Seismic Vulnerability Assessment of Water Pipe Networks under Network Uncertainties

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ABSTRACT

Earthquakes disrupt the operation of critical lifelines in a community, such as underground water and gas infrastructure systems. The importance of the seismic vulnerability assessment of water pipe networks cannot be exaggerated as it has a critical role in preventive seismic rehabilitation decision-making performed to avoid costly repairs. Existing seismic vulnerability assessment methods do not consider water pipe network uncertainties (e.g., uncertainties in nodal demand, reservoir head, and pipe roughness coefficient) despite the considerable susceptibility of these assessment methods to these uncertainties. Examining the effect of network uncertainties on post-earthquake serviceability of water pipe networks is the first step towards assessing the vulnerability of water pipe networks under uncertainties. The objective of this research is to investigate the effect of network uncertainties on the post-earthquake serviceability of water networks. Demand and pipe roughness coefficient were the network parameters selected for this study. Design of the experiment, Monte Carlo simulation, and one-way analysis of variance (ANOVA) tests were used to examine the individual and combined effects of two water pipe network uncertainties (nodal demand and pipe roughness coefficient). The approach was tested on the Modena network, which is a city-scale benchmark network that is commonly used in the literature for seismic vulnerability assessment of water pipe networks. The results show that the uncertainty of these two selected network parameters has a statistically significant impact on the post-earthquake serviceability of water pipe networks. Hence, it is recommended to integrate the network uncertainties with the seismic vulnerability assessment of water pipe networks.

INTRODUCTION

Water networks are one of the critical infrastructure systems supporting residential, industrial, and commercial activities of any modern city. Past earthquakes such as the San Francisco earthquake of 1906, the San Fernando earthquake of 1971, the Northridge earthquake of 1994, the Kobe earthquake of 1995, the Christchurch earthquake of 2011, and the Central Mexico earthquake of 2017 revealed the vulnerability of the water networks (O'Rourke 1996; O'Rourke et al. 2014). Any kind of disruption in water pipe networks can result in enormous direct losses such as disruption in water distribution and indirect losses such as the cost of repair (Piratla et al. 2015, Yerri et al. 2016). Therefore, it is important to evaluate the seismic vulnerability of water networks so that acceptable post-earthquake serviceability can be guaranteed.

Several studies have been conducted on seismic vulnerability assessment of water pipe networks. In most of these studies, either topological analysis (Adachi and Ellingwood 2008; Christodoulou and Fragiadakis 2014) or hydraulic simulation-based analysis (Shi 2006; Wang et al. 2010) was used. Few of these studies have also considered the uncertainties related to leaks and breaks induced by a seismic event on the water network. (Shi 2006; Wang et al. 2010; Pudasaini and Shahandashti 2018; Shahandashti and Pudasaini 2019).

Current seismic vulnerability assessment of water pipe networks assumed that established hydraulic network analysis models could accurately estimate serviceability measures of water pipe networks. However, several studies have identified significant shortcomings of the hydraulic models to follow real-world field conditions (Sabzkouhi and Haghighi 2016; Seifollahi-Aghmiuni et al. 2013; Bargiela and Hainsworth 1989). These shortcomings are mostly due to the high sensitivity of hydraulic models to their input variables, like demand, pipe roughness coefficient or reservoir head (Kang and Lansey 2009, Shibu and Janga Reddy 2011). Sabzkouhi and Haghighi (2016) showed that a slight 15% uncertainty in pipe's roughness and nodal demands could result in as much as a 50% deviation in flow velocities and an 11.2% deviation in predicted nodal pressures. This result represents the high sensitivity of network hydraulic analysis models to uncertainties. Therefore, a crucial need exists for incorporating uncertainties into the current seismic vulnerability assessment models.

