EFFECTS OF NETWORK UNCERTAINTY ON SEISMIC VULNERABILITY ASSESSMENT OF WATER PIPE NETWORKS

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ABSTRACT

Past earthquakes revealed that earthquakes disrupt operations of underground water infrastructure systems. Assessment of the seismic vulnerability of underground water pipe networks plays a critical role in formulating preventive rehabilitation decision making to avoid high repair costs. Although existing seismic vulnerability assessment methods are sensitive to water pipe network uncertainties (e.g., uncertainties in nodal demand, reservoir head, pipe roughness coefficient), the extent of the effects of these uncertainties on the post-earthquake serviceability of the networks has not been examined. This research investigates the effects of water pipe network uncertainties on the seismic vulnerability assessment of networks. Transient ground displacements due to seismic wave propagation are considered for this investigation. The methodology includes seven steps: uncertainty identification and quantification, design of experiments, integrated multi-physics modeling, seismic repair rate calculations, Monte Carlo simulation, statistical analysis of the data (Analysis of Variance (ANOVA), and Tukey tests), and sensitivity analysis. Uncertainties in nodal demand, reservoir head, and pipe roughness coefficient were examined in this study. An integrated multi-physics model was created to simulate hydraulic network behavior and seismic vulnerability assessment. The approach was tested on two networks (New York Tunnel Network and Oberlin Network). The statistical analysis results indicate that the combined impact of the three selected water pipe network uncertainties on the seismic vulnerability assessment of networks is statistically significant. Nodal demand and pipe roughness coefficient uncertainties do not individually have a statistically significant effect. The individual effect of reservoir head

uncertainty is statistically significant. Sensitivity analysis determined the minimum value of the coefficient of variation to have a statistically significant effect. Sensitivity analysis was divided into three parts to investigate the individual and combined effects of network uncertainties. The results from sensitivity analysis show that small uncertainty in reservoir head results in a statistically significant effect on seismic vulnerability assessment. By contrast, the coefficient of variation for uncertainties in nodal demand and pipe roughness has to be quite large to significantly affect seismic vulnerability assessment. Statistical analysis and sensitivity analysis results show that water pipe network uncertainties have a statistically significant impact on seismic vulnerability assessment of networks. Hence, it is recommended to integrate water pipe network uncertainties with existing methods for assessing seismic vulnerabilities.

INTRODUCTION

Water pipe networks are among the lifelines of modern cities (Eidinger and Avila 1999). Past earthquakes (e.g., the San Fernando earthquake of 1971, the Northridge earthquake of 1994, the Kobe earthquake of 1995) and some recent earthquakes (e.g., the Christchurch earthquake of 2011, the East Japan earthquake of 2011, the Gorkha earthquake of 2015, and the Central Mexico earthquake of 2017) have divulged the vulnerability of the underground water pipe networks (Knight 2017; Thapa et al. 2016; O' Rourke et al. 2014; Maruyama et al. 2011; Cubrinovski et al. 2011; O'Rourke 1996). Residential, industrial, and commercial activities get disrupted due to the damages to the water pipe networks. Any disruption in such networks can cause extensive direct and indirect losses such as repair costs or disturbance in water distribution (Yerri et al. 2017; Piratla et al. 2015). In the Northridge earthquake of 1994, utilities performed around 1400 repairs in water pipes, of which approximately 100 repairs were carried out in pipes with large diameters (O'Rourke 1996). About 50,000 people were disconnected from the drinkable water supply for over seven days after the Northridge earthquake (Scawthorn et al. 2005). The Kobe earthquake caused damages at 23 locations of the water pipeline (Yoo et al. 2016). Although an earthquake is a rare event, it can significantly degrade the performance of water supply networks. Therefore, assessing seismic vulnerability underground water pipe networks is crucial to ensure acceptable post-earthquake serviceability.

