Risk-Averse Proactive Seismic Rehabilitation Decision-Making for Water Distribution Systems

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ABSTRACT

Earthquakes could have enormous destructive impacts on water distribution networks. Utility managers are challenged to make proactive rehabilitation decisions under seismic and network uncertainties. These utility managers have different risk appetites. However, existing seismic rehabilitation decision-making models of water distribution networks do not consider decision-makers' attitudes toward risk making existing models practically limited. The objective of this research is to formulate a risk-averse stochastic combinatorial optimization model to identify the critical pipes of a water distribution network for proactive seismic rehabilitation with controllable risk aversion levels. The functionality of the water distribution system is quantified by the post-earthquake serviceability index, the expected value of which is maximized by the objective function. A Value-at-Risk (VaR) constraint is used to control risk levels. This methodology includes four steps: seismic repair rate calculations, integrated multi-physics modeling, Monte Carlo simulation, and risk-averse stochastic combinatorial optimization. The repair rate of each pipe subjected to seismic loads was calculated using empirical fragility curves. These curves were generated based on the locations of the pipes, soil corrosivity in different locations, pipe diameters, pipe materials, and pipe joint properties. Network's hydraulic behavior and seismic vulnerability assessment were simulated using an integrated multi-physics model. Monte Carlo simulations were performed to consider the probabilistic nature of damages to the water distribution systems. These damages were represented by leaks as well as breaks in the individual pipes. The model used to ascertain the susceptibility of the water distribution system to earthquake hazard was fused with a stochastic formulation of combinatorial optimization to maximize the serviceability index of the distribution system while minimizing risk. The solution to the optimization problem of detecting the critical pipes for a given resource constraint was obtained through a risk-averse simulated annealing approach. The approach was implemented on a widely used benchmark network to detect the critical pipelines of that water network. The introduction of risk-averse stochastic combinatorial optimization models equips decision makers with a proper model to make rehabilitation decisions at a controllable risk aversion level.

INTRODUCTION

The vulnerability of water distributions systems has been demonstrated by the Northridge, Wenchuan, Kobe, and Christchurch earthquakes (O'Rourke et al. 1996; Guo et al., 2008; Hwang et al. 1998; O'Rourke et al. 2014). Either direct damages (e.g., repairing cost of pipelines) or indirect damages (e.g., water supply disruption) make up the destructive damages. Hence, it is crucial to quantify the seismic vulnerability of water distribution pipelines to ensure satisfying post-earthquake serviceability. Previous research conducted to determine the susceptibility of water distribution systems to earthquakes took approaches focusing on hydraulic simulations (Shi 2006; Wang et al. 2010) or topological based analysis (Christodoulou and Fragiadakis 2014, Adachi and Ellingwood 2008).

Previously, stochastic combinatorial optimization models have been proposed to select rehabilitation policies in civil infrastructure systems. For example, stochastic combinatorial optimization models have been created for maintenance planning of deteriorating water and wastewater infrastructure systems (Wang and Chen 2015; Yazdi et al. 2014) and transportation infrastructure (Frangopol and Liu 2007). Shahandashti and Pudasaini (2019) developed a method to determine the susceptibility of water distribution systems to earthquake hazards given limited budget constraint. More specifically, they developed a simulated annealing (SA)-based optimization method to detect critical pipelines in a water distribution network (Shahandashti and Pudasaini 2019).

Although stochastic combinatorial optimization models were used for selecting rehabilitation policies in water supply systems, they lack mechanisms to assure that the risk of selecting a rehabilitation policy is not too high. A risky decision may not be favorable for utilities even if it provides the highest average post-disaster system serviceability. This research aims to develop a risk-averse stochastic combinatorial optimization algorithm to assess the susceptibility of water distribution networks subjected to seismic loads.

METHODOLOGY

The general expression of the objective function is as Equation 1.

$$\max_{p \in P} E[PSI(p)] \tag{1}$$

Subject to,

$$C(p) \leq C_{max}$$

$$VaR_{\alpha} \leq Pr[PSI(p) < B]$$

where p represents a policy chosen by the decision-makers to reconstruct selected pipelines, P is the set of all policies to choose, $C(p)$ is the cost of rehabilitation policy p, and C_{max} indicates budget constraint of a rehabilitation policy. VaR_{α} is the value at risk at α confidence level, and B is a lower limit of the post-earthquake serviceability index (PSI). In order to demonstrate the application, we assumed C_{max} to be 12.5 million USD, α to be 95% confidence level, and the threshold value of VaR_{95} to be less than 25% of the loss in PSI.

