

IMPACT OF WATER NETWORK UNCERTAINTIES ON SEISMIC REHABILITATION DECISION-MAKING FOR WATER PIPELINES

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ABSTRACT

Past earthquakes have revealed the vulnerability of water infrastructure to earthquakes as water networks are vulnerable to pipe damage (breaks and leaks). These damages cause disruption in the supply of water distribution. Seismic vulnerability assessment is essential for seismic rehabilitation decision-making. Although water pipe network uncertainties play a critical role in seismic vulnerability assessment methods, the impacts of these uncertainties have not been explored in optimal proactive seismic rehabilitation decision-making. Extant pertinent literature ignores the uncertainty related to water network properties. This research aims to explore the impacts of water network uncertainties on determining the most critical pipes vulnerable to seismic events within the limited budget constraint. Pipe roughness coefficient, demand, and reservoir head were selected as uncertain network parameters for this study. Sensitivity analysis was performed to quantify selected network uncertainties. A stochastic combinatorial optimization problem was formulated considering network uncertainties and seismic ground motion intensities to identify the most critical pipes of a network for limited rehabilitation budget. A simulated-annealing algorithm was used to solve the stochastic combinatorial optimization problem. Modena network was used to demonstrate the method. The optimization results showed that the selected network uncertainties significantly affect the identified critical pipes of the water pipelines. Also, the maximum achievable serviceability index for selected rehabilitation budget reduces significantly if network uncertainties are considered. This index reduces by 3-4% due to the consideration of all three network uncertainties. It can be concluded that network uncertainties must be included with the current methodology of proactive rehabilitation decision-making due to seismic events.

INTRODUCTION

Water pipe networks get severely disrupted due to earthquake events. Previous earthquakes (e.g., 1994 Northridge, 1995 Kobe) and more recent earthquakes (e.g., 2011 Christchurch, 2011 East Japan, 2015 Gorkha, and 2017 Central Mexico) clearly indicate that water network pipes are vulnerable to seismic events (Cubrinovski et al. 2011; Maruyama et al. 2011; O'Rourke et al. 2014; Knight 2017). Water network disruption causes major direct and indirect losses (Yerri et al. 2017). Utilities had conducted approximately 1400 repairs in water pipes after the 1994 Northridge earthquake. Hence, the water pipes network must be gone through rehabilitation work to increase the serviceability of the network and reduce the losses. (Davis 2016). As a result, utilities are

required to determine the most critical pipes of the network to maximize serviceability due to seismic events.

In the current practice of identification of critical pipes vulnerable to earthquakes, it is assumed that current hydraulic analysis methodologies can determine the serviceability measures accurately (Pudasaini and Shahandashti 2018; Shahandashti and Pudasaini 2019; Pudasaini and Shahandashti 2020; Pudasaini and Shahandashti 2021; Shavreen et al. 2022). A 15% variation in the value of pipe roughness coefficient and demand could result in an 11% variation in nodal pressure prediction and a 50% variation in flow velocity prediction (Roy et al. 2021). Roy et al. (2021) showed that a 20% deviation pipe roughness coefficient significantly affects the post-earthquake serviceability index. Roy et al. (2022) identified the minimum value of CV (coefficient of variation) for which there was a significant effect on the post-earthquake serviceability index. This study showed that a little 1% deviation in reservoir head could significantly impact the result. These studies indicate that seismic vulnerability assessment of water networks are highly sensitive to water network uncertainties. However, the impact of these uncertainties on rehabilitation decision making is not studied. It is important to explore the effects of water network uncertainties on optimal proactive seismic rehabilitation decision-making for water pipelines.

METHODOLOGY

The methodology for exploring the impacts of water network uncertainties on optimal seismic rehabilitation decision-making is described in Figure 1.