In the current practice of vulnerability assessment of underground water pipe networks subjected to seismic events, it is implicitly assumed that currently established hydraulic network analysis models can accurately estimate reliability and serviceability measures. However, several studies have identified significant shortcomings of the hydraulic models representing actual networks (Sabzkouhi and Haghighi 2016; Seifollahi-Aghmiuni et al. 2013; Lansey et al. 2001; Bargiela and Hainsworth 1989). These shortcomings are mostly due to the high sensitivity of hydraulic models to their input variables. The bottleneck is the highly limited knowledge about the actual input values, which drive the hydraulic models. These values include nodal demands, pipe roughness coefficients, reservoir head, pipe material, pipe age, and pipe diameter (Kang and Lansey 2009, Shibu and Janga Reddy 2011). Sabzkouhi and Haghighi (2016) showed that a slight 15% uncertainty in a demand and pipe's roughness coefficient could cause around 11% deviation in predicted nodal pressures and 50% deviation in flow velocities. These results represent the high sensitivity of network hydraulic analysis models to uncertainties. Therefore, it is crucial to investigate the effects of water pipe network uncertainties on seismic vulnerability assessment of the networks. This study investigates the effects of network uncertainties on seismic vulnerability assessment considering transient ground displacements due to seismic wave propagation.

RESEARCH BACKGROUND

Component-level and system-level seismic vulnerability assessments are two broadly classified categories of the methods for assessing the vulnerability of water pipe networks subjected to seismic events. Individual components can be evaluated by component-level assessment models. The seismic performance of an entire network can be evaluated by system-level assessment models. The methods for assessing the vulnerability of individual pipes can be further divided into two categories: analytical and empirical. Newmark and Rosenblueth (1971) proposed an analytical method to investigate the response of an underground pipeline assuming negligible soil-pipe interaction. Since then, these interactions have been studied using quasi-static analysis (Singhal and Zuroff 1990; Wang et al. 1982), shell theory (Liu et al. 2004; Luco and De Barros 1994), dynamic plain-strain modeling (Datta et al. 1984), finite element analysis (Saberi et al. 2014; Vazouras et al. 2010), probabilistic fault displacement hazard analysis and beam-type finite element modeling (Melissianos et al. 2016), and nonlinear modeling of seismic response (Hosseini and Tahamouli Roudsari 2010). Honegger and Eguchi (1992) estimated the failure rate of brittle pipes subjected to permanent ground deformation. American Lifeline Airlines (ALA 2001) formulated seismic fragility relations for a wide range of pipes based on 81 data points from 12 earthquakes. Christodoulou and Fragiadakis (2015) investigated the effects of a network's historical performance on seismic vulnerability through the introduction of the number of observed previous breaks (NOPB) risk factor. Although these component-level models are useful to gain a good insight into failure mechanisms of small-scale cases, they are impractical for large-scale vulnerability assessment (Hosseini and Tahamouli Roudsari 2010).

While it is necessary to understand the performance of individual pipes, their network resilience depends on these pipes' dynamic interactions. Advancements in network simulation, probabilistic modeling, and computational engineering have helped researchers to conduct system-level seismic vulnerability assessments of networks (Pudasaini et al. 2017; Wang et al. 2010; Shi 2006). Individual pipe failure probabilities are used to generate damages in pipes for system-level vulnerability assessment (Pudasaini and Shahandashti 2020b). Damages were integrated with hydraulic models using Monte Carlo simulation. Shi (2006) combined fragility relations with hydraulic principles to model the seismic response of water networks. Shi's methodology was further expanded to generate various system serviceability and reliability indices (Wang et al. 2010; Huang et al. 2008). System serviceability index (SSI) was used by Wang et al. (2010) to measure the performance of a water pipe network susceptible to seismic damages. SSI was used to locate the critical pipes of the network and rank them accordingly. Fragiadakis and Christodoulou (2013) proposed a methodology for assessing the reliability of water pipe networks combining data of past non-seismic damage and the vulnerability of network's components against seismic loading. Fragiadakis et al. (2013) created an assessment method considering data of past non-seismic damage, the vulnerabilities of the network components against seismic loading, and the topology of a water pipe network. Farahmandfer et al. (2017) proposed a metric that quantifies resilience of water pipe networks. Networks' spatial distributions and correlations related to ground motion intensities were not taken into consideration in their analysis. Few recent studies considered these spatial distributions and correlations (Shahandashti and Pudasaini 2019; Pudasaini and Shahandashti 2018). Most recently, Boskabadi et al. (2020) developed a two-stage stochastic programming approach for enhancing seismic resilience of water pipe networks. Pudasaini and Shahandashti (2020a) identified topological surrogates for computationally efficient seismic robustness optimization of water pipe networks. Mazumder et al. (2020a) proposed a methodology to calculate seismic repair rate. This study proposed a renewal strategy addressing the vulnerability of pipelines from the topological viewpoint. Mazumder et al. (2020b) presented a framework to evaluate both component-level and system level seismic resilience of water pipe networks considering time-variant corrosion of pipeline. Despite all advancements in assessing the vulnerability networks due to seismic events, the impacts of uncertainties on these seismic vulnerability assessments are not known.