The methodology of this research contains four steps: seismic repair rate calculations, integrated multi-physics modeling, Monte Carlo simulation, and risk-averse stochastic combinatorial (Figure 1).

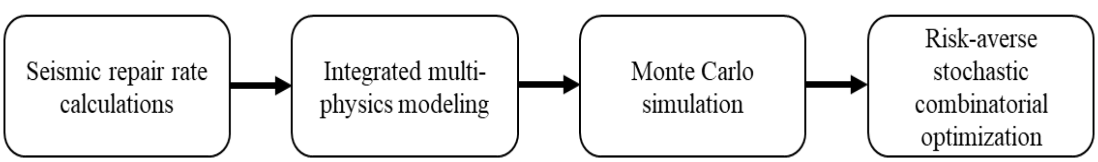

Figure 1. Step-by step diagram of the methodology

Post-earthquake serviceability index (PSI)

The ratio of the post-hazard to pre-hazard demands of a water distribution system is termed as the post-earthquake serviceability index. Equation 2 presents the PSI's formulation (Shi 2006; Wang et al. 2010).

$$\mathrm{PSI} = \frac{\sum_{j=1}^{M} p_j * D_j}{\sum_{j=1}^{M} D_j} \quad (2)$$

Subject to,

$$p_j = 0 \text{ if } \mathrm{Pressure}_j < \mathrm{Pressure}_{min}$$
$$p_j = 1 \text{ if } \mathrm{Pressure}_j \geq \mathrm{Pressure}_{min}$$

where M is the node count of the water distribution system, $\mathrm{Pressure}_j$ is the existing hydraulic pressure at node j, $\mathrm{Pressure}_{min}$ is the minimum hydraulic pressure mandatory for firefighting water demand and at node j the demand for water is D_j. $\mathrm{Pressure}_{min}$ was assumed 0.14 MPa (20 psi) as recommended by Trautman et al. (2013).

Value at Risk (VaR)

Value at Risk (VaR) is borrowed from quantitative finance for quantifying the extent of possible losses. It describes the peak loss on an investment given a fixed temporal limit and probability of occurrence (Linsmeier et al. 1996, Duffie and Pan 1997, Jorion 1996, Jorion 2000). Although value at risk is commonly used in the financial sector, it shows potential to conduct the risk assessment in other industries (Kang et al. 2014, Jiménez-Rodríguez et al. 2018, Toumazis and Kwon 2013).

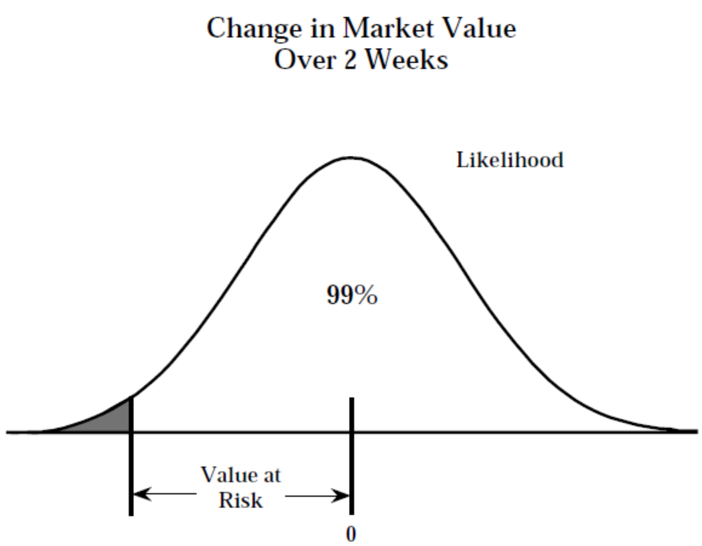

Figure 2. VaR values when confidence level is 99%. (Source: Duffie and Pan 1997)