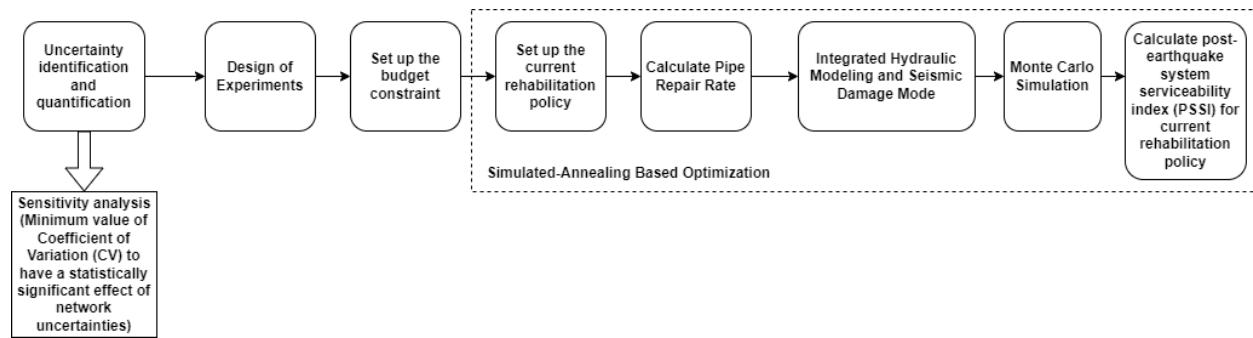


Figure 1: Methodology of exploring the impacts of water network uncertainties on optimal seismic rehabilitation decision-making

Selection of Network

The Modena network was used in this study (Center of Water Systems 2018).

Uncertainty Quantification

Three water network parameters were selected for this study: pipe roughness coefficient, nodal demand, and reservoir head. The probabilistic distribution for these parameters was assumed- ‘Normal distribution’. CV was used as the parameter to quantify the uncertainties in this study (Roy et al. 2021). The minimum value of CV was used in this study. The minimum value of CV was determined using sensitivity analysis. Using the minimum value of CV ensures the integration of network uncertainty with the optimization algorithm. This study could have been

conducted using a fixed value of CV (Roy et al. 2021). Selecting the fixed value of CV is not feasible for the optimization problem as there are chances of no effects for the predefined value of CV. The selected values of CV for all three uncertain parameters are listed in Table 1.

Table 1: Sensitivity analysis result

Network Uncertainty Parameter	Minimum Value of CV
Pipe Roughness Coefficient	0.15
Demand	0.50
Reservoir Head	0.10

Design of Experiments

To explore the effects of network uncertainty on optimal proactive seismic rehabilitation decision-making, this study was constructed as a full factorial design. All three selected network parameters were studied at two levels: uncertainty included (coded as 1) and uncertainty excluded (coded as -1) (Roy et al 2021). Table 2 shows the design of experiment for this study.

Table 2: Name of the experiments along with design matrix

Experiment Name/Notation	Pipe Roughness Coefficient	Demand	Reservoir Head
Exp A	-1	-1	-1
Exp B	-1	1	-1
Exp C	1	-1	-1
Exp D	-1	-1	1
Exp E	1	1	-1
Exp F	1	-1	1
Exp G	-1	1	1
Exp H	1	1	1

Seismic Repair Rate Calculation

Figure 2 demonstrates the method of determining the pipe repair rate for each peak ground velocity field (Shahandashti and Pudasaini 2019).