Although the impacts of uncertainties on the seismic vulnerability assessments are unknown, uncertainty quantification and analysis have been applied to study the effects of water pipe network uncertainties on their no-hazard design and operation procedures. For example, Seifollahi-Aghmiuni et al. (2011) combined a shuffled frog algorithm with Monte Carlo simulation to examine water network efficiency considering the uncertainty of demand. Their study was primarily focused on identifying the effects of demand uncertainty on operation using a probabilistic normal distribution. They concluded that network efficiency decreases if demand uncertainty is not considered while operating a network. Seifollahi-Aghmiuni et al. (2013) used a similar methodology to examine water network performance in its operational period considering pipe roughness uncertainty. They concluded that if pipe roughness uncertainty increases, network performance decreases. Xu and Goulter (1998) proposed a methodology for assessing water pipe networks considering uncertainties in pipe capacity, nodal demands, and reservoir/tank levels.

Lansey et al. (1989) developed a methodology to determine an optimal design process for water pipe networks. They considered several network uncertainties, such as pressure head requirements, future demands, and pipe roughness. They illustrated that uncertainties in those parameters have substantial effects on the network design process. Kapelan et al. (2005) defined the water distribution design problem as a multi-objective optimization problem under uncertainty. They considered pipe roughness coefficient and water consumption as uncertain variables. Probability density functions were used to model the uncertain variables. The obtained results demonstrated that the proposed methodology could identify robust Pareto optimal solutions in spite of the considerably less calculation effort. Sabzkouhi and Haghighi (2016) introduced a methodology to analyze water pipe networks considering uncertainty based on fuzzy set theory. They showed that uncertainties in network input parameters lead to imprecise hydraulic responses. Implementing the method in a real-time network revealed that a 15% change in the nodal demand and pipes' roughness could result in -41.7% to +50.1% uncertainty in the pipe velocities and -11.2% to +6.4% uncertainty in the nodal pressures.

Existing methods for assessing the seismic vulnerability of water pipe networks did not consider the network uncertainties. Hence, a methodology was created in this study to investigate the effects of water pipe network uncertainties on the seismic vulnerability assessment of the networks.

METHODOLOGY

The methodology includes seven steps: uncertainty identification and quantification, design of experiments, integrated multi-physics modeling, seismic repair rate calculations, Monte Carlo simulation, statistical analysis of the data (ANOVA test and Tukey Test), and sensitivity analysis. Figure 1 demonstrates the methodology adopted for this study.

Uncertainty Identification and Quantification

Sources of water pipe network uncertainties were identified and quantified based on the literature. Probability and possibility models were used to characterize pipe network uncertainties. Table 1 summarizes the previous efforts to characterize the network uncertainties. Normal and uniform distributions were two widely used probability models (Seifollahi-Aghmiuni et al. 2013; Lansey et al. 2001). Alternatively, fuzzy logic was used as a possibility model (Sabzkouhi and Haghighi 2016; Shibu and Janga Reddy 2011).

Through a thorough literature review, three water pipe network uncertainties were selected: nodal demand, pipe roughness coefficient, and reservoir head. These uncertainties are widely acknowledged in the literature as critical sources of uncertainties for performance modeling and analysis of the water pipe networks (Table 1). It is assumed nodal demands, pipe roughness coefficient, and reservoir head to be normally distributed. The coefficient of variation (CoV) was used to investigate the effect of uncertainty. CoV is the ratio between the mean and standard deviation. The mean value associated with the selected three network parameters were considered equals to the design value. The design value was collected from water distribution system research database. The value of standard deviation was calculated using the mean and the assumed CoV. The assumption of value of CoV was relaxed by conducting a sensitivity analysis to investigate and determine the minimum value of CoV to have a statistically significant impact. The value of CoV was initially assumed to be 0.2 (Seifollahi-Aghmiuni et al. 2013; Seifollahi-Aghmiuni et al. 2011). The initial value of CoV was selected based on Seifollahi-Aghmiuni et al. (2013) and Seifollahi-Agmiuni et al. (2011). Later, different values of CoV were used to conduct the sensitivity analysis.