METHODOLOGY

The methodology is focused on identifying the effects of network uncertainties on the post-earthquake serviceability of the water pipe networks. Several uncertain network parameters can be found in the literature, such as pipe roughness coefficient, nodal demand, reservoir/tank level, pipe materials, age, and pipe diameter (Seifollahi-Aghmiuni et al. 2013; Lansey et al. 1989; Xu and Goulter 1998; Kang and Lansey 2009). Pipe roughness coefficient and nodal demand are two parameters selected for this study. The methodology can be broken down into four steps: seismic repair rate calculation, hydraulic and seismic modeling, Monte Carlo simulation, and analysis of the result. The methodology is summarized in Figure 1.

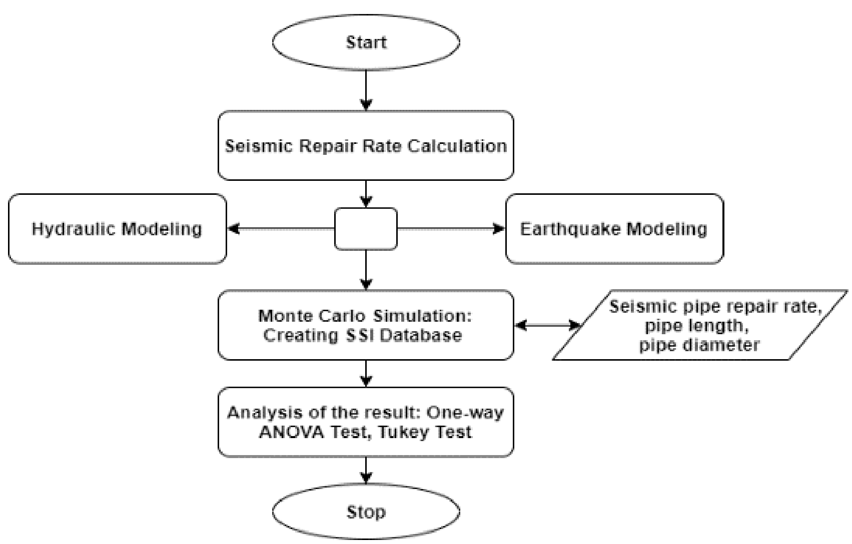

Figure 1. Flowchart of the methodology adopted for this study

Monte Carlo Simulation to Create SSI Database. Monte Carlo simulation begins with a seismic repair rate calculation for the selected scenario earthquake. Seismic repair rate is the number of repairs per 1000 feet of pipe (ALA 2001). The seismic repair rate was calculated for each pipe using the method proposed by Shahandashti and Pudasaini (2019). A seismic deaggregation analysis was conducted to identify the scenario earthquake for this study (Adachi and Ellingwood 2008). To calculate seismic repair rate for the pipes, a spatially correlated peak ground velocity (PGV) field was generated using ground motion prediction equations (GMPE) proposed by Abrahamson and Silva (2007). The general expression for the GMPE is given by Eq. 1.

$$log_{10}\,(PGV_{ij}) = f\,(M_i, R_{ij}, \theta_i) + \sigma_B\, v_i + \sigma_w \varepsilon_{ij} \quad (1)$$

where PGV_{ij} is the peak ground velocity for site j from source i at a distance R_{ij} during an earthquake event; M_i is the magnitude of the earthquake event; θ_i is the geological parameters which define the seismogenic source i; $\sigma_B v_i$ is the interevent residual and $\sigma_w \varepsilon_{ij}$ is the intra-event residual.

The seismic fragility function proposed by ALA (2001) was used to calculate the probability of damages and seismic repair rate due to seismic events. The general expression of the fragility function used to calculate the repair rate is given by Eq. 2.

$$RR_{k,m} = K1 \; x \; 0.00187 \; x \; PGV_{k,m} \quad (2)$$

where RR_k is seismic repair rate per 1000 ft of pipe k for m^{th} seismic PGV field; $K1$ is the modification factor which adjusts the value of repair rate based on the pipe material, pipe diameter, pipe joint characteristics, and soil corrosivity (ALA 2001); $PGV_{k,m}$ is the average peak ground velocity for m^{th} seismic PGV field at the location of the k (in./s).