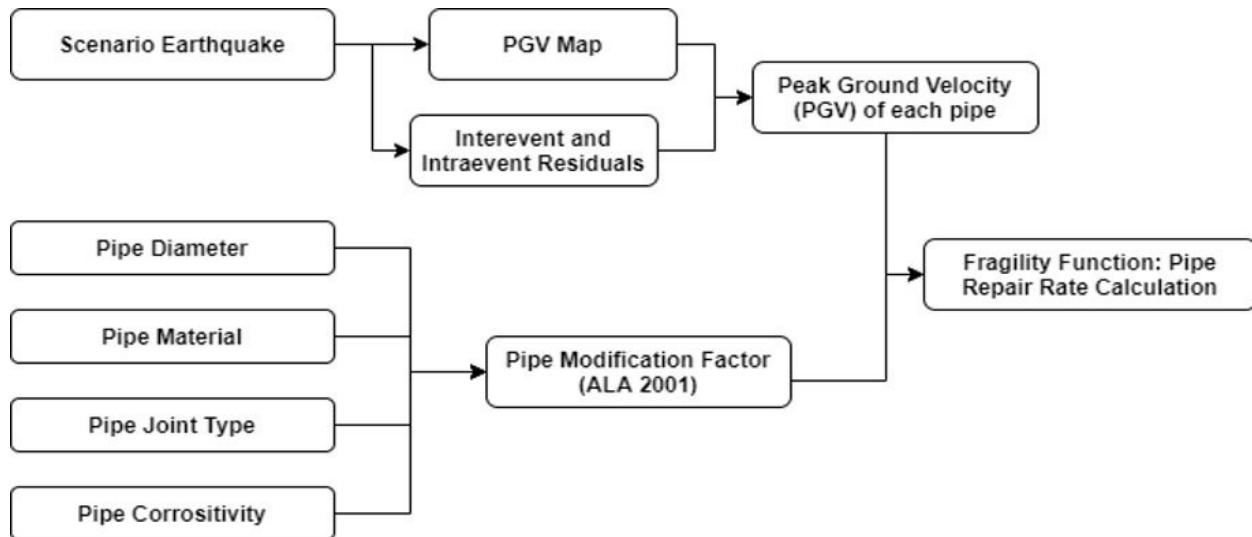


Figure 2: Process of determining pipe repair rate for each peak ground velocity field

Calculating PSSI for Each Random PGV Field

Post-earthquake system serviceability index (PSSI) is used as a serviceability measure for this study (Wang 2010; Shi 2006). After calculating the repair rate of each pipe, PSSI was calculated for each random PGV (Shahandashti and Pudasaini 2019).

Determining a Sufficient Number of Monte Carlo Runs

A sufficient number of Monte Carlo runs was identified based on a convergence study (Figure 3). From the convergence study, 3000 Monte Carlo runs were selected for this analysis.

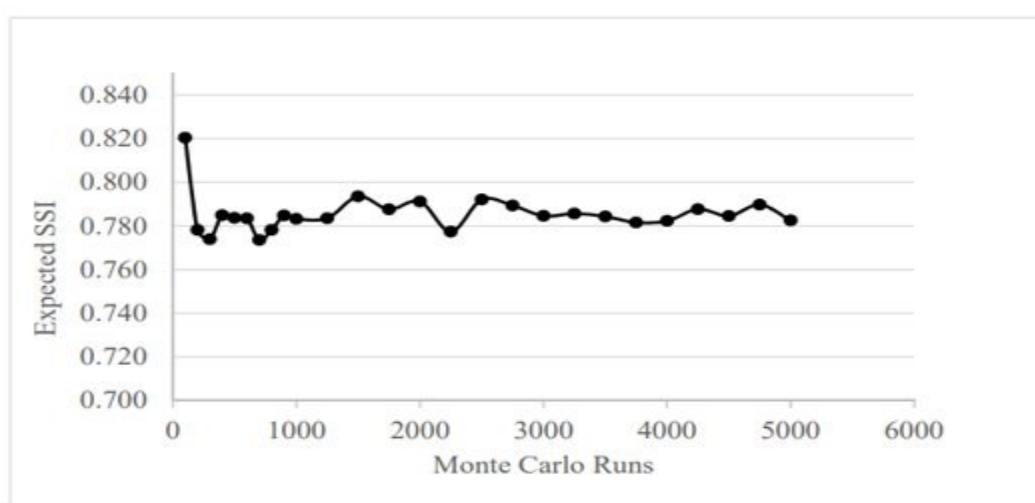


Figure 3: Result of Convergence Study

Optimization Problem Formulation

The problem targets maximizing the expected PSSI. The mathematical model can be represented by Eq. (1).

$$\max_{x \in X} E[PSSI(x)] \quad (1)$$

Subject to

$$Cost(x) \leq Cost_{max} \quad (2)$$

where all rehabilitation policies are denoted by set X , $Cost(x)$ is the cost of rehabilitation to implement policy x , $Cost_{max}$ is the cost constraints.

The combinatorial stochastic optimization problem was solved using a simulated-annealing-based optimization algorithm (Shahandashti and Pudasaini 2019). This study was conducted for five cost limits: \$2.5 million, \$5 million, \$7.5 million, and \$10 million.

RESULTS AND DISCUSSION

In the following part of the manuscript, the result from the simulated-annealing based optimization will be demonstrated. Tables 3 to 6 shows the maximum expected SSI and actual cost of rehabilitation for different experiments of this study. Figure 4 to Figure 7 display the most critical pipes for each experiment considering the budget limitation. The critical pipes are highlighted using bold red marks.

