Water Distribution System Recovery Strategies Considering Economic Consequences from Business Loss

Seungyub Lee[1], Sangmin Shin[1], Dave Judi[2], Timothy McPherson[2], Steven Burian[1]

[1] Dept. of Civil and Environmental Engineering, University of Utah, Salt Lake City, UT
[2] Pacific Northwest National Laboratory, Richland, WA
seungyub.lee@utah.edu

Abstract

Water distribution systems (WDSs) recovery methods have been assessed primarily using hydraulic deficit. However, hydraulic deficit does not reflect all performance goals needed to effectively guide resilience strategies. In this paper, a new approach is presented to measure resilience based on the idea of economic consequence loss in businesses due to WDS failure. Economic consequence loss of industry, classified by the NAICS code, are defined by relating GDP value added and water usage. Three different resilience objectives were investigated using a hypothetical water network: (1) identification of pipe criticality; (2) defining recovery strategies for different failure scenarios; and (3) development of recovery pathways by considering system resilience. Hydraulic analysis was performed using pressure driven analysis based on EPANET2.0. Results of pipe criticality proved high hydraulic deficit not always translated to high economic productivity loss. Also, the proposed system resilience quantification measure effectively serves as a guide for recovery pathways more resilient than other measures tested. In conclusion, considering both hydraulic resilience and economic consequence provides a more effective approach toward enhancing overall system resilience.

Keyword: Economic consequence, Resilience, Recovery strategies

1. INTRODUCTION

A water distribution system (WDS) is one part of the interdependent critical infrastructure supporting the expected quality of life for society [1], and as such maintaining WDS functionality (i.e., meeting demand) is of paramount importance. In general, a wide array of internal and external disturbances can affect the functionality of a WDS, and over time, the disturbances are becoming more acute and complex [2]. Common causes of failure include climate change, population growth, aging, natural disaster, terrorist attack [3]. As those disturbances become severe, numbers of studies addressed resilience in order to identify optimal pathway through those disturbances.

Resilience has been defined in several ways, however, all lead to the goal of developing solutions that reduce the magnitude and duration of failure [4]. Magnitude of failure usually focused on the loss of system functionality, i.e. unmet demand. Numbers of studies applied surplus energy [5] or hydraulic availability [6] to measure functionality. Duration of failure often thought as improve on the recovery (and maintenance) strategies. Some studied pre-disaster resilience enhancing strategies by rehabilitating critical pipes using resilience metrics [7, 8], while others focused on post-disaster recovery [9, 10]. Also, some researchers explored recovery time [11, 12]. In sum, most of the previous studies focused on reduction in hydraulic functionality such as pressure or delivered demand or associated cost for recovery.

The important issue with failure is that hydraulic deficit might not always translate to the broader losses of the consequence of that failure for a community. Since the purpose of WDS is to deliver water to meet each end-user's demands, the consequence of water service loss is a key outcome to consider from a community perspective [13]. Considering consequence beyond hydraulic deficit and interdependency with other infrastructure (or end users) different recovery strategies might be chosen. However, even though economic consequence loss may outweigh direct economic loss, the interdependency between them has been less explored. Given the criticality of WDS and the broad array of failure scenarios and consequences, developing new resilience measures for the planning of WDS is now essential.

Here, we define the interdependency between water input and economic output as "Economic Dependency". Based on the concept of economic dependency of a business, the economic loss may be higher at demand nodes with higher economic dependency on water system reliability. Therefore, we propose that a more accurate way to quantify impacts of water system failures is to consider the idea of economic resilience and seek to reduce business productivity loss due to WDS failure. This paper demonstrates economic consequences of businesses owing to WDS failure. Accordingly, economic dependency of businesses, classified by NAICS code, are introduced, and case studies demonstrated for a hypothetical network.

