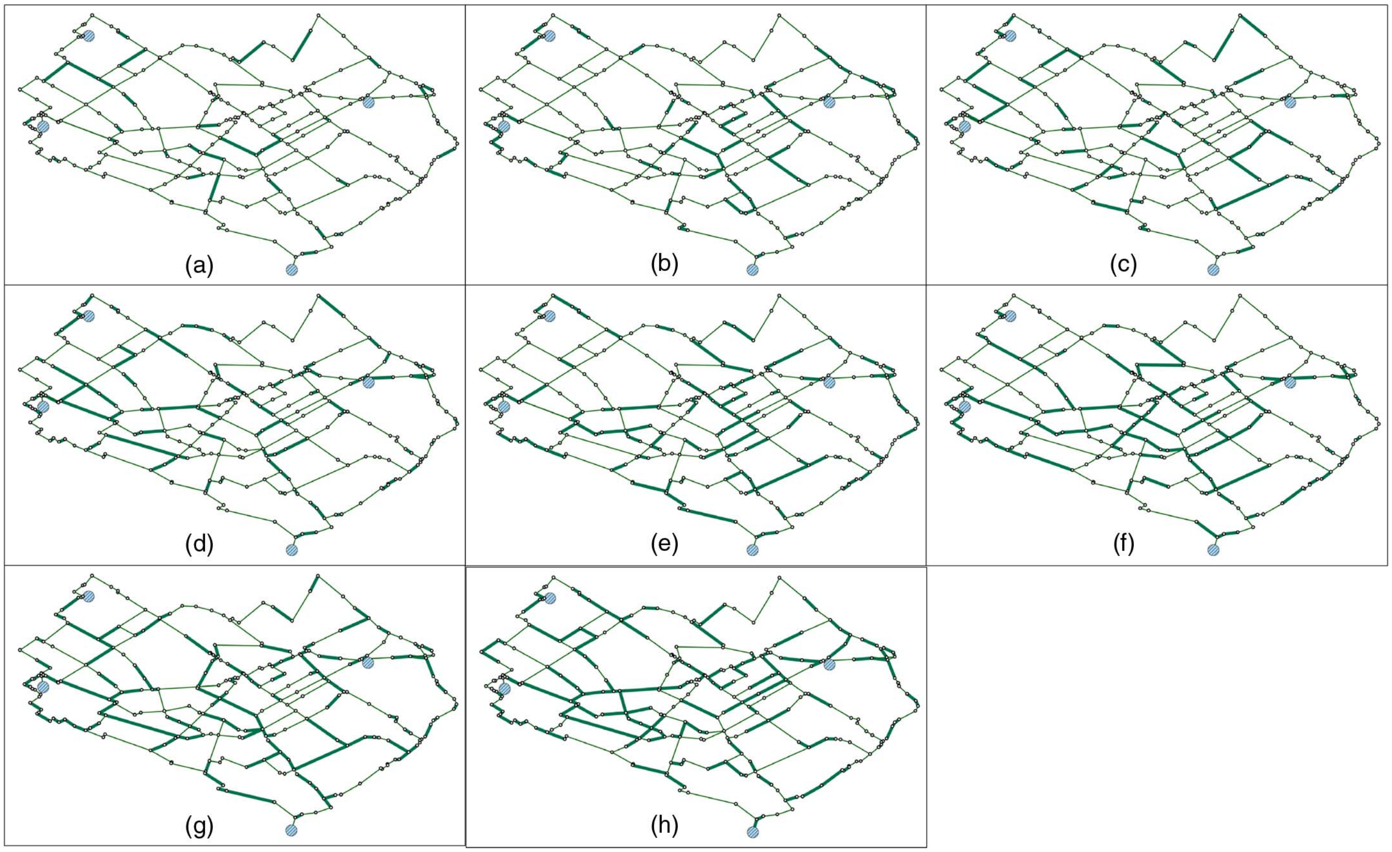

Fig. 7. Critical pipes identified by the devised approach for Modena network.

Table 3. Results based on simple length-based prioritization scheme for Modena network

Percentage of total pipe length			
Allowed for rehabilitation (%)	Actually rehabilitated (%)	Expected SSI	Variance
Not more than 15	14.741	0.8290	0.0318
Not more than 20	19.417	0.8426	0.0288
Not more than 25	24.454	0.8455	0.0295
Not more than 30	29.599	0.8528	0.0281
Not more than 35	34.735	0.8702	0.0252
Not more than 40	39.516	0.8818	0.0246
Not more than 45	44.987	0.8902	0.0225
Not more than 50	49.964	0.9002	0.0202

the expected SSI of the policy based on the simple prioritization scheme for the respective rehabilitation constraint.

