Table 2. Thermo-physical Properties of Panel Layers

Item	*Conventional Sandwich Panel*	*UHP-FRC Panel*
Insulation Conductivity (W/m-K)	0.005769	0.005769
Insulation Specific Heat (J/kg-K)	645	645
Insulation Density (kg/m^3)	28	20
Concrete Conductivity (W/m-K)	2.31	1.77
Concrete Specific Heat (J/kg-K)	832	1010
Concrete Density (kg/m^3)	2322	2403

Uncertainty Quantification. Probabilistic models were created to represent uncertainties of two critical input parameters of the simulation model due to their highly acknowledged importance in the literature of probabilistic building energy performance assessment: occupancy level and Infiltration rate (Li et al., 2015; de Wilde et al., 2011; Pettersen, 1994). Since the objective of this paper is the energy performance evaluation of two competing façade systems, the uncertainties in physical properties of different layers of these facade systems were also taken into account. These uncertainties were also acknowledged in the literature (Eisenhower et al., 2011; Petr et al., 2007). Table 3 shows the uncertain parameters and their probability distributions' types and parameters.

Table 3. Uncertain parameters and their probability distributions

Uncertain Parameters	*Distribution*	*Distribution Parameters*	
		Conventional Sandwich Panel	*UHP-FRC Panel*
Insulation Conductivity	Normal	μ=0.005769, σ=0.0023076	μ=0.005769, σ=0.0023076
Insulation Specific Heat	Normal	μ=645 , σ=38.7	μ=645 , σ=38.7
Insulation Density	Normal	μ=28 , σ=5.3	μ=20 , σ=3.78
Infiltration rate	Normal	μ=0.21 , σ=0.01373	μ=0.21 , σ=0.01373
Concrete Conductivity	Normal	μ=2.31, σ=0.13	μ=1.77, σ=0.1
Concrete Specific Heat	Normal	μ=832 , σ=49.9	μ=1010 , σ=60.6
Concrete Density	Normal	μ=2322 , σ=441	μ=2403 , σ=456
Infiltration rate	Normal	μ=0.21 , σ=0.01373	μ=0.21 , σ=0.01373
Occupancy	Triangle	a=1, c=2.5, b=5.2	a=1, c=2.5, b=5.2

Monte Carlo Simulation. We randomly sampled from the probabilistic models of the uncertainties and propagated the sampled values through the energy simulation model using Monte Carlo simulation for 100 iterations to create a pool of randomly generated buildings with different energy consumptions for the prototype building with UHP-FRC panel and the prototype building with conventional panel for each scenario. This number of iterations is more than 80 that is proposed in the literature to achieve valid results independent of the number of varied parameters (Macdonald, 2002). Latin hypercube sampling (LHS) (Li et. al., 2015; Hopfe et al., 2007a; Macdonald, 2002; Mckay et. al., 1979) was used to effectively explore the input space of the energy models with reasonable computational cost.

Probabilistic Energy Reduction Calculation. The simulated energy consumption of the prototype building with UHP-FRC panel was compared with the simulated energy consumption of the similar prototype building with conventional panel for each scenario to calculate the energy reductions attributed to the use of UHP-FRC panels. 100 iterations of the Monte Carlo simulation for each scenario will result in 100 energy reductions for each scenario.

Hypothesis Testing. The simulated energy reductions for each scenario were used to test the hypothesis that the average of the annual energy consumptions of the randomly generated prototype buildings with the proposed panels is less than the average of the annual energy consumptions of the prototype buildings with conventional panels. T-test (parametric) and sign test (non-parametric) were used to test this hypothesis. The null hypothesis of these tests is that the average of the annual energy consumptions of the randomly generated DOE prototype buildings with the proposed panels is equal or greater than the average of annual energy consumptions of the buildings with the conventional panels. Successful rejection of the null hypothesis provides us with adequate evidence to claim that using UHP-FRC panels result in energy savings.