2. METHODOLOGY

The goal of this research is to explore the benefit and importance of consequence-based resilience measures. Therefore, several assumptions were made that will need to be addressed in the future to make the estimation outputs more accurate in specific applications. First, the industry type for the end user is defined based on NAICS code. Second, water usage at an industry connection is assumed to be entirely process water, and thus directly related to income. This assumption may lead to an underestimate of economic dependency because each industry will use water for cleaning, sanitizing, irrigating, and other uses not directly linked to income [14]. But the assumption is necessary since sufficiently detailed and accurate water data are not readily available, and the initial research step does not warrant an extensive field monitoring campaign. However, since the framework is readily developed into a model, the methodology demonstrated herein can simply be updated to produce a more accurate result. The last major assumption is that economic dependency is linearly related to water usage and business outcome. The actual relationship has not been studied, and may be linear or may be non-linear (e.g. step function). Although these assumptions are important for the accuracy of the results they do not affect the point of the study, in addition, the model proposed here can easily be adapted with updates in data or methodology.

2.1. Economic Dependency

For the economic dependency calculation, this research involved building a database using three types of data. First, water usage data for businesses in the State of California were extracted from [15], already categorized according to the 3-digit NAICS code. Such data formed the basis for developing economic dependency relationships between hydraulic deficit and economic productivity loss. Second, census data (e.g., number of employees) were collected from the State of California Employment Development Department. Data were also classified according to the 3-digit NAICS code and used to calculate the water usage per employee for each NAICS code category. Lastly, Gross Domestic Product (GDP) value added data were gathered from Bureau of Economic Analysis (BEA). These data were needed to translate the water usage into economic value, which was also grouped into 3-digit NAICS codes.

All data were expressed as per employee per year, for example, WPY (water each employee used per year, in gallons) and EPY (economic output per employee per year, U.S. dollars). Having these unit usages enabled simple application with the water usage of an end user known. The economic dependency is defined as the ratio of WPY (gallons of water each employee used per year) to EPY (economic output per employee per year):

$$ED = \frac{EPY}{WPY} \tag{1}$$

where, economic dependency is the economic profit per gallon of water in M$/Gal, EPY is economic output per employee per year in M$/yr, and WPY is gallons of water each employee used per year in Gal/yr. This study estimated economic dependency for 3-digit NAICS code levels.

2.2. Resilience Measure

In this study, resilience is calculated as the integral of the availability index (AI) for both hydraulic deficit and economic productivity loss (or damage). The hydraulic availability was first used as resilience of WDSs by [6] in order to quantify reparability of WDS based on resilience, as shown in equation (2).

$$AI = \frac{\sum_{t=1}^{t_r}\sum_{i=1}^{NCount} w \cdot Q_{i,t,del}}{\sum_{t=1}^{t_r}\sum_{i=1}^{NCount} w \cdot Q_{i,t,act}} \tag{2}$$

where, AI is the availability index, $Q_{i,t,act}$ and $Q_{i,t,del}$ are actual demand and delivered demand, respectively, in flow units, t_r is repair time in hours, w is weighting factor, and $NCount$ is the number of demand nodes. Repair time is determined as following equation (3) [16]:

$$t_{repair} = 6.5D^{0.285} \tag{3}$$

where, t_{repair} is repair time in hours, D is diameter in inches.

The weighting factor in equation (2) is new in this study to distinguish two different AIs considered here: hydraulic availability index (HAI) and economic availability index (EAI). Weighting factor for HAI is 1 and for EAI is the economic dependency. In addition, temporal damage or loss is equal to one minus any type of AI. Since HAI and EAI is derived from different categories, combining two AIs requires criteria to be established. This study combines two AIs as system availability index (SAI) which is calculated as the length from point (0,0) to point (HAI, EAI):

$$SAI = \left\{\frac{\sqrt{HAI^2 + EAI^2}}{\sqrt{2}}\right\} \tag{4}$$

Finally, resilience in this study is quantified in three types: (1) Hydraulic Resilience (HR), (2) Economic (consequence) Resilience (ER), and (3) System Resilience (SR). Each resilience measure is based on integration of AIs, as following:

$$R = \int_{t=0}^{T_r} AI_t \, dt \tag{5}$$

where, R is any type of resilience, AI_t is any type of availability index at time t, and T_r is total time for recovery.