Design of Experiments

The experiments were designed as a full factorial design. Each of the three parameters considered in this study was studied at two levels: including uncertainty and excluding uncertainty. The levels were coded as +1 (including uncertainties) and –1 (excluding uncertainties). The +1 (including uncertainties) were the experiments considering normal distribution using mean values plus one standard deviation and mean minus one standard deviation of uncertainties. The -1 (excluding uncertainties) were performed considering the mean values. Table 2 shows selected water pipe network uncertainties with their levels for the experiment.

It is essential to analyze all the two-factor interactions to identify the effects of all three selected water pipe network uncertainties. Therefore, a 2^3 full factorial design was chosen for this experiment. The coded design for the experiment is shown in Table 3.

Seismic Repair Rate Calculation

Figure 2 illustrates the steps to calculate the seismic repair rate for each pipe.

At the beginning of the seismic repair rate calculation, an earthquake scenario was identified based on deaggregation analysis using USGS (2018b) considering the spatial relationship among seismic intensities (Zanini et al. 2017; Zanini et al. 2016; Weatherill et al. 2013; Jayaram and Baker 2009; Adachi 2007). Deaggregation maps were generated using USGS (2018b). Deaggregation analysis was conducted using the spectral acceleration of 1.0-s. The earthquake that had the highest percentage of contribution was selected from the deaggregation analysis.

Next, for the selected earthquake scenario, peak ground velocity (PGV) was determined. PGV was used as the intensity parameter because of its direct relationship with the induced transient strains in the soil during a seismic event. These induced strains are major causes of underground pipe damages (Pineda-Porras and Najafi 2010).

A spatially correlated peak ground velocity field was produced using the ground motion prediction equation (GMPE) (Abrahamson and Silva 2007, Zanini et al. 2016, Zanini et al. 2017). The general equation is given by Eq. (1).

$$log_{10}\,(PGV_{ab}) = f\,(M_a, R_{ab}, \theta_a) + \sigma_B\, v_a + \sigma_w \varepsilon_{ab} \quad (1)$$

where PGV_{ab} = value of peak ground velocity at location b from source a; R_{ab} = distance between location a and location b; M_a = earthquake magnitude; θ_a = fault geological parameters at location

a. $\sigma_B\, v_a$ is the interevent residual, and $\sigma_w \varepsilon_{ab}$ is the intra-event residual. Initially, the peak ground velocity map, i.e., $f\,(M_a,\ R_{ab},\ \theta_a)$ was created based on Abrahamson and Silva (2007). A peak ground velocity map was created using the scenario shake map calculator (Field et al. 2005). In the following step, the interevent and intra-event variabilities were incorporated in this map. E_{ab} and v_a are random variables with normal distribution which has a mean value (K) of 0 and standard deviations of σ_B and σ_w. The value of ε_{ab} was calculated using Eq. (2) (Zanini et al. 2016; Weatherill et al. 2013).

$$\varepsilon = K + \mathbf{Z}^*\mathbf{L} \tag{2}$$

where $K = 0$; $\mathbf{L}$ = Lower triangular matrix; $\mathbf{Z}$ = vector of random variables with normal distribution. The value of $\mathbf{L}$ was calculated by applying the Cholesky decomposition method, such that $\mathbf{LL^T} = \mathbf{P}$. $\mathbf{P}$ is the positive-definite covariance matrix. The value of $\mathbf{P}$ can be calculated using Eq. (3).

$$\mathbf{P} = \begin{bmatrix} 1 & 6(d_{1,2}) & \cdots & 6(d_{1,N}) \\ \vdots & 1 & \cdots & 6(d_{2,N}) \\ \vdots & \vdots & \ddots & \vdots \\ sym & \vdots & \cdots & 1 \end{bmatrix} \tag{3}$$

where $6(d_{a,b})$ is a correlation coefficient between intra-event residuals for location a and location b. N is the total number of locations. The value of $6(d_{a,b})$ can be calculated using Eq. (4) (Jayaram and Baker 2009).

