DYNAMICS OF COUPLED HUMAN-WATER INFRASTRUCTURE SYSTEMS UNDER WATER MAIN BREAKS AND WATER-RATES INCREASE EVENTS

by

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To my family, in gratitude for their love, encouragement, and infinite support

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ABSTRACT

The aging water infrastructure system in the United States has posed considerable hindrance to policy-makers as they seek to provide safe, reliable, and clean drinking water for communities. The deterioration of the physical water infrastructure negatively affects the economics of water utilities and can lead to increases in water rates for consumers, so that utilities can recover the financial losses. However, the dynamics emerging from the interactions among changes in water service reliability, water-rates, consumer behavior (with respect to water consumption and willingness to support water-rate changes in response to changes in water rates, and water utility economics, are still unknown factors in the management of water infrastructure systems.

The overarching objective of this dissertation is the creation and demonstration of the dynamics of coupled human and water infrastructure systems under conditions of water main breaks and water-rate increases. First, using water-main break data for a 21-year period from two U.S. cities in the Great Lakes region, the dissertation demonstrates a methodology to estimate the system-wide monthly frequency of water main breaks as a function of a number of explanatory variables. Using a random-parameters negative-binomial approach, the statistical estimations show that pipe diameters, average pipe age, distribution of pipe age, pipe material, time of year, and mean monthly temperature all have a significant impact on monthly water main break frequencies. The results can assist asset managers in quantifying the effect of factors may have on the likelihood of water main breaks, as well as in making cost-effective decisions regarding pipe renewal.

Next, by incorporating qualitative survey data and using quantitative econometric methods, consumer behaviors in responses to the water-rate increases, and based on perceptions of water service reliability and quality in a Midwestern U.S. city was evaluated. Using a multivariate binary probit approach, the results provide insights as to how individuals are likely to respond to water-rate increases based on the reliability of current water services and the quality of the supplied water. The outputs of the econometric enable utility managers to better understand the behavior of consumers under different rate conditions and help water utilities in their long-term and short-term financial analyses.

Finally, the aforementioned two components are integrated into the interdependency analysis to evaluate the interactive effects of features of the physical water infrastructure (pipeline

characteristics, water and associated energy losses, and the revenue loss for water utilities) and the behavior of stakeholders (water utilities and consumers). The developed hybrid system dynamics and agent-based model examines interdependencies between the physical water infrastructure, the water utility, and the water consumers to explore possible emergent behavior patterns of water users during water rate increases over time. The model is demonstrated over the 2001–2010 period on a case study city with a large water distribution system that includes 4,000 miles of pipeline and nine water treatment plants serving a population of 863,000. This model was then verified and validated throughout the development of simulation models and included the following steps: 1) data validity, 2) conceptual model validity, 3) computerized model validity, and 4) operational validity. The results suggest the simulated behavior of the model was reasonable and the output of the simulation model regrading water main break frequency, amount of water and associated energy losses, generated revenue, and payoff periods for implementing proactive maintenance strategies had the accuracy required for the model's intended purpose.

The framework developed in this doctoral study can be applied to different size classifications of cities, as well as different classifications of utility companies (such as electricity and gas) by updating the parameters in the model to reflect the characteristics of the infrastructure system components. The distinctive methodological approach in this doctoral work could capture the emergent behaviors of human-water infrastructure interactions such as the impact of increasing water-rates on residential consumers, the impact of water price elasticity cascading into the water utility revenue, and the impact of residential consumers' water consumption on water utility revenues. In conclusion, the results of this doctoral research can assist asset managers in understanding their systems, identify pathways for growing revenue through reducing non-revenue water and increasing water-rates, and implementing a proactive pipeline asset management program towards the provision for safe, reliable, and clean drinking water.

1. INTRODUCTION

Water infrastructure systems play a primary role in providing our communities with basic sanitation, clean drinking water, promoting economic growth, and improving the quality of life. The issue of aging water infrastructure and retrofitting and maintaining them in a sustainable manner poses significant challenges to decision-makers who are charged with providing safe and clean drinking water for communities. Failure to address these challenges in an integrated approach will impact our environment as well as communities and the nation's economy.

1.1 Motivation

An obvious sign of deterioration in the water distribution system is main breaks. Large amounts of water are lost from the 700 or more water main breaks that occur each day in the U.S. (Folkman 2018). A 2013 study by the Center for Neighborhood Technology (CNT) of the Great Lakes States indicated that 6.5 billion gallons of drinking water (enough water to meet the demand of 1.9 million Americans for a year) are lost annually from 63,000 leaking and old pipes in that region alone (CNT 2013). These breaks can have significant social, economic, and environmental consequences. Water losses from main breaks cascade into energy losses due to the interdependencies of infrastructure systems, subsequently leading to additional energy expenditures for extracting water from natural resources and treating, pumping, and transporting it to the end users. Evaluating the physical condition of water pipes using direct inspection of the entire pipeline network in a water distribution system is prohibitively laborious and expensive. Therefore, modeling water main breaks frequency using historic data relating pipe failures can provide important guidance to asset managers in their efforts to maintain their water distribution system and minimize service disruptions.

Over the years, a variety of different models have been developed to estimate the frequency of pipe failures using the limited available water-system information such as pipe age, pipe material, and pipe diameter (Marks et al. 1985; Rostum 2000; Yamijlala et al. 2009; Wang et al. 2009; Singh and Adachi 2012). However, many existing water main break models use restrictive assumptions with regard to the impact of specific explanatory variables (parameters that are constrained to be the same across observations) and often cannot be applied to estimate the number of breaks for city-wide water system using currently available data such as diameter, material type, length and age of pipes.

The resulting outcomes of main breaks (non-revenue water, leakage repair, and additional use of energy) negatively affect the economics of the water utilities and can lead to increases in water-rates for consumers to recover the losses. When significant investments in renewal and rehabilitation of aging water system are needed, and when federal and state funding for infrastructure renewal is limited, the primary source of funding for water utilities comes from revenue generated by consumers (Curtis, 2014). Public perceptions and attitudes regarding water-rate increases are influenced by different factors including personal characteristics, living environment, and water service reliability and quality. Understanding the consumption patterns under different rate conditions is important because revenues generated from consumers form the backbone of the financial models of water utilities. Scholarly literature (Yoo et al. 2014; Vasquez 2014; Castro et al. 2016) on the assessment of the impact of water-rates on water consumption pattern are restricted to model single questions (choice); however, modeling interrelated questions such as water service reliability, supplied water quality, and willingness to pay simultaneously will enable the exploration of cross-equation correlation, and thus allow additional inferences and more precise parameter estimates.

The main challenge facing water utilities is finding a solution to reduce operation and maintenance expenses while maintaining/growing revenue to improve financial resiliency. Although the issues related to infrastructure aging have been examined in prior studies (Gat 2014; Mazumder et al. 2018), an analysis of the interactive effects of features of the physical water infrastructure (pipeline characteristics, water and associated energy losses, and the revenue loss for water utilities) and the behavior of stakeholders (water utilities and consumers) have been less explored. Researchers have used statistical modeling to predict the frequency of pipe failures in water distribution systems (e.g., Kleiner and Rajani 2010; Zamenian et al. 2017), hydraulic modeling and integral equations to optimize the water leakages in water distribution systems (e.g. Pelli and Hitz 2000; Cabera et al. 2010), Life Cycle Energy Analysis (LCEA) to quantify the operational costs of maintaining water distribution systems (e.g. Filion et al. 2004), and optimization techniques to minimize failure costs in water distribution systems (e.g. Wu et al. 2010; Piratla and Ariaratnam 2012). Prior research has provided important guidance to asset managers in their efforts to maintain their water distribution systems when the problems were static and defined, the underlying relationships between variables were known, the level of uncertainty was zero, and the goal was to manage a well-understood system. However, such models could not capture uncertainties, interdependencies, and emergent behaviors of human-water infrastructure systems, when the problem is dynamic, and components (such as consumers) were capable of making independent/interdependent decisions. Therefore, a dynamic modeling framework is required to more realistically evaluate management strategies in addressing human-water infrastructure systems under water main breaks and water-rates increase events.

1.2 Research Questions

To address the existing knowledge gap in the assessment of the human and water infrastructure dynamics stemming from main breaks and water-rates increase events, three interrelated clusters of research questions are addressed in this dissertation. The research questions fall into three categories including: water pipeline network, public (household) attitudes, and human-water infrastructure interdependencies.

(1) Water Infrastructure: What is the number of main breaks occurring in a pipeline network system city-wide per month? What are the effects of pipeline characteristics on the likelihood of main breaks?

(2) Public (household) attitudes: What are the households' perceptions and awareness toward water infrastructure reliability and quality? What are the households' attitudes and behaviors toward water-rates increases? What are the demographic characteristics significant for supporting water-rate increases?

(3) Human-water infrastructure interdependencies: How can the water and energy losses stemming from main breaks be assessed? What are the emergent behavior outcomes of the interactions between the water utilities and their customers in response to main break events and water-rate increases?

1.3 Research Objectives

To answer the research questions mentioned in Section 1.2, the objective of this dissertation is to create and evaluate an integrated analytical framework for a systemic assessment of human-water infrastructure interactions during water main break events and water-rate increases. Figure 1.1

shows the research framework and the links between the research questions, research objectives, and research approaches. Specifically the research objectives for this study are:

1) Estimating the number of water main breaks in a water distribution system in order to assess the water and associated energy losses stemming from main breaks
2) Assessment of public support toward water-rates increases considering their perceptions of water service reliability and quality
3) Analysis of human-water infrastructure systems interactions during main break events and water-rate increases

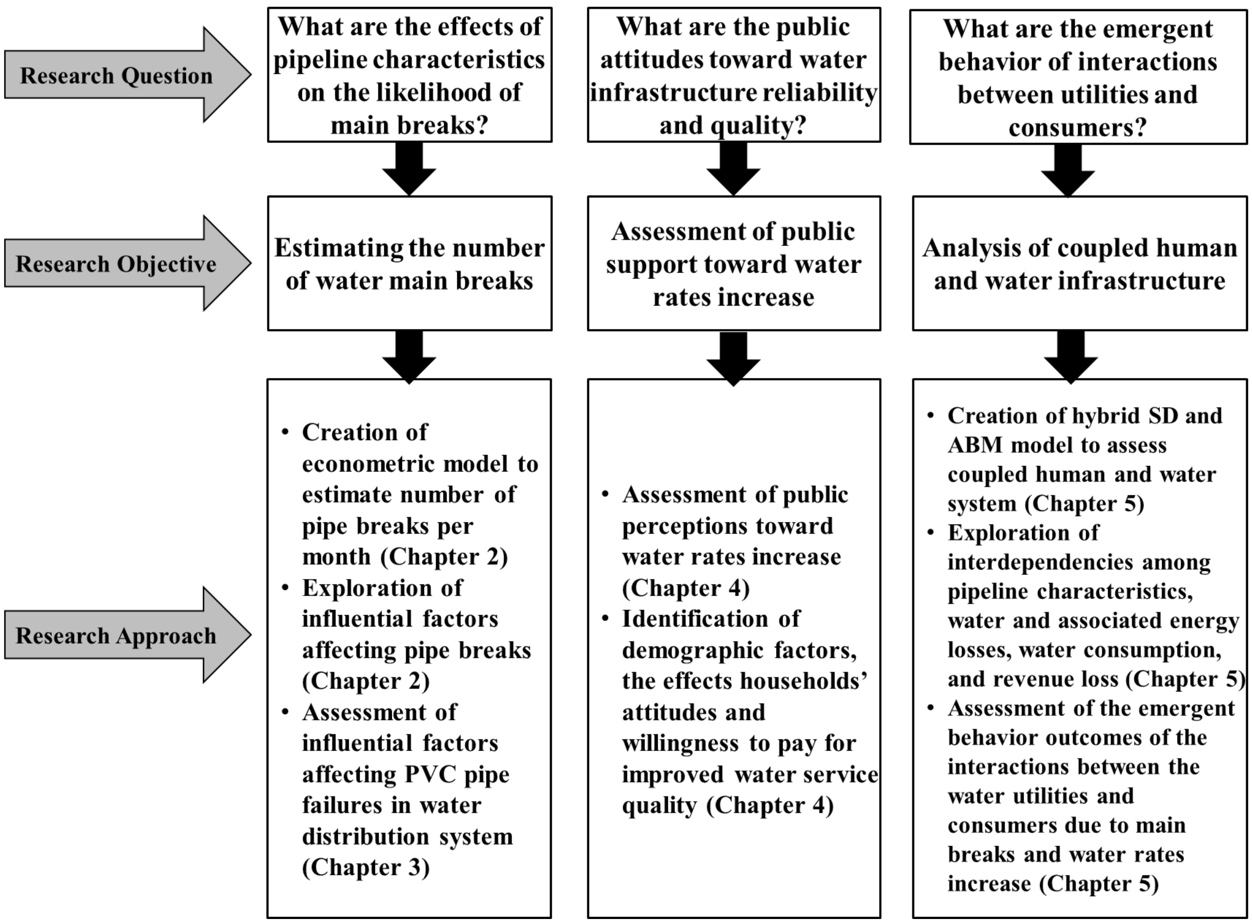

Figure 1.1. Research Objectives

1.4 Research Overview

The research methodology utilizes a mixed method approach, incorporating qualitative and quantitative analyses to accomplish the research objectives. Qualitative analyses of the data collected from literature, the case study cities, and survey data provides the foundation of the quantitative analyses. The quantitative analyses consist of four related, yet independent, components which are examined in the context of the coupled human and water infrastructure dynamics. Integration of the different components and the interrelationships between the themes are shown in Figure 1.2.

The first component of this research involves advancing the analysis and estimation of water main breaks in aging water distribution systems in order to quantify the amount of water lost. Existing water main break models were unable to predict the number of breaks for entire distribution systems (community-wide) using currently available data, such as the length and age of the pipelines, and these models therefore cannot be extended to the water loss problem. Statistical modeling, which is commonly used to predict the likelihoods of failures from a set of uncertain explanatory variables, was utilized in this research to predict the frequency of water main breaks based on historic water main break data. This component used random parameter negative binomial regression since the number of water main breaks per month is count data and the main breaks data are overdispersed. Overdispersion of count data (related to water main break data in this research) describes the observations for which statistical variations among data are higher than would be expected under the assumed distribution. If overdispersion is present in water main break data, the estimated standard errors and the overall goodness-of-fit will be distorted.

The second component of this research used an econometric modeling approach to better understand the views of the general public toward increasing water-rates. A survey was deployed to assess the public attitudes, perceptions, and responses toward water-rate increases in a Midwestern city and a western city in the U.S. The responses from this survey was used to: (1) assess the public attitudes towards an increase in the water-rate, (2) quantify the differences in the consumption rates of drinking water after the public adapts to the new rate, and (3) evaluate the effects of word of mouth or other communication methods between the agents regarding changes in their water consumption rates. The three interrelated questions with binary outcomes were as follows: (1) If the water service provider proposes a water-rate increase in order to improve the quality of water, will you support a rate increase? (2) If the water service provider proposes to water-rate increase in order to improve the reliability of the water service, will you support a rate increase? (3) If the water service provider doubles the water-rate, how would you change your water consumption pattern? Moreover, the most influential demographic factors that affect the attitudes of customers and their willingness to pay for improved water service quality and related water service improvements were explored.

The third component of this research involves an assessment of the behavior of stakeholders (water utilities and customers) in response to water main break and water-rate increase events. Hybrid System Dynamics (SD) and Agent-based modeling (ABM) were used to capture the emergent behavioral outcomes stemming from the interactions between the water utilities and the communities under water-rates increases events. The SD component in the model focuses on the interactions between the pipeline characteristics, water and associated energy losses, and water consumption, which affect the future trajectories of these interrelationships and ultimately the revenue losses for water utilities from water and energy losses. The ABM component explores the emergent behavior outcomes of the interactions between the water utilities and the customers in response to infrastructure failure (main break events) and water-rate increases. ABM is used to model the water utilities and the communities (customers) as autonomous agents in order to understand their behaviors toward water main breaks and potential increases in costs that may be passed on to the customers due to non-revenue water and energy losses. The agents (water utilities and customers) have beliefs, desires, and intentions that will determine what types of decision are made based on the influences of other agents and the environment. The dynamic environment of the model allows the agents to update their decisions and behaviors based on their interactions. For example, the customer agent's behavior toward water-rate increases can be updated by word of mouth communication among the customer agents within the community. The updated decision can result in the consumer agents reducing their water consumption to reduce their water costs.

1.5 Organization

This dissertation is organized into six chapters and follows the "multiple publications" format. Each of the Chapters 2, 3, 4, 5 has its own introduction, literature review, methodology, analysis, and conclusion sections. Significant portions of these chapters have been published or submitted for review and publication in peer reviewed journals and/or refereed conferences. Chapter 1 discusses the motivations, research questions, objectives, and provides an overview of the methodological approach.

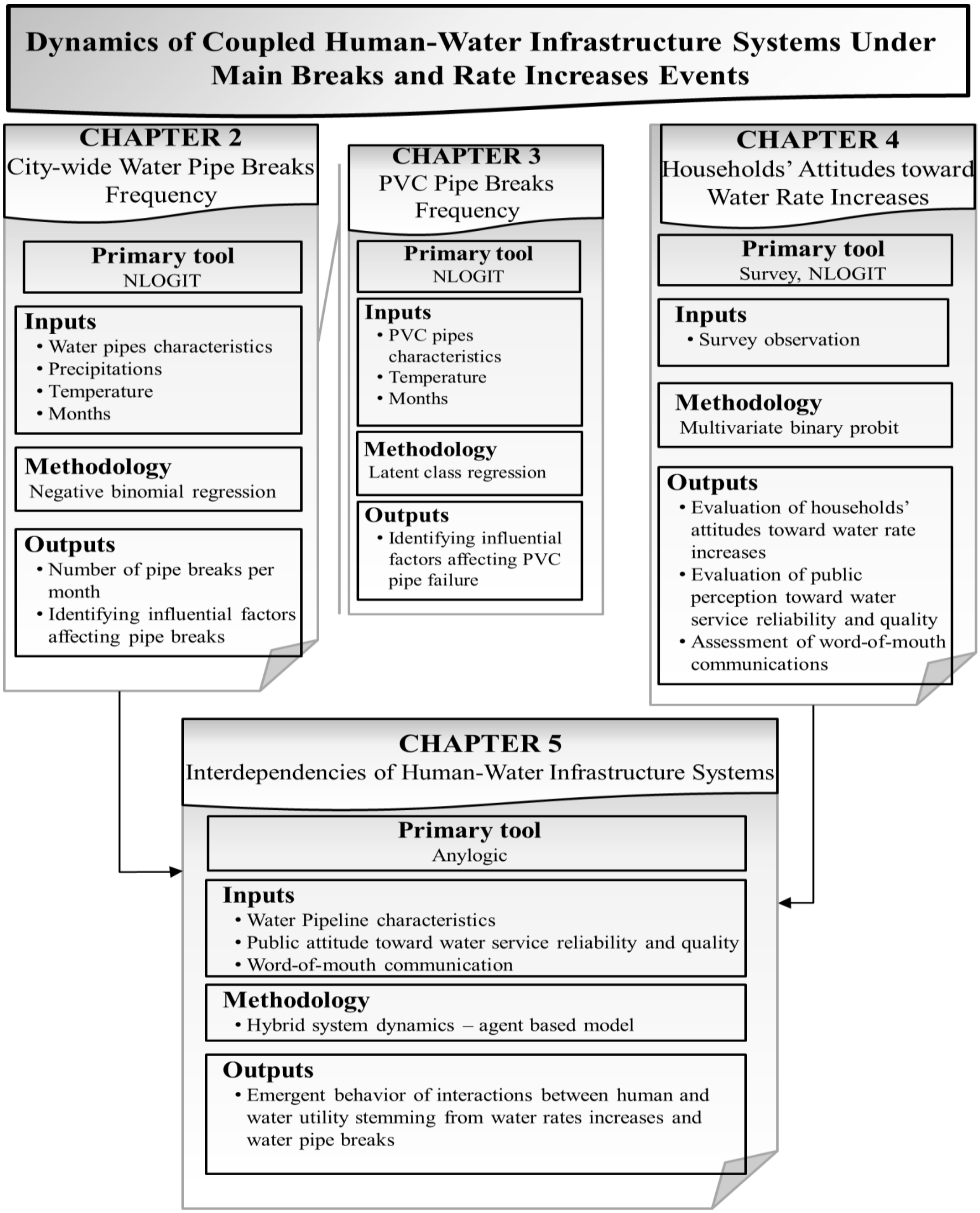

Figure 1.2. Research Overview

Chapter 2 describes the methodology used to model the frequency of water main breaks in water distribution systems and discusses the case study cities used to demonstrate the proposed methodology. ***This chapter is reprinted in part from the ASCE Journal of Infrastructure Systems, 2016, Hamed Zamenian, Fred L. Mannering, Dulcy M. Abraham, Tom Iseley, Modeling the Frequency of Water Main Breaks in Water Distribution Systems: Random Parameter Negative Binomial Approach, 23 (2) 04016035, Copyright (2016), with permission from American Society of Civil Engineers Society (see Appendix A). Tables and figures captions have been modified to maintain the form of the dissertation.***

Chapter 3 takes a deeper look into the failure of PVC pipes in water distribution systems and explains the influential factors affecting PVC pipe breaks, which constitute 32% of the water pipe stock in the case study city. ***This chapter is reprinted in part from the ASCE Journal of Performance of Constructed Faculties, 2017, Hamed Zamenian, Kasey M. Faust, Fred L. Mannering, Dulcy M. Abraham, Tom Iseley, Empirical Assessment of Unobserved Heterogeneity and Polyvinyl Chloride Pipe Failures in Water Distribution Systems, 31 (5) 04017073, Copyright (2017), with permission from American Society of Civil Engineers (see Appendix B). Tables and figures captions have been modified to maintain the form of the dissertation***

Chapter 4 evaluates the households' attitudes toward water-rate increases based on perceptions of water service reliability and quality. ***This chapter is under review in the ASCE Journal of Water Resources Planning and Management, 2019, Hamed Zamenian, Dulcy M. Abraham, Fred L. Mannering, Household Attitudes toward Water-Rate Increases based on Perceptions of Water Service Reliability and Quality. Tables and figures captions have been modified to maintain the form of the dissertation.***

Chapter 5 combines the analyses from Chapters 2, 3, and 4 to evaluate the impact of human interactions with water infrastructure systems during water main break and water-rate increase events using hybrid system dynamics and agent-based model. Chapter 6 concludes the dissertation with a summary of the work, the contributions to the body of knowledge and practice, the limitations of the research, and recommendations for future research.