Next, the devised methodology was compared with an approach proposed by Wang et al. (2010), who used the efficient frontier approach to identify a network's critical pipes. The EPANET example network (Fig. 9) developed by the USEPA was used to validate the approach created in this study. This network is a commonly used benchmark for testing models involving hydraulic simulation (Gorev et al. 2011; Liu and Auckenthaler 2014; Romero-Gomez et al. 2011). It consists of 92 junctions and 117 pipes. The network has two sources, a river and a lake, and three tanks manage the water demand of the system. The total length of the pipes of the entire network is 65,748.96 m (215,711.80 ft). For the calculation of the seismic repair rate, the material of the pipe was assumed as per Wang et al. (2010) so that the results could be later validated by comparison. Therefore, pipes with diameters greater than 24 inches were assumed to be steel pipes with welded joints, whereas pipes with diameters less than 24 inches were assumed to be cast-iron pipes with brittle joints. Nodal water demand assignment was also per Wang et al. (2010).

Wang et al. (2010) used a uniform PGV contour of 50 cm/s for their study, ignoring interevent and intraevent variability of the PGV. To make our results comparable with those of Wang et al. (2010), for this validation case we also had to use a uniform PGV contour of 50 cm/s, without any random interevent or intraevent residual, for the entire network. Using the Monte simulation, the expected SSI of the network without any rehabilitation was calculated as 0.889 for an earthquake hazard with a peak ground velocity value of 50 cm/s. The devised algorithm was used to calculate the best seismic rehabilitation policy, and consequently the critical pipes, for different rehabilitation constraints. A genetic algorithm with the parameters provided in Table 1 was used for this validation case as well. Fig. 10 shows the critical pipes identified by the devised approach for different rehabilitation constraints highlighted with thick lines, and Table 4 provides a summary of the results. Fig. 10 shows the critical pipes for rehabilitation with lengths less than or equal to 15% [Fig. 10(a)], 20% [Fig. 10(b)], 25% [Fig. 10(c)], 30% [Fig. 10(d)], 35% [Fig. 10(e)], 40% [Fig. 10(f)], 45% [Fig. 10(g)], and 50% [Fig. 10(h)] of the total pipe length.

On the basis of an optimal policy identified by Wang et al. (2010), it is necessary to rehabilitate about 38% of the pipes in the network to achieve an expected SSI of slightly less than 95% if the approach proposed by Wang et al. (2010) is used. Critical pipes, based on Wang et al. (2010), are highlighted by thick lines in Fig. 11, and Table 5 presents a summary of the results of a seismic vulnerability assessment performed after the rehabilitation of these