RESULTS

Figure 1 presents the annual energy consumptions (heating and cooling) of building prototypes with UHP-FRC panels and building prototypes with conventional sandwich panels for each scenario using boxplots. As this figure clearly shows the average (shown by x symbol) of the annual energy consumptions of the randomly generated DOE prototype buildings with the UHP-FRC panels is less than the average of the annual energy consumptions of the buildings with the conventional panels for all scenarios. The results of T-tests (Table 4) and sign tests (Table 5) show that we can accept the alternative hypothesis that the average of the annual energy consumptions of the randomly generated DOE prototype buildings with the UHP-FRC panels is less than the average of annual energy consumptions of the buildings with the conventional panels for eight scenarios: high-rise buildings in Chicago and Fairbanks, midrise buildings in Chicago, El Paso, and Fairbanks, and hospitals in Chicago, El Paso, and Fairbanks. In other words, the energy consumption is decreased if UHP-FRC panels are used in these scenarios. Although, the average of the annual energy consumptions (heating and cooling) of high-rise buildings with UHP-FRC panels was less than the annual energy consumptions of the high-rise buildings with the conventional panels in El Paso, there is not enough evidence to reject the null hypothesis.

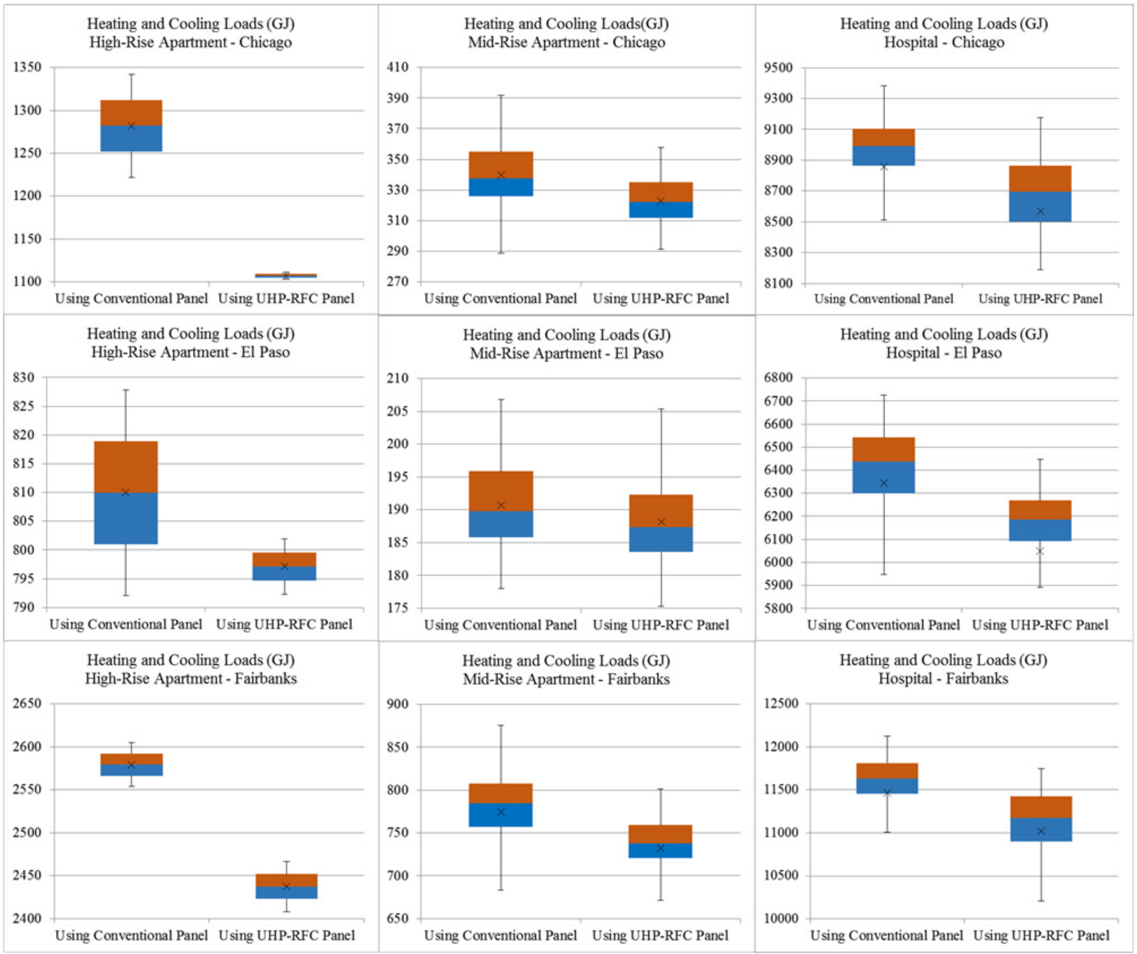

Figure 1. Box Plots of Annual total (heating and cooling) energy consumptions

Table 4. T-test Statistics

Building Type	*Location*		
	Chicago	*El Paso*	*Fairbanks*
High-Rise Building	6.51***	1.12	8.74***
Mid-Rise Building	5.79***	7.06***	7.89**
Hospital	4.87***	1.68*	8.10***

Notes: Null hypothesis is that the average of the annual energy consumptions of the randomly generated DOE prototype buildings with the proposed panel is equal or greater than the average of annual energy consumptions of the buildings with the conventional Panel; *, **, and *** represent rejection of null hypothesis at the 5%, 1%, and 0.1% significance levels, respectively.

Table 5. Sign test Statistics

Building Type	*Location*		
	Chicago	*El Paso*	*Fairbanks*
High-Rise Building	74***	57.00	74***
Mid-Rise Building	73***	61**	80***
Hospital	76***	83***	82***

Notes: Null hypothesis is the same as null hypothesis in Table 4; *, **, *** represent rejection of null hypothesis at the 5%, 1%, and 0.1% significance levels, respectively.

CONCLUSION