Table 3: Maximum Expected SSI and Actual Cost of Rehabilitation (Cost Limit 2.5 million)

Experiment Name	Actual Cost (USD)	Expected PSSI	Solution Time (h)
Exp A	2,446,678.20	0.89126	301.49
Exp B	2,424,668.47	0.87759	310.67
Exp C	2,463,207.89	0.87521	301.81
Exp D	2,456,355.10	0.87945	291.35
Exp E	2,425,674.12	0.86561	307.67
Exp F	2,486,782.03	0.86754	311.73
Exp G	2,410,405.86	0.87201	302.35
Exp H	2,494,608.35	0.85469	306.53

Table 3 indicates that the value of maximum expected PSSI decreases by 2% for consideration of single uncertain parameter, while this value reduces by 3% for consideration of two uncertain parameters combinedly. The maximum expected PSSI decreases by 4%, if we consider three uncertain parameters (Exp H)

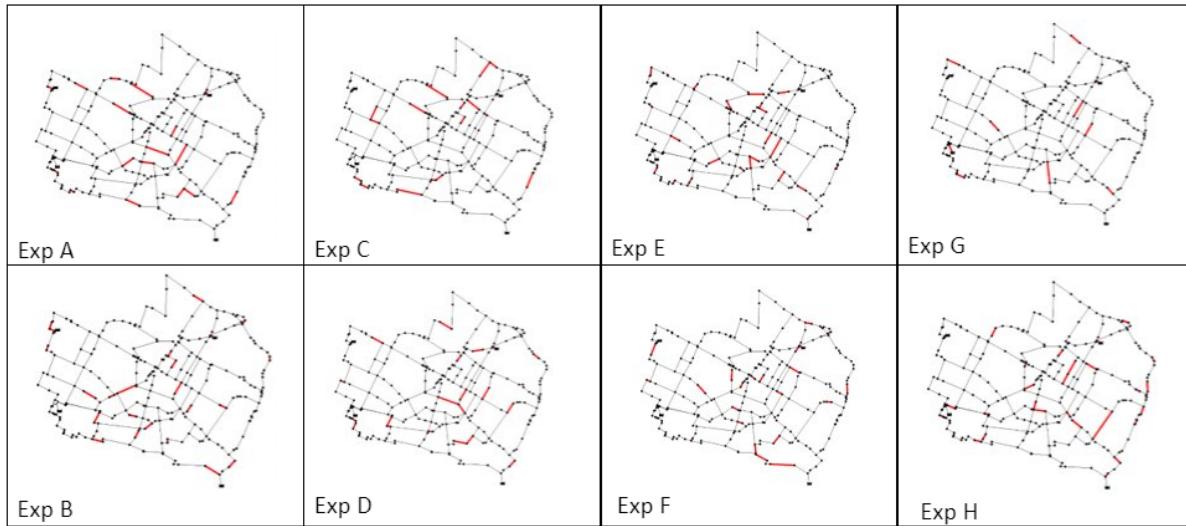


Figure 4: Critical pipes identified for different experiments (Cost Limit 2.5 million)

Table 4: Maximum Expected SSI and Actual Cost of Rehabilitation (Cost Limit 5 million)

Experiment Name	Actual Cost (USD)	Expected PSSI	Solution Time (h)
Exp A	4,934,950.25	0.90347	292.37
Exp B	4,950,759.17	0.89703	319.79
Exp C	4,944,895.50	0.89168	321.95
Exp D	4,964,728.78	0.89965	314.36
Exp E	4,984,015.11	0.88349	302.82
Exp F	4,969,679.08	0.88628	294.23
Exp G	4,981,896.25	0.88881	294.23
Exp H	4,993,185.62	0.87733	312.4

Table 4 indicates that the value of maximum expected PSSI decreases by 1% for consideration of single uncertain parameter, while this value reduces by 2% for consideration of two uncertain parameters combinedly. The maximum expected PSSI decreases by 3%, if we consider three uncertain parameters (Exp H).