3. CASE STUDY

3.1. Description of Hypothetical City

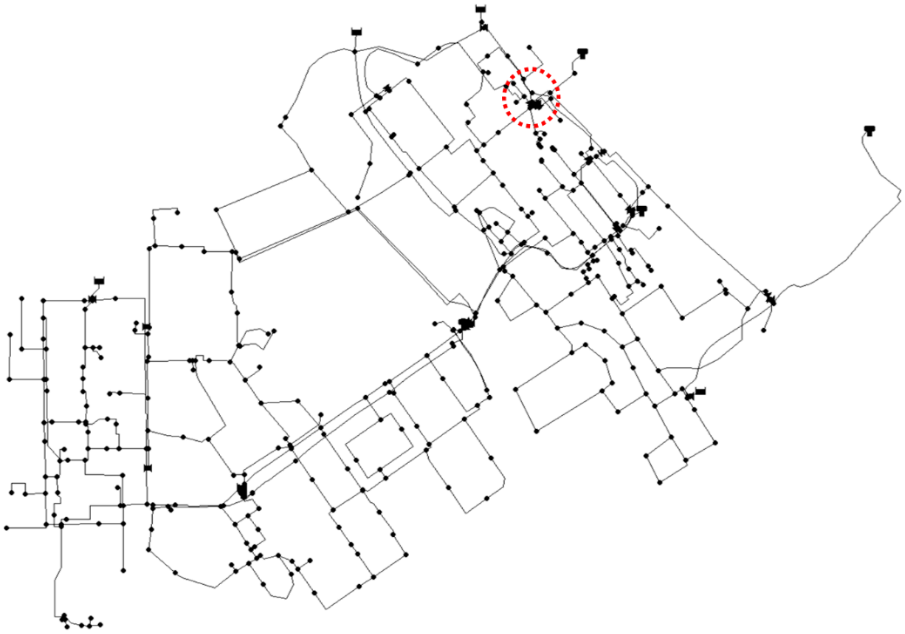

Figure 1. Layout of U-City. Note that the numbers are the pipes with top ten criticality ranked. Dotted circles are HAI based and solid circles are EAI based.

The developed framework was tested using a hypothetical WDS, U-City (Figure 1). U-City is comprised of 496 pipes and 432 nodes, and water is delivered to the network from five small tanks and reservoirs by gravity. A minimum pressure of 40 psi is assumed to be the constraint at each node in the network. A total of 12 NAICS codes in the 3-digit classification were selected for this study as Table 1.

Table 1. Candidate NAICS code for U-City and water cost information, number of node, and total demand data

3-digit	Description	WD	# of Node	Demand
515	Broadcasting (except Internet)	0.0283	6	179.7
518	Internet Service Providers, Web Search Portals, and Data Processing Services	0.0068	8	313.1
517	Telecommunications	0.0053	5	41.0
491	Postal Service	0.0022	5	69.3
446	Health and Personal Care Stores	0.0019	8	354.2
621	Ambulatory Health Care Services	0.0013	7	135.0
334	Computer and Electronic Product Manufacturing	0.0010	16	304.0
447	Gasoline Stations	0.0009	4	18.4
622	Hospitals	0.0008	11	762.9
325	Chemical Manufacturing	0.0007	21	428.1
335	Electrical Equipment, Appliance, and Component Manufacturing	0.0005	15	317.2
611	Educational Services	0.0001	23	649.3

3.2. Failure and Recovery Scenarios

In total, three case studies were analyzed with three different failure and recovery scenarios. First, a single pipe failure scenario will be performed to identify criticality of pipes for all AIs. The first case study will depict and provide insight for the need of economic dependency in resilience studies and projects. The second case study included multiple failure scenarios (overall 10 pipe breakage scenarios) based on different AI criticality ranking. The framework applied different recovery strategies based on different AI criticality ranking. The final case study investigated recovery pathways for three recovery scenarios based on different criticality ranking. Here, recovery pathway was defined as the tendency or trajectory of resilience recovery in terms of SR. For the final case study, the comprehensive pipe failure scenario was introduced based on HAI and EAI.