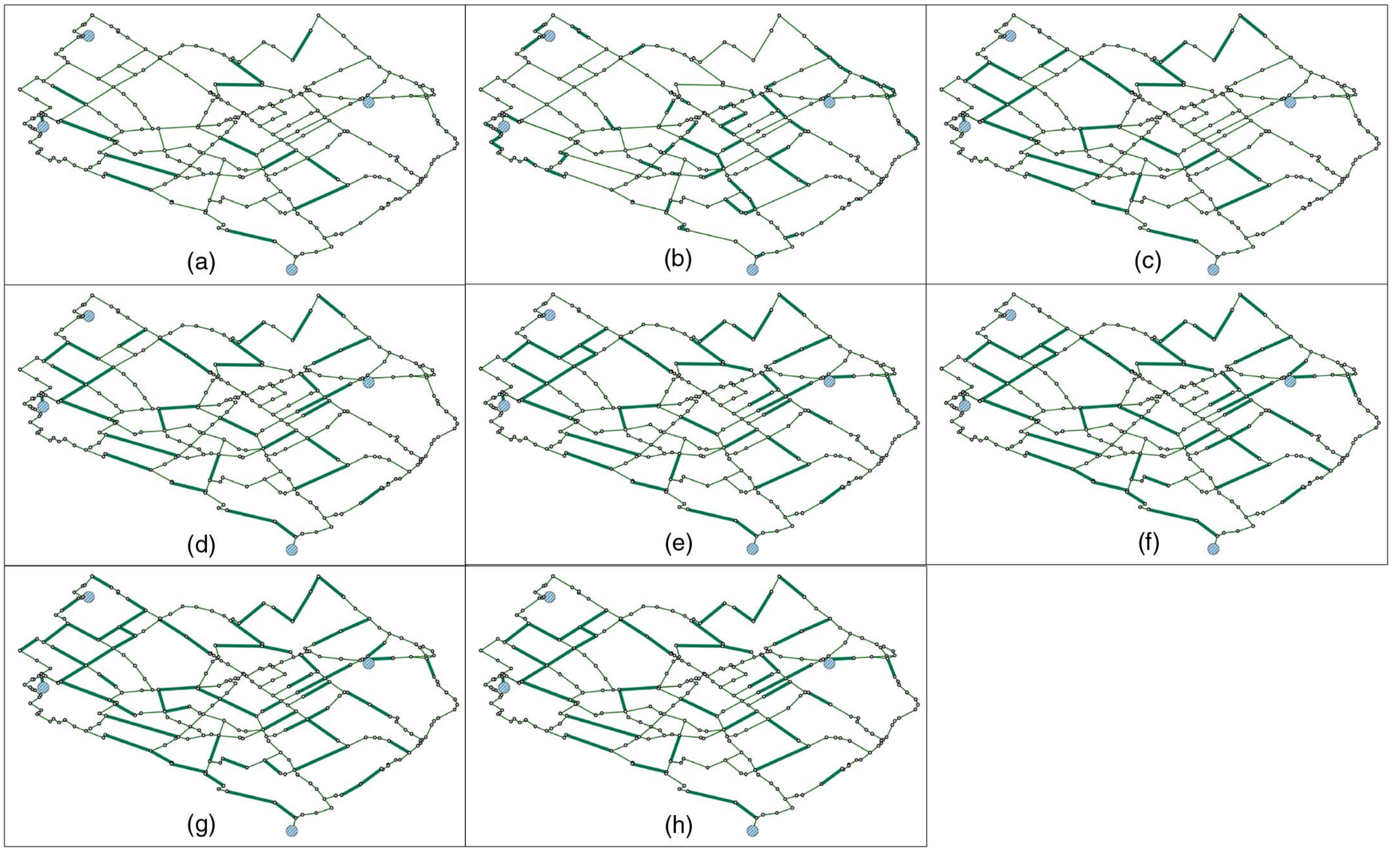

Fig. 8. Critical pipes identified by simple length-based prioritization scheme for Modena network.

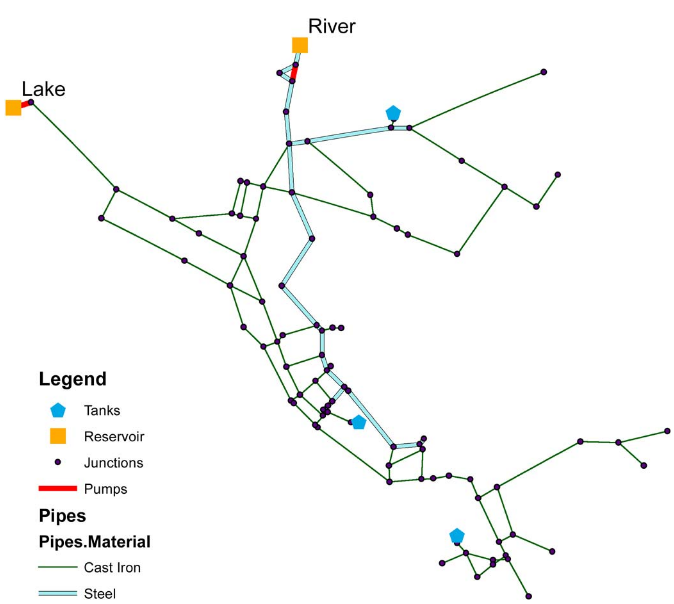

Fig. 9. EPANET example network.

pipes. Comparing these results with the results of the developed methodology (Table 4) shows that the approach created in this study requires rehabilitating only about 32% of the pipes in the network to achieve an expected SSI of slightly more than 95%.

Statistical hypothesis testing, using a two-tailed Z-test with a 95% level of confidence, was conducted to compare the expected SSI obtained by using the policy suggested by Wang to the expected SSIs obtained using the devised approach. The test showed that the policy identified by using the devised approach for rehabilitation lengths of not more than 25% of the total pipe length had an expected SSI statistically equal to the expected SSI of policy suggested by Wang et al. (2010). This clearly shows that the approach created in this study outperforms the most current approach in identifying critical pipes in a network by providing a statistically equivalent expected SSI and rehabilitating approximately 35% fewer pipes.