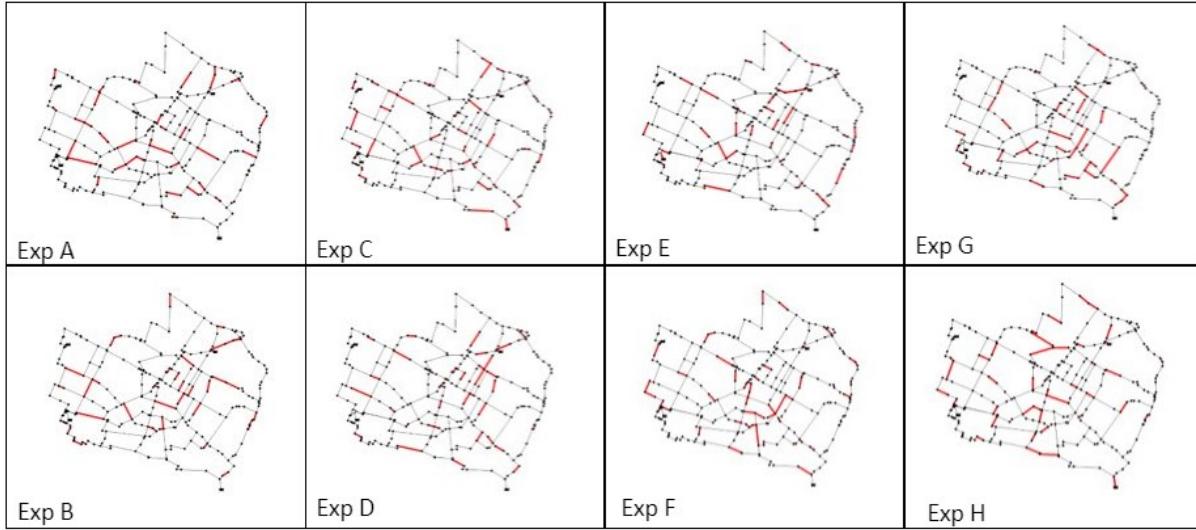


Figure 5: Critical pipes identified for different experiments (Cost Limit 5 million)

Table 5: Maximum Expected SSI and Actual Cost of Rehabilitation (Cost Limit 7.5 million)

Experiment Name	Actual Cost (USD)	Expected PSSI	Solution Time (h)
Exp A	7,459,746.89	0.92102	282.84
Exp B	7,427,872.94	0.91548	292.75
Exp C	7,499,606.00	0.91601	288.61
Exp D	7,409,872.44	0.91407	282.12
Exp E	7,484,498.65	0.90451	293.49
Exp F	7,461,259.29	0.90709	294.46
Exp G	7,453,702.13	0.90571	298.53
Exp H	7,472,016.03	0.89395	294.4

Table 5 indicates that the value of maximum expected PSSI decreases by 1% for consideration of single uncertain parameter, while this value reduces by 2% for consideration of two uncertain parameters combinedly. The maximum expected PSSI decreases by 3%, if we consider three uncertain parameters (Exp H)