For a confidence level α and fixed time limit t, VaR_α of an investment is the loss in value over the time limit that has an exceedance probability of $1 - \alpha$. In Figure 2, VaR at 99% confidence level measures the ‘0.01 critical value’ of the probability distribution of changes in market value over two weeks. Equation 3 shows the general formulation of Value at Risk (VaR).

$$\mathrm{VaR}_{\alpha}(\mathrm{S}) = \inf\{s\epsilon\mathbb{R}: \Pr(\mathrm{S} > s) \leq 1 - \alpha\} \qquad (3)$$

For a specified confidence level α, s is the smallest number such that the probability that the loss S exceeds s is at most (1 - α). Hence, VaR_{α} (S) is the level α-quantile, if S is the loss of an investment value (Artzner et al., 1999).

A scenario earthquake is selected from a seismic deaggregation analysis (Adachi and Ellingwood 2008). Then, a peak ground velocity (PGV) field was constructed for the selected scenario earthquake (Abrahamson and Silva 2007). Next, the seismic rate of repair, which is a count of the repairs required for each one thousand feet of pipe, is calculated for the selected scenario earthquake (ALA 2001). Then, an integrated multi-physics model (hydraulic model) of the water distribution network is constructed (Shi 2006, Shahandashti and Pudasaini 2018). Finally, the post-earthquake serviceability index (PSI) is calculated using Equation 2. The general expression to determine the expected post-earthquake serviceability index is given by Equation 4, where M is the number of Monte Carlo simulations. Then, post-earthquake serviceability index (PSI) values of the Monte Carlo simulations were used to calculate VaR_{95} of each rehabilitation policy using Equation 3.

$$\mathrm{E[PSI]} = \frac{1}{\mathrm{M}} * \sum_{m=1}^{\mathrm{M}} \mathrm{PSI}_m \qquad (4)$$

Risk-averse Simulated Annealing

A simulated annealing approach integrated with a controllable risk aversion level was designed to solve the optimization problem due to the objective function’s stochastic nature. This algorithm mimics the physical annealing process of solid materials, a technique involving heating and controlled cooling of a material to alter its physical properties (Kirkpatrick et al. 1983, Metropolis et al. 2005). Susceptibility assessment of water network systems to earthquake hazards using risk-averse simulated annealing algorithm followed is illustrated in Figure 3.

First, the objective function is evaluated for one rehabilitation policy. Then, another rehabilitation policy is selected around the neighborhood of the first rehabilitation policy. This neighborhood search is achieved by randomly mutating twenty percent of the binary strings representing the old rehabilitation policy (Shahandashti and Pudasaini 2019). The expected post-earthquake serviceability index (PSI) and VaR_{95} of the old and new policies are calculated. It is an iterative process where each step updates the rehabilitation policy depending on wether a condition is met or not. At each step, the policy is updated based on two possible cases: whether the expected PSI of the old policy is larger than the new policy or not.