Limitations of the Proposed Model

Even though the proposed model can identify economical rehabilitation policies, the model has the following limitations:

1. The seismic vulnerability relations used in this problem (ALA 2001) to calculate the repair rate are empirical. Hence, the prediction of these seismic vulnerability relations can be further improved by adding more data and recalibrating the model.
2. In this paper, the problem of rehabilitation is confined to water pipe networks. However, the modularity of the proposed methodology makes this approach highly applicable to other areas of infrastructure systems with minimal modifications. The optimization framework, infrastructure network, and stochastic modeling of damages are the three key features of this methodology. The applicability to some other cases includes the following:
   a. For other hazards: The given model could be modified to identify rehabilitation policy against other hazards to which water pipe networks are exposed. For example, the seismic damage could be replaced by some other probabilistic damage caused by other hazards such as terrorism or vandalism.

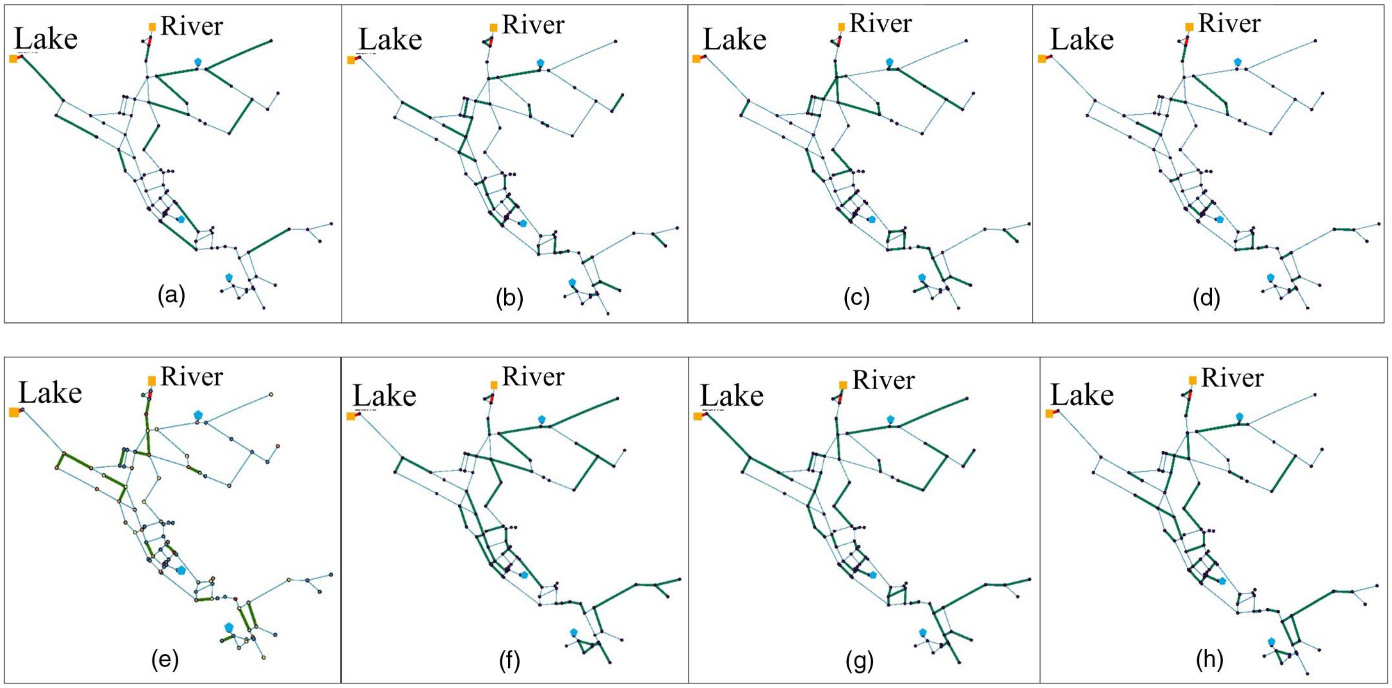

Fig. 10. Critical pipes identified by our approach for different rehabilitation length constraints.