$$6(d_{a,b}) = e^{\left(\frac{-3da,b}{h}\right)} \tag{4}$$

where $d_{a,b}$ = distance between location a and location b. h is the intersite distance among which spatial relationships can be neglected. According to Wang and Takada (2005), when peak ground velocity is used to calculate spatial correlation, the value of h can be considered between 20 km to 40 km. For this study, the value of h was selected to be 30 km. This process was repeated for M times to create M random peak ground velocity fields (Zanini et al. 2017). The value of PGV for each pipe was calculated. Seismic pipe repair rates were then determined based on ALA (2001) using Eq. (5).

$$RR_{k,m} = C * 0.00187 * PGV_{k,m} \tag{5}$$

where $RR_{k,m}$ is the seismic repair rate per 1000 ft of pipe k for the mth seismic PGV field, C is the modification factor, and $PGV_{k,m}$ is the peak ground velocity at the location of pipe k for the mth seismic PGV field (in./s). The modification factor (C) adjusts the value of the repair rate considering the corrosivity of soil, pipe diameter, pipe material, and pipe joint characteristics.

Integrated Multi-physics Modeling and Monte Carlo Simulation

System Serviceability Index (SSI) database was created using Monte Carlo simulation. SSI is a post-earthquake serviceability indicator that measures the serviceability of a water network after a seismic event. SSI is the ratio between demand fulfilled after a seismic incident and the total demand of the network at the regular operational period (Wang et al. 2010; Shi 2006). For this study, it was assumed that the demand is fulfilled at a node if the pressure at that node is more than a threshold pressure. Using the definitions, SSI is formulated as Eq. (6).

$$\mathrm{SSI} = \frac{\sum_{n=1}^{TN} x_n * Dn}{\sum_{n=1}^{TN} Dn} \tag{6}$$

subject to

$$x_n = 1 \text{ if } P_n \geq P_{threshold}$$

$$x_n = 0 \text{ if } P_n < P_{threshold}$$

where SSI is the system serviceability index; D_n is the demand at node n; TN is the nodes in the network; $P_{threshold}$ is the minimum pressure required at the node, which is selected by the demand for firefighting, and P_n is the pressure at node n. Hydraulic pressure of 20 psi (0.14 MPa) was used as the $P_{threshold}$ (Trautman et al. 2013).

Seismic damages (breaks and leaks) were modeled using the Poisson process. The location of the p^{th} damage (break or leak) in a pipe k was determined by Eq. (7).

$$l_{k,p} = l_{k,p-1} - \frac{1}{RRk,m} * \ln(1 - Q1) \quad where \quad l_{k,0} = 0 \tag{7}$$

where $l_{k,p}$ is the distance of p^{th} damage (break or leak) in pipe k from its start node, $RR_{k,m}$ is the seismic repair rate of pipe k, and $Q1$ is a uniformly distributed random number. The value of $Q1$ ranges from 0 to 1. If the distance of initial damage (break or leak), i.e., $l_{k,1}$ was less than the total length of pipe k, then another random number ($Q2$) between 0 and 1 was generated. The value of $Q2$ classifies the damage as either a leak or a break. If the value of $Q2$ was not more than 0.8, it was considered a leak; otherwise, it was considered a break (Shi 2006). The diameter of each leak was determined by further classifying those leaks based on Shi (2006).

The process can be explained using the following numerical example. Let's assume a 300-feet ductile iron pipe (Pipe p) and a repair rate of 0.02 in/s. A uniformly distributed random number (*Q1*) between 0 and 1 was generated. Let's assume the number is 0.001. The value of $l_{k,p}$ for the first iteration ($l_{k,1}$) is 50.01 feet using Eq. (7) ($l_{k,0} = 0$). The value of $l_{k,1}$ is less than the total length of the pipe. So, another uniformly distributed random number (*Q2*) between 0 and 1 is generated. Let's assume 0.5 as the value of *Q2*. As the value of *Q2* is less than 0.8, this is a leak. To calculate the diameter of the leak, another uniformly distributed random number was generated between 0 and 1. The leak scenario was then classified into five categories based on the random number and pipe material: annular disengagement, round crack, longitudinal crack, local loss of pipe wall, and local tear of pipe wall. The diameter of the leaks was then calculated based on Shi (2006). This process was repeated until the value of $l_{k,p}$ is more than the total length of the pipe.