Three DOE prototype buildings (high-rise building, mid-rise building, and hospital), EnergyPlus building energy simulation, and Monte Carlo simulation were used to assess the probabilistic energy performance of the UHP-FRC façade system in comparison with conventional sandwich panel façade system in three cities in different climate zones (Chicago, Fairbanks, and El Paso). The results of probabilistic building energy simulation analysis show that the average of the annual energy consumptions of the randomly generated DOE prototype buildings with the UHP-FRC panels is less than the average of the annual energy consumptions of the buildings with the conventional panels for all scenarios. The results of the T-test (parametric) and sign test (non-parametric) show that we can accept the alternative hypothesis that the average of the annual energy consumptions of the randomly generated DOE prototype buildings with the UHP-FRC panels is less than the average of annual energy consumptions of the buildings with the conventional panels for all but one scenario (High-rise building in El Paso). It is expected that this result help building energy professionals select proper building façade systems considering uncertainties in decision-making.

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Identifying Critical Links in Water Supply Systems Subject to Various Earthquakes to Support Inspection and Renewal Decision Making

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Abstract

Widespread damage of water supply systems during recent earthquakes clearly shows the need for seismic planning. However, water supply seismic planning is subject to uncertainties in location, magnitude, and resulting damage of earthquakes. This problem is further complicated by complex topology of water supply systems along with the use of different materials, joint characteristics, pipe diameters and soil corrosivities. The objective of this paper is to identify critical links of water supply networks subject to various earthquakes and find optimum renewal decision given resource constraints. The methodology comprises of four interconnected components: (1) Repair Rate Probabilistic Modeling; (2) Monte Carlo Simulation; (3) Hydraulic Damage Modelling; and (4) Resource Allocation Optimization. The first component calculates repair rate for each pipe in the network based on empirical fragility curves. Empirical fragility curves depend on the pipes' location, material, diameter, joint property and soil corrosivity. Monte Carlo simulation generates probabilistic damages (i.e., leaks and breaks) in the pipe network. The hydraulic model calculates serviceability index considering simulated damages. Resource allocation optimization model uses genetic algorithm to find the optimum renewal decision to maximize serviceability index given resource constraints. The proposed model was validated using a water supply network. The network consists of 117 pipes and 92 junctions. The results show that the proposed methodology outperforms the latest proposed methodology in the literature to identify critical links in a water network. The network serviceability index is used as the measure to compare the results with the latest proposed methodology in the literature.