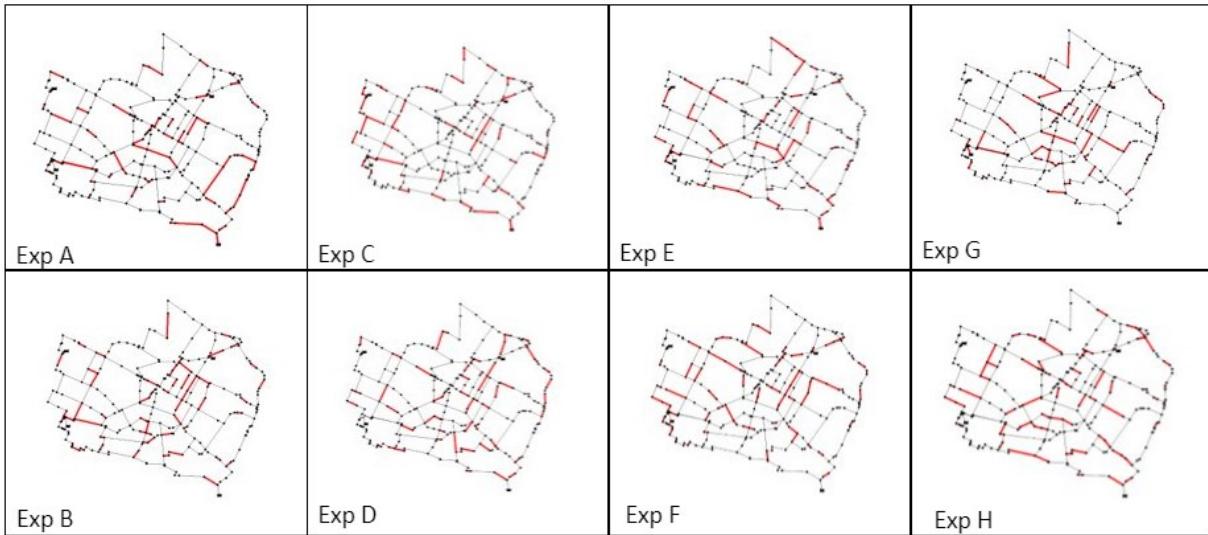


Figure 6: Critical pipes identified for different experiments (Cost Limit 7.5 million)

Table 6: Maximum Expected SSI and Actual Cost of Rehabilitation (Cost Limit 10 million)

Experiment Name	Actual Cost (USD)	Expected PSSI	Solution Time (h)
Exp A	9,907,577.89	0.93961	278.85
Exp B	9,954,538.61	0.93360	284.57
Exp C	9,966,648.94	0.93236	281.78
Exp D	9,983,349.85	0.93470	281.47
Exp E	9,930,515.41	0.92378	295.93
Exp F	9,944,432.66	0.92712	280.64
Exp G	9,988,638.55	0.92609	286.89
Exp H	9,851,908.10	0.91806	299.59

Table 6 indicates that the value of maximum expected PSSI remains same for consideration of single uncertain parameter, while this value reduces by 1% for consideration of two uncertain parameters combinedly. The maximum expected PSSI decreases by 3%, if we consider three uncertain parameters (Exp H)

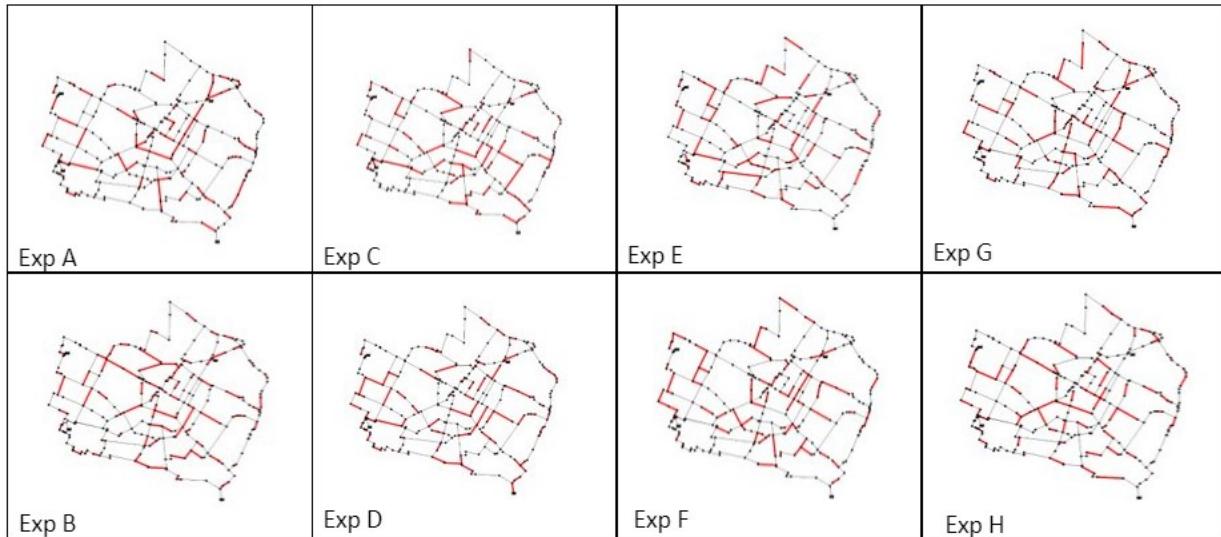


Figure 7: Critical pipes identified for different experiments (Cost Limit 10 million)

CONCLUSION

The analysis results conclude that there is a significant impact of selected network uncertainties on proactive seismic rehabilitation decision-making for the selected values of coefficient of variation. The value of PSSI reduces by 3-4% due to the consideration of all three network uncertainties. The value of PSSI reduces by 1-2% if only one network uncertainty is considered. So, it is recommended to include selected water network uncertainties with the current seismic rehabilitation decision-making model. Further studies are required to explore the impacts of other uncertainties that may impact seismic rehabilitation of water networks.