For all case studies, hydraulic analysis of new conditions and original conditions were calculated by the interconnected EPANET2.0 [17] and resilience model framework written in Python. Note that EPANET source code were modified to investigate pressure dependent demand under abnormal condition. The model closed a single pipe or multiple pipes to simulate failure conditions and open after repair to reflect recovery state. Thus, the failure simulation was indicative of a full breakage situation and recovery action was replacement, and assumed no leakage at normal condition before or after the recovery period.

4. RESULTS

4.1. Criticality (Case Study 1)

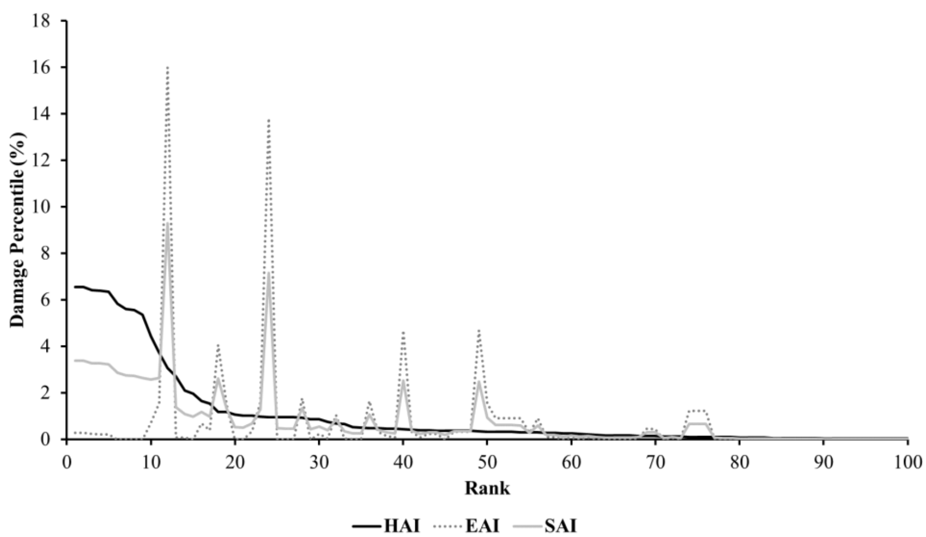

Figure 2. System damage based ranking and corresponding damage percentile for hydraulic, economic, and system damage

Figures 2 displays the criticality analysis results ranked by HAI and corresponding EAI and SAI results. In general, the results are different among the three different forms of damage ranking and do not display a clear trend. The key differences among the results set are best explained by the weighting factor in equation (2), and based on the WD, criticality in terms of hydraulic damage and economic damage show almost no relationship. In other word, hydraulic damage does not always translate to mitigating economic consequence damage in those contexts. In addition, system damage does not relate to either hydraulic damage or economic consequence damage. However, system damage is showing one trend – a sensitivity to higher values of HAI or EAI. This implies that considering system damage might prevent a bias damage analysis toward hydraulic or economic consequences.

Another interesting result is the HAI-based criticality is related to proximity. On the upper right region (Figure 1), the group of pipes are identified as having the highest HAI-based criticality, which are delivering water to node of high demand. So, the geometric arrangement of the U-City network leads to high hydraulic damage for pipes serving high demand nodes. However, economic damage based criticality is found to be less dependent on pipe arrangement leading to unclear repair needs if economic criticality is important and economic dependency is not defined.