INTRODUCTION

Past earthquakes, such as the 1906 San Francisco earthquake, the 1994 Northridge earthquake, and the 1995 Hyogoken-Nanbu (Kobe) earthquake have demonstrated that water delivery systems are vulnerable to earthquakes (Hwang et al. 1998). 1994 Northridge earthquake resulted in more than 1,400 repairs due to leaks and breaks on pipelines; about 100 repairs in critical large diameter pipes (O'Rourke 1996). These repairs put significant financial burden on utilities. To put this burden into context, it is sufficient to know that the average cost of a large diameter water main failure is about $12 million (Yerri et al. 2016). Although it is widely acknowledged that water infrastructure is in appalling condition and there exists desperate need of renewal, there is enormous gap between funds needed to renew or rehabilitate the deteriorating drinking water infrastructure and available funds. USEPA estimated $485 billion to $895 billion funding gap projected over next 20 years' period (Cagle 2003). In such situation, limited resources should be invested in highly efficient way; optimal renewal decisions should be identified. Therefore, it is essential to identify critical links in the network for inspection and renewal decision making. Identification of the critical links in an existing network requires a seismic vulnerability assessment model of the network that considers seismic performance of pipes and hydraulic principles along with an optimization algorithm that can identify optimal renewal decision to maximize serviceability of the network.

Early seismic vulnerability assessment methods for water pipe networks focused on individual pipes. Development of empirical seismic vulnerability relations (Eguchi et al., 1983; Honegger and Eguchi, 1992; O'Rourke and Ayala, 1993; O'Rourke and Jeon 1999; ALA 2001; O'Rourke and Deyoe 2004) has been the most common seismic vulnerability assessment approach. These empirical relations are based on performance of various classes of buried pipes against historical earthquakes. They provide likelihood of damage of pipes (i.e. Repair Rate) for a given earthquake hazard parameter, such as Peak Ground Velocity (PGV). Although understanding the performance of individual pipes is critically important, the network resilience depends on dynamic interactions of these individual pipes and principles driving these interactions, such as hydraulic principles. Recent advances in computational engineering, probabilistic modeling, and network simulation motivated researchers to go beyond component-level assessment and create seismic vulnerability assessments for water pipe networks in the last two decades.

A water pipe network is composed of several components to reliably meet water demands. Therefore, water network resilience should be described based on the performance of these interacting components. Monte Carlo simulation is often used to propagate the empirically modeled seismic response of individual network components and their consequent damages into hydraulic models for a range of earthquakes. Hydraulic pressure and flow principles are used to estimate the networks' reliability and serviceability for each scenario created by Monte Carlo simulation. Shi (2006) followed this approach and empirically modeled the seismic response of water supply systems considering both hydraulic principles and fragility relations. This approach has been further expanded by other researchers to create several system reliability and serviceability indices (Wang et al. 2010) and visualize the assessment spatially using Geographic Information System (Zolfaghari and Niari 2009). Wang et al. (2010) used efficient frontier approach to identify and rank a network's critical links.

Most of the literature on seismic vulnerability assessment of water pipe networks do not propose an approach for resource allocation to enhance seismic resilience of the networks. In rare studies, the simple prioritizations of retrofit interventions solely based on the vulnerability assessment have been proposed (Wang et al. 2010). This simple prioritization does not distribute resources at the system-level and may not provide an economical solution. For example, suppose there is a long pipe with the highest priority. The cost of rehabilitation of this pipe is equal to rehabilitation of several short pipes with lower priority in the network. Perhaps, the rehabilitation of these short pipes collectively could result in much higher enhancement of network resilience. Therefore, there is a need to develop an approach to determine the best rehabilitation strategy to maximize the network's expected system serviceability given limited resources. The major contribution of this paper is to develop a resource allocation algorithm and integrate it with the seismic vulnerability assessments of water pipe networks.

The objective of this paper is to identify critical links of water supply networks subject to various earthquakes and find optimum renewal decision given resource constraints. Resource constraints refer to the funding limitation that water utilities have: they can only renew up to a specific length of their pipes per year. The methodology is explained in the following section. Then, the results and validation are presented which is followed by conclusions.

METHODOLOGY

The methodology comprises of four interconnected components: (1) Repair Rate Probabilistic Modeling; (2) Hydraulic Damage Modelling; (3) Monte Carlo Simulation; and (4) Resource Allocation Optimization. These components are explained in the rest of this section.