After locating all the damages (breaks and leaks) and determining the diameters of all leaks for each pipe of the network for the present Monte Carlo simulation, the damages (breaks and leaks) were combined into the hydraulic model of the original network. Pressure at each node (P_n) was determined. Pressure-driven steady-state hydraulic analysis was used to calculate the pressure at each node. The demand-driven analysis considers that the demand at every node is obtained, and this consideration is not a valid consideration for water networks disrupted by seismic events (Shi 2006; Cheung et al. 2005). To investigate the performance of actual networks after earthquakes, the following two assumptions are necessary according to Shi (2006):

- water demand at each node is not always met. In other words, immediately after the earthquake, demand of every node cannot be met fully due to leaks and breaks in the pipe.
- nodes cannot have negative pressure.

These two assumptions are necessary to investigate the performance of a water pipe network as they imitate the performance of actual networks after earthquakes (Shi 2006). An open-source package software, EPANET 2.0, was used for the pressure-driven steady-state hydraulic analysis. This software is recommended by Environmental Protection Agency (EPA) for hydraulic simulation of water networks. For every run of the Monte Carlo simulation, the following steps were followed:

1) Analyzing hydraulic model of the network including seismic damages (breaks and leaks)
2) Removing any nodes having negative pressure

3) Step 1 and step 2 were repeated if there is any node with negative pressure.

Hydraulic pressure at each node (P_n) was calculated and recorded. SSI was calculated based on the demand at available nodes after removing all nodes with negative pressure for the predefined maximum Monte Carlo runs using Eq. (8):

$$SSI_r = \frac{1}{M} * \sum_{m=1}^{M} SSI_m \tag{8}$$

where SSI_r is the average value of SSI for r^{th} Monte Carlo simulation; SSI_m is the value of SSI calculated using Eq. (6) for the m^{th} PGV field; M is the total number of PGV fields generated for the selected earthquake scenario.

The value of SSI for each Monte Carlo run was then recorded to create the SSI database. The SSI database was used for statistical analysis (ANOVA test and Tukey test). The steps of the Monte Carlo simulation to create the database are shown in Figure 3.

Statistical Analysis of the SSI Database

The one-way analysis of variance (ANOVA) and the Tukey test were used for statistical analysis of the SSI database. ANOVA is a statistical tool that determines any significant difference between the means of SSI of individual experiment groups. The following null hypothesis is tested:

$$H_0: \mu_1 = \mu_2 = \mu_3 = \ldots\ldots\ldots\ldots = \mu_k \tag{9}$$

where μ is the mean of the individual experiment group, and k is the total number of individual experiment groups. If the result is significant from the ANOVA test, the null hypothesis is rejected, which implies that a minimum of two individual experiment groups are statistically different from each other.

The one-way ANOVA cannot determine which specific experiment groups are statistically different from each other. A Tukey test was performed to determine which particular groups differed from each other.

APPLICATION AND RESULTS

Two different networks were selected to demonstrate the application of the methodology. The first network was the New York Tunnel network (Water Distribution System Research Database), having 42 pipes,19 junctions, and one reservoir. The second network was the Oberlin network (Water Distribution System Research Database), having 289 pipes, 262 junctions, and one reservoir. The Oberlin network is in Harrisburg, Pennsylvania. These two networks were available to download from an open-source website. These two networks were selected from two different classification of networks: medium size networks and large size networks. We demonstrated the application of the methodology on two different classifications of networks to identify the impacts of network uncertainties on seismic vulnerability assessment of different classification of networks.

The material of pipes having diameters less than 12 inches (300 mm) was assumed to be cast iron. The joint type for the cast-iron pipe was considered lead joints. If the diameter of the pipes were greater than 12 inches (300 mm), then the material was ductile iron. The joint type for the ductile iron pipe was considered rubber-gasketed joints. These assumptions were necessary to calculate the pipe repair rate based on ALA (2001). The pipe modification factor (C) depends on the types of material and joint type. The mean value and standard deviation of the selected three normally distributed network uncertainties were not impacted by this assumption of pipe material. These values were selected based on network design values.

In order to select an earthquake scenario to thoroughly analyze the impact of uncertainties on the seismic vulnerability assessment, networks' centroid was presumed to be in Pasadena, California (34.146267^{o} N, 118.144040^{o} W) for the deaggregation analysis. Deaggregation analysis was conducted using USGS (2018b). For the deaggregation analysis, the return period was selected to be 2,475 years. From the deaggregation results conducted in Pasadena, California, an earthquake at the Raymond fault was selected as the scenario earthquake (magnitude 7.13) for this study as it had the highest contribution ratio (13.96%).