Table 2. Recovery Scenario Description and Results (Case study 2 and 3)

Scenario	**Failure Scenario**	**Recovery Strategy**	**Resilience**		
			HR	ER	SR
RS1	HAI-based Criticality	HAI	0.906	0.992	0.950
RS2		EAI	0.934	0.998	0.966
RS3		SAI	0.906	0.992	0.950
RS4	EAI-based Criticality	HAI	0.972	0.829	0.906
RS5		EAI	0.949	0.888	0.921
RS6		SAI	0.969	0.889	0.931
RS7	Comprehensive	HAI	0.934	0.918	0.926
RS8		EAI	0.885	0.968	0.927
RS9		SAI	0.925	0.932	0.929

4.2. Recovery Strategy (Case Study 2)

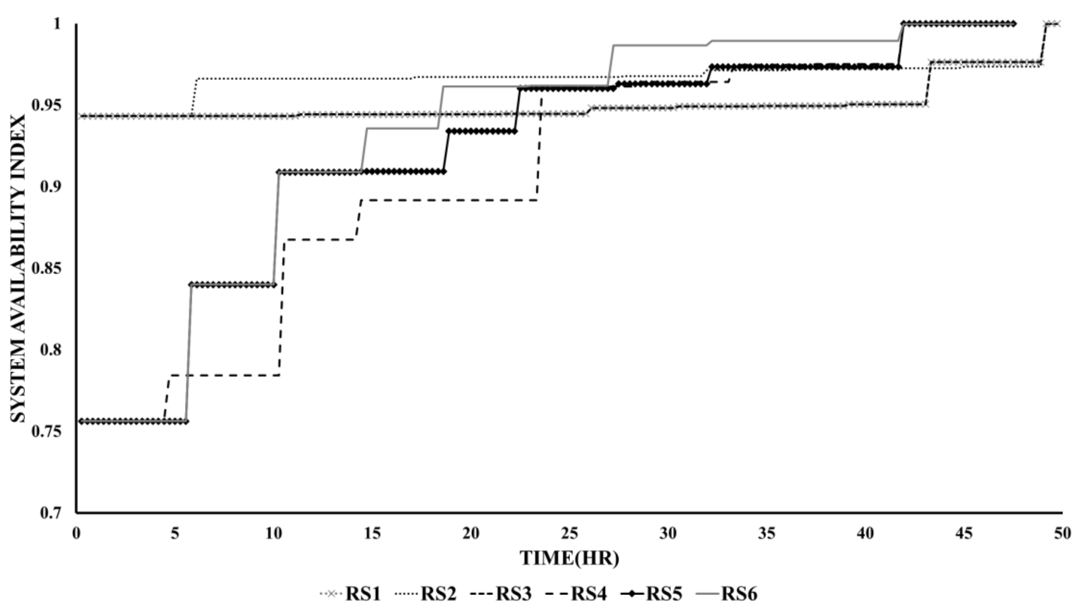

Figure 3. Resilience trend for RS1, RS2, and RS3 scenario

The second case study demonstrates multi-pipe failure scenario, and different recovery strategies (RS) were selected based on the criticality. The description and summary of results are shown in Table 2. When considering HAI-based criticality failure scenario (RS1-RS3), EAI-based RS2 results the highest SR. This is owing to the close proximity within the system as discussed earlier. RS2 recover other pipes rather than the grouped pipe shown in Figure 1, and this lead to the faster recovery on SAI, as shown in Figure 3. In addition, RS3 which takes SAI-based recovery showed lower SR compare to the RS2, and same as RS1. This is that the HAI-based failure scenario has significant difference between HAI and EAI. This difference is not only indicating the quantitative gaps, but also the economic damage is extremely low compared to the hydraulic damage. Such a difference drives SAI based recovery strategy (RS3) and tends to follow the recovery sequence of HAI based recovery strategy (RS1).