Repair Rate Probabilistic Modeling. Pipe repair rate (RR) determines the likelihood of a pipe to be damaged (by leaks or breaks) after an earthquake. Empirical fragility models could be used to determine repair rate for each pipe of a network for a given earthquake. Fragility relations proposed by ALA (2001) is used in this study as they take into account major characteristics of pipes, such as material, diameter, joint properties, and soil corrosivity to determine the likelihood of pipe to be damaged. These fragility relations are based on damage statistics collected from large number of earthquakes.

Repair rate of a pipe is dependent on two factors; pipe property and seismic hazard. These factors are the inputs to the ALA (2001) fragility relations. Pipe properties include pipe material, pipe joint characteristics, pipe diameter, and soil corrosivity around the pipe. Seismic hazard is typically modeled by Peak Ground Velocity (PGV) and Peak Ground Acceleration (PGA) of the earthquake for which the repair rate is being calculated. Peak Ground Acceleration (PGA) maps are available from USGS (2016) for probabilistic earthquakes. These PGA values can be converted to PGV values using Wald et al. (1999). Since earthquakes are probabilistic, these repair rates become probabilistic.

Hydraulic Damage Modeling and Monte Carlo Simulation. The hydraulic damage modeling proposed by Shi (2006) is used in this study. Location of damage is modeled as Poisson process where location of i^{th} damage in a pipe P is given by:

$$l_{p,i} = -\frac{1}{RR} * \ln(1 - U) \qquad \text{Eq. (1)}$$

Where $l_{p,i}$ is the location of i^{th} discontinuity (leaks or breaks) in pipe P from its start node, RR is repair rate calculated for the pipe and U is uniformly distributed random number between 0 and 1. Damages are characterized as leaks and breaks based on the approach proposed by Shi (2006). Monte Carlo simulation was used to create 5000 damaged networks where the locations of damaged pipes were calculated using Eq. (1). The damaged networks were analyzed using a quasi-pressure driven hydraulic analysis model to determine the pressure at each node.

Resource Allocation Optimization. The objective of the resource allocation optimization is to maximize the serviceability of the network assuming that the water agencies can only rehabilitate a certain length of pipes ($l_{rehab.}$) due to budget limitations. The repair rate of a pipe becomes zero if pipe is rehabilitated. The resource allocation is formulated as maximization of expected value of the system serviceability index (SSI) for a water distribution network subjected to earthquakes where SSI is defined as the ratio of demand fulfilled after an earthquake to inherent (original) demand of a water distribution network. The optimization is formulated as below.

$$Max\ \frac{\sum_{r=1}^{NMCS}\sum_{i=1}^{N} x_{ri}D_i}{NMCS*\sum_{i=1}^{N} D_i} \qquad \text{Eq. (2)}$$

Subject to:

$$\sum_{k=1}^{N_p} a_k l_k \le l_{rehab.}$$
$$x_{ri} = 1\ if\ P_{ri} \ge P_{threshold}$$
$$x_{ri} = 0\ if\ P_{ri} \le P_{threshold}$$
$$a_k = 1\ if\ pipe\ k\ is\ retrofitted.$$
$$a_k = 0\ if\ \ pipe\ k\ is\ not\ retrofitted.$$
$$x_{ri}, P_{ri}, D_i, l_k, a_k \ge 0$$

where N is number of nodes in the network, N_p is number of pipes in the network, $NMCS$ is number iterations of Monte Carlo simulation, D_i is the demand on node i, P_{ri} is pressure at node i during r^{th} run of Monte Carlo simulation, $P_{threshold}$ is minimum pressure required at node imposed by firefighting demand and l_k is length of pipe k. The pressures at the network's nodes are calculated using a quasi-pressure driven hydraulic analysis model for each run of Monte Carlo simulation.

The probabilistic nature of damage generation along with the combinatorial nature of the selection of pipes for rehabilitation makes this formulation stochastic combinatorial optimization. Solving this optimization problem is extremely challenging due to non-convex and non-continuous objective function and lack of closed form representation for the objective function. Since 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 with tournament selection, two-point cross over, and random mutation were devised to maximize the serviceability of the network assuming that the water agencies can only rehabilitate a certain length of pipes due to budget limitations.