In the following step, a peak ground velocity field was generated using scenario shake-map calculator (Abrahamson and Silva 2007; Field et al. 2005). Inter-event and intra-event residuals were not considered in the shake-map calculator. The generated peak ground velocity field is shown in Figure 5. Figure 6 shows the same peak ground velocity filed magnified to the scale of the network for New York Tunnel network. Figure 7 shows the peak ground velocity field magnified to the scale of the network for Oberlin network.

Each junction and four equally spaced nodes along the length of each pipe were chosen to generate the intra-event and inter-event residuals. These residual vectors were combined with a peak ground velocity field to generate twenty random PGVs (M=20). The value of M was selected based on literature (Zanini et al. 2016; Zanini et al. 2017; Shahandashti and Pudasaini 2019). The average PGV was quantified for each pipe using the PGV determined at the start junction of the pipe, at the end junction of the pipe, and four intermediate points along the pipe. The average PGV of each pipe was then used to measure the SSI of the network.

A convergence study was conducted to determine the suitable number of Monte Carlo runs (Figure 8). Oberlin network (Water Distribution System Operations) was selected to conduct the convergence study. Experiment 8, for the selected earthquake, was selected for the convergence study. The same number of Monte Carlo runs that was found from the convergence study was used both for both New York Tunnel network and the Oberlin network (Water Distribution System Operations). From the convergence study result shown in Figure 8, it was concluded that 3000 Monte Carlo runs were sufficient for this study.

A one-way ANOVA test was conducted (considering a 5% level of significance) to determine if the experimental results were statistically significant. Table 4 and Table 5 summarize the mean and variance of SSI for each experiment for the New York Tunnel network and Oberlin network, respectively.

For the ANOVA test, a null hypothesis (H_0) and an alternative hypothesis (H_1) were selected.

Null hypothesis, H_0: $\mu_1 = \mu_2 = \ldots \ \ldots \ \ldots = \mu_8$

Alternative hypothesis, H_1: Not all μ are equal

Level of Significance: 5%

From the ANOVA test results, the *p*-values for New York Tunnel and Oberlin networks were much less than 0.05. Therefore, there were significant differences between the means of SSI in different groups or different experiments. The ANOVA test could not determine which specific experiments were statistically different from each other. It only implies that at least two experiments were. The Tukey test that is often used for multiple pairwise comparisons was conducted to determine which experiments have significantly different means. As this study was only considering the effects of uncertainty, the Tukey test was conducted only for seven pairs, comparing no-uncertainty experiment (Com_Exp 1) with the other experiments: (Com_Exp 1, Com_Exp 2); (Com_Exp 1, Com_Exp 3); (Com_Exp 1, Cop_Exp 4); (Com_Exp 1, Com_Exp 5); (Com_Exp 1, Com_Exp 6); (Com_Exp 1, Com_Exp 7); (Com_Exp 1, Com_Exp 8). Table 6 and

Table 7 summarize the results of the Tukey test for the New York Tunnel network and Oberlin network, respectively.

The Tukey test results of both the New York Tunnel network and Oberlin network show that demand uncertainty (Com_Exp 2) and pipe roughness coefficient uncertainty (Com_Exp 3) do not have statistically significant individual effects; the null hypothesis could not be rejected. For all other pairwise comparisons, the null hypothesis was rejected, and it was concluded that the effects of uncertainty are significant considering a 5% level of significance.

From the ANOVA and Tukey test results, it can be concluded that uncertainty of demand and pipe roughness coefficient uncertainty do not have statistically significant effects. On the other hand, the effects of reservoir head uncertainty are statistically significant. The combined effect of the three selected water pipe network uncertainties is statistically significant for the selected value of CoV. In the next part of the study, sensitivity analysis was conducted to find the minimum value of CoV to create a statistically significant effect.