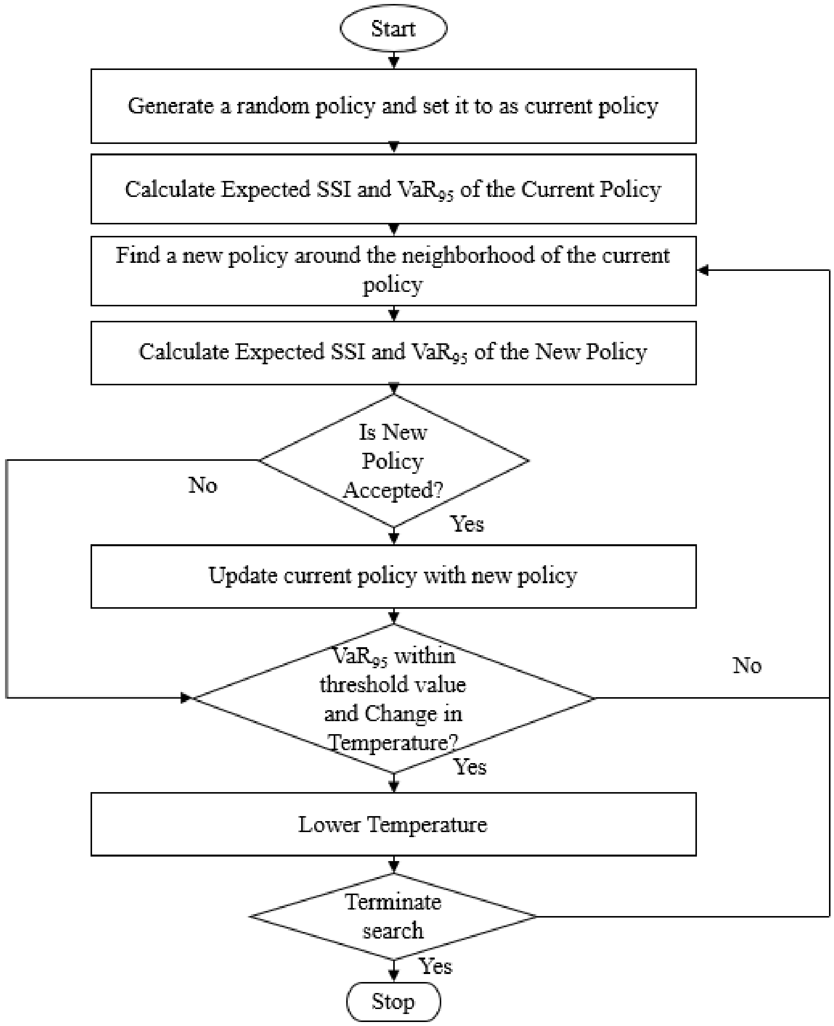

Figure 3. Susceptibility assessment of water network systems to earthquake hazards using risk- averse simulated annealing

Case 1: $\mathbf{E[PSI]_{new} \geq E[PSI]_{old}}$

If the new policy's expected PSI exceeds that of the old policy, and VaR_{95} is less than 25% of the loss in PSI, then the old policy is replaced by the new one in the next risk-averse SA step. However, if the new policy's VaR_{95} is greater than 25% of the loss in PSI, then the state of energy Δ and a random variable λ which is uniformly distributed in the range zero to one are determined using Equations 5 and 6.

$$\Delta = \exp\left(\frac{-\left(\mathrm{VaR}_{95}(\mathrm{old})\right) - \left(\mathrm{VaR}_{95}(\mathrm{new})\right)}{\mathrm{temp}}\right) \quad (5)$$

$$\lambda = \text{ random } [0,1] \quad (6)$$

where 'temp' is the current temperature of the risk-averse SA. When $\lambda < \Delta$, the new policy is taken to the next step. Otherwise, the old policy goes in the next iteration (Metropolis et al. 2005).

Case 2: $\mathbf{E[PSI]_{new} < E[PSI]_{old}}$

If the old policy's expected PSI exceeds that of the new policy, the state of energy D and a random variable R which is uniformly distributed in the range zero to one are calculated using Equations 7 and 8.

$$D = \exp\left(\frac{-(E[PSI_{old}] - E[PSI_{new}])}{temp}\right) \tag{7}$$

$$R = random\ [0,1] \tag{8}$$

where 'temp' is the current temperature of the risk-averse SA. There can be two possible sub-cases here:

Subcase A: When $R < D$ and VaR_{95} of the new policy is less than 25% of the loss in PSI, the new policy replaces the old one in the next iteration. Otherwise, Δ and λ are determined. If $\lambda < \Delta$, a new policy is selected for the next iteration of risk-averse SA. If not, the old policy goes in the following step.

Subcase B: When $R \geq D$, and VaR_{95} of the old policy is less than 25% of the loss in PSI, it goes to the next iteration. If that is not the case, Δ and λ are determined. If $\lambda < \Delta$, then the old policy is retained. If $\lambda \geq \Delta$, the new policy substitutes it.

APPLICATION AND RESULTS

The data for the Modena water distribution system which is a benchmark network for resilience studies of water distribution systems, was obtained from the Center of Water Systems (2018) to illustrate the application of the proposed approach. Figure 4. illustrates the water distribution system. The center of the network was assumed to be located in Pasadena, California. An earthquake originating at Raymond fault with a magnitude of 7.12 was selected as the scenario earthquake after deaggregation analysis (Adachi and Ellingwood 2008).