RESULTS

We used the methodology detailed in the previous section to identify best rehabilitation policy for a fairly complex water distribution network (**Figure 1**) analyzed by Wang et al (2010). We selected this network to be able to compare the proposed algorithm in this study with the most recent algorithm proposed by Wang et al. (2010) for seismic risk assessment of water supply networks.

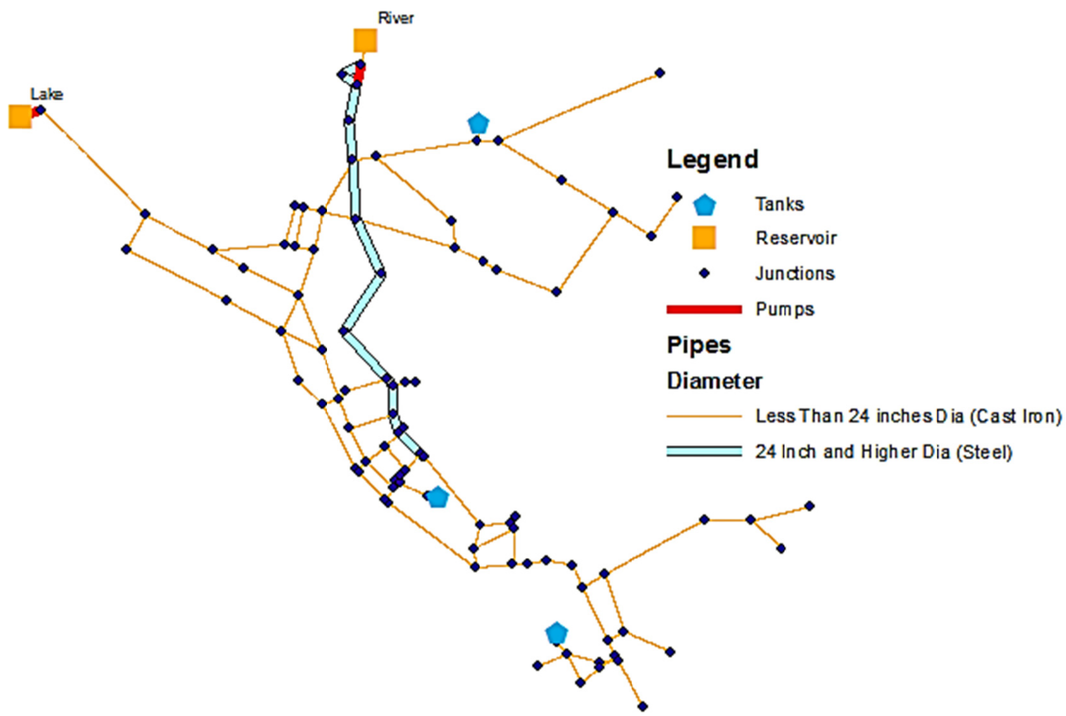

Figure 1. Test Network

This network consists of 92 junctions and 117 pipes. The network has 2 sources; a river and a lake while 3 tanks are provided to manage the demand of the system. Total length of the pipes of the entire network is 65,748.96 m. (215,711.80 ft). For seismic repair rate calculation, material of the pipe was assumed as per Wang et al. (2010) so that results could be later validated by comparison. Therefore, pipes with diameters above 24 inches were assumed as steel pipes with welded joints while pipes with diameters less than 24 inches were assumed to be cast iron pipes with brittle joint. Nodal demand assignment was also consistent with Wang et al. (2010).

Based on 5000 Monte Carlo simulations, the expected SSI of the network without any retrofitting was 0.889 for an earthquake hazard with PGV value of 53.4 cm/s (21.38 in/s). Then genetic algorithm was used to determine optimal rehabilitation plan. **Table 1** shows the parameters of the genetic algorithm while **Table 2** summarizes the results.

Table 1. Genetic Algorithm Parameters

GA Parameter	*Values*
Maximum Generation	50
Initial Mutation Rate	90%
Cross Over Type	2 Point
Decrease of Mutation Rate	3% every generation
Number of bits mutated	20% of chromosome=24 bits