2. MODELING THE FREQUENCY OF WATER MAIN BREAKS IN WATER DISTRIBUTION SYSTEMS USING A RANDOM-PARAMETERS NEGATIVE-BINOMAL APPROACH

[A version of this chapter was published in the ASCE Journal of Infrastructure Systems].[1]

Water main breaks can have significant adverse social, economic, and environmental impacts. As a result, water utilities seek to be proactive and implement asset management programs to reduce the frequency of water main breaks and mitigate their impacts. A key to the success of these asset management programs is the ability to quantify the effect that a variety of factors may have on the likelihood of water main breaks and hence identify those pipes which need to be inspected frequently. Using water-main break data for a 21-year period from two cities in the Midwestern region of the U.S., this chapter demonstrates a methodology to estimate the system-wide monthly frequency of water main breaks as a function of a number of explanatory variables including pipe diameters, average pipe age, distribution of pipe age, pipe material, time of year, and mean monthly temperature. The effect that some of these explanatory variables have on break frequencies also varies across months in several cases. Finally, the results clearly show that the relationship between explanatory variables and monthly break frequencies is system specific, as reflected by the many differences in the estimation results between the two water systems considered in this study.

2.1 Introduction

The U.S. Environmental Protection Agency has estimated that over $334.8 billion is needed over the next 20 years for capital investment in drinking water infrastructure components including pipes, treatment plants, storage tanks, and other key assets (Environmental Protection Agency 2013). The water distribution system in the United States is extensive (consisting of approximately 880,000 miles of pipelines) and an obvious sign of deterioration in the system is main breaks, which can result from a number of factors including corrosion, cracks, leakage at joints, pressure

[1]Zamenian, H., Mannering, F., Abraham, D., Iseley, T., 2017. Modeling the frequency of water main breaks in water distribution systems: A random parameters negative binomial approach. Journal of Infrastructure Systems 23(2), 04016035. DOI: 10.1061/(ASCE)IS.1943-555X.0000336.

cycling, water hammer, and fatigue failure (Environmental Protection Agency 2009). It has been estimated that roughly 240,000 water main breaks occur per year in the United States (American Society of Civil Engineering 2013). These breaks can have significant social, economic, and environmental consequences. In addition, water main breaks result in the loss of treated water, which cascades into energy loss due to the interdependencies between these infrastructure systems (water and energy systems), and inevitably leads to additional energy expenditures relating to water acquisition, treatment, and distribution (Zamenian et al. 2015).

An effective asset management plan enables water utilities to optimize investment in their assets through better strategic and capital planning processes. An asset management plan for a water pipeline network typically includes strategies to prioritize water main assets for inspection, utilize condition assessment programs to identify the level of pipe deterioration and the impact it has on the probability of failure, and incorporate the results from condition assessment of the water main asset to prioritize capital planning regarding pipe renewal. Understandably, assessing the physical condition of water pipes using direct inspection of the entire pipeline network in a water distribution system is prohibitively laborious and expensive (Kleiner and Rajani 2002). Thus, statistical modeling of water main breaks using historic data relating pipe failures can provide important guidance to asset managers in their efforts to maintain their water distribution system and minimize service disruptions.

Prior research has considered two general approaches to the statistical modeling of water main breaks: single-pipe breaks analysis and group-pipes breaks analysis, where pipes are analyzed in groups characterized by their homogeneous features. The first approach attempts to develop a prediction model for future pipe breaks based on the failure characteristics of a single pipe segment (Shamir and Howard 1979; Andreou et al. 1987; Watson et al. 2004). This approach focuses on a specific pipe segment and its characteristics which enables an understanding of a single pipe failure pattern and helps water utilities in their renewal and replacement decision making regarding individual pipes. However, detailed information relating to the condition of single pipe can be difficult to obtain. In addition, water pipes with similar characteristics, for instance, cast iron pipes with a diameter of 6”, may have different failure patterns and can be impacted differently by variables not necessarily observed by the analyst such as temperature, soil moisture, and traffic load above the pipes. Also, deterioration in the inner walls of metallic pipes (due to tuberculation and/or corrosion) could impact the pipes' structural strength and increase the probability of pipe failure (Rajani and Kleiner 2004). Furthermore, predicting of breaks for a single pipe has proven to be quite challenging due to the lack of pipe-break records for individual pipes (Kleiner and Rajani 2010).

The second approach for the statistical modeling of water main breaks aggregates pipes into the homogeneous groups with respect to their age, material, and diameter (Berardi et al. 2008; Wang et al. 2009; Kleiner and Rajani 2010; Gat 2014). The need to aggregate pipes into homogeneous groups including age, material, and diameter has been previously discussed in the literature (Walski and Pelliccia 1982; Kleiner and Rajani 1999; Pelliccia et al. 2003; Berardi et al. 2008; Kleiner and Rajani 2010). In fact, analyzing water main breaks data based on pipe age has been shown to provide helpful insights on determining the optimal timing of pipe replacement, as has analyzing water main breaks based on material cohorts, such as cast iron, ductile iron, PVC, and HDPE. For instance, Wang et al. (2009) developed water main breaks models for five different pipe-material groups including gray cast iron, ductile iron without lining, ductile iron with lining, polyvinyl chloride (PVC), and hyprescon. The authors concluded that age, length, and diameter of each pipe have different impacts on the failure patterns for specific pipe-material groups. Also, considering pipe diameter as a homogeneous group has been shown to provide useful insights into water main break patterns (Berardi et al. 2008; Gat 2014). Generally, smaller diameter pipes have thinner pipe wall thicknesses which can result in shorter wall-penetration times resulting from corrosion and other factors. Even though larger diameter water main breaks have a larger failure consequences in terms of their impact on the water system, the higher number of breaks often experienced with smaller diameter pipes can make the total cost comparable. This chapter follows this pipe-segmentation approach by developing water main break models for six pipe groups with respect to the pipe diameter.

Over the years, a variety of different models have been developed to estimate the frequency of pipe failures using the limited available water-system information (Marks et al. 1985; Rostum 2000; Yamijlala et al. 2009; Wang et al. 2009; Kleiner and Rajani 2010; Singh and Adachi 2012). However, many existing water main break models use the restrictive assumption with regard to the impact of specific explanatory variables that parameters that are constrained to be the same across observations. Hence, these models cannot be applied to estimate the number of breaks for city-wide water system using currently available data such as diameter, material type, length and age of pipes. The intent of this chapter is to develop a model for estimating the frequency of water main breaks in a water distribution system using readily available water-main data and allow for the possibility that the effect of explanatory variables on this frequency may change by month and over time.

2.2 Previous Research

The research conducted by Shamir and Howard (1979) was one of the first studies in the United States to investigate the likelihood of water pipe failure in a distribution system using a time-exponential model. The model used only one independent variable (pipe age) in order to predict water pipe failures, and hence it was not possible to assess the impact of many other potentially relevant factors such as pipe diameter, material type, and length.

In other early work, Marks et al. (1985) utilized a proportional hazards model to study water main breaks by estimating the duration of time between sequential breaks in one segment of water pipe. The model revealed that the probability of pipe breaks tends to decrease as the pipe "matures" after installation, however, 28 years after installation the frequency of pipe breaks starts to increase (see also, Kleiner and Rajani 2001). The application of this model requires access to data, such as operating pressure, percentage of low-land development, period of pipe installation, pipe age at second breaks, number of previous breaks in pipes, and soil characteristics, which unfortunately are not likely to be readily available in most water utility databases. Typically, historic water main break data includes pipe material, pipe diameter, pipe age, and date of incident (as shown in Figure 2.1).

Andreou et al. (1987) further enhanced Marks et al.'s (1985) proportional hazards model for water pipe breaks by analyzing the breaks in two stages. The first stage followed the Marks et al.'s proportional hazards model and confirmed that the probability of pipe break is low after the installation, and each break shortens the time of successive break. The authors state that the pipe-failure rates became constant after the third break in a pipe segment. However, their analysis did not provide information regarding breaks in individual pipe segments. The second stage used the Poisson regression (which implies an exponential distribution of the time between breaks) to estimate the average break frequency after the pipe-failure rate became constant (the exponential distribution translates into a flat hazard function, which gives a constant failure rate that is not a function of time, see Washington et al. 2011).

Main ID	Break Year	Size	Material	Install Year
A19 012A19 013	2007	12	DI	1993
B06 004C06 010	2011	16	DI	1987
B06 016B06 017	2008	16	DI	1999
C10 003C10 004	2007	6	DI	1972
C10 003C10 004	2003	6	DI	1972
D02 001D02 003	2010	12	CI	1971
D02 001D02 003	1985	12	CI	1971
D03 001E03 012	1998	12	DI	1967
D03 029D03 030	2008	8	CI	1969
D06 001D06 002	2005	16	DI	1971
D06 001D06 002	2004	16	DI	1971
D07 003E07 017	1993	12	DI	1968
D51 003D51 005	1992	30	DI	1985
E02 003E03 051	2007	12	DI	1977
E02 006E02 008	2011	8	DI	1979
E02 006E02 008	2006	8	DI	1979
E02 008E02 013	2005	6	DI	1985
E02 018E02 020	2012	16	DI	1971
E02 018E02 023	1994	16	DI	1971
E02 022E03 042	2012	6	CI	1956
E02 022E03 042	2011	6	CI	1956
E02 022E03 042	2008	6	CI	1956
E02 022E03 042	2008	6	CI	1956

Figure 2.1. Example of historic water main break data

Herz (1996) proposed a mathematical group survival model for the water-pipe renewal decision-making process. This model divided the water distribution system into a group of pipes with same characteristics such as same age, same materials, same diameter, and so on. This model estimates the renewal rates and specifies when the service life of the pipe is over. In other work, Deb et al. (1998) developed a decision-making tool based on a cohort survival model to assess pipe renewal needs in five water utilities in North America (Rostum 2000). The model can predict when a pipe section will reach the end of its service life based on a group survival model. The limitation of this model is its inability to predict the number of pipe failures based on pipeline characteristics.

Other studies have applied proportional hazards models for assessing water main breaks (Lei 1997; Eisenbeis et al. 1999). For instance, Eisenbeis et al. (1999) applied the Weibull accelerated life model in two cities in France and one city in Norway using the available pipeline network data including pipe age, pipe length, soil characteristics, traffic load, and number of previous failures. The authors identified three primary factors affecting pipe failures; the diameter of pipe, material, and number of previous failures. Although the pipeline network data in the region of Charente-Maritime in France included different pipe materials such as cast iron pipe, ductile iron pipe, polyvinyl chloride (PVC), and asbestos cements, the effect of different pipe materials on pipe breaks frequency was not discussed by the authors.

Watson et al. (2004) proposed a Bayesian model along with non-homogenous Poisson Process for estimating the failure rate of a single pipe. This approach requires the recorded failure of pipes combined with engineering knowledge in the form of beliefs about the failure rate. The model considered the same prior distribution, (hyperprior) for assessing failure rates of each pipe. Then, the hyperprior determines how the individual pipe failure information updates the belief regarding the failure rate of other pipes in a water distribution system. Random pipe breaks were generated using an object-oriented discrete-event simulation for two pipes in a water distribution system, assuming a constant failure of 0.1 break per year for 50 years. The results indicate that the enhanced Bayesian model improved the natural estimation of failure rates (that assumed a Poisson distribution) by overcoming the deficiencies of missing data, lack of data, and truncation of data.

Bernardi et al. (2008) utilized evolutionary polynomial regression for predicting pipe failures in a U.K. water distribution system. The approach in this study included two successive steps; the optimization of the failure model using an integer-coded Multi-Objective Genetic Algorithm (MOGA) and the estimation of the coefficient of variables for an assumed model using the ordinary least squares. Pipeline asset data from a U.K. water distribution system for the period of 1986-1999 was used to validate this model. The pipe data included pipe diameter, pipe length, number of breaks, and number of properties supplied. The case study analysis was limited to the small diameter pipes, and the information about pipe material was not included in the discussion. Findings of the study indicate that pipe age and pipe length play primary roles for the estimation of the number of water main breaks. The authors stated that in contrast to larger diameter pipes (pipes over 8” diameter), smaller diameter pipes are more prone to failure under excessive external stresses than larger ones. “This behaviour could be due to numerous reasons including pipe manufacturing issues and/or typically low quality of workmanship involved when installing small diameter pipes” (Bernardi et al. 2008).

Wang et al. (2009) utilized a multiple regression model to predict the annual water pipe break rates based on available pipeline data including pipe age, pipe diameter, and pipe length using data from three municipalities in Canada over a period of 15 years (1987-2001). This team developed five regression models for different pipe materials including cast iron, ductile iron without lining, ductile iron with lining, polyvinyl chloride (PVC), and hyprescon concrete pipe materials. This model can be easily implemented by water utilities because it uses a simple regression analysis and requires only data that is already typically collected by water utilities (age, size, and length of the pipes). However, the models do not recognize that the possibility that the effect of explanatory variables may vary across observations (a random parameter approach is not used).

Asnaashari et al. (2009) developed a pipe failure frequency model using multiple and Poisson regression models. The data for this analysis were gathered from the Sanandaj Water and Wastewater Utility in Iran during the 1995-2004 time frames. The explanatory data includes pipe diameter, wall thickness, and depth of buried pipe, pipe age, pipe length, operating pressure, pipe location, and failure history. Although the authors used the Poisson regression model in order to study the frequency of water main breaks, the limitations of the traditional Poisson model (its inability to account for overdispersed data and parameters that may vary in magnitude across observations) are potentially problematic.

Kleiner and Rajani (2010) developed a tool to assess the breakage patterns of individual water mains. The tool is based on the non-homogeneous Poisson process model combined with zero-inflated Poisson regression that allows the consideration of static factors (relating pipe material, pipe diameter, and soil type) and dynamic factors (climate, pressure zone change, and cathodic protection). Their model considered three classes of explanatory variables; pipe-dependent, time-dependent, and pipe and time-dependent variables. The model was applied to a 6” diameter unlined cast iron pipeline system in western Canada with a total length of 91 miles. Although the estimated results show that the model was appropriate for predicting breakage rates based on goodness-of-fit tests, and was successful in estimating the total number of breaks per year, consideration of other pipeline characteristics including different types of pipe materials and pipe diameter would have enhanced the applicability of the model for other water distribution systems. In addition, because this study used count data (number of breaks) for the non-homogeneous Poisson process modeling purpose, consideration of possible overdispersion in the data could have result in a different statistical fit.

Singh and Adachi (2012) developed a Poisson regression model to estimate the expected failure rate of cast iron pipe, ductile iron pipe, polyvinyl chloride (PVC), and concrete cylinder pipes with respect to length of installation. The data were gathered from the 1988 to 2008 records of County of Homolukus Board of Water Supply in Hawaii. The authors used rank order structuring to assess the relative performance of each pipe types and found that cast iron pipes have a higher life expectancy compared to polyvinyl chloride (PVC) pipes based on failure rates of pipes (expressed in terms of breaks/100miles/day) in their network However, the analysis only indicated the presence of one explanatory variable, namely pipe length, which may result in an omitted- variable bias since past research has shown that many other factors are known to influence pipe failure frequencies.

Gat (2014) further enhanced previously studied non-homogeneous Poisson process models by developing a linear extension of Yule process with respect to the zero-inflation and to address possible overdispersion issues of count data modeling process. The model was applied to the analysis of 400 miles of steel core concrete pipes in a major French water distribution system. The model considered three different pipe diameter groups including 10” to 20” diameter pipes, 24” diameter pipes, and 28” to 32” diameter pipes, as well as the cast lead joint type, traffic load conditions, and bedding materials as independent variables. The study showed that failure rates of the pipes with diameters lower than 20” have higher coefficients (2.6 times higher) compared to those with diameters greater than 32”. Also, pipes that are not subjected to the traffic load have a lower failure rates (21 percent lower) compared to the pipes under the road traffic.

A critical concern with past research on this subject is the assumption that the effect of any explanatory variable is the same for all observations. This is a potentially severe limitation since the effect of one or more explanatory variables may vary across the observations. In fact, there is a growing body of literature from a number of fields that clearly show this to be the case in many applications (for example, Mannering and Bhat 2014, Mannering et al. 2016). One of the most popular methods of addressing this limitation is the application of random parameter models, which allows unobserved factors to vary across the population with the pre-specified distribution.

2.3 Methodological Approach

Because the number of water main breaks per month is count data, the application of a standard ordinary least squares regression is not appropriate. As a result, count data are commonly modeled using Poisson regression and negative binomial regression (Milton and Mannering 1998; Washington et al. 2011). The probability $P(n_i)$ of month i having n water main breaks can be represented as follows:

$$P(n_i) = \frac{EXP(-\lambda_i)\lambda_i^{n_i}}{n_i!} \qquad (2.1)$$

where λ_i is the Poisson parameter for month *i*, which is month i's expected number of breaks, $E[n_i]$. For model estimation, the effect of explanatory variables is included as:

$$\lambda_i = EXP(\mathbf{\beta X}_i) \qquad (2.2)$$

where Xi is a vector of the explanatory variables and β is a vector of the estimable parameters (Washington et al. 2011).