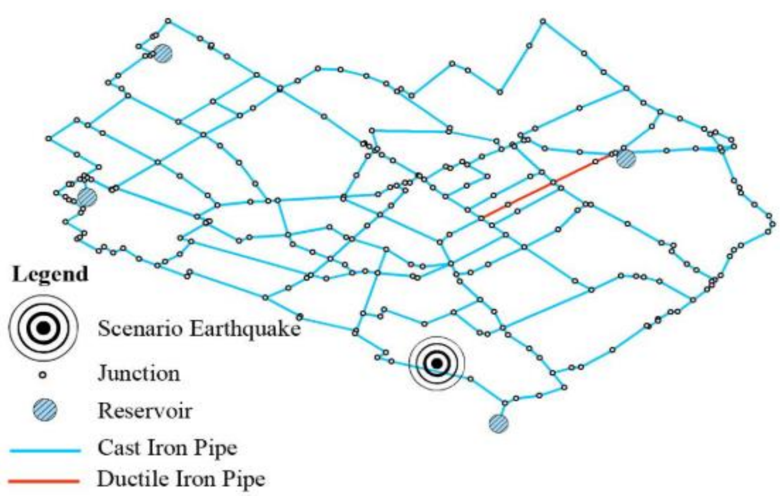

Figure 4. Map of Modena Network

The parameters used for the risk-averse simulated annealing are starting and final temperature, cooling rate, iterations per temperature change, Monte Carlo simulations per iteration and the threshold value of VaR_{95}. The starting and final temperatures are 100 and 1 with a cooling rate of 2. Ten iterations are performed at each temperature decrement. Therefore, the total number of iterations is five hundred. At each iteration, three thousand Monte Carlo simulations are performed for evaluating the expected PSI of each rehabilitation policy. It was observed that three thousand Monte Carlo simulations were enough for seismic assessment of the Modena network without any rehabilitation subjected to chosen scenario earthquake (Shahandashti and Pudasaini 2019). The cost data for the rehabilitation of Modena network pipes are recommended by Shahandashti and Pudasaini 2019.

The optimum rehabilitation policy was identified for the specified budget constraint (12.5 million USD) and risk-aversion level ($VaR_{95} \leq 25\%$ of loss in PSI) using the risk-averse simulated annealing approach. The optimum poicy's cost predicted by the algorithm, expected PSI and VaR_{95} value are 12,476,528 USD, 0.94856 and 18.42% of the loss in PSI. Therefore, the proposed approach could identify the optimum policy with a controllable risk aversion level. Table 1 contrasts these results against those of the SA-based approach developed by Shahandashti and Pudasaini (2019).

Table 1. Results of Risk-averse SA-based approach in Modena Network

	Cost Constraint (USD)	Cost predicted by the algorithm (USD)	Expected PSI	VaR_{95}	Total solution time (hour)
Risk- averse SA-based approach	12,500,000	12,476,528	0.94856	18.42%	323.79
SA-based	12,500,000	12,463,533	0.95095	-	284.05
Percentage difference (%)	-	0.104	0.252	-	12.27

The critical pipes detected by risk-averse SA-based and SA-based methods for the study network are highlighted in red lines in Figure 4. Some of the detected critical pipes are different in risk-averse SA-based method from SA- based method.

Value at Risk (VaR) of a system is dependent on its time-indexed values in the literature. In this study, we used PSI values to evaluate VaR_{95} instead of a portfolio. Since these values are not time-indexed, we randomly time-indexed PSI values. To see the effect of this assumption, the PSI values of 3000 Monte Carlo simulations were shuffled three times to calculate VaR_{95} value. The results are shown is Figure 5. The VaR_{95} values for three shuffles are 23%, 22%, and 23% of the loss in PSI. Therefore, time indexing did not have aconsiderable effect when it comes to calculating VaR_{95}, using post-earthquake serviceability index (PSI).