After locating the leaks and breaks using the methodology proposed by Shahandashti and Pudasaini (2019), the hydraulic model of the network was created using the methodology developed by Shi (2006). The nodal pressure of each node was calculated and recorded using steady-state quasi pressure-driven hydraulic analysis. The calculated nodal pressures were then used to calculate System Serviceability Index (SSI), a post-earthquake serviceability indicator. The general expression for calculating SSI is given by Eq. 3. Monte-Carlo simulation was used to calculate the expected network serviceability.

$$SSI_p = \frac{1}{M} * \sum_{m=1}^{M} SSI_m \quad (3)$$

where SSI_p is the system serviceability index, which is a post-earthquake serviceability indicator for p^{th} number of Monte Carlo Runs; SSI_m is the system serviceability index calculated using Eq. 4 for the m^{th} peak ground velocity field; M is the number of random peak ground velocity field generated for a single earthquake scenario.

$$\mathrm{SSI_m} = \frac{\sum_{i=1}^{N} xi * Di}{\sum_{i=1}^{N} Di} \quad (4)$$

subject to

$$x_i = 1 \text{ if } P_i \geq P_{threshold}$$

$$x_i = 0 \text{ if } P_i < P_{threshold}$$

where D_i is the water demand at node i; N is the number of nodes in the network; $P_{threshold}$ is the minimum hydraulic pressure required at the node, which is imposed by the firefighting demand and P_i is the hydraulic pressure at node i.

The SSI value for each Monte Carlo run was then recorded to create the SSI database for further statistical analysis. Monte Carlo simulation was conducted for a predefined maximum number of Monte Carlo runs for each of the selected experiments discussed in the following section of the paper. From the result of the convergence study conducted by Shahandashti and Pudasaini (2019), it can be concluded that 3000 Monte Carlo runs are adequate for this study. The process of creating the SSI database using Monte Carlo simulation is shown in Figure 2.

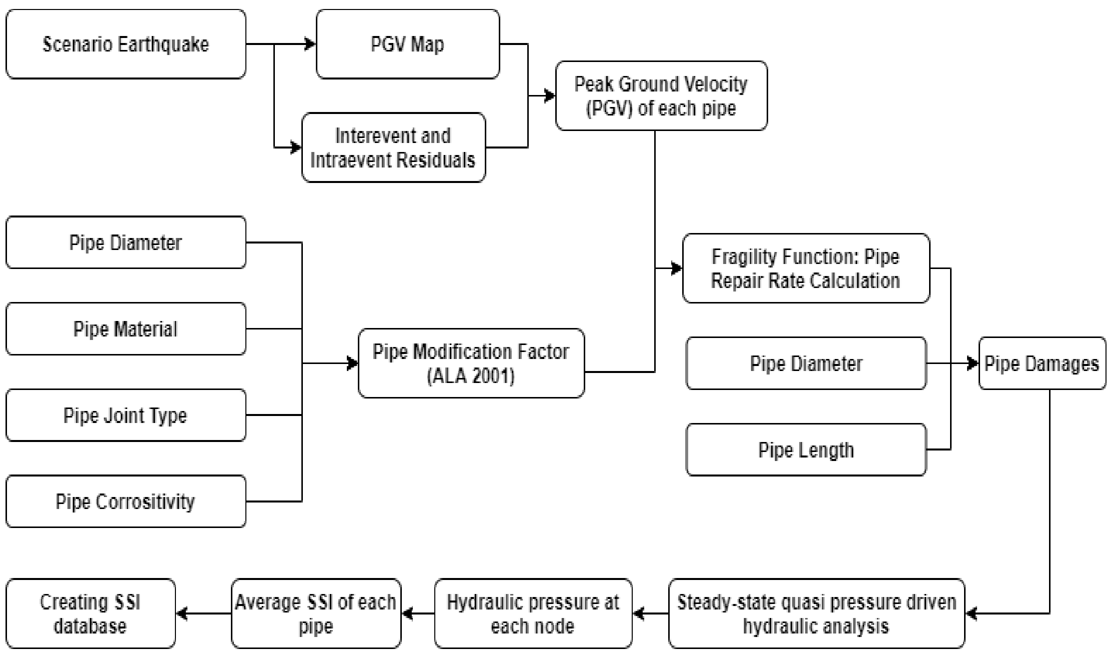

Figure 2. Flowchart showing the process of creating SSI database for statistical analysis