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REFERENCE

Center of Water Systems. (2018). “Large Problems.” (Sep. 1, 2019).
<http://emps.exeter.ac.uk/engineering/research/cws/resources/benchmarks/design-resilience-pareto-fronts/large-problems/>.

Cubrinovski, M., Bradley, B., Wotherspoon, L., Green, R., Bray, J., Wood, C., & Taylor, M. 2011. “Geotechnical aspects of the 22 February 2011 Christchurch earthquake.” *Bulletin of the New Zealand Society for Earthquake Engineering*, 44(4), 205-226.
<https://doi.org/10.5459/bnzsee.44.4.205-226>.

Davis, C. (2016). "Pipe Rehabilitation for a Seismic Resilient System." Large Pressure Pipe Structural Rehabilitation Conference.

Knight, B. 2017. Mexico City earthquake reconnaissance – day 3. *What's Happening*. Retrieved from <http://www.wrkengrs.com/mexico-city-earthquake-reconnaissance-day-4/>.

Maruyama, Y., K. Kimishima, and F. Yamazaki. 2011. "Damage assessment of buried pipes due to the 2007 Niigata Chuetsu-Oki earthquake in Japan." *Journal of Earthquake and Tsunami* 5 (1): 57–70. <https://doi.org/10.1142/S179343111100098X>.

O'Rourke, T. D., S. S. Jeon, S. Toprak, M. Cubrinovski, M. Hughes, S. Van Ballegooy, and D. Bouziou. 2014. "Earthquake response of underground pipeline networks in Christchurch, NZ." *Earthquake Spectra* 30 (1): 183–204. <https://doi.org/10.1193%2F030413EQS062M>.

Pudasaini, B., and Shahandashti, M. (2018), Identification of Critical Pipes for Proactive Resource-constrained Seismic Rehabilitation of Water Pipe Networks, *Journal of Infrastructure Systems*, ASCE, 24(4): 04018024.

Pudasaini, B., and Shahandashti, M. (2020), Topological Surrogates for Computationally Efficient Seismic Robustness Optimization of Water Pipe Networks, *Computer-Aided Civil and Infrastructure Engineering*, Wiley, 35(10), 1101-1114.

Pudasaini, B., and Shahandashti, M. (2021), Seismic Rehabilitation Optimization of Water Pipe Networks Considering Spatial Variabilities of Demand Criticalities and Seismic Ground Motion Intensities, *Journal of Infrastructure Systems*, ASCE, 27(4), 04021028.

Roy, A., Pudasaini, B., & Shahandashti, M. (2021). Seismic Vulnerability Assessment of Water Pipe Networks under Network Uncertainties. In *Pipelines 2021* (pp. 171-179).

Roy, A., Shahandashti, M., & Rosenberger, J. M. (2022). Effects of Network Uncertainty on Seismic Vulnerability Assessment of Water Pipe Networks. *Journal of Pipeline Systems Engineering and Practice*, 13(3), 04022016.

Shahandashti, S. M., & Pudasaini, B. 2019. "Proactive seismic rehabilitation decision-making for water pipe networks using simulated annealing." *Natural Hazards Review*, 20(2), 04019003. [https://doi.org/10.1061/\(ASCE\)NH.1527-6996.0000328](https://doi.org/10.1061/(ASCE)NH.1527-6996.0000328).

Sharveen, S., Roy, A., & Shahandashti, M. (2022). Risk-Averse Proactive Seismic Rehabilitation Decision-Making for Water Distribution Systems. In *Pipelines 2022* (pp. 81-90).

Shi, P. 2006. *Seismic response modeling of water supply systems*. Ithaca, NY: Cornell University.

Wang, Y., Au, S.-K., & Fu, Q. 2010. "Seismic risk assessment and mitigation of water supply systems." *Earthquake Spectra*, 26(1), 257 –274. <https://doi.org/10.1193%2F1.3276900>.

Yerri, S. R., Piratla, K. R., Matthews, J. C., Yazdekhasti, S., Cho, J., & Koo, D. 2017. Empirical analysis of large diameter water main break consequences. *Resources, Conservation and Recycling*, 123, 242-248. <https://doi.org/10.1016/j.resconrec.2016.03.015>.