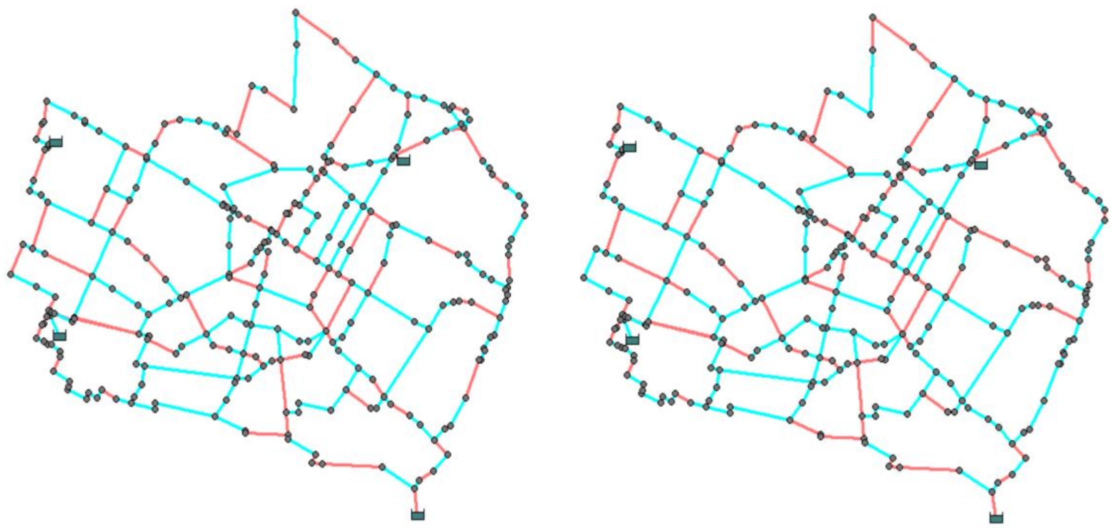

Figure 4. Critical pipes identified by Risk-averse SA-based method (left) and SA-based method (right) for the network at Modena.

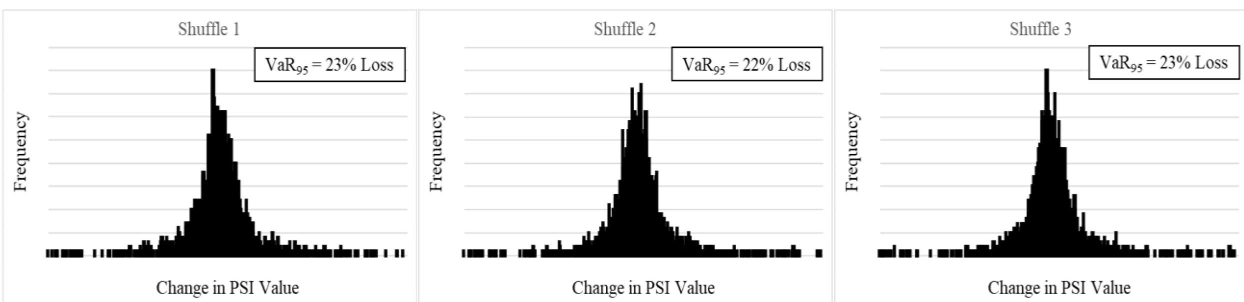

Figure 5. Shuffling 3000 PSI values to illustrate the effect of time while evaluating VaR_{95} of a rehabilitation policy.

CONCLUSION

The developed risk-averse simulated annealing methodology was applied to detect the crucial pipes in the network at Modena that must be rehabilitated. A comparison was made between the results obtained against the rehabilitation measures recommended by a simulated annealing process. The proposed approach could determine the optimum combinations for rehabilitation assuming a constraint in the budget (12.5 million USD), with a controllable risk aversion level ($VaR_{95} \leq$ 25% of loss in PSI). The recommended rehabilitation policy is different in the risk-averse SA-based method from SA- based method. While selecting the optimum rehabilitation policy, the expected PSI value decreased in risk-averse SA-based approach in comparison with SA-based approach. This difference is because the risk aversion level of selecting that optimum policy is controlled in the risk-averse SA-based approach. This decision may be favorable for utilities even if it provides lower post-disaster system serviceability since it helps them limit risks.

Further analysis is recommended to identify the best rehabilitation policies for different budget constraints and risk aversion levels. A risk-averse stochastic algorithm for combinatorial optimization can effectively enhance the post-earthquake serviceability of water supply networks with controllable risk aversion level. This methodology is expected to help water utilities make decisions that provide the maximum average post-earthquake system serviceability while control the decision-making risk.

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