Design of Experiments. Previous studies conducted on network uncertainties used either probability models or possibility models. Normal distribution and uniform distribution are two widely used probability models (Seifollahi-Aghmiuni et al.2013, Kang and Lansey 2009). On the other hand, fuzzy logic is used as a possibility model (Sabzkouhi and Haghighi 2016, Dongre and Gupta 2017). In this study, a normal distribution is used to quantify the network uncertainties. Nodal demands and pipe roughness coefficient were assumed to be normally distributed, and the coefficient of variation (CV) is used to evaluate the effect of uncertainties. The coefficient of variation (CV) is the ratio between the mean and standard deviation. We have assumed the value of CV to be 0.2 (Seifollahi-Aghmiuni et al. 2013).

The experiment was designed as a full factorial design. Each of the two network uncertainities considered in this study were studied at two levels (including uncertainty and excluding uncertainty). Table 1 shows the network uncertainties with their levels for the experiment.

The coded design for the experiment is shown in Table 2.

Table 1. Network parameters with their levels for the experiment

Water Pipe Network Uncertainty Name	Notation	Including Uncertainty	Excluding Uncertainty
Demand	A	1	-1
Pipe Roughness Coefficient	B	1	-1

Table 2. Design matrix of the experiment

Experiment Name	Experiment Notation	A	B	AB
Experiment 1	Comp_Exp 1	-1	-1	-1
Experiment 2	Comp_Exp 2	+1	-1	-1
Experiment 3	Comp_Exp 3	-1	+1	-1
Experiment 4	Comp_Exp 4	+1	+1	+1

Statistical Analysis of SSI Database. The one-way analysis of variance (ANOVA) was used to determine whether there were any statistically significant differences between the means of the selected experiments. Specifically, the following null hypothesis was tested:

$$H_0: \mu_1 = \mu_2 = \mu_3 = \ldots\ldots\ldots\ldots = \mu_k \tag{5}$$

where μ is the group mean and k is the number of groups. If the one-way ANOVA returns a statistically significant result, the alternative hypothesis was accepted, which means there are at least two group means that are significantly different from each other. The one-way ANOVA cannot specifically determine which specific groups are significantly different from each other. To determine which specific groups differed from each other, a Tukey test, which is a pairwise comparison, was performed.

APPLICATION AND RESULTS

The proposed methodology was applied to the Modena network, a widely used benchmark network (Center of Water Systems 2018). Modena network has 317 pipes, 268 junctions, and four reservoirs with a total pipe length of 71,806.11 m. The layout of the Modena network is shown in Figure 3. For the deaggregation, the location of the network centroid was assumed to be Pasadena, California (34.146267º N, 118.144040º W). A deaggregation analysis was performed using the methodology proposed by Shahandashti and Pudasaini (2019). From the deaggregation result, an earthquake with a magnitude of 7.12 was selected as the scenario earthquake.

Statistical Analysis Result. A one-way ANOVA test was conducted to find out the significance of uncertainty of the parameters. We considered the level of significance to be 0.05. Table 3 summarizes the mean and variance of SSI for each factor-level combination for the Modena network.