Regarding the EAI-based criticality failure scenario (RS4-RS6), again EAI-based RS5 showed higher SR than RS4, but lower than RS6. Results of RS5 verifies the limitation of considering single measure for recovery, concretely, it only considers the economic loss that leads to an unexpected long duration (repair time) of hydraulic loss. On the other hand, RS6 determines recovery sequence by balancing two AIs. Thus, the RS6 can have higher SR compare to the RS5.

Case study 2 results show that an SAI-based recovery might have advantages, since SAI-based recovery strategy weights the criticality between HAI and EAI. This doesn't mean that SAI-based recovery scenario stands out among the recovery scenarios, since other recovery scenarios have strength from different perspectives. One obvious finding from this case study is that EAI should be considered in order to reduce economic damage of the overall system.

4.3. Recovery Pathway (Case Study 3)

In the final case study, the recovery pathway has been analyzed. RS10-RS12 consider both hydraulic and economic criticality, but avoid multiple choices in grouped nodes to avoid a geometric limitation. Figure 4 shows the recovery pathway of RS7-RS9. The "Ideal" linear graph is "y=x" graph that shows HR and ER is same and (1, 1) is the actual "Ideal Point" that represents fully functioning system. The terminology "Ideal" is not indicating perfect, but more likely meaning the line when hydraulic and economic consequence is similar so no need to separate two different losses.

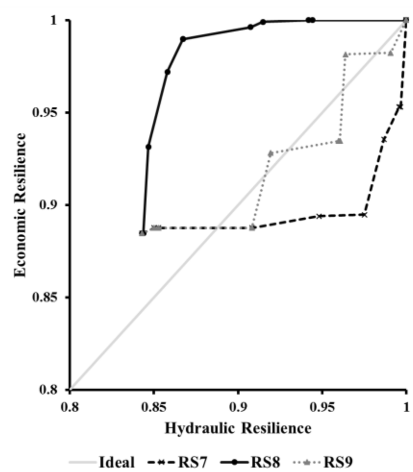

Figure 4. Recovery pathway for RS10-RS12

Since all scenarios have the same failure scenario, the starting point is the same. Whenever the recovery of certain pipe completes, a new SRI point will be marked. The recovery pathway showed differences between recovery strategies. RS7, which recovers based on HAI, tended to increase HR value by moving horizontally, while RS8, which recovers based on EAI, tended to move vertically. The interesting pathway is RS9, which recovers based on SRI. It tends to recover following to the "Ideal" line. If the point is above the “Ideal” line, pathway tended to move horizontally. On the other hand, it responded vertically if below. Each time step, SRI has a different weight from either HAI or EAI. Thus, SRI based recovery tended to move in pathway shown in Figure 4.

In short, when recovery occurs based on either HAI or EAI, the prior time period tends to move in direction that increases, regardless of whichever AI is in consideration. And when considering both HAI and EAI, it can increase the chance to improve SRI by not limiting pathway in one direction, but flexibly controlling the pathway.

5. CONCLUSIONS AND SUMMARIES

This study concludes the need to use economic dependency for estimating economic consequence due to water distribution system failure. A framework was developed and demonstrated to test the use of an economic-based resilience measure in three case study scenarios. In the framework, the economic dependency is quantified using the 3-digit NAICS code categories. The demonstration of the framework was conducted using a small hypothetical water distribution system. The case studies considering economic dependency for economic-based resilience measure has three main findings:

1) Criticality based on HAI, EAI, and SAI have different trends and no obvious relationship, suggesting they provide different answers.
2) HAI criticality tends to be higher based on the actual demand value, while EAI criticality based on economic dependency value. And HAI criticality is more geometric dependent compare to EAI criticality.
3) SAI criticality weights the importance between HAI and EAI criticality, it increases the chance to improve SRI by not limiting the pathway in one direction, but flexibly controlling direction within the pathway.