However, for pipe-failure data, a Poisson model may not be appropriate because the Poisson distribution restricts the mean and variance to be equal $(E[n_i] = VAR[n_i])$. Overdispersion of count data (in this research related to water main break data) describes the observations for which statistical variations among data are higher than would be expected under the assumed distribution. If overdispersion is present in water main break data, the estimated standard errors and the overall goodness-of-fit will be distorted. With pipe-failure data, it is quite likely the data will be overdispersed $(E[n_i] < VAR[n_i])$ and, if a Poisson model is estimated on overdispersed data, the parameters will be incorrectly estimated. To account for possible overdispersion, a negative binomial model can be derived by rewriting Equation 2.2 as,

$$\lambda_i = EXP(\mathbf{\beta X}_i + \varepsilon_i) \qquad (2.3)$$

where $EXP(\varepsilon_i)$ is a Gamma-distributed error term with mean 1 and variance α. The addition of this term allows the variance to differ from the mean as $VAR[n_i] = E[n_i][1+ \alpha E[n_i]]$. The negative binomial probability density function has the form (Washington et al. 2011):

$$P(n_i) = \left(\frac{1/\alpha}{(1/\alpha)+\lambda_i}\right)^{1/\alpha} \frac{\Gamma[(1/\alpha)+n_i]}{\Gamma(1/\alpha)n_i!} \left(\frac{\lambda_i}{(1/\alpha)+\lambda_i}\right)^{n_i} \qquad (2.4)$$

where $\Gamma(.)$ is a gamma function. Note that as α approaches zero, this negative binomial formulation reduces to a Poisson model (with mean equal to variance), implying that if α is significantly different from zero, the negative binomial is statistically superior relative to the Poisson model (Washington et al. 2011).

However, there is a potential limitation to this traditional negative binomial formulation shown above in that β is fixed across months (not subscripted by i). There is a growing body of work in the infrastructure literature that suggests that the effect of explanatory variables may vary across observations (Anastasopoulos et al. 2011; Anastasopoulos and Mannering 2014, Mannering et al., 2016). Following this work, and relaxing the restriction that the vector of estimable parameters β is fixed across observations, random parameters can be readily introduced in a negative binomial model. Following Greene (2007) and Anastasopoulos and Mannering (2009), allowing parameters to vary across observations can be done by introducing a randomly distributed term, φ_i, such that,

$$\beta_i = \beta + \varphi_i \qquad (2.5)$$

where φ_i can follow any specified distribution (for example, a normal distribution with mean zero and variance σ^2), β_i is the observation specific parameter, and is the mean parameter value over all observation. With this equation, the Poisson parameter becomes $\lambda_i|\varphi_i = EXP\ (\boldsymbol{\beta}\mathbf{X}_i + \varepsilon_i)$ in the negative binomial model with the corresponding probabilities now $P(n_i|\varphi_i)$ (see Equation 2.4), and the log-likelihood can be written as (see Washington et al. 2011),

$$LL = \sum_{\forall i} ln \int_{\varphi_i} g\left(\varphi_i\right) P\left(n_i \mid \varphi_i\right) d\varphi_i \qquad (2.6)$$

where g(.) is the probability density function of the φ_i.

Because maximum likelihood estimation of the random-parameters negative binomial models is computationally cumbersome (due to the required numerical integration of the negative binomial function over the distribution of the random parameters), a simulation–based maximum likelihood method is used (the estimated parameters are those that maximize the simulated log-likelihood function to allow for the possibility that parameters vary across observations, which would mean that the variance of the assumed distribution of φ_i will be significantly greater than zero). The most popular simulation approach for this estimation uses Halton draws, which has been shown to be more efficient than purely random draws for the numerical integration (see Bhat 2003; Train 1999).

To understand the magnitude of the relationship between pipe breaks and the explanatory variables in negative binomial estimation, marginal effects can be estimated. Marginal effects are used to measure the instantaneous rate of change in dependent variable by a 1-unit change in independent (explanatory) variable. In the case of the monthly pipe-break frequencies considered in the current study, marginal effects give the change in the mean number of pipe breaks per month given a unit change in any independent variable, x (see Washington et al. 2011).

2.4 Empirical Setting

Two sets of water main break data were retrieved, one from a large water utility (Indianapolis, Indiana) and one from a medium-sized water utility (Fort Wayne, Indiana). Indianapolis, founded in 1821, has an area of 372 square miles and is the 12th most populous city in the U.S. with a population of 848,788 (2014 census estimate). Fort Wayne was founded in 1794 and has an area of roughly 111 square miles and a population of 258,522 (2014 census estimate). For both cities, a total of two hundred fifty two (252) observations of water main breaks per month were gathered from January 1990 to December 2010 using the pipeline databases maintained by the utilities in these cities, and reflects the changes in the pipeline network based on information related to maintenance, replacement, or new installation activities. Corresponding weather information (temperature and precipitation) was also added to these data to complete the data set. Table 2.1 provides system-wide summary statistics for the variables available in the Indianapolis and Fort Wayne data sets. In Table 2.1, the number of water main breaks per month, mean monthly temperature, and average precipitation per month variables are based on the 21-year observation from January 1990 to December 2010. However, water pipeline characteristics including average age of distribution system, 25th percentile of distribution age, 50th percentile of distribution age, 75th percentile of distribution age, 90th percentile of distribution age, length of cast iron pipe, length of ductile iron pipe, length of polyvinyl chloride (PVC) pipe, length of high-density polyethylene pipe, average age of cast iron pipe, average age of ductile iron pipe, average age of polyvinyl chloride (PVC) pipe, and the average age of high-density polyethylene pipe are based on the entire life cycle of pipelines, starting since the pipe was laid down until the time of observation. Standard deviation in Table 2.1 demonstrates the variation of each variable during 21-year period of analysis. For instance, the mean for length of Ductile Iron Pipe for City of Indianapolis is 344.91 miles, with standard deviation of 21.08 miles. Also, the mean for length of High-Density Polyethylene Pipes for City of Indianapolis is 84.69 miles, with standard deviation of 62.04 miles. The standard deviation shows the fact that although the average length of Ductile Iron Pipe is higher than High-Density Polyethylene Pipe in the water distribution system; the rate of installation for High-Density Polyethylene Pipe was higher than ductile iron pipe during 1990-2010.

Table 2.1. Summary Statistics for Model Variables

Variable Description	**Indianapolis mean (std. dev.)**	**Fort Wayne mean (std. dev.)**
Variables Related to Water Distribution Characteristics:		
Number of Water Main Breaks per Month:		
January	75.10 (25.30)	43.52 (26.18)
February	47.80 (33.10)	29.57 (23.73)
March	22.85 (9.88)	14.95 (9.42)
April	21.65 (7.61)	13.23 (11.60)
May	22.30 (10.09)	14.00 (9.28)
June	25.35 (10.49)	16.28 (10.20)
July	26.70 (10.89)	24.80 (21.67)
August	28.20 (9.46)	28.00 (22.05)
September	29.70 (12.37)	28.90 (21.30)
October	37.50 (14.57)	36.95 (30.04)
November	52.10 (18.99)	39.38 (28.76)
December	69.25 (21.93)	51.85 (37.69)
Average Age of Distribution System in Years	35.63 (29.32)	40.25 (29.73)
25^{th} Percentile of Distribution Age in Years	9.36 (2.63)	15.20 (1.86)
50^{th} Percentile of Distribution Age in Years	27.66 (3.15)	29.90 (1.88)
75^{th} Percentile of Distribution Age in Years	51.58 (1.76)	59.28 (3.05)

Table 2.1 continued

90th Percentile of Distribution Age in Years	80.58 (1.13)	80.60 (2.35)
Length of Cast Iron Pipe in Miles	1493 (0.003)	549.24 (0.77)
Length of Ductile Iron Pipe in Miles	344.91 (21.80)	299.65 (60.75)
Length of Polyvinyl Chloride (PVC) Pipe in Miles	698.19 (464.83)	69.16 (31.59)
Length of High-Density Polyethylene Pipe in Miles	84.69 (62.04)	9.64 (12.01)
Average Age of Cast Iron Pipe in Years	68.46 (20.35)	67.01 (23.08)
Average Age of Ductile Iron pipe in Years	25.66 (10.52)	19.59 (10.31)
Average Age of Polyvinyl Chloride (PVC) Pipe in Years	10.22 (4.62)	11.81 (7.09)
Average Age of High-Density Polyethylene Pipe in Years	9.53 (4.11)	8.76 (7.43)
Variables Related to the Climate and Environments		
Mean Monthly Temperature in Degrees Fahrenheit	55 (16)	50 (17)
Average Precipitation per Month in Inches	3.5 (0.82)	3.3 (1.86)
Average Snow Depth per Month in Inches	0.7 (3.77)	1.14 (1.22)

Key factors in the reliability of pipes include their material and diameter. In the current study, four pipe materials are present (cast iron pipe, ductile iron pipe, polyvinyl chloride pipe, and high-density polyethylene pipe) and six diameters are considered (4”, 6”, 8”, 12”, 16”, and higher than 16” diameter). Figures 2.1 and Figure 2.2 show the lengths of different pipe materials in Indianapolis and Fort Wayne respectively and how the installation of different pipe materials has evolved over the 21-year period of study. Figures 2.3 and Figure 2.4 provide the lengths of different pipe by diameter and how the different pipe diameters have evolved over the 21-year period of study.

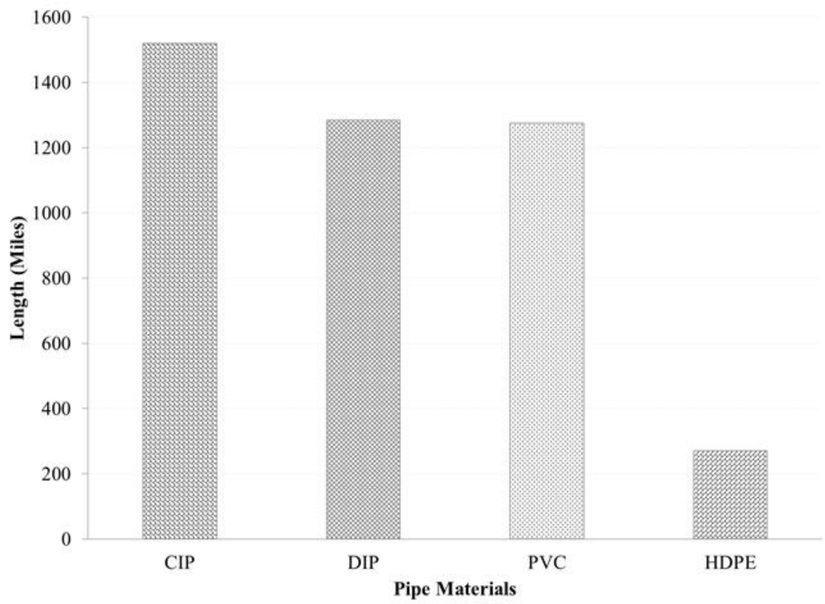

Figure 2.2. Water Pipe Materials Distributions in Indianapolis (CIP = cast iron pipe; DIP = ductile iron pipe; PVC=polyvinyl chloride; HDPE= high-density polyethylene)

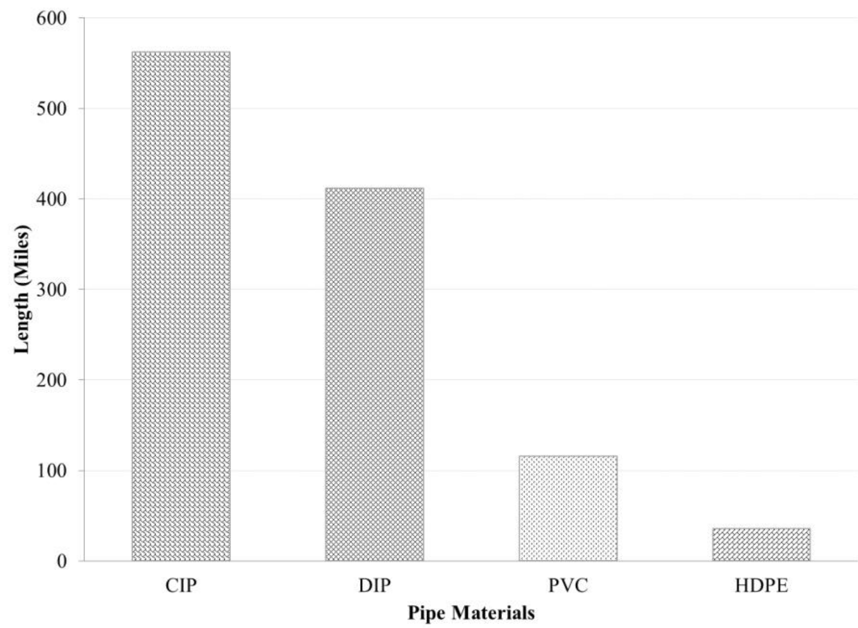

Figure 2.3. Water Pipe Materials Distributions in Fort Wayne (CIP = cast iron pipe; DIP = ductile iron pipe; PVC=polyvinyl chloride; HDPE= high-density polyethylene)

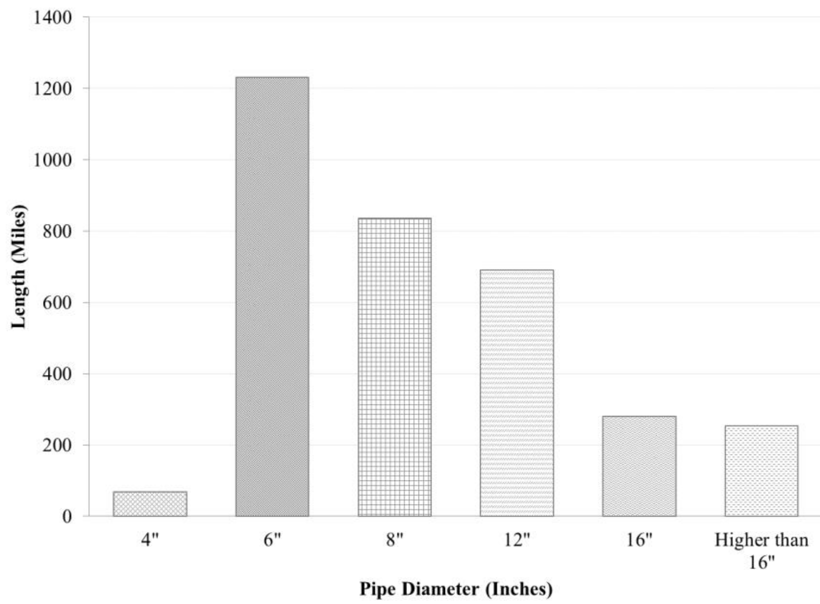

Figure 2.4. Length of Each Diameter Water Pipe in Indianapolis

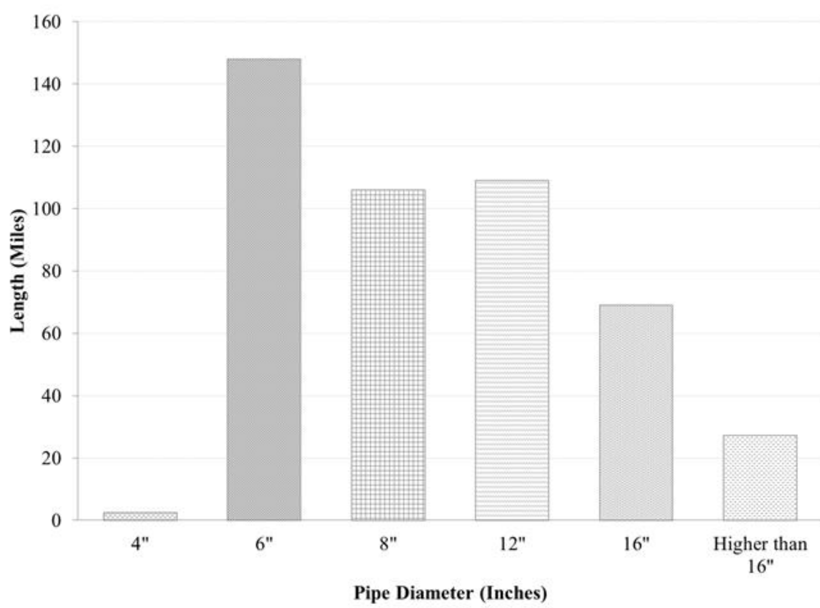

Figure 2.5. Length of Each Diameter Water Pipe in Fort Wayne

2.5 Estimation Results

A total of 252 observations of water main breaks were categorized into six homogeneous groups with respect to pipe diameter including 102, 152, 203, 305, 406, and higher than 406 millimeters (4", 6", 8", 12", 16", and higher than 16") diameter pipes. A key initial concern is whether water main breaks in pipes of 102, 152, 203, 305, 406, and higher than 406 millimeters (4", 6", 8", 12", 16", and higher than 16") diameter are fundamentally different for each size. If they are found to be fundamentally different, this implies that separate count-frequency models would need to be estimated for each pipe diameter. In order to statistically test if water main breaks in 102, 152, 203, 305, 406, and higher than 406 millimeters (4”, 6”, 8”, 12”, 16”, and higher than 16”) diameter pipes are fundamentally different for each size, a likelihood ratio test is appropriate where the test statistic is (Washington et al. 2011),

$$X^2 = -2\left[LL(\beta_T) - LL(\beta_a) - LL(\beta_b)\right] \qquad (2.7)$$

where $LL(\beta_T)$ is the log-likelihood at convergence of the model estimated with the data from two pipe diameters (diameters a and b), $LL(\beta_a)$ is the log likelihood at convergence of the model using only data from pipe diameter *a*, and $LL(\beta_b)$ is the log-likelihood at convergence of the model using only data from pipe diameter *b*. This X^2 statistic is χ^2 distributed with degrees of freedom equal to the summation of the number of estimated parameters in the separate pipe models minus the number of estimated parameters in the combined two-pipe diameter model. The likelihood ratio test provides the confidence level so that the null hypothesis that the models of two pipe diameters (*a* and *b*) are the same can be evaluated. The likelihood ratio tests for both Indianapolis and Fort Wayne revealed that the null hypothesis that different pipe diameters were the same could be rejected with high confidence (over 99% confidence in most cases), suggesting that separate models by pipe diameter are warranted.

Using separate models by pipe diameters, estimation results for Indianapolis are presented in Tables 2.2 through Table 2.7, and estimation results for Fort Wayne are presented in Tables 2.8 through Table 2.12 (note that we were unable to estimate a model for the Fort Wayne higher than 406 millimeters (16”) diameter pipe system, likely because of insufficient variation in the data). Before turning to specific findings, note that in all of the models (Tables 2.2 - Table 2.12) that the negative binomial dispersion parameter (see Equation 2.4) is statistically greater than zero with a minimum of 94% confidence. This suggests overdispersion in the data and that the negative binomial model is statistically preferred relative to a Poisson regression (likelihood ratio tests also confirm this). In addition to assessing the statistical significance of the negative binomial dispersion parameter (which is a measure of the statistical superiority of the negative binomial model relative to the Poisson model), a likelihood ratio test was conducted to confirm that the random parameter negative binomial models could improve the fixed-parameter negative binomial model. The likelihood ratio test results indicate that the 7 random parameter negative binomial models estimated were statistically superior to their fixed-parameter counterparts at over a 95% level of confidence. Thus, with regard to random parameters, of the 11 models estimated, 7 had statistically significant random parameters and the remaining 4 where estimated as traditional fixed-parameters negative binomial models. This suggests that unobserved heterogeneity is not necessarily always a significant factor in model estimation and depends on pipe diameters and other factors. Specific estimation findings are discussed below.

For the functional form of the random parameter density function, normal, log-normal, uniform, triangular distributions were all considered to determine the best statistical fit for the models. For all parameters found to be random, the normal distribution was found to provide the best statistical fit as confirmed by likelihood-ratio tests.