The hypotheses for ANOVA test are as follows-

Null Hypothesis, H_0: $\mu_1 = \mu_2 = \mu_3 = \mu_4$

Alternative Hypothesis, H_1: Not all μ are equal

Level of Significance: 0.05

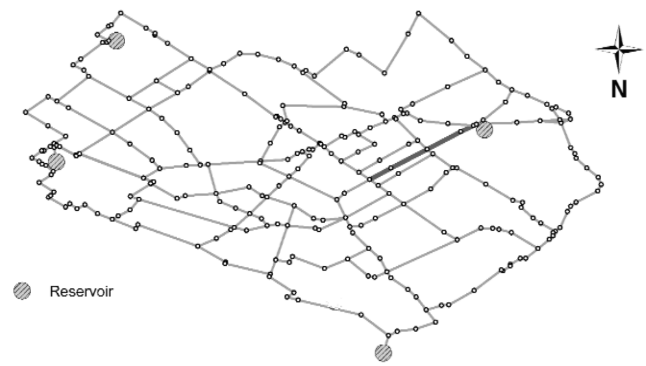

Figure 3. Layout of Modena network

Table 3. Mean and variance of SSI for Modena network

Experiment Name	Experiment Notation	Observations	Average	Variance
Experiment 1	Comp_Exp 1	3000	0.762205	0.026013
Experiment 2	Comp_Exp 2	3000	0.763732	0.024513
Experiment 3	Comp_Exp 3	3000	0.73048	0.036809
Experiment 4	Comp_Exp 5	3000	0.731184	0.036133

Table 4 summarizes the results from the ANOVA test for the Modena network.

Table 4. ANOVA test result for Modena network

Source of Variation	SS	df	MS	F	p-value	F crit
Between Groups	26.6748	7	3.810685	92.17002	3E-133	2.00997126
Within Groups	991.9273	23992	0.041344			
Total	1018.602	23999				

From the Anova test result of the Modena network, the *p*-value was much less than 0.05, and, therefore, there was a significant difference in the mean SSI between different groups or between experiments. ANOVA test could not determine which group of experiment differed from each other. Tukey test was conducted to come up with a decision on which experiment was significant. Table 5 summarizes the results of the Tukey test for the Modena network.

From the Tukey test for the Modena network, the difference of mean between Comp_Exp 1 and Comp_Exp 2 was not significant enough; therefore, the null hypothesis could not be rejected. For all other pairwise comparisons, the null hypothesis was rejected, and it was concluded that the change of SSI values was significant, considering a 5% level of significance.

Summarizing the results from ANOVA and Tukey test, it can be concluded that, for the selected value of CV, the uncertainty of demand is not significant individually. In contrast, the uncertainty of the pipe roughness coefficient is significant. The combined effect of demand and pipe roughness coefficient is also significant according to the Tukey test result. Detailed cost-benefit analysis is essential to make proper rehabilitation decisions (Zahed et al. 2018). Therefore, the recommended future work includes the detailed benefit-cost analysis of seismic rehabilitation decisions for water pipe networks. It is recommended to consider lifecycle costs while assessing the rehabilitation decisions (Zahed et al. 2019; Janbaz et al. 2017).

Table 5. Results of Tukey HSD test for Modena network

Group 1	Group 2	meandiff	p -adj	Lower	Upper	Reject
Comp_Exp 1	Comp_Exp 2	0.0015	0.9	-0.0144	0.0174	FALSE
Comp_Exp 1	Comp_Exp 3	-0.0317	0.001	-0.0476	-0.0158	TRUE
Comp_Exp 1	Comp_Exp 4	-0.031	0.001	-0.0469	-0.0151	TRUE

CONCLUSION

From the statistical analysis of the SSI database created using Monte Carlo simulation, it can be concluded that uncertainty of demand individually does not have any effect on the SSI of the network for our selected value of the coefficient of variance. Though uncertainty of demand does not have statistical significance, it cannot be ignored as the combined effect of uncertainty demand and pipe roughness coefficient has an impact on the value of SSI.

From the analysis result, it can be concluded that current seismic vulnerability assessment methods are vulnerable to network uncertainties as the value post-earthquake serviceability indicator is sensitive to network uncertainties. It is recommended to consider network uncertainties in current seismic vulnerability assessment methods. Further analysis is required to identify the effects of other network uncertainties. It is also recommended to consider methods for the investment valuation under uncertainty, e.g., real options analysis (Zahed et al. 2020; Kashani et al. 2015) when evaluating various investment decisions to enhance the seismic resiliency of water pipe networks.

ACKNOWLEDGEMENT

This material is based upon work supported by the National Science Foundation under Grant No. 1926792. Hence, the authors are grateful to the National Science Foundation for this support.

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