Although the study confirmed the hypothesis, there remain numerous issues to overcome in the future. First, even though all the work is based on real data, the data do have uncertainty and errors. In other words, this study also reveals that there is no efficient database that can support decision making for enhancing either economic or system resilience. More accurate data must be acquired by continuous monitoring water usage for all end users in the future and used to improve the method. Second, this study estimates SR using a simple form that might overlook better measures in resilience. One improvement or gap shown in this study is consideration of geometric features. HAI often related to geometric feature that often SAI cannot lead to the better recovery option. Methodology such as graph (or network) theory may help to overcome such situation.

Acknowledgments

This research was supported by the Pacific Northwest National Laboratory (PNNL). PNNL is operated for DOE by Battelle Memorial Institute under contract DE-AC05-76RL01830.

References

[1] J. Moteff, C. Copeland, and J. Fischer, "Critical infrastructures: what makes an infrastructure critical?," 2003.

[2] D. Butler, S. Ward, C. Sweetapple, M. Astaraie-Imani, K. Diao, R. Farmani*, et al.*, "Reliable, resilient and sustainable water management: the Safe & SuRe approach," *Global Challenges,* 2016.

[3] K. A. Klise, R. Murray, and L. T. N. Walker, "Systems Measures of Water Distribution System Resilience," Sandia National Laboratories (SNL-NM), Albuquerque, NM (United States)2015.
[4] S. Shin, S. Lee, S. Burian, D. Judi, T. McPherson, M. Parvania*, et al.*, "Review of Resilience Measures of Water Infrastructure Systems," *Journal of Water Resources Planning and Management,* vol. Under Review, 2017.
[5] E. Todini, "Looped water distribution networks design using a resilience index based heuristic approach," *Urban water,* vol. 2, pp. 115-122, 2000.
[6] B. Zhuang, K. Lansey, and D. Kang, "Resilience/availability analysis of municipal water distribution system incorporating adaptive pump operation," *Journal of Hydraulic Engineering,* vol. 139, pp. 527-537, 2012.
[7] N. Jayaram and K. Srinivasan, "Performance-based optimal design and rehabilitation of water distribution networks using life cycle costing," *Water resources research,* vol. 44, 2008.
[8] H. Jin and K. R. Piratla, "A resilience-based prioritization scheme for water main rehabilitation," *Journal of Water Supply: Research and Technology-Aqua,* vol. 65, pp. 307-321, 2016.
[9] X. Zhao, Z. Chen, and H. Gong, "Effects Comparison of Different Resilience Enhancing Strategies for Municipal Water Distribution Network: A Multidimensional Approach," *Mathematical Problems in Engineering,* vol. 2015, 2015.
[10] M. A. Nayak and M. A. Turnquist, "Optimal Recovery from Disruptions in Water Distribution Networks," *Computer-Aided Civil and Infrastructure Engineering,* 2016.
[11] C. R. Zorn and A. Y. Shamseldin, "Post-disaster infrastructure restoration: A comparison of events for future planning," *International Journal of Disaster Risk Reduction,* vol. 13, pp. 158-166, 2015.
[12] G. P. Cimellaro, A. Reinhorn, and M. Bruneau, "Quantification of seismic resilience," in *Proceedings of the 8th US National conference on Earthquake Engineering*, 2006, pp. 18-22.
[13] U. Shamir and C. D. Howard, "Reliability and risk assessment for water supply systems," in *Computer Applications in Water Resources:*, 1985, pp. 1218-1228.
[14] P. H. Gleick, G. H. Wolff, and K. K. Cushing, *Waste not, want not: the potential for urban water conservation in California*: Pacific Institute for Studies in Development, Environment, and Security Oakland, CA, 2003.
[15] U. D. o. t. I. B. o. Reclamation, "Cataloguing Commercial, Industrial, and Institutional Customer Classes," vol. Volume 2 of 5, 2009.
[16] T. M. Walski and A. Pelliccia, "Economic analysis of water main breaks," *Journal of American Water Works Association,* pp. 140-147, 1982.
[17] L. A. Rossman, "EPANET 2: users manual," 2000.