Table 4. Results based on proposed approach for different rehabilitation length constraints for EPANET example network

Percentage of total pipe length: Allowed for rehabilitation (%)	Percentage of total pipe length: Actually rehabilitated (%)	Expected SSI	Variance
Not more than 15	14.49	0.924	0.0346
Not more than 20	18.46	0.932	0.0319
Not more than 25	24.76	0.937	0.0274
Not more than 30	29.50	0.940	0.0274
Not more than 35	31.89	0.951	0.0161
Not more than 40	39.61	0.952	0.0216
Not more than 45	42.76	0.957	0.0183
Not more than 50	47.36	0.972	0.0096

The only limitation is that the probability distribution of the damage due to the new hazard should be well defined.

b. For other infrastructure systems: This paper was primarily about water supply systems' seismic vulnerability. However, we could easily replace this water supply network with another infrastructure system and the created framework would still be applicable with some minor modifications. However, the following criteria should be met by the new infrastructure system:
   (1) Hazards for the new system should be identified and be well defined.
   (2) The performance metric to be maximized should be well defined.
   (3) Constraints to rehabilitation should be defined clearly.
   (4) The decision space should be well defined and combinatorial.

3. The optimization constraint used in this paper is a knapsack constraint (Wolsey and Nemhauser 1999), which is based only on the length of the pipes. However, our proposed model is flexible enough to accommodate any other constraints such as prioritizing a subset of pipes for rehabilitation.

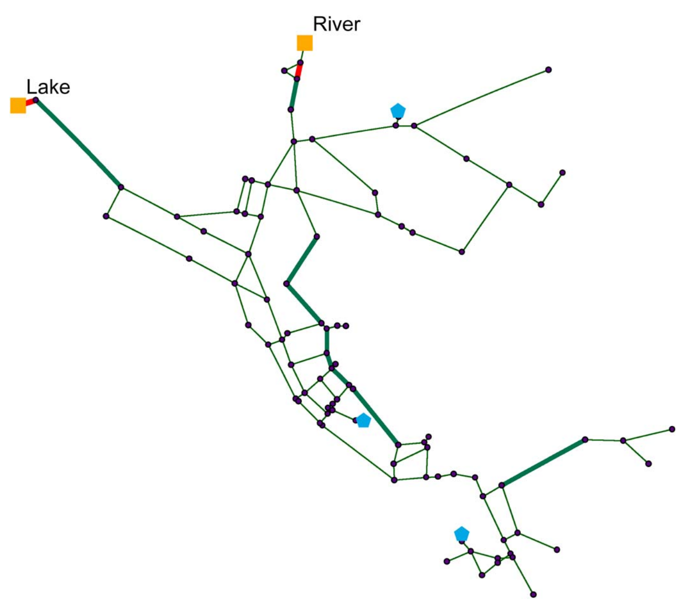

Fig. 11. Critical pipes based on Wang et al. (2010).

4. The optimization algorithm used in this paper is based on the genetic algorithm that is a metaheuristic-based algorithm. Such algorithms, despite their fast and effective performance, cannot guarantee the global optimality of the solution. However, the results of this study exhibited that the genetic algorithm performs well when applied to the optimization of seismic rehabilitation of water pipes.

Conclusion

An approach to identify critical pipes for resource-constrained seismic rehabilitation and to improve postearthquake serviceability of a

Table 5. Results based on critical pipe selection proposed by Wang et al. (2010)

Policy attribute	Value
Percentage of total pipe length actually rehabilitated	38.20
Expected SSI	0.945
Variance	0.024

Source: Data from Wang et al. (2010).

water pipe was created by integrating a genetic algorithm with a network-level seismic vulnerability assessment. This integration enables the identification of critical pipes, for distribution of rehabilitation resources at the system level. The application of the created approach was demonstrated using benchmark networks developed for testing algorithms that deal with formulating resilient designs of large water pipe networks. The results obtained from our proposed methodology were compared with the results obtained by using a simple length prioritization scheme. The results demonstrated that the methodology created in this study outperforms the simple prioritization scheme practiced by utilities. The created approach was also validated by identifying critical pipes for seismic rehabilitation in a water distribution network developed by the USEPA. These results were then compared with the latest methodology in the literature. The comparison showed that our methodology identified more economical seismic rehabilitation policy in comparison with the most recent proposed approach in the literature when there are limitations on the length of pipes that can be rehabilitated. It is expected that the result of this study will help water utilities make informed decisions that will enhance the postearthquake serviceability of water pipe networks.

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