Table 2.2. Random Parameters Negative Binomial Regression of Water Main Breaks Frequency per Month for 4" Diameter Pipe in Indianapolis

Variable Description	**Parameter Estimate (t-statistic)**	**Parameter Standard Deviation (t-statistic)**	**Marginal Effect**
Fixed Parameters			
Constant	-5.094 (-2.868)	–	-2.168
Month Indicator (1 if March, 0 if otherwise)	-0.890 (-1.674)	–	-0.378
Month Indicator (1 if November, 0 if otherwise)	0.445 (1.687)	–	0.189
Average Age of Cast Iron Pipe in Years	0.040 (1.757)	–	0.017
Average Age of Ductile Iron Pipe in Years	0.094 (1.883)	–	0.040
Random Parameters			
Average Temperature per Month in Degrees Fahrenheit	-0.0142 (-2.323)	0.0033 (1.844)	-0.006
Negative binomial dispersion parameter (α)	6.587 (1.645)	–	–
Log likelihood at zero	-285.56		
Log likelihood at convergence	-228.16		
ρ^2 [$1 - LL(\boldsymbol{\beta})/LL(\mathbf{0})$]	0.20		
AIC	18.74		
BIC	19.86		
Number of observations	252		

Table 2.3. Negative Binomial Regression of Water Main Breaks Frequency per Month for 6” Diameter Pipe in Indianapolis

Variable Description	Parameter Estimate (t-statistic)	Parameter Standard Deviation (t-statistic)	Marginal Effect
Fixed Parameters			
Constant	0.039 (0.027)	–	0.916
Month Indicator (1 if January, 0 if otherwise)	0.548 (4.277)	–	12.589
Month Indicator (1 if March, 0 if otherwise)	-0.637 (-5.248)	–	-14.625
Month Indicator (1 if April, 0 if otherwise)	-0.723 (-4.176)	–	-16.609
Month Indicator (1 if November, 0 if otherwise)	0.312 (2.147)	–	7.163
Month Indicator (1 if December, 0 if otherwise)	0.522 (3.771)	–	11.996
90^{th} Percentile of Pipeline Age	0.049 (2.477)	–	1.125
Length of Polyvinyl Chloride (PVC) Pipe in Miles	0.001 (2.643)	–	0.024
Average Temperature per Month in Degrees Fahrenheit	-0.018 (-8.214)	–	-0.414
Average Age of Polyvinyl Chloride (PVC) Pipe in Years	-0.042 (-2.714)	–	-0.972
Negative binomial dispersion parameter (α)	0.169 (10.485)	–	–
Log likelihood at zero	-14231.58		
Log likelihood at convergence	-902.92		
ρ^2 [$1 - LL(\boldsymbol{\beta})/LL(\mathbf{0})$]	0.93		
AIC	72.53		
BIC	74.07		
Number of observations	252		

Table 2.4. Random Parameters Negative Binomial Regression of Water Main Breaks Frequency per Month for 8” Diameter Pipe in Indianapolis

Variable Description	**Parameter Estimate (t-statistic)**	**Parameter Standard Deviation (t-statistic)**	**Marginal Effect**
Fixed Parameters			
Constant	2.463 (13.392)	–	15.055
Month Indicator (1 if February, 0 if otherwise)	-0.488 (-5.106)	–	-2.986
Month Indicator (1 if March, 0 if otherwise)	-0.822 (-7.057)	–	-5.026
Month Indicator (1 if April, 0 if otherwise)	-0.554 (-5.679)	–	-3.385
Month Indicator (1 if May, 0 if otherwise)	-0.554 (-4.033)	–	-3.388
Month Indicator (1 if June, 0 if otherwise)	-0.449 (-3.216)	–	-2.745
Month Indicator (1 if July, 0 if otherwise)	-0.333 (-2.297)	–	-2.037
Month Indicator (1 if August, 0 if otherwise)	-0.269 (-2.078)	–	-1.645
50^{th} Percentile of Pipeline Age in Years	0.067 (2.005)	–	0.411
Average Temperature per Month in Degrees Fahrenheit	-0.014 (-5.684)	–	-0.086
Average Age of Polyvinyl Chloride (PVC) Pipe in Years	-0.0711 (-4.918)	–	-0.434
Random Parameters			
Length of Polyvinyl Chloride (PVC) Pipe in Miles	0.00143 (6.911)	0.000510 (6.976)	0.008
Negative binomial dispersion parameter (α)	45.119 (3.845)	–	–
Log likelihood at zero	-2218.74		
Log likelihood at convergence	-619.96		
ρ^2 [$1 - LL(\boldsymbol{\beta})/LL(\mathbf{0})$]	0.72		
AIC	50.31		
BIC	52.27		
Number of observations	252		

Table 2.5. Random Parameters Negative Binomial Regression of Water Main Breaks Frequency per Month for 12” Diameter Pipe in Indianapolis

Variable Description	Parameter Estimate (t-statistic)	Parameter Standard Deviation (t-statistic)	Marginal Effect
Fixed Parameters			
Constant	-3.112 (-2.427)	–	-17.944
Month Indicator (1 if January, 0 if otherwise)	0.529 (4.403)	–	3.050
Month Indicator (1 if March, 0 if otherwise)	-0.403 (-2.725)	–	-2.325
Month Indicator (1 if November, 0 if otherwise)	0.302 (2.246)	–	1.743
Month Indicator (1 if December, 0 if otherwise)	0.433 (3.689)	–	2.497
25^{th} Percentile of Pipeline Age	-0.222 (-3.432)	–	-1.282
75^{th} Percentile of Pipeline Age	0.052 (2.375)	–	0.304
Average Temperature per Month in Degrees Fahrenheit	-0.003 (-1.600)	–	-0.022
Average Age of Cast Iron Pipe in Years	0.127 (3.950)	–	0.737
Random Parameters			
Length of Polyvinyl Chloride (PVC) Pipe in Miles	-0.0121 (-4.815)	0.00127 (8.017)	-0.070
Average Age of Polyvinyl Chloride (PVC) Pipe in Years	0.0520 (2.010)	0.0156 (2.775)	0.300
Negative binomial dispersion parameter (α)	32.037 (2.991)	–	–
Log likelihood at zero	-2343.377		
Log likelihood at convergence	-627.32		
ρ^2 $[1 - LL(\boldsymbol{\beta})/LL(\mathbf{0})]$	0.73		
AIC	50.89		
BIC	52.85		
Number of observations	252		

Table 2.6. Negative Binomial Regression of Water Main Breaks Frequency per Month for 16" Diameter Pipe in Indianapolis

Variable Description	**Parameter Estimate (t-statistic)**	**Parameter Standard Deviation (t-statistic)**	**Marginal Effect**
Fixed Parameters			
Constant	3.025 (1.196)	–	3.793
Month Indicator (1 if April, 0 if otherwise)	-0.631 (-1.944)	–	-0.791
25^{th} Percentile of Pipeline Age	0.223 (2.932)	–	0.279
50^{th} Percentile of Pipeline Age	0.150 (2.096)	–	0.189
75^{th} Percentile of Pipeline Age	-0.253 (-2.307)	–	-0.317
Length of Polyvinyl Chloride (PVC) Pipe in Miles	0.017 (2.348)	–	0.022
Average Temperature per Month in Degrees Fahrenheit	0.011 (3.281)	–	0.014
Negative binomial dispersion parameter (α)	12.648 (1.574)	–	–
Log likelihood at zero	-482.78		
Log likelihood at convergence	-358.98		
ρ^2 [$1 - LL(\boldsymbol{\beta})/LL(\mathbf{0})$]	0.25		
AIC	29.20		
BIC	30.65		
Number of observations	252		

Table 2.7. Negative Binomial Regression of Water Main Breaks Frequency per Month for Diameters Greater than16” in Indianapolis

Variable Description	**Parameter Estimate (t-statistic)**	**Parameter Standard Deviation (t-statistic)**	**Marginal Effect**
Fixed Parameters			
Constant	-3.048 (-2.947)	–	-2.019
Month Indicator (1 if January, 0 if otherwise)	0.710 (1.964)	–	0.470
Month Indicator (1 if December, 0 if otherwise)	0.587 (1.714)	–	0.388
Month Indicator (1 if November, 0 if otherwise)	0.533 (1.655)	–	0.353
Average Temperature per Month in Degrees Fahrenheit	0.016 (2.498)	–	0.010
Average Age of Cast Iron Pipe in Years	0.022 (1.585)	–	0.015
Negative binomial dispersion parameter (α)	29.365 (1.639)	–	–
Log likelihood at convergence	-269.86		
Log likelihood at zero	-391.52		
ρ^2 [$1 - LL(\boldsymbol{\beta})/LL(\mathbf{0})$]	0.31		
AIC	21.97		
BIC	22.95		
Number of observations	252		

Table 2.8. Random Parameters Negative Binomial Regression of Water Main Breaks Frequency per Month for 4” Diameter Pipe in Fort Wayne

Variable Description	**Parameter Estimate (t-statistic)**	**Parameter Standard Deviation (t-statistic)**	**Marginal Effect**
Fixed Parameters			
Constant	-1.983 (-2.445)	–	-1.636
Month Indicator (1 if April, 0 if otherwise)	-0.697 (-1.762)	–	-0.575
Month Indicator (1 if November, 0 if otherwise)	-0.559 (-2.414)	–	-0.461
Month Indicator (1 if September, 0 if otherwise)	0.489 (1.652)	–	0.404
Average Age of Cast Iron Pipe in Years (CIP)	0.052 (4.052)	–	0.043
Random Parameters			
Average Temperature per Month in Degrees Fahrenheit	-0.0316 (-7.535)	0.00288 (2.014)	-0.026
Negative binomial dispersion parameter (α)	7.359 (1.586)	–	–
Log likelihood at zero	-395.52		
Log likelihood at convergence	-314.38		
ρ^2 $[1 - LL(\boldsymbol{\beta})/LL(\mathbf{0})]$	0.20		
AIC	25.58		
BIC	26.70		
Number of observations	252		

Table 2.9. Random Parameters Negative Binomial Regression of Water Main Breaks Frequency per Month for 6” Diameter Pipe in Fort Wayne

Variable Description	**Parameter Estimate (t-statistic)**	**Parameter Standard Deviation (t-statistic)**	**Marginal Effect**
Fixed Parameters			
Constant	-5.551 (-3.008)	–	-90.604
Month Indicator (1 if January, 0 if otherwise)	0.428 (5.116)	–	6.986
Month Indicator (1 if March, 0 if otherwise)	-0.611 (-6.516)	–	-9.975
Month Indicator (1 if April, 0 if otherwise)	-0.767 (-7.845)	–	-12.519
Month Indicator (1 if November, 0 if otherwise)	0.379 (4.817)	–	6.197
Month Indicator (1 if December, 0 if otherwise)	0.544 (6.747)	–	8.888
75^{th} Percentile of Pipeline Age	0.131 (4.341)	–	2.142
Random Parameters			
Length of Polyvinyl Chloride (PVC) in miles	-0.05557 (-2.538)	0.00806 (7.578)	-0.907
Average Temperature per Month in Degrees Fahrenheit	-0.00612 (-3.625)	0.00739 (18.057)	-0.099
Negative binomial dispersion parameter (α)	24.953 (4.724)	–	–
Log likelihood at zero	-11103.34		
Log likelihood at convergence	-889.85		
ρ^2 $[1 - LL(\boldsymbol{\beta})/LL(\mathbf{0})]$	0.91		
AIC	71.57		
BIC	73.25		
Number of observations	252		

Table 2.10. Random Parameters Negative Binomial Regression of Water Main Breaks Frequency per Month for 8” Diameter Pipe in Fort Wayne

Variable Description	**Parameter Estimate (t-statistic)**	**Parameter Standard Deviation (t-statistic)**	**Marginal Effect**
Fixed Parameters			
Constant	-101.7287 (-2.496)	–	-166.606
Month Indicator (1 if February, 0 if otherwise)	-0.330 (-1.633)	–	-0.540
Month Indicator (1 if March, 0 if otherwise)	-0.623 (-2.981)	–	-1.021
Month Indicator (1 if December, 0 if otherwise)	0.450 (3.110)	–	0.737
Month Indicator (1 if April, 0 if otherwise)	-0.789 (-3.337)	–	-1.293
Month Indicator (1 if June, 0 if otherwise)	-0.746 (-2.870)	–	-1.223
Length of Cast Iron Pipe in miles	1.790 (2.235)	–	2.932
Length of Polyvinyl Chloride (PVC) Pipe in Miles	-0.124 (-1.835)	–	-0.204
Average Age of Ductile Iron Pipe in Years	0.147 (1.705)	–	0.241
Random Parameters			
Month Indicator (1 if July, 0 if otherwise)	-0.478 (-2.264)	0.482 (2.307)	-0.784
Month Indicator (1 if May, 0 if otherwise)	-1.096 (-4.137)	0.331 (1.618)	-1.795
Negative binomial dispersion parameter (α)	12.220 (1.788)	–	–
Log likelihood at zero	-589.69		
Log likelihood at convergence	-419.02		
ρ^2 [$1 - LL(\boldsymbol{\beta})/LL(\mathbf{0})$]	0.28		
AIC	34.44		
BIC	36.54		
Number of observations	252		

Table 2.11. Random Parameters Negative Binomial Regression of Water Main Breaks Frequency per Month for 12" Diameter Pipe in Fort Wayne

Variable Description	**Parameter Estimate (t-statistic)**	**Parameter Standard Deviation (t-statistic)**	**Marginal Effect**
Fixed Parameters			
Constant	-4.570 (-2.888)	–	-5.812
Month Indicator (1 if January, 0 if otherwise)	0.646 (2.813)	–	0.821
Month Indicator (1 if November, 0 if otherwise)	0.758 (3.600)	–	0.964
Month Indicator (1 if December, 0 if otherwise)	0.839 (4.130)	–	1.067
25th Percentile of Pipeline Age	-0.119 (-2.741)	–	-0.151
Average Age of Cast Iron Pipe in Years	0.093 (3.022)	–	0.119
Average Age of Polyvinyl Chloride (PVC) Pipe in Years	-0.211 (-2.808)	–	-0.268
Random Parameters			
Average Temperature per Month in Degrees Fahrenheit	-0.00626 (-1.692)	0.00635 (5.971)	-0.007
Negative binomial dispersion parameter (α)	36.445 (1.588)	–	–
Log likelihood at zero	-574.34		
Log likelihood at convergence	-359.65		
ρ^2 $[1 - LL(\boldsymbol{\beta})/LL(\mathbf{0})]$	0.37		
AIC	30.92		
BIC	32.32		
Number of observations	252		

Table 2.12. Negative Binomial Regression of Water Main Breaks Frequency per Month for 16” Diameter Pipe in Fort Wayne

Variable Description	**Parameter Estimate (t-statistic)**	**Parameter Standard Deviation (t-statistic)**	**Marginal Effect**
Fixed Parameters			
Constant	-1.458 (-2.623)	–	-0.625
Month Indicator (1 if May, 0 if otherwise)	-0.517 (-1.807)	–	-0.221
25th Percentile of Pipeline Age	0.139 (2.621)	–	0.059
Average Temperature per Month in Degrees Fahrenheit	-0.015 (-2.470)	–	-0.006
Negative binomial dispersion parameter (α)	21.712 (1.569)	–	–
Log likelihood at zero	-276.16		
Log likelihood at convergence	-209.05		
ρ^2 $[1 - LL(\boldsymbol{\beta})/LL(\mathbf{0})]$	0.25		
AIC	16.98		
BIC	17.68		
Number of observations	252		

2.5.1 Effects of Temperature and Month on Water Main Breaks

For Indianapolis, an increase in average temperature per month was found to decrease the number of water main breaks in 4”, 6”, 8”, 12”, 16” pipes, and pipes with diameters higher than 16” (Tables 2.2 through Table 2.7). For the 4” pipeline network in Indianapolis (Table 2.2), this variable resulted in a normally distributed random parameter with a mean of -0.0142 and standard deviation of 0.0033, showing significant variation across monthly observations. This normally distributed random parameter indicates that for almost all observations higher temperatures result in fewer water main breaks per month. However, the significance of the standard deviation of this parameter means that there is considerable heterogeneity of the effect of temperature across observations. From a materials perspective, dropping temperature clearly has negative impacts on the water pipes, and the numbers of breaks are likely to increase as the result of thermal stresses created by temperature differences between soil and water inside the pipe (Makar et al. 2001; Kleiner and Rajani 2002). However, the random parameter reflects the fact that there are unobserved factors, which can affect the pipe breaks. For instance, the depth of buried pipe, when combined with soil moisture content (which is not available in typical pipe-related data), has a direct impact on water main breaks in colder climates due to the frost penetration. The average marginal effect for this variable shows that a one-degree increase in the average temperature per month decreases the mean break frequency per month by a rather modest 0.006 on average.

For Fort Wayne, in the 4”, 6”, and 12” diameter models the average temperature per month was found to be random parameter with a statistically significant mean and standard deviation. Interestingly, the 6” and 12” pipe-diameter models resulted in temperature random parameters with high standard deviations relative to their mean. For the 6” model, the parameter estimate for average monthly temperature is -0.00612 with a standard deviation of 0.00739 (Table 2.9). This suggests (with the assumed normal distribution) that for 79.54% of the observation (205 observations with negative sign), higher average temperature per month decreases the probability of water main breaks per month, but that for 20.46% of the observation (47 observations with positive sign), higher average temperature per month increases the probability of water main breaks per month. This finding reflects the influence of many unobserved factors (such as such as soil moisture, soil type, depth of buried pipes, pipe wall thickness, pressure fluctuation, and water temperature inside the pipes) that can affect the pipe failures. For instance, if water temperature inside the pipes drops while the temperature of the soil surrounding the pipe is maintained or increases, a thermal gradient across the pipe wall will result in differential strains and circumferential stresses (Habibian 1994). This unobserved factor may be sufficient to increase the number of breaks per month for some pipes (in this case, 47 observations) as the average temperature per month increases. Soil type, soil moisture and soil shrinkage also contribute to the unobserved heterogeneity across observations since these factors are unobserved to the analyst, but potentially interact with temperature as our results indicate. The variation of soil type, moisture and shrinkage across the water distribution system in the City of Indianapolis appear to be playing a role in this finding.

For the Fort Wayne 12” pipeline network (Table 2.11), the average temperature per month parameter has a mean of -0.00626 and standard deviation of 0.00635, which suggests that for 83.94% of the 12” pipeline network, higher average temperature per month decreases the probability of water main breaks per month, but that for 16.06% higher average temperature per month increases the probability of water main breaks per month. This variation in the effect of temperature in Fort Wayne is again likely capturing unobserved factors relating to the pipe network such as soil type, depth of pipe, and so on, and the varying effect that temperature fluctuations have with regard to these unobserved factors.

Turning to other results, many of the estimated models show that the likelihood of water main breaks occurring in the months of November, December, and January are higher and have a higher break frequency compared to the other months of the year. According to National Oceanic and Atmospheric Administration climate data, January had the lowest average temperature for the 21-year period of this study (1990-2010), followed by December and November (as shown in Table 2.1, as the temperature drops during November to January the number of breaks increase). The effect of temperature during these months is likely a combination of the effect of soil moisture content increases and the temperatures decreases. Dropping soil temperatures result in thermal stresses created by temperature differences between soil and water inside the pipe (Makar et al. 2001). The effects of climate and temperature on water main breaks have been studied previously by a number of researchers. For example, Habibian (1994) studied the effects of air temperature and water temperature on water main breaks and observed rapid increases in the number of main breaks from August to November. The breaks remained at high level from November to January, and then the number of breaks declined from January to March. Kleiner and Rajani (2002) analyzed the effects of temperature and soil moisture on water main breaks and stated that during cold winter months (December to April) the number of main breaks increases, due to low soil moisture level because of rain deficit at the beginning of the winter.

2.5.2 Effects of Pipe Age on Water Main Breaks

As the average age of cast iron pipe for both Indianapolis and Fort Wayne in 4” and 12” pipeline network increased, the number of breaks per month in 4” and 12” pipes also increased. In Indianapolis, as the average age of cast iron pipe for higher than 16” diameter pipes increased, the number of breaks per month also increased. The marginal effects are also quite high for some of the diameters. For example, for 12” diameter cast iron pipes in Indianapolis (Table 2.5), a one-year increase in average age results in an average increase of 0.737 breaks per month. The relationship between pipe age and the frequency of cast iron pipe failure has been discussed at length in prior studies (Shamir and Howard 1979; Rostum 2000; Yamijala et al. 2008; Singh and Adachi 2012) with failure typically being cited as the result of external and internal corrosion. However, to the author's knowledge, no root cause analysis of water pipe failures has been reported in literature to date.

The average age of 6" and 8" polyvinyl chloride (PVC) pipe in the Indianapolis water distribution system, and 12" PVC in both Indianapolis and Fort Wayne, was also found to affect the number of breaks per month. In Indianapolis, marginal effects in Tables 2.3 and Table 2.4 show that a one-year increase in the age of 6" and 8" PVC pipes decreases the mean break frequency per month by 0.972 and 0.434 on average, respectively. Also, for 12" PVC pipes in Fort Wayne, a one-year increase in pipe age decreases the mean break frequency per month by 0.268 (Table 2.11). These findings can be explained by the fact that older 6" and 8" PVC pipes (with possible initial defects addressed) have a lower likelihood of failure. As evidence of this, when Folkman (2012) surveyed 188 water utilities in North America to assess water main breaks that utilities were experiencing, it was observed that over half of the failed PVC pipes were between zero and 20 years in age. Moser and Kellogg's (1994) survey of 162 water utility and 29 engineering firms in North America to assess the behavior of PVC pipes in water distribution systems, concluded that around 50 percent of the failures in PVC pipes occurred in the first year due to poor installation, damage during excavation (third-party damages), and the effects of ultraviolet light (Moser and Kellogg 1994).

In contrast to the aforementioned findings, in Indianapolis, a one-year increase in the age of 12" PVC pipes increased the mean break frequency per month by 0.300 on average (Table 2.5). However, it is noteworthy that this variable resulted in a normally distributed random parameter with a mean of 0.052 and standard deviation of 0.015, which indicates that for almost all of the observations (252 observations), a higher age of 12" PVC pipe increases the number of main breaks per month with considerable heterogeneity in the effect of age across monthly observations. This heterogeneous finding may reflect the fact that the average age of 12" PVC pipe in Indianapolis was just over five years, so that these data do not have the older PVC pipes that smaller diameter pipes do. In addition, the observed variation with respect to age may be picking up variations in installation practices or installation locations that are correlated with pipe age.

In Fort Wayne, the average age of cast iron pipes was found to increase monthly break frequencies for 4” pipe (Table 2.8) and 12” pipe (Table 2.11), and for Indianapolis the average age of cast iron pipes was found to increase monthly break frequencies for 4” pipe (Table 2.2), 12” pipe (Table 2.5) and for pipes greater than 16” diameter (Table 2.7). The average age of ductile iron pipe was found to increase monthly break frequency in Indianapolis for 4” pipe (Table 2.2), and increase monthly break frequency for 8” pipe in Fort Wayne (Table 2.10).

The age distribution of pipes was also an important factor in many of the models. For example, model estimation results show that for 6” diameter pipes in Indianapolis (Table 2.3), a one-year increase in the 90th percentile of pipe age increases the mean break frequency by 1.125 on average. This can be partially explained by the fact that most pipes in the Indianapolis system above the 90th percentile for 6” diameter pipes are cast iron that happens to be nearing the end of their life span. Although cast iron pipe is a stronger material compared to plastic pipe (load bearing) and has an estimated life expectancy of 64 to 115 years (Rajani et al. 2000), the internal corrosion (water with pH lower than 7.2) and external corrosion (surrounding soil with pH lower than 5), deteriorates cast iron pipe over time and leads to breaks (Seica and Packer 2004; Bonds et al. 2005).

2.5.3 Effects of Pipe’s length on Water Main Breaks

Estimation results show that pipe length by type of pipe is statistically significant in many of the models. For Indianapolis, as the length of 6” and 8” diameter PVC pipe in the water distribution system increases, the number of breaks throughout the pipe network also increases. The marginal effects for this variable indicated that a one-mile increase in the length of 6” PVC pipe increases the mean break frequency by a modest 0.024 per month on average (Table 2.3). The length of 8” PVC pipe in a water distribution system was found to be a random parameter (Table 2.4) and more likely to increase the number of breaks throughout 8” diameter pipe network. This normally distributed random parameter reflects that for almost all observations, higher installation of the 8” PVC pipe (increase in length) increases the probability of water main breaks. However, the significance of the standard deviation of the parameter estimate suggests there is considerable heterogeneity across observations in the effect of length on frequency, and the average marginal effect is quite small with a one-mile increase in length increasing average monthly break frequency by only 0.008. The dominant modes of failures for PVC pipes are joint leakage and longitudinal cracks, which are caused by improper tapping and/or installation and third-party damages (initial cracks leading to longitudinal fractures, see Burn et al. 2005). A one-mile increase in 6” and 8” PVC pipe in a water distribution system increases the number of joints along the PVC pipes (Uni-Bell 2001), as well as an increase in the number of service connections to the main line (tapping). According to the Burn et al. (2005), a 34.3 percent of failures in PVC pipes occur due to joint leakage at tapping spots. Because 6” and 8” PVC pipes are the common small diameter pipes for distributing potable water to neighborhoods, they are more likely to be affected by poor tapping and poor installation at joints. This reason could partially explain the variation in the effect of length across observations.

Interestingly, the length of 16” PVC in Indianapolis (Table 2.6) also had an impact of increasing break frequencies with a one-mile increase in 16” pipe increasing monthly breaks by 0.022 (Table 2.6). This result can be explained by the improper joint installation for large diameter PVC pipes (higher than 14” diameter). Gasketed joints are typically used for assembling of bell and spigot PVC pipes. One of major drawbacks of this joint installation for large size diameter pipes (higher than 14” diameter) is improper alignment of the spigot to the bell during pipe assembly (Uni-Bell 2001), which causes pipe failures and leakage at joints. The improper alignment during joint assembling causes the pipe failure and leakage at joints. Also, adverse climate condition, such as cold weather, can affect the performance of gaskets and lead to leakage at the joints (Uni-Bell 2001).

For 12” diameter pipes in Indianapolis, the length of 12” PVC pipe in a water distribution system was found to decrease the number of breaks throughout a 12” diameter pipe network. This variable resulted in a random parameter that is normally distributed, with mean a mean -0.0121 and standard deviation 0.00127. For most of the water main breaks that occurred in the 12” pipeline network, a greater length of 12” PVC pipes was associated with decreases in the number of main breaks per month, but the random parameter findings show that there is substantial variation in the effect of length across observations (Table 2.5). The estimation results show that a one-mile increase in the length of 12” PVC pipe decreases the mean break frequency by 0.07 on average. In contrast to the small diameter pipes (6” and 8”), 12” PVC pipes have fewer service connections along the pipe (Najafi 2010) and therefore, the likelihood of poor tapping and installation is lower.

Also, based on the GIS layout of 12" pipes in the Indianapolis water system, 12" PVC pipes have a lower rate of installation (12 miles/year) compared to the 6" and 8" PVC pipes (which were 18 miles/year and 24 miles/year, respectively).

The results for Fort Wayne were quite different. For 6" and 8" diameter PVC pipes (Tables 2.9 and 2.10), increasing PVC pipe length decreased break frequency, with marginal effect showing a one-mile increase in pipe length decreasing monthly break frequency by 0.907 and 0.204 for 6" and 8" diameter pipes, respectively (the 6" diameter parameter was random and thus varied across observations). It is suspected that these conflicting findings between Indianapolis and Fort Wayne are an artifact of their systems. As Figures 2.1 and Figures 2.2 show, the Indianapolis system has a much higher proportion of PVC pipes, whereas Fort Wayne water distribution system has more recent installations of PVC pipes. One can speculate that, as Fort Wayne's system gets a higher percentage of PVC pipe, the effect of pipe length will fall more in line with Indianapolis results.

It is also noteworthy that for 8" diameter pipes in Fort Wayne the length of cast iron pipe significantly increases monthly failure frequencies with a one-mile increase in length producing a 2.932 increase in monthly break frequency (from the marginal effect in Table 2.10). This result is most certainly an artifact of the characteristics and condition of the 8" cast iron pipes in the Fort Wayne network. The city engineer of Fort Wayne conjectured that the reason might be the lack of cathodic protection for small diameter mains (18" and" lower).

2.6 Conclusion

As water utilities attempt to be proactive and implement sustainable asset management programs, quantifying the effect that various system and environmental characteristics have on water-pipe failure is extremely important. This chapter demonstrates the application of an appropriate statistical methodology (random parameters negative binomial) that utilities can apply to forecast monthly breaks in their water system. Significant dispersion parameters from the random parameter negative binomial estimated models suggest the statistical superiority of this model relative to the Poisson or a fixed-parameter negative binomial. Likelihood ratio test results revealed that the 7 random parameter negative binomial models are statistically superior with a 95% level of confidence relative to their fixed-parameter counterparts. The preliminary statistical analyses presented in this chapter show the importance of pipe diameter and many other factors in estimating monthly-break frequency.

For both case-study cities, in regard to the month and temperature variables, the months of November, December, and January tend to have higher frequencies of water main breaks per month relative to other months of the year, likely due in large part to the thermal stresses created by temperature differences between the soil and water inside the pipe, which has been found, by other research efforts, to lead to breaks in metallic pipes such as cast iron pipe and ductile iron pipe. Among all of the water pipe characteristics affecting water main breaks presented in this chapter, an interesting and representative finding relates to the effects of the age and length of polyvinyl chloride (PVC) pipe. In the context of pipe age in Indianapolis, 6” and 8” PVC pipes (with an average age of 12 years in the Indianapolis system) showed a fewer number of water main breaks. Also, 12” PVC pipes (with an average age of five years in the Indianapolis system) had higher break frequencies. In contrast, the age of PVC pipe for the Fort Wayne was not found to be a significant variable, likely because of the much lower use of PVC pipe. Also, in Indianapolis, increasing length of 6” and 8” PVC in water distribution systems was found to increase the break frequency whereas, in Fort Wayne, increasing the length of 6” and 8” PVC in water distribution systems was found to decrease the break frequency.

This and other findings in the chapter underscore the need for each city to develop its own statistical models. Even though both Indianapolis and Fort Wayne are Midwestern cities that share similar climate, soil conditions, and so on, their systems are quite different and this explains the many substantive differences in findings when comparing the Fort Wayne and Indianapolis model-estimation results. Transferability of statistical models from one city to the next is not really possible because the effect of specific variables is clearly dependent on specific system characteristics.

In terms of future work, it would be interesting to apply the random parameters negative binomial modeling approach to more detailed data bases that could include expanded data on soil types, temperature extremes, water pressures, and so on. More detailed data bases would undoubtedly improve statistical modeling and provide additional insights into the factors that affect break frequencies in specific cities. There is also the potential that breaks may be spatially correlated (with pipes in close spatial proximity sharing unobserved effects), which is a promising direction for future research (incorporating potentially complex spatial correlations into the statistical estimation).

3. EMPIRICAL ASSESSMENT OF UNOBSERVED HETEROGENEITY AND POLY VINYL CHLORIDE PIPE FAILURES IN WATER DISTRIBUTION SYSTEMS

[A version of this chapter was published in the ASCE Journal of Performance of Constructed Facilities][2].

An understanding of the failure patterns of pipes in water distribution systems is critical to cost effective system-maintenance planning. Failure patterns, which typically measure the frequency of water main breaks in a water distribution system, can vary widely depending on the type of pipe material being considered, and the statistical analysis of pipe frequency-of-failure data is complicated by limited data on soil conditions, freeze-thaw cycles, construction quality, and so on, which manifests itself as unobserved heterogeneity. This chapter considers failure frequencies in polyvinyl chloride (PVC) pipes using pipe-break data from a 21-year period in Indianapolis, Indiana. Failure frequencies are studied using a random parameters negative binomial (and a latent class negative binomial) to account for possible unobserved heterogeneity in the data and to assess the system-wide monthly frequency of PVC pipe breaks as a function of a number of observable explanatory variables.

3.1 Introduction

Aging drinking water systems in the U.S., and elsewhere, have presented water utilities with challenging issues that relate to rapid infrastructure deterioration (Environmental Protection Agency 2009). In the U.S., an estimated 700 water main breaks occur each day (Water Research Foundation, 2014). In addition, in 2013 the Center for Neighborhood Technology of the Great Lakes region of the U.S. estimated that 6.5 billion gallons of treated water are lost each year from roughly 63,000 leaking and aged pipes in that region alone, which is enough to meet the demand of 1.9 million people for a year (Center for Neighborhood Technology 2013). When a water main

[2] Zamenian, H., Faust, K., Mannering, F., Abraham, D., Iseley, T., 2017. Empirical assessment of unobserved heterogeneity and polyvinyl chloride pipe failures in water distribution systems. Journal of Performance of Constructed Facilities 31(5), 04017073. DOI: 10.1061/(ASCE)CF.1943-5509.0001067.

breaks, there are not only water losses but energy losses as well due to the interdependencies between the water and energy infrastructure systems. These energy losses manifest as additional energy expenditures for extracting water from natural resources as well as treating, pumping, and transporting it to the end users (Zamenian et al. 2015).

Understanding the relative characteristics of various pipe materials can assist in making more cost-effective decisions as to whether existing pipes are adequate to continue in service or in need of replacement. Information on pipe breaks, and many of the characteristics of the pipeline network (pipe material, pipe diameter, pipe length, pipe age, and so on), are often available from various water-utility databases, and these data can be statistically analyzed to provide a basis for pipeline renewal programs. Although a high number of water main breaks are often the result of the pipe-aging process (Makar et al. 2001), recent studies (Burn et al. 2005; Folkman 2012; Zamenian et al. 2017) have observed that a large number of breaks in more recently installed polyvinyl chloride (PVC) pipes.

The existing literature on the analysis of PVC pipe failures has often been limited to the comparison of PVC pipe failures in cast iron and ductile iron pipes (Wang et al. 2009). In addition, with few exceptions (Zamenian et al. 2017), most past studies have not addressed issues relating to factors such as local soil conditions, fluctuating pressures in pipes due to freeze-thaw cycles, and construction quality, all of which could significantly influence pipe-failure frequencies and the inferences drawn from the statistical analysis of pipe-failure data.

The intent of this chapter is to build on previous work by focusing solely on the analysis of PVC pipe failures, and considering the possibility of incomplete data, which would manifest itself as unobserved heterogeneity. Specifically, to account for potential unobserved heterogeneity, this chapter will consider models that allow estimated parameters to vary among monthly failure-frequency observations in response to potential unobserved effects (as opposed to traditional statistical approaches that estimate a fixed effect for each variable across all observations). Using readily available pipe-related data, it will be shown that the approach presented can provide new insights into the identification of PVC pipe failures.

3.2 Background and Literature Review

In the 1970s, the application of polyvinyl chloride (PVC) pipes in water distribution systems in North America resulted in a significantly lower material and labor cost relative to many competitive pipe materials such as cast iron and ductile iron (Leung et al. 2012). Based on a 2012 survey of 188 water utilities in North America (Folkman 2012), PVC pipe constituted 23% of the installations in the water pipeline networks, behind only the cast iron pipe (29%), and ductile iron pipe (28%). PVC pipes can be used in very corrosive environments, but they are likely to be affected by deterioration if they are exposed to weather, chemical attacks, or physical degradation from improper installation methods (Rajani and Kleiner 2001).

PVC pipes have failure modes that can be much different from those of other pipe materials. The five primary PVC failure modes are (Knight 2002): longitudinal crack failure; circumferential crack failure; blown section failure; softening failure; and degradation failure. Studies have shown that longitudinal cracking failure is the most common failure mode (Burn et al. 2005; Folkman 2012), and such cracks are often caused by varying temperatures, internal pressure or vacuum, third party damage, beam bending, and poor installation (Rahman and Watkins 2005). With regard to other PVC failures modes, circumferential crack failures are caused primarily by axial stresses induced by factors such as lateral ground movement, soil expansion around poorly supported pipe, friction between the pipe and soil interface, ground temperature change, and third-party damage (Burn et al. 2005). Blown section failures result when a section of the pipe wall weakens and gives way (Burn et al. 2005), mainly due to the cyclic pressure surge and fatigue. Softening failures can result from simple exposure to temperatures in excess of the material's general capability (Knight 2002). And finally, degradation failures typically result from chemical attacks from solvents and other corrosive elements.

Over the years there has been an abundance of research that has studied pipe failures in water distribution systems (Kirby 1981; Carroll 1985; Broutman et al. 1990; Moser and Kellogg 1994; Davis et al. 2007; Wang et al. 2009; Najafi 2010; Folkman 2012; Zamenian et al. 2017). Early research that considered the performance of PVC pipes included the work of Kirby (1981), which provided an assessment of 15 years of PVC pipe-breaks data in the U.K. The two main reasons given for choosing PVC pipes by these agencies were the material cost and the laying cost, with the only identified disadvantage of using PVC pipe being the occurrence of unexpected failures.

The failure rate (failures/mile/year) for PVC pipe was lower than cast iron pipe in 65% of the cases, higher in 29% of the cases and roughly equal in 6% of the cases. The causes of PVC pipe failures were categorized into failures due to adjacent excavation, tapping for service connections, and joint failures (poor performance of solvent welded joint and displacement of rubber rings). Also, the author stated that the manufacturing defects including inclusions, voids, spider-line defects, and surface defects, were the cause of a relatively high initial rate of failure for PVC pipes and higher rates of failure for large diameter PVC pipes (those more than 12-inch in diameter).

In other work, Carroll (1985) assessed failure modes of PVC pipes in high pressure applications (such as gas pipeline distribution systems), in response to a number of incidents being reported as having unrecognizable causes of failure. The author identified voids in the PVC material as the cause of weakening in the PVC pipe and fittings. It was determined that the observed voids in PVC pipes and fitting materials were primarily due to gas being entrained in the PVC material, or due to the incorporation of foreign particles, such as sand, during manufacturing process. The research recommended that the PVC pipe should be used only for low-pressure liquid, at or near ambient temperature, and that care should be taken to protect the PVC pipe from UV light and temperature cycling before installation.

Broutman et al. (1990) utilized experimental analysis of the failure of PVC pipe as a part of a forensic investigation of PVC pipe failures in water distribution systems that occurred in 1979 and 1982. Fractures along the pipe (longitudinal cracks) were diagnosed as the primary mode of failure. Their field investigation and material testing of the PVC pipe failures determined that the mechanical properties of the pipes were appropriate under loading stress, and the results of PVC material testing did not show any deterioration in the pipe material. The authors therefore surmised that the fractures along the PVC pipes were due to improper installation that created stress causing settlement and poorly compacted backfills.

Moser and Kellogg (1994) conducted a survey of 162 water utilities and 29 engineering firms in North America to assess the performance of 2” to 36-inch diameter PVC pipes in water distribution systems. The survey results indicated that approximately half of the failures in PVC pipes that occurred in the first year were due to poor installation, damage during excavation (third-party damages), and the effects of ultraviolet light (sunlight exposure).

Davis et al. (2007) developed a physical probabilistic model using linear elastic fracture mechanics theory to analyze PVC pipe failures in water distribution systems. Due to limited recorded failure data for PVC pipes, linear elastic fracture mechanics was proposed to analyze brittle fracture failures and the failure rates. The time to failure (physical fracture) in PVC pipes resulting from internal pressure, soil deflection, and residual stress was identified using linear elastic fracture mechanics. The crack sizes then were modeled as a stochastic variable, and the lifetime probability distribution was approximated by Monte Carlo simulation. The study estimated the average failure rate (breaks/100km/year) of three different types of PVC pipes: 2-inch diameter, 4-inch diameter, and 6-inch diameter pipes. The comparison between the predicted failure rates and the observed failure rates indicated that the predicted failure curve had a reasonable agreement within 95% confidence limits with the actual failure data. Results indicated that when the age of the 4" and 6" diameter PVC pipes in distribution system increases, the average failure rates increase proportionally, but the exact failure rate was not captured. In addition, it was observed that the 2", 4", and 6" diameter PVC pipes had higher rates of failure in the early years of installation (between years one to five). By plotting the curves of the predicted average failure rate versus the ages of the 2", 4", and 6" diameter PVC pipes, the study also found that as PVC pipes aged, the rates of failure generally decreased.

Wang et al. (2009) utilized a multiple regression model to study the annual water pipe break rates (breaks/km/year) based on a pipeline database from three municipalities in Canada for a period of 15 years (1987-2001). They concluded that the annual break rate for 6-inch PVC pipe decreased as the length of the PVC pipe increased. The study also found that newer PVC pipes (those in place 10 years ago) had higher rates of failure compared to the aged PVC pipe (those in place for 25, 50, and 75 years) due to poor quality installation. The range of PVC pipe age in this study was between 10 and 75 years. However, the models do not account for the possibility that the effect of explanatory variables may vary across observations (a random parameters approach is not used).

Folkman (2012) conducted a survey to assess the water main break rates among 188 water utilities in North America. The survey respondents were divided into four utility classifications (small, medium, large, and very large) based on the size of the utility and the total length of pipe. The survey indicated that cast iron pipe comprised 29 percent of the total pipes in a distribution system, ductile iron pipe accounted for 28 percent, and PVC accounted 23 percent. PVC pipes contributed to five percent of the water pipe failures in the distribution system, and 51.5 percent of the failed PVC pipes were between 0 and 20 years of age.

Finally, Zamenian et al. (2017) attempted to account for unobserved heterogeneity (factors known to affect failure frequencies but not included in the data) by estimating a random parameters negative binomial model to study the frequency of water main breaks in a water distribution system using readily available water-main data from two cities in the Midwest region of the U.S. (Indianapolis and Fort Wayne, Indiana). Their statistical approach allowed for the possibility that the effect of explanatory variables on failure frequencies may vary across the observations, thus accounting possible unobserved factors affecting pipe failures. The findings of this study regarding PVC pipes (one of the pipe materials considered) indicate that statistical models from one city to the next are not really possible because the effect of specific variables is clearly dependent on specific system characteristics, and hence there is a need for each city to develop its own statistical models. For instance, increasing length of 6” and 8” PVC pipes in the water distribution system in the City of Indianapolis, IN was found to increase the break frequency whereas, in Fort Wayne, IN increasing the length of 6” and 8” PVC pipes was found to decrease the break frequency.

Past research on PVC pipe failures has undoubtedly provided important insights into the failure process and performance of this pipe material. However, the review of the literature shows that the many factors known to affect pipe-failure probabilities are unlikely to be available in conventional data bases. These factors include temperature variation, internal pipe pressures, possible third-party damage, pipe stresses due to changing soil conditions (settlement, compaction, water saturation, etc.), poor installation, PVC material imperfections during manufacture, and possible exposure of the PVC pipe to ultraviolet light and temperature cycling before installation. These unobserved factors can be statistically addressed as unobserved heterogeneity (as in the Zamenian et al. study discussed above). In this chapter, the authors will address issues relating to unobserved heterogeneity using a random parameters negative binomial model for PVC pipes in particular (as opposed to the early Zamenian et al. study which considered all pipe materials in a single failure-frequency model). This will be addressed using a rich database that covers a 21-year period of water-system pipe failures in Indianapolis, Indiana.

3.3 Methodological Approach

Statistically modeling failures of PVC pipes in water distributions systems is usually undertaken as a study of break frequencies over some specified time period (such as a month). Statistically, the dependent variable in such models will be a non-negative integer, and explanatory variables can include commonly collected factors such as the length and age of the PVC pipes, possible environmental observations (related to month of year, etc.) and so on. To develop an estimable model of the frequency of PVC breaks in a water distribution system, the Poisson regression and its variants are a natural staring point (Washington et al. 2011). This approach starts by letting $P(n_i)$ be the probability of observing n PVC breaks in a water distribution system in observation-month i. The Poisson equation is then written as,

$$P(n_i) = \frac{EXP(-\lambda_i)(\lambda_i)^{n_i}}{n_i\,!} \qquad (3.1)$$

where λ_i is the Poisson parameter for observation month i.

To incorporate explanatory variables into the model, a Poisson regression specifies the Poisson parameter λ_i (which is also the expected number of water system failures in month i) as a function of explanatory variables using the log-linear function (this avoids the possibility of a negative λ_i which would make estimation of Equation 3.1 impossible),

$$\lambda_i = EXP(\boldsymbol{\beta}\mathbf{X}_i) \qquad (3.2)$$

where Xi is a vector of explanatory variables and β is a vector of estimable parameters (Washington et al. 2011).

In pipe-failure data, a Poisson model may not always be appropriate since the Poisson distribution restricts the mean and variance to be equal $(E[n_i] = VAR[n_i])$. In the case of pipe failures, the data are typically overdispersed (Zamenian et al. 2017) with the mean number of failures being much less than the variance $(E[ni] << VAR[ni])$. With over dispersed data, estimation of a standard Poisson regression would result in the standard errors of the estimated parameter vector β to be incorrect. To account for the possibility of overdispersion, a negative binomial model can be derived by rewriting, $\lambda_i = EXP(\boldsymbol{\beta}\mathbf{X}_i + \varepsilon_i)$, where $EXP(\varepsilon_i)$ is a Gamma-distributed error term with mean 1 and variance α. The addition of the $EXP(\varepsilon_i)$ term allows the variance to differ from the mean as $VAR[n_i] = E[n_i][1+ \alpha E[n_i]] = E[n_i]+ \alpha E[n_i]^2$. With this, the negative binomial probability density is (Washington et al., 2011),

$$P(n_i) = \left(\frac{\Gamma\left[(1/\alpha)+n_i\right]}{\Gamma(1/\alpha)n_i!} \right) \left(\frac{1/\alpha}{(1/\alpha)+\lambda_i} \right)^{1/\alpha} \left(\frac{\lambda_i}{(1/\alpha)+\lambda_i} \right)^{n_i} \qquad (3.3)$$

where $\Gamma(.)$ is a gamma function and all other terms are as previously defined.

Note that in Equation 3, the Poisson regression becomes the limiting model of the negative binomial regression as α approaches zero. Thus, if α is significantly different from zero, the negative binomial is statistically correct and, if it is not, the simple Poisson model is correct. The Poisson and negative binomial models can be readily estimated using standard maximum likelihood methods (Washington et al. 2011).

As previously discussed, the probability of pipe failure is likely to be affected by many factors that are not included in traditional databases (such as internal pipe pressures and temperature, pipe stresses due to changing soil conditions, poor installation, PVC material imperfections during manufacture, and possible exposure of the PVC pipe to ultraviolet light and temperature cycling before installation). Statistically, these factors can be treated as unobserved heterogeneity. In recent years, models that address unobserved heterogeneity have become widely used in a number of fields including economics and highway-safety analysis (see Mannering et al. 2016 for a review of methods). These "heterogeneity" models attempt to account for unobserved factors by allowing the effect of observed variables (Xi in the above equations) to vary across individual observations or groups of observations. Thus, the β vector in the above equation will be subscripted *i* for individual observation months or g for groups of observation months. Consider the case where unobserved heterogeneity is accounted for by allowing the effects of observed explanatory variables to vary across individual observation months, *i*. To incorporate this into a statistical model, each estimable parameter was written on explanatory variable k in the vector Xi as (Anastasopoulos and Mannering 2009; Mannering et al. 2016),

$$\beta_{ik} = \beta_k + \varphi_{ik} \qquad (3.4)$$

where β_{ik} is the parameter of the kth explanatory variable for observation-month $_i$, β_k is the mean parameter estimate across all months for the kth explanatory variable, and φ_{ik} is a randomly distributed scalar term that captures unobserved heterogeneity across observation months. The φ_{ik}

term can assume any specified distribution (such as the normal distribution or others). Because of the assumed distribution, models that capture unobserved heterogeneity in this way are referred to as random-parameters models, even though the model estimation produces a fixed parameter for each observation-month *i*. With a specified distribution of φ_{ik} for each included explanatory variable k in the model, if the variance of this distribution is not significantly different from zero, a conventional fixed parameter (one parameter estimate for all observations) will result and if the variance of this distribution is significantly different from zero each observation *i* will have its own β_{ik} (referred to as a random parameter). Estimation of such random parameters models is typically achieved with maximum simulated likelihood (Bhat 2003; Washington et al. 2011).

A potential drawback of this random parameters approach in capturing unobserved heterogeneity is that a parameter distribution must be assumed for estimation purposes, and that it is inherently assumed that each observation has its own parameter (although groups of observations having the same parameter can be estimated, these groups must be specified). An alternative approach is to consider the possibility that unknown groups (or classes) of observations have shared the same unobserved heterogeneity. For this study PVC-pipe example, suppose that 20% of the PVC pipes installed were subjected to ultraviolet light and temperature cycling before installation, but it is unclear (it is thus unobserved heterogeneity). The authors would naturally expect this group of pipes to have a much different failure rate than the other 80% of PVC pipe installations. In this case, the previous random-parameters approach would not be appropriate since the heterogeneity is not from one observation to the next, but between just two groups of observations. To account for this type of heterogeneity, a latent class approach can be applied where each unobserved class (group) has its own parameter vector β. To do this, consider a model where the probability of belonging to a latent class is specified by a multinomial logit model with (Greene and Hensher, 2003; Mannering et al. 2016),

$$P_i(c) = \frac{EXP(\boldsymbol{\theta}\mathbf{Z}_{ic})}{\sum_C EXP(\boldsymbol{\theta}\mathbf{Z}_{ic})} \qquad (3.5)$$

where $P_i(c)$ is the probability of observation-month *i* belonging to latent class *c*, Z_{ic} is a vector of explanatory variables specific to observation *i* and latent class *c* (including a constant) and θ is a vector of estimable parameters that determines the probability of observation month *i* belonging to class c. With Equation (5), and $\lambda_i \mid c = EXP\left(\boldsymbol{\beta}_c \mathbf{X}_i + \varepsilon_i\right)$, the negative binomial model becomes (compare to Equation 3.3),

$$P(n_i) \mid c = \left(\frac{\Gamma\left[(1/\alpha_c) + n_i\right]}{\Gamma(1/\alpha_c) n_i!}\right)\left(\frac{1/\alpha_c}{(1/\alpha_c) + \lambda_i \mid c}\right)^{1/\alpha_c}\left(\frac{\lambda_i \mid c}{(1/\alpha_c) + \lambda_i \mid c}\right)^{n_i} \qquad (3.6)$$

where $P_{(ni)|c}$ is the probability of observation month i having n failures conditional on the observation month i belonging to class c, α_c is the dispersion parameter for class c, and other terms are as previously defined.

To fully assess the possible impacts of unobserved heterogeneity in this research data, the authors considered both random parameters and latent class models of PVC pipe-break frequencies. Both modeling approaches uncovered significant unobserved heterogeneity in the data and showed broadly similar results (it should be noted that in all estimated latent class models, two latent classes were found since extensions to 3 or more latent classes did not significantly improve the log-likelihood at convergence).

Finally, to determine the impact of individual variables on monthly break frequencies, average marginal effects are calculated for each statistically significant explanatory variable. The computed average marginal effect gives the influence that a one-unit increase in explanatory variable x has on the expected number of water system failures per month, λ.

3.4 Empirical Setting

Data regarding the PVC pipe breaks that occurred in the City of Indianapolis, Indiana between January 1990 and December 2010 were collected from the City of Indianapolis pipeline database. The Indianapolis water system has PVC pipes ranging in diameter from less than 4” to 36”. However, roughly 85% of the PVC pipe-kilometers are 6”, 8”, and 12” diameter pipes. Due to the relative rarity of PVC pipes in other diameters, the statistical analysis was restricted to consider only 6”, 8”, and 12” diameter pipes. Thus, a total of 252 observations of water main breaks (over 21-year period) were categorized into three homogeneous cohorts with respect to pipe diameter (6”, 8”, and 12” diameter pipes). Table 3.1 provides summary statistics for the available variables for the statistical analysis over the 21-year period of analysis.

Table 3.1. Summary Statistics

Variable Description	**Units**	**Mean (Std. Dev.)**
Number of PVC Pipe Breaks per Month: January	Breaks/Month	10.19 (5.21)
Number of PVC Pipe Breaks per Month: February	Breaks/Month	15.12 (4.63)
Number of PVC Pipe Breaks per Month: March	Breaks/Month	13.41 (8.14)
Number of PVC Pipe Breaks per Month: April	Breaks/Month	14.26 (4.83)
Number of PVC Pipe Breaks per Month: May	Breaks/Month	11.69 (6.53)
Number of PVC Pipe Breaks per Month: June	Breaks/Month	13.81 (5.76)
Number of PVC Pipe Breaks per Month: July	Breaks/Month	16.68 (6.35)
Number of PVC Pipe Breaks per Month: August	Breaks/Month	9.63 (4.32)
Number of PVC Pipe Breaks per Month: September	Breaks/Month	13.28 (6.13)
Number of PVC Pipe Breaks per Month: October	Breaks/Month	10.86 (3.28)
Number of PVC Pipe Breaks per Month: November	Breaks/Month	12.53 (7.38)
Number of PVC Pipe Breaks per Month: December	Breaks/Month	11.86 (5.74)
Average Age of Polyvinyl Chloride (PVC) Pipeline System	Year	10.22 (4.62)
25th Percentile of Polyvinyl Chloride (PVC) Pipeline Age	Year	5.36 (1.23)
50th Percentile of Polyvinyl Chloride (PVC) Pipeline Age	Year	12.89 (3.94)
75th Percentile of Polyvinyl Chloride (PVC) Pipeline Age	Year	15.52 (1.76)
90th Percentile of Polyvinyl Chloride (PVC) Pipeline Age	Year	19.21 (1.27)
Length of Polyvinyl Chloride (PVC) Pipe	Miles	700 (465.07)
Mean Monthly Temperature	Degrees Fahrenheit	54.86 (33.47)
Average Precipitation per Month	Inches	3.5 (21)
Average Snow Depth per Month	Inches	0.7 (0.4)

To test if the monthly frequency of water main breaks in 6", 8", and 12" diameter pipes are fundamentally different for each pipe size, a likelihood ratio test is conducted. In this case the test statistic is (Washington et al. 2011),

$$X^2 = -2\left[LL(\boldsymbol{\beta}_T) - LL(\boldsymbol{\beta}_6) - LL(\boldsymbol{\beta}_8) - LL(\boldsymbol{\beta}_{12})\right] \qquad (3.7)$$

where $LL(\boldsymbol{\beta}_T)$ is the log-likelihood at convergence of the model estimated with the data from all pipe diameters (diameters 6", 8" and 12"), $LL(\boldsymbol{\beta}_6)$ is the log likelihood at convergence of the model using only data from the 6" pipe diameter, $LL(\boldsymbol{\beta}_8)$ is the log-likelihood at convergence of the model using only data from the 8" pipe diameter, and $LL(\boldsymbol{\beta}_{12})$ is the log-likelihood at convergence of the model using only data from the 12" pipe diameter. This X^2 statistic is χ^2 distributed with degrees of freedom equal to the summation of the number of estimated parameters in the separate pipe models minus the number of estimated parameters in the combined three-pipe diameter model. The likelihood ratio test provides the confidence level at which the null hypothesis that the models of the three pipe diameters (6", 8" and 12") are the same, can be rejected. Using the random parameters negative binomial model, the likelihood ratio test for the three pipe diameter models revealed that the null hypothesis that different pipe diameters were the same, could be rejected with over 95% confidence (using the latent class modelling approach, the null hypothesis is also rejected, with over 90%). This test result clearly suggests that separate models by pipe diameter are warranted.

3.5 Results and Discussion

The random parameters model estimations of monthly-failure frequencies for 6", 8", and 12" diameter pipes in the Indianapolis water distribution system are shown in Tables 3.2, 3.3, and 3.4 respectively. Table 3.5, 3.6, and 3.7 present the estimations results from latent-class negative binomial estimation for 6", 8", and 12" diameter pipes in the Indianapolis water distribution system respectively. In addition to parameter estimates, marginal effects are also calculated and provided in these tables. Marginal effects provide the effect that a one-unit change in the explanatory variable (x) has on the expected number of water system failures per month. For both models, estimated results indicate that many variables were found statistically significant in influencing the number of PVC water-main breaks per month, and also show that the negative binomial dispersion parameter (α in the above equations) is statistically significant, thus validating the negative binomial over the simple Poisson regression.

Table 3.2. Random Parameters Negative Binomial Regression of Polyvinyl Chloride (PVC) Pipe-Break Frequency per Month for 6-inch Diameter Pipe in Indianapolis

Parameter Type	**Variable Description**	**Parameter Estimate (t-statistic)**	**Parameter Standard Deviation (t-statistic)**	**Marginal Effect**
Fixed Parameters	Constant	1.489 (1.69)	–	–
	February Indicator (1 if month is February, 0 if otherwise)	0.698 (2.63)	–	6.196
	March Indicator (1 if month is March, 0 if otherwise)	-0.146 (-3.37)	–	-2.125
	November Indicator (1 if month is November, 0 if otherwise)	0.538 (4.82)	–	5.163
Random Parameters (*all normally distributed*)	90^{th} Percentile of 6” Pipe Age in Years	-0.866 (-1.80)	1.902 (2.72)	-2.892
	Length of 6” PVC Pipe in Miles	0.021 (1.97)	0.036 (3.89)	0.682
	Average Temperature per Month in Degrees Fahrenheit	-0.056 (-3.46)	1.016 (2.61)	-1.703
	Negative binomial dispersion parameter (α)	1.863 (2.37)	–	–
	Log likelihood at zero	-2093.01		
	Log likelihood at convergence	-893.38		
	Number of observations	252		

Table 3.3. Random Parameters Negative Binomial Regression of Polyvinyl Chloride (PVC) Pipe-Break Frequency per Month for 8-inch Diameter Pipe in Indianapolis

Parameter Type	**Variable Description**	**Parameter Estimate (t-statistic)**	**Parameter Standard Deviation (t-statistic)**	**Marginal Effect**
Fixed Parameters	Constant	3.020 (7.01)	–	–
	November Indicator (1 if month is November, 0 if otherwise)	1.365 (2.21)	–	1.986
	August Indicator (1 if month is August, 0 if otherwise)	-0.731 (-1.65)	–	-1.012
	Average Temperature per Month in Degrees Celsius	-0.360 (-2.41)	–	-0.091
Random Parameters (*all normally distributed*)	Average Age of 8" PVC Pipe in Years	-0.0072 (-2.92)	2.358 (4.73)	-0.613
	Length of 8" PVC Pipe in Miles	0.0503 (6.91)	0.2301 (2.36)	0.041
	Negative binomial dispersion parameter (α)	12.104 (5.01)	–	–
	Log likelihood at zero	-2805.98		
	Log likelihood at convergence	-719.33		
	ρ^2 [$1 - LL(0)/LL(\boldsymbol{\beta})$]	0.64		
	Number of observations	252		

Table 3.4. Random Parameters Negative Binomial Regression of Polyvinyl Chloride (PVC) Pipe-Break Frequency per Month for 12-inch Diameter Pipe in Indianapolis

Parameter Type	**Variable Description**	**Parameter Estimate (t-statistic)**	**Parameter Standard Deviation (t-statistic)**	**Marginal Effect**
Fixed Parameters	Constant	-3.112 (-2.43)	–	–
	January Indicator (1 if month is January, 0 if otherwise)	0.529 (4.40)	–	3.050
	November Indicator (1 if month is November, 0 if otherwise)	0.302 (2.25)	–	1.743
	December Indicator (1 if month is December, 0 if otherwise)	0.433 (3.69)	–	2.497
	25th Percentile of 12” Pipe Age in Years	1.867 (3.17)	–	2.017
Random Parameters(*all normally distributed*)	Average Age of 12” PVC Pipe in Years	2.035 (2.95)	0.556 (2.14)	0.601
	Length of 12” PVC Pipe in Miles	-0.219 (-8.02)	0.0176 (4.91)	-0.023
	Average Temperature per Month in Degrees Celsius	-0.0013 (-1.99)	2.689 (2.02)	-0.122
	Negative binomial dispersion parameter (α)	9.127 (4.31)	–	–
	Log likelihood at zero	-1468.12		
	Log likelihood at convergence	-837.10		
	Number of observations	252		

Table 3.5. Latent-Class Negative Binomial Regression of Polyvinyl Chloride (PVC) Pipe-Break Frequency per Month for 6-inch Diameter Pipe in Indianapolis

	Latent Class I		**Latent Class 2**		
Variables Description	Parameter Estimate	t-statistics	Parameter Estimate	t-statistics	Marginal Effects
Constant	1.397	1.138	-2.020	-2.368	-3.689
Month Indicator (1 if January, 0 if otherwise)	2.422	4.028	1.985	2.633	11.901
Month Indicator (1 if November, 0 if otherwise)	1.025	8.061	0.141	0.259	7.215
Month Indicator (1 if December, 0 if otherwise)	1.487	16.152	0.524	1.068	20.830
Average Age of Polyvinyl Chloride (PVC) Pipe in Years	-0.361	-0.093	-0.201	-2.222	-0.029
Length of Polyvinyl Chloride (PVC) Pipe in Miles	0.061	1.732	0.483	0.052	1.209
Class Probability	0.594	7.179	0.405	4.912	-
Log likelihood at zero	-13768.49				
Log likelihood at convergence	-816.766				
Number of observations	252				

Table 3.6. Latent-Class Negative Binomial Regression of Polyvinyl Chloride (PVC) Pipe-Break Frequency per Month for 8-inch Diameter Pipe in Indianapolis

	Latent Class I		**Latent Class 2**		
Variables Description	Parameter Estimate	t-statistics	Parameter Estimate	t-statistics	Marginal Effects
Constant	0.649	0.961	2.086	17.267	10.461
Month Indicator (1 if May, 0 if otherwise)	-0.426	-0.380	-0.596	-2.485	-3.354
Month Indicator (1 if July, 0 if otherwise)	-0.466	-0.432	-0.516	-2.316	-3.052
Month Indicator (1 if November, 0 if otherwise)	0.567	0.363	0.195	0.363	1.747
Length of Polyvinyl Chloride (PVC) Pipe in Miles	0.002	2.0558	0.001	4.449	0.010
Average Age of Polyvinyl Chloride (PVC) Pipe in Years	0.082	0.932	-0.089	-3.765	-0.282
Class Probability	0.250	1.902	0.749	5.687	
Log likelihood at zero	-3183.723				
Log likelihood at convergence	-663.5809				
Number of observations	252				

Table 3.7. Latent-Class Negative Binomial Regression of Polyvinyl Chloride (PVC) Pipe-Break Frequency per Month for 12-inch Diameter Pipe in Indianapolis

	Latent Class I		Latent Class 2		
Variables Description	Parameter Estimate	t-statistics	Parameter Estimate	t-statistics	Marginal Effects
Constant	8.646	1.576	-3.311	-2.686	-5.858
Month Indicator (1 if March, 0 if otherwise)	-1.184	-1.700	-0.455	-2.357	-3.382
75th Percentile of Pipeline Age	-0.514	0.176	0.134	4.164	0.062
Length of Polyvinyl Chloride (PVC) Pipe in Miles	0.009	0.887	-0.012	-3.659	-0.047
Average Precipitation per Month in Inches	-3.343	-1.672	0.199	0.398	-2.713
Average Age of Polyvinyl Chloride (PVC) Pipe in Years	0.620	2.282	0.296	3.941	1.708
Class Probability	0.190	2.488	0.809	10.550	-
Log likelihood at zero	-2790.347				
Log likelihood at convergence	-648.890				
Number of observations	252				

3.5.1 Effects of Pipe Age on PVC Pipe Failure

Tables 3.2, 3.3, 3.4, 3.5, 3.6, and 3.7 show that the age of the PVC pipes in the 6”, 8”, and 12” pipeline networks was found to be a statistically significant variable in both models. In the 6” PVC pipeline network (Table 3.2), a one-year increase in the 90th percentile of PVC pipe age decreased the monthly break frequency by 2.892 on average, as reflected by the calculated marginal effect. This variable was found to be a normally distributed random parameter with a mean -0.886 and standard deviation of 1.902, which shows that the effect of the 90th percentile of PVC pipe age on monthly break frequencies has considerable heterogeneity across observations. With this mean and standard deviation, an increase in the 90th percentile age decreases monthly-failure frequencies for 67.9% of the monthly observations and increases them for 32.1% of the monthly observations.

Turning to the effects of PVC pipe age in latent-class model, the average age of 6” PVC pipes (as opposed to the 90th-percentile age) was found to produce the best statistical fit. The estimation results (Table 3.5) indicated that a one-year increase in the average age of PVC decreased the probability of monthly break frequency by 0.029 on average. The result in both models (random parameter model and latent-class model) indicates as the PVC pipes “mature” in the water distribution system, the likelihood of failure generally decreases, but the effects vary by monthly observation. This result supports previous findings relating to the higher failure of PVC pipes during the early stage of the pipe’s life-cycle (Moser and Kellogg 1994; Burn et al. 2005; Davis et al. 2007; Wang et al. 2009; Folkman 2012; Zamenian et al. 2017), but also accounts for the effects of the natural aging of pipes and the resulting increase in failure frequencies.

In the 8” PVC pipeline network, average age (as opposed to the 90th-percentile age) was found to produce the best statistical fit. The model estimation results show that a one-year increase in the average age of PVC pipes decreases the monthly break frequency by 0.613 on average (Table 3.3). However, this variable produced a normally distributed parameter with a mean of -0.0072 and standard deviation of 2.358 (Table 3.3). This distribution shows that as the average age increases roughly half of the monthly observations have an increase in frequency and half have a decrease in frequency. With regard to latent-class negative binomial model, the average age of 8” PVC pipe variable was found to be significant on monthly break frequency. The estimation results (Table 3.6) indicated that a one-year increase in the average age of PVC decreased the probability of monthly break frequency by 0.282 on average. The parameter estimates for this variable show negative sign in one of the classes and positive sign in the other one (Table 3.6), indicated possibility of having latent classes with parameters distributed across observations within each class. The average age of 8” diameter PVC pipes in the City of Indianapolis water distribution system was 12 years over the study period. In looking at the failure data, older 8” PVC pipes (in this case more than 10 years old) tended to have a lower percentage of failure. Based on the estimated model (Table 3.3), PVC pipes installed over 10 years ago are less likely to break. This result supports the previous finding (90th percentile of PVC pipe age) in 6” PVC pipe model that the probability of failure in PVC pipes may decrease as the pipes get older.

In contrast to the 8” PVC pipe model, as the average age of the 12” PVC pipes increases in the water distribution system, the frequency of water main breaks tended to more consistently increase (Table 3.4). This variable resulted in a normally distributed random parameter with a mean of 2.035 and standard deviation of 0.556. In this case, the random parameter model estimation indicated that (with this mean and standard deviation), for nearly all monthly observations a higher average age of 12” PVC pipe increased the number of main breaks per month, although there is significant variability in the effect of age across observations (as indicated by the significant random parameter). The 2010 GIS data from the City of Indianapolis shows that the average age of the 12” PVC pipe was five years and these pipes had a higher likelihood of failure compared to pipes more than 10 years old. Also, the estimated model (Table 3.4) shows that as the 25th percentile of the age of PVC pipe increases, the number of breaks increase (by an average of 2.017 per month as indicated by the marginal effect). This result supports the observation of a higher number of breaks in PVC pipes during the early stage of pipe installation.

3.5.2 Effects of Pipe Length on PVC Pipe Failure

Tables 3.2, 3.3, 3.5, and 3.6 show that the number of breaks in 6” and 8” diameter PVC pipes tend to increase as the length of PVC pipes increase in the water distribution system. With regard to latent-class model, the marginal effects estimates (Tables 3.5 and 3.6) showed that a one-mile increase in the length of 6” and 8” diameter PVC pipe in a water distribution system increased the break frequency per month by 1.209 and 0.010 on average, respectively. The variable effects of length may reflect a complex relationship between pipe length, joints, and monthly variations in temperatures, water pressures, etc. The marginal effects for random parameter model estimates (Tables 3.2 and 3.3) indicate that a one-miles increase in the length of 6” and 8” diameter PVC pipe increased the break frequency per month by 0.682 and 0.041 on average, respectively. However, both 6” and 8” PVC pipes estimation results produced statistically significant random parameters. The normally distributed random parameter for the length of 6” PVC pipe (Table 3.2) shows that for 72% of the monthly observations longer pipe lengths increased failure frequencies and that for 28% of monthly observations failure frequencies decreased. The length of 8” diameter PVC pipe was also found to be a normally distributed random parameter (with a mean of 0.0503 and standard deviation of 0.2301, Table 3.3) which indicates that for roughly 59% of the observations higher installation lengths of 8” diameter PVC pipe in the water distribution system increases the frequency of water main breaks, and for 41% of observations it decreases the frequency of breaks.

Analysis of PVC pipe installation in the GIS database of the City of Indianapolis indicated that the length of 6" PVC pipe in the water distribution system increased by 327 miles from 1990 to in 2010 period. In addition, the length of 8" PVC pipe in the water distribution system has increased by 500 miles from 1990 to 2010 period. Both 6" and 8" diameter PVC pipes are classified as small diameter pipes, and the main application of 6" and 8" diameter PVC pipes are in service connections to the main line. Installation of 6" and 8" PVC pipe in a water distribution system increases the number of joints along the PVC pipes, as well as increases the number of service connections to the main line. Because 6" and 8" diameter PVC pipes are classified as small diameter pipes for distributing drinking water in a neighborhood area, these pipes are more likely to be affected by poor tapping and installation at service line connections. When the length of 6" and 8" PVC pipes is increased, the likelihood of breaks in these small diameter pipes is also increased. In order to improve the installation of service connections, Burn et al. (2005) recommended that water utilities conduct a training program for their crews and contractors on PVC pipe connection installation.

The number of monthly breaks in 12" diameter PVC pipes decreased as the length of PVC pipes of this diameter increased in the water distribution system for virtually all observations, but again the parameter was found to vary significantly across observations (normally distributed with a mean of -0.219 and a standard deviation of 0.0176, Table 3.4). Similar results for the effects of 12" PVC pipe length on monthly break frequency was found in latent-class model. Estimated results indicated that a one-mile increase in the length of 12" diameter PVC pipe in a water distribution system decreased the break frequency per month by 0.047 on average. The 12" diameter PVC pipes tend to have fewer service connections along the pipe, therefore, the likelihood of improper installation at the joints was lower which likely reflect the effect-of-length findings. Based on the assessment of the PVC pipe installation in the Indianapolis GIS database, 82% of the 12" diameter PVC pipes were used in the distribution and transmission system, and therefore there are fewer service line connections in 12" diameter PVC pipes, leading to a lower likelihood of failure at connection points.

3.5.3 Effects of Temperature on PVC Pipe Failure

The estimated results for the 6”, 8”, and 12” PVC pipes show (Tables 3.2, 3.3 and 3.4) that the frequency of PVC pipe breaks decreases as the average temperature per month increases. For the 6” PVC pipe model, this variable was found to be a normally distributed random parameter (with a mean of -0.056 and a standard deviation of 1.016, Table 3.2), implying that the effect of increasing temperatures decreased failure frequencies in roughly 52% of the monthly observations and increased them in 48% of the monthly observations. For the 12” PVC pipe model, this variable was found to be a normally distributed random parameter (with a mean of -0.0013 and a standard deviation of 2.689, Table 3.2), implying that the effect of increasing temperatures decreased failure frequencies in roughly 50% of the monthly observations and increased them in 50% of the monthly observations. The random parameter reflects the fact that there are unobserved variables (such as level of soil moisture, depth of buried pipes, pipe wall thickness) that may influence the break frequency. For instance, the depth of buried pipe has a direct impact on water main breaks in cold temperature climate due to the frost penetration. Finding that increasing temperature decreases the failure frequency is consistent with issues caused by cold weather, and with previous research on the effects of climate and temperature on water main breaks (Zamenian et al. 2017). However, the significance of standard deviation in 6” and 12” PVC pipes shows significant heterogeneity of temperature effects across observations.

With these results, it is important to keep in mind that the temperature effects must also be viewed in light of the various monthly indicator variables that were found to be significant in the models. For example, in the random parameters models, in the 6” PVC model (Table 3.2), February and November indicators showed in significant increases in monthly break frequencies in these months (6.196 and 5.163 more breaks per month, respectively, as indicated by the marginal effects). In the 8” PVC model (Table 3.3), the November indicator showed in significant increases in monthly break frequencies (1.986) more breaks per month as indicated by the marginal effect. Finally, in the 12” PVC model (Table 3.4), January, November and December indicators all showed in significant increases in monthly break frequencies (3.050, 1.743, 2.497 more breaks per month, respectively, as indicated by the marginal effects). While there are clearly complex relationships among temperature effects and various pipe diameters, it is also clear that the month of November has higher break frequencies likely due to a combination of falling temperatures, freeze-thaw cycles, and soil moisture conditions.

3.6 Conclusion

This chapter focused on the development of a model for assessing the monthly frequency of water main breaks in water distribution systems using a statistical analysis of readily available pipe data. It demonstrates a methodological approach that accounts for the effects of unobserved heterogeneity, which is a potentially important consideration given data limitations typically encountered in the assessment of pipe failures. The findings show that the random parameters negative binomial model discussed herein is statistically superior to traditional fixed parameters Poisson and negative binomial models, and that additional insights can be gained by looking at patterns of unobserved heterogeneity that are reflected in the distribution of parameter estimates across observations.

The statistical analysis clearly shows the importance of diameter, age, and length in determining the frequency of PVC pipe failures, and the statistical significance of random parameters in the pipe-diameter models underscores the importance of unobserved heterogeneity in the data. The source of this unobserved heterogeneity likely relates to unobserved variations in soil types and conditions (water saturation levels and soil temperatures), pipe/water temperatures, water pressure, tapping and joint installation quality, and other factors that are not typically available in data bases. For the future work, having comprehensive pipeline characteristics data, such as depth of buried pipe, surrounding soil characteristics, water pressure inside the pipe, pipe wall thickness, and conditions above the pipe, material specifications, and construction procedures can improve the model provide and provide additional insights into the factors that affect break frequencies. More elaborate databases will reduce such heterogeneity and improve model estimation results further, but these data can be costly and time-consuming to collect. In the absence of such elaborate data, this chapter shows that heterogeneity models, such as those based on random parameters and latent class concepts, have the potential to provide important new insights into pipe-failure frequencies relative to traditional statistical approaches.

4. HOUSEHOLD ATTITUDES TOWARD WATER-RATE INCREASES BASED ON PERCEPTION OF WATER SERVICE RELIABILITY AND QAULITY

[A version of this chapter is under review at the ASCE Journal of Water Resources Planning and Management].[3]

Due to the high costs associated with maintaining and upgrading water infrastructure systems, selecting an appropriate water-rate to charge for water service is a crucial step for water utilities. Understanding the consumption patterns under different rate conditions is important because revenues generated from consumers form the backbone of water utilities' financial model. This chapter describes the results of a statistical analysis based on a survey of household attitudes towards water service reliability and quality in a Midwestern U.S. city, to identify influential factors that are likely to be associated with supporting or opposing water-rate increases, as well as influencing water consumption patterns after such rate increases. Using a multivariate binary probit approach, the statistical estimations cover a range of socioeconomic factors affecting individuals' likelihood of supporting increases in water-rates. The results could provide insights as to how individuals are likely to respond to water-rate increases based on the reliability of current water services and the quality of the supplied water.

4.1 Introduction

Declining amounts of freshwater resources and the increasing population, combined with concerns globally about deteriorating water infrastructure systems and climate change events, have posed significant challenges to the decision-makers as they seek to provide safe, reliable, and clean drinking water for communities (Motoshita et al. 2018). According to the American Society for Civil Engineers' Report Card 2017, six billion gallons of treated water are lost every day due to water pipe failures in the United States; an amount of water that could support 15 million households on a daily basis (American Society of Civil Engineers 2017). When significant

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investments in renewal and rehabilitation of aging water system are needed, and when federal and state funding for infrastructure renewal is limited, the primary source of funding for water utilities comes from revenue generated by rate payers (Curtis 2014). Although water demand is generally inelastic with respect to price (suggesting that a 1% increase in price results in less than a 1% decrease in demand), increasing water-rates affects both short-term and long-term residential and commercial water-consumption patterns. Based on 124 estimates of the price elasticity of the demand for residential water use in the United States between 1963 and 1993, the mean price elasticity was -0.51, the short-run median was -0.38 and the long-run median was -0.64 with 90% of all estimates between 0 and -0.75 (Espey et al. 1997; Olmstead et al. 2007). For residential water usage, demand has been found to be a function of water quality, location, household characteristics, water price, household incomes, and other related factors (Vasquez 2014; Tanellari et al. 2015). Therefore, public perceptions and attitudes regarding water-rate increases are influenced by personal characteristics, living environment, and water service reliability and quality.

Prior research has considered different statistical modeling approaches for evaluating consumers' attitudes toward water service reliability including utility-theory frameworks, stated-choice analyses, and contingent valuation methods (Espey et al. 1997; Alcubilla and Lund 2006; Olmstead et al. 2007; Yoo et al. 2014; Vasquez 2014; Tanellari et al. 2015; Castro et al. 2016; Faust et al. 2018). These models focused on the assessment of the willingness to pay to improve water service, quantification of the elasticity of water demand, or the identification of influential factors affecting water usage. For example, Espey et al. (1997) utilized meta-analysis to show that differences in estimated price elasticities were due to a combination of explanatory variables in the demand function, statistical estimation techniques used, characteristics of the data used, and environmental setting including location and time. They considered 124 estimated price-elasticity models from 24 studies published between 1967 and 1993. Their analysis indicated that evapotranspiration rates, rainfall, price structure, and the season (spring/summer/fall/winter) all influence the price elasticity. While their study provides important qualitative information regarding water-price elasticities, it is understood that consideration of other factors, such as socio-economic and demographic characteristics of households, are important considerations.

Dalhuisen et al. (2003) extended the analysis of the earlier work by Espey et al. (1997) to include income elasticities in addition to price elasticities. Conducting a meta-regression analysis, the authors concluded that the residential water demand is price elastic but that incomes are inelastic under different pricing systems such as flat rate, increasing block rates, and decreasing block rates. In other work, Yoo et al. (2014) used regression models to assess the price elasticity of residential water demand in Phoenix, Arizona. Using explanatory variables such as water usage, precipitation, temperature, household income, value of residential property, they found water demand to be generally inelastic, but found it could be elastic depending on factors such as temperature, precipitation, and having large water usage (for instance, having a pool in the household). They also found the price elasticity of water demand to be higher among lower-income water consumers than in higher-income water consumers.

Vasquez (2014) used contingent valuation to investigate households' willingness to pay and willingness to work for improvements in the water services in Guatemala. Their study indicates that households that were serviced by the local water utility were willing to pay a substantial increase (approximately 200%) in their water bill for reliable water service (consistent and safe supply of drinking water). The results of their analysis also indicated that households were willing to work approximately 19 hours per month for improved water services. Tanellari et al. (2015) further enhanced Vasquez's (2014) contingent-valuation approach by assessing the determinants of household's willingness to pay for improvement programs that address three issues; water quality, pinhole leaks in home plumbing, and aging public infrastructure. Their analysis indicated that the willingness to pay for public-infrastructure upgrade programs (including replacing aged water pipeline and upgrading water treatment plants) was higher relative to other programs (such as improvement in water quality, and addressing pinhole leaks in home plumbing), with respondents who had experienced water main breaks in their homes being willing to pay more for infrastructure-upgrade programs.

Castro et al. (2016) also used contingent valuation to assess how social perceptions and willingness to pay for preserving ecosystems varied among stakeholder groups including people residing in watersheds, tourists, business visitors, and potential water users. The study utilized face-to-face surveys to assess social perceptions and willingness to pay for ecosystem services in the Kiamichi watershed in Oklahoma. Using a probit regression model, this study provided evidence on how socioeconomic factors can influence people's overall willingness to pay, and the amount that they are willing to pay for watershed conservation. They found that individuals who had higher income level were more willing to provide financial support to maintain ecosystem services. In addition, their results indicated that individuals who were socially or politically active in the community were more likely to be willing to pay for watershed conservation. Faust et al. (2018) proposed a latent class approach to assess the willingness to pay for the provision of water and wastewater services in shrinking cities in the U.S. Their analysis showed factors determining an increased willingness to pay for improved reliability of water and wastewater service include the responsibility of paying the water bill (both water and wastewater services), homeownership (for water service only), and having an income level between $35,000 and $49,999 (for wastewater service only).

The intent of this chapter is to build on this past work by assessing households' attitudes toward water-rate increases based on perceptions and beliefs regarding water service reliability and water quality. To do this, and in contrast to past research that considered responses to single questions, the following three questions will be statistically modeled simultaneously; (1) if your water service provider proposes to increase the water-rate in order to improve the quality of water, would you support a rate increase? (1 if yes, 0 if no), (2) if your water service provider proposes to increase the water-rate in order to improve the reliability of the water service, would you support a rate increase? (1 if yes, 0 if no), and (3) if the water service provider doubles the water-rate, how would you change your water consumption pattern? (1 if decrease consumption, 0 if no change). Modeling these three interrelated questions simultaneously will enable the exploration of cross-equation correlation and thus allow additional inferences and more precise parameter estimates (Washington et al. 2011). Regarding explanatory variables influencing the respondents' responses to these three questions, a wide range of household and respondent attributes will be considered in the statistical estimations.

4.2 Survey Development and Deployment

To better understand attitudes of the general public toward increasing water-rates, and to specifically study the three interrelated questions mentioned above, a survey was distributed to the residents of Indianapolis, Indiana. Residents chosen were above 18 years of age, had access to the water service provided by local water utility, and were responsible for paying their water bill or a portion of the water bill. The survey questionnaire was categorized into three sections. The first section gathered information regarding household water bill, and the household's experiences related to water service reliability, water service performance, and water quality. The second part included questions related to the household's willingness to support water-rate increases, willingness to pay for improved water service reliability and quality, and consumption patterns due to water-rate increases. The third section collected demographic information of the survey respondents.

Qualtrics, a web-based survey software program, was used to distribute the survey to the sample population and gather responses in September 2015. In order to test the accuracy of design and measurement of survey, face validity and content validity was conducted (Mora 2011). Face validity includes the cursory review of survey questionnaires by people with limited knowledge of the subject area, while content validity is defined as subjective measure of how appropriate the questionnaires seem to a set of reviewers who have knowledge of the subject matter. To ensure that a population with limited knowledge on these issues can easily understand the survey and respond to the questions, the survey was pre-deployed to 20 people with limited knowledge of water-rates, the water system, and engineering issues. In addition, the survey's content validity was determined through a content review by 10 subject matter experts with backgrounds in water infrastructure system, water-rate regulations, and public perception surveys. Data generated or analyzed during the study are available from the corresponding author by request.

The respondent pool consisted of residents of the city of Indianapolis, which has an area of 372 square miles and is the 16th most populous city in the U.S (population of 863,002 based on 2018 census estimate). Four hundred and five (405) complete surveys were collected from the residents of the city of Indianapolis and the summary statistics of this sample are provided in Table 4.1. This table shows that, 37% of the respondents were male and 63% were female, 66% percent of the respondents had a technical college degree or higher, and 50% of the respondents had individual annual income higher than $35,000. The survey results also indicated that 65% of the respondents use tap water as a primary source of drinking water; while 30% of the respondents use bottle water. From the aggregate survey data, 85% of the survey sample stated that they have experienced water service disruption during past three years in their households. Although 73% of the survey respondents classified the service of drinking water as good, 62% of the respondents categorized the quality of drinking water as fair.

With regard to the three variables of interest for the forthcoming statistical analysis, 230 of the 405 respondents indicated that they would support a rate increase to improve the quality of water, 191 of the 405 respondents indicated that they would support a rate increase to improve the reliability of water service, and 301 of the 405 respondents indicated that they would decrease their water consumption in response to a doubling of water-rates.

Table 4.1. Descriptive statistics of survey respondents

Characteristic	**Mean**	**Std. Dev.**	**Min/Max**
Age			
18-25 years old indicator (1 if 18-25 years old, 0 otherwise)	0.15	0.36	0/1
16-35 years old indicator (1 if 16-35 years old, 0 otherwise)	0.33	0.47	0/1
36-50 years old indicator (1 if 36-50 years old, 0 otherwise)	0.29	0.45	0/1
Above 50 years old indicator (1 above 50 years old, 0 otherwise)	0.21	0.41	0/1
Marital status			
Single indicator (1 if single, 0 otherwise)	0.71	0.45	0/1
Married indicator (1 if married, 0 otherwise)	0.21	0.41	0/1
Civil Union indicator (1 if civil union, 0 otherwise)	0.01	0.13	0/1
Divorced indicator (1 if divorced, 0 otherwise)	0.04	0.21	0/1
Separated indicator (1 if separated, 0 otherwise)	0	0.04	0/1
Classification of area grew up			
Urban indicator (1 if urban, 0 otherwise)	0.26	0.44	0/1
Suburban indicator (1 if suburban, 0 otherwise)	0.53	0.49	0/1
Rural indicator (1 if rural, 0 otherwise)	0.19	0.39	0/1
Area Classification of area living			
Urban indicator (1 if urban, 0 otherwise)	0.30	0.46	0/1
Suburban indicator (1 if suburban, 0 otherwise)	0.57	0.49	0/1
Rural indicator (1 if rural, 0 otherwise)	0.10	0.31	0/1
Highest Level of Education			
Some high school indicator (1 if some high school is highest level of education, 0 otherwise)	0.04	0.20	0/1
High school diploma indicator (1 if high school diploma is highest level of education, 0 otherwise)	0.30	0.45	0/1

Table 4.1 continued

Technical college degree indicator (1 if technical college degree is highest level of education, 0 otherwise)	0.14	0.35	0/1
College degree indicator (1 if college degree is highest level of education, 0 otherwise)	0.39	0.48	0/1
Post Graduate Degree indicator (1 if post graduate degree is highest level of education, 0 otherwise)	0.11	0.32	0/1
Employment Status			
Employed for wages or salary indicator (1 if employed for wages or salary, 0 otherwise)	0.60	0.50	0/1
Self-employed indicator (1 if self-employed, 0 otherwise)	0.06	0.24	0/1
Out of work and looking for work indicator (1 if out of work and looking for work, 0 otherwise)	0.03	0.17	0/1
Out of work and not currently looking for work indicator (1 if out of work and not looking for work, 0 otherwise)	0.03	0.17	0/1
Homemaker indicator (1 if a homemaker, 0 otherwise)	0.03	0.17	0/1
Student indicator (1 if a student, 0 otherwise)	0.03	0.17	0/1
Retired indicator (1 if a retired, 0 otherwise)	0.03	0.17	0/1
Unable to work indicator (1 if unable to work, 0 otherwise)	0.03	0.17	0/1
Respondent Approximate Income			
No Income indicator (1 if respondent has no income, 0 otherwise)	0.08	0.28	0/1
Under $19,999 indicator (1 if respondent income is less than $19,999, 0 otherwise)	0.15	0.36	0/1
$20,000-$34,999 indicator (1 if respondent income is between $20,000-$34,999, 0 otherwise)	0.27	0.44	0/1
$35,000-$49,999 indicator (1 if respondent income is between $35,000-$49,999, 0 otherwise)	0.21	0.41	0/1
$50,000-$74,999 indicator (1 if respondent income is between $50,000-$74,999, 0 otherwise)	0.15	0.36	0/1
$75,000-$99,999 indicator (1 if respondent income is between $75,000-$99,999, 0 otherwise)	0.07	0.26	0/1
$100,000 and above indicator (1 if respondent income is greater than $100,000, 0 otherwise)	0.03	0.18	0/1
Primary Source of News			
Newspaper indicator (1 if primary source of news is the newspaper, 0 otherwise)	0.36	0.48	0/1
Internet indicator (1 if primary source of news is the Internet, 0 otherwise)	0.66	0.45	0/1
Television indicator (1 if primary source of news is the television, 0 otherwise)	0.75	0.42	0/1
Radio indicator (1 if primary source of news is the radio, 0 otherwise)	0.26	0.44	0/1

Table 4.1 continued

Social media indicator (1 if primary source of news social media, 0 otherwise)	0.15	0.32	0/1
Household Approximate Income			
No Income indicator (1 if respondent has no income, 0 otherwise)	0.01	0.11	0/1
Under $19,999 indicator (1 if household income is less than $19,999, 0 otherwise)	0.07	0.26	0/1
$20,000-$34,999 indicator (1 if household income is between $20,000-$34,999, 0 otherwise)	0.20	0.40	0/1
$35,000-$49,999 indicator (1 if household income is between $35,000-$49,999, 0 otherwise)	0.20	0.40	0/1
$50,000-$74,999 indicator (1 if household income is between $50,000-$74,999, 0 otherwise)	0.20	0.40	0/1
$75,000-$99,999 indicator (1 if household income is between $75,000-$99,999, 0 otherwise)	0.14	0.35	0/1
$100,000 and above indicator (1 if household income is greater than $100,000, 0 otherwise)	0.14	0.35	0/1
Other			
Female indicator (1 if Female, 0 otherwise)	0.29	0.45	0/1
Number of people living in household	3	1.47	1/8
Number of children under the age of 6 living in household	0.50	0.88	0/4
Number of children between the age of 6-18 living in household	0.7	1.83	0/3
Number of people living in household, work outside the home	1.4	0.86	0/3

4.3 Methodological Approach

Recall that we seek to study respondents' responses to the following three questions with binary outcomes; (1) if your water service provider proposes to increase the water-rate in order to improve the quality of water, would you support a rate increase? (1 if yes, 0 if no), (2) if your water service provider proposes to increase the water-rate in order to improve the reliability of the water service, would you support a rate increase? (1 if yes, 0 if no), and (3) if the water service provider doubles the water-rate, how would you change your water consumption pattern? (1 if decrease consumption, 0 if no change). To statistically model these responses, a multivariate binary outcome model is appropriate since the response variables are binary discrete variables and the multivariate aspect is introduced since the three decisions are interrelated responses. The model is defined as,

$$
\begin{aligned}
z_{1n} &= \mathbf{X}_{1n}\boldsymbol{\beta}_1 + \varepsilon_{1n}, \quad y_{1n} = 1 \text{ if } z_{1n} > 0,\ y_{1n} = 0 \text{ otherwise}, \\
z_{2n} &= \mathbf{X}_{2n}\boldsymbol{\beta}_2 + \varepsilon_{2n}, \quad y_{2n} = 1 \text{ if } z_{2n} > 0,\ y_{2n} = 0 \text{ otherwise}, \qquad (4.1) \\
z_{3n} &= \mathbf{X}_{3n}\boldsymbol{\beta}_3 + \varepsilon_{3n}, \quad y_{3n} = 1 \text{ if } z_{3n} > 0,\ y_{3n} = 0 \text{ otherwise},
\end{aligned}
$$

where: y_{1n}, y_{2n}, and y_{3n} are one/zero response variables for respondent n supporting *a* rate increase to improve quality (1 if yes, 0 if no), supporting a rate increase to improve reliability (1 if yes, 0 if no), and decreasing water consumption if rates are doubled (1 if decrease consumption, 0 if no change), respectively; z_{1n}, z_{2n}, and z_{3n} are functions that determine the probabilities of supporting a rate increase to improve quality, supporting a rate increase to improve reliability, and decreasing water consumption if rates are doubled, respectively, for respondent n; $\mathbf{X}_{1n}$, $\mathbf{X}_{2n}$, and $\mathbf{X}_{3n}$ are vectors of explanatory variables that determine individual n's response probabilities, $\boldsymbol{\beta}_1$, $\boldsymbol{\beta}_2$, and $\boldsymbol{\beta}_3$ are corresponding vectors of estimable parameters, and ε_{1n}, ε_{2n}, and ε_{3n} are multivariate normally distributed disturbances with mean zero and variance one giving,

$$
\begin{pmatrix} \varepsilon_{1n} \\ \varepsilon_{2n} \\ \varepsilon_{3n} \end{pmatrix} = N\left(\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \begin{pmatrix} 1 & \rho_{12} & \rho_{13} \\ \rho_{12} & 1 & \rho_{23} \\ \rho_{13} & \rho_{23} & 1 \end{pmatrix} \right) \qquad (4.2)
$$

where ρ's are correlation coefficients. This multivariate binary probit model can be readily estimated by standard maximum likelihood methods (Greene 2018; Washington et al. 2011). To determine the effect of explanatory variables found to be statistically significant, marginal effects (which give the effect that one-unit increase in an explanatory variable had on the probability of saying yes in response to questions 1 and 2, and probability of respondents indicating that they would decrease water consumption if water-rates were doubled in response to question 3) were also computed as part of the model estimation (Washington et al. 2011).

4.4 Estimation Results

Summary statistics for the variables found to be statistically significant are presented in Table 4.2, and the multivariate binary probit estimation results, including marginal effects, are presented in Table 4.3. As shown in Table 4.3, overall model fit is quite good as reflected by the convergence of the log-likelihood, with a ρ^2 value of 0.56.

Table 4.2. Summary statistics for variables found to be statistically significant in model estimations

Variable Description	**Mean**	**Std. Dev.**	**Min/Max**
Variables related to supporting a rate increase to improve the quality of water			
Indoor water usage indicator (1 if water supplied by utility is used for drinking, cooking, shower and bath, laundry, dishwasher)	0.62	0.51	0/1
Low average monthly water bill indicator (1 if less than $21, 0 otherwise)	0.46	0.50	0/1
Highest completed level of education indictor indicator (1 if have college degree and post graduate degree, 0 otherwise)	0.43	0.35	0/1
Water service disruption indicator (1 if yes, 0 if no)	0.66	0.50	0/1
Variables related to supporting a rate increase to improve the reliability of water service			
Good water quality opinion indicator (1 if good, 0 otherwise)	0.31	0.47	0/1
Lower-intermediate annual household income indicator (1 if $20,000-$34,999, 0 otherwise)	0.58	0.38	0/1
Lower water main breaks experience indicator (1 if lower than 3 times, 0 otherwise)	0.20	0.40	0/1
Urban area indicator (1 if living in an urban area, 0 otherwise)	0.30	0.46	0/1
Non-tap water drinking source indicator (1 if drinking water supplies from bottled water or groundwater, 0 otherwise)	0.35	0.62	0/1
Midwest native indicator (1 if originally a native of Midwest, 0 otherwise)	0.71	0.41	0/1
Variables related to decreasing consumption if water rates were doubled			
Large water uses indicator such as swimming pool and house garden (1 if yes, 0 if no)	0.38	0.53	0/1
Number of people living in household	3.01	1.47	1/8
Female (1 if female, 0 otherwise)	0.29	0.45	0/1
Tap water drinking source indicator (1 if supplies from my local water utility indicator (tap water), 0 otherwise)	0.72	0.20	0/1
Intermediate monthly water bill indicator (1 if $21.00-$50.99, 0 otherwise)	0.27	0.32	0/1

Table 4.3. Multivariate binary probit model estimation results

Variable Description	Parameter Estimate	t-statistic	Marginal Effect
Correlation coefficients			
Support rate increase for improved quality of water and support rate increase for improved reliability of water service, ρ12	0.209	10.745	
Support rate increase for improved quality of water and decrease consumption with rate doubling, ρ13	0.316	9.716	
Support rate increase for improved reliability of water service and decrease consumption with rate doubling, ρ23	-0.108	-3.419	
Variables related to supporting a rate increase to improve the quality of water			
Constant	0.158	2.418	-
Indoor water usage indicator (1 if water supplied by utility is used for drinking, cooking, shower and bath, laundry, dishwasher)	0.326	2.065	0.136
Low average monthly water bill indicator (1 if less than $21, 0 otherwise)	-0.165	-2.615	-0.131
Highest completed level of education indictor indicator (1 if have college degree and post graduate degree, 0 otherwise)	0.217	2.021	0.168
Water service disruption indicator (1 if yes, 0 if no)	0.171	1.982	0.032
Variables related to supporting a rate increase to improve the reliability of water service			
Constant	-0.830	-3.495	-
Good water quality opinion indicator (1 if good, 0 otherwise)	-0.475	-3.825	-0.480
Lower-intermediate annual household income indicator (1 if $20,000-$34,999, 0 otherwise)	-0.967	-1.727	-0.152
Lower water main breaks experience indicator (1 if lower than 3 times, 0 otherwise)	-0.279	-3.202	-0.205
Urban area indicator (1 if living in an urban area, 0 otherwise)	-0.716	-2.351	-0.128
Non-tap water drinking source indicator (1 if drinking water supplies from bottled water or groundwater, 0 otherwise)	-0.521	-2.121	-0.359
Midwest native indicator (1 if originally a native of Midwest, 0 otherwise)	-0.216	-1.810	-0.128
Variables related to decreasing consumption if water rates were doubled			
Constant	-0.168	-2.253	-
Large water uses indicator such as swimming pool and house garden (1 if yes, 0 if no)	-0.614	-2.200	-0.126
Number of people living in household	0.136	3.258	0.121

Table 4.3 continued

Female (1 if female, 0 otherwise)	0.316	1.968	0.010
Tap water drinking source indicator (1 if supplies from my local water utility indicator (tap water), 0 otherwise)	0.963	1.901	0.357
Intermediate monthly water bill indicator (1 if \$21.00-\$50.99, 0 otherwise)	-0.102	-1.575	-0.057
Number of observations	405		
Log-likelihood at zero, $LL(0)$	-1752.97		
Log-likelihood at convergence, $LL(\boldsymbol{\beta})$	-766.12		
ρ^2 $[1 - LL(\boldsymbol{\beta})/LL(0)]$	0.56		

Regarding the correlations among the three binary responses, Table 4.3 shows that all three correlations are highly significant as indicated by reported t-statistics, although the degree of correlation varies among the various question pairs. For example, the correlation between willingness to support a rate increase for improved quality of water and willingness to support a rate increase for improved reliability of water service is positive, but relatively low at only 0.209. This relatively low correlation suggests that respondents viewed these two elements as distinctively different. This difference between people's willingness to support rate increases for quality and reliability is borne out in the relationships with decreasing consumption with a water-rate doubling. Table 4.3 shows a positive correlation of 0.316 between willingness to support a rate increase for improved quality of water and indicating they would decrease consumption with water-rates doubling. This suggests that people likely to support a rate increase for improved quality were also likely to be price sensitive with regard to their consumption. In contrast, there was a negative correlation (-0.108) between willingness to support a rate increase for improved reliability of water and indicating they would decrease consumption with rate doubling. This suggests that people willing to support a rate increase for improved reliability were less likely to be price sensitive. This is an important finding in that it indicates that, when controlling for all other factors that could affect these three questions (see the many variables found to be statistically significant in Table 4.3), people that supported quality improvements were moderately price sensitive and people that supported reliability improvements were generally not price sensitive. Knowing this could be of value to water utility companies in setting their rates and prioritizing capital investments.

Turning to the specifics of the individual parameter estimates in Table 4.3, and variables found to be statistically significant in determining whether individuals would support a rate increase to improve water quality, it was found that individuals who use utility-supplied water as their indoor water usage (such as drinking, cooking, shower and bath, laundry, dishwasher) were more likely to support a water-rate increase by water utility in order to improve the quality of water. The marginal effect for this variable indicates that an increase in indoor water usage will increase the probability of supporting water-rate increases to improve water quality by 0.136 on average.
If the average monthly water bill for the respondents was lower than $21, respondents were less likely to support a water-rate increase to improve the quality of water (with an average decrease on the probability of supporting water-rate increases by 0.131), reflecting the fact that these lower-bill people tend to be more price sensitive. Individuals who have a college degree and/or a post graduate degree, were more likely to support a water-rate increase in order to improve the quality of water. The marginal effect for this variable shows that a respondent with a higher educational degree had a probability of supporting a water-rate increase to improve water quality that was 0.168 higher than their lower-educated counterparts, on average. Interestingly, past research has reported that providing public education programs geared toward water conservation would affect households' water consumption patterns and their willingness to support water-rate increases (Nieswiadomy 1992; Gaudin 2006; Gober et al. 2016). Also, previous studies found that level of formal education (high school through graduate school) is an important factor driving attitudes towards water reuse (Robinson et al. 2005; Hurlimann 2008; Gu et al. 2015) and having a post graduate degree typically corresponds to the highest percentage of reclaimed water supporters (Garcia-Cuerva et al. 2016).

Finally, estimation results indicated that respondents who had experienced water service disruptions were more likely to support rate increase in order to improve the reliability of water service. In this study, water service disruption is defined as no water service, boil alert, and low water pressure at home or at place of work. This variable reflects the fact that the reliability of water service has a higher priority for these respondents.

Regarding variables found to be statistically significant in determining whether individuals would support a rate increase to improve the reliability of water service, individuals who classified the quality of water (such as the color of the water, odor of the water, particles in the water), as "good", were less likely to support the rate increases in order to improve the reliability of the water service. The marginal effect for this variable indicates that respondents who classified the quality of water as “good” had, on average, a 0.480 lower probability of supporting a water-rate increase to improve the reliability of water service, on average.

Regarding household income, those households making between $20,000 and $34,999 per year were found to be less likely to support a water-rate increase in order to improve the reliability of the water service relative to other income groups. Water main breaks events were also found to affect respondents’ likelihood of supporting water-rate increases to improve reliability. Model estimation results in Table 4.3 show that respondents who had experienced few (less than 3) interruptions (such as flooding, traffic jam, and road closure) in Indianapolis because of water pipe breaks during the past three years were less likely to support a water-rate increase in order to improve the reliability of the