SENSITIVITY ANALYSIS

Sensitivity analysis was conducted to find the minimum value of the coefficient of variation (CoV) for which water pipe network uncertainties were statistically significant. Sensitivity analysis was divided into three major parts based on the effect of water pipe network uncertainties:

(i) Effect of uncertainties in demand, pipe roughness coefficient, and reservoir head individually

(ii) Combined effects of uncertainties in
   (a) demand and pipe roughness coefficient;
   (b) pipe roughness coefficient and reservoir head;
   (c) demand and reservoir head

(iii) Combined effect of uncertainties in demand, reservoir head, and pipe roughness coefficient

Effect of Individual Water Pipe Network Uncertainties

All three water pipe network uncertainties were studied individually for both networks. The results for both the networks are shown graphically in Table 8.

From the sensitivity test result of both the networks, the minimum value of CoV for reservoir head uncertainty is 0.01, indicating that a small uncertainty in reservoir head results in a statistically significant SSI change in both networks. By contrast, the CoV value for uncertainties in nodal demand and pipe roughness has to be quite large, more than the 0.2 value assumed in the literature (Seifollahi-Aghmiuni et al. 2013), to significantly affect mean SSI.

Joint Effect of Water Pipe Network Uncertainties

Two water pipe network uncertainties were considered together here:

(i) Joint effect of uncertainties in demand and pipe roughness coefficient
(ii) Joint effect of uncertainties in pipe roughness coefficient and reservoir head
(iii) Joint effect of uncertainties in demand and reservoir head

While considering the joint effect of water pipe network uncertainties, the selected two parameters (among demand, pipe roughness coefficient, and reservoir head) were considered normally distributed. The other parameter was considered equal to the mean value associated with that. The The analysis result of all three sections for both the networks are shown graphically from Figure 9(a) to Figure 9(f). The marked zone indicates the area inside which the joint effect of the water pipe network uncertainties is not statistically significant.

Figure 9(a) and Figure 9(b) show that the minimum value of CoV for either uncertainty of demand or uncertainty of pipe roughness coefficient has to be high to results in a statistically significant change in SSI for both networks. By contrast, while checking the combined effects with reservoir head, the minimum value of CoV does not depend on the pipe roughness coefficient or demand to result in statistically significant SSI change for both networks as the value of SSI changes for any uncertainty in reservoir head.

Combined Effect of Three Water Pipe Network Uncertainties

All three water pipe network uncertainties were considered here. The results of the sensitivity analysis for both the networks are shown in Figure 10(a) and Figure 10(b). The marked zone indicates the zone inside which the combined effect of the water pipe network uncertainties is not statistically significant.

Figure 10(a) and Figure 10(b) show that the minimum value of CoV to have a statistically significant effect on the value of SSI does not depend on the uncertainty of demand and pipe roughness coefficient. A small uncertainty in reservoir head results in a statistically significant change in SSI for both networks.

CONCLUSIONS

A methodology has been proposed to identify the effects of water pipe network uncertainties on seismic vulnerability assessment of networks. Three water pipe network uncertainties were selected: uncertainties in nodal demand, reservoir head, pipe roughness coefficient. Two different networks were used to apply the proposed methodology.

The statistical analysis results show that the individual effect of uncertainty of demand and uncertainty of pipe roughness coefficient on seismic vulnerability assessment of water pipe networks can be ignored for the fixed value of coefficient of variation (CoV = 0.2). On the contrary, the individual effect of uncertainty of reservoir head is statistically significant for the selected value of CoV (CoV = 0.2). The combined effect of uncertainty of the selected water pipe network uncertainties on the post-earthquake serviceability is statistically significant.

Based on the results from sensitivity analysis, the individual effect of uncertainty of reservoir head on seismic vulnerability assessment is found to be statically significant, even at low levels of uncertainty (minimum value of CoV = 0.01). By contrast, the individual effects of demand and pipe roughness coefficient uncertainties are statistically significant for higher levels of uncertainties (CoV ranges from 0.03 to 1).

Based on the results of statistical analysis and sensitivity analysis, it can be concluded that selected water pipe network uncertainties have statistically significant effects on the post-earthquake serviceability. Therefore, it is highly recommended that water pipe network uncertainties be integrated with seismic vulnerability assessment of water pipe networks. Future studies are recommended to investigate the impact of other water pipe network uncertainties that were not considered in this study.

The results correspond to a single high-intensity scenario selected based on deaggregation analysis. Further analysis is recommended to identify whether these parameters remain statistically significant in case the earthquake randomness is considered.

DATA AVAILABILITY STATEMENT

Some or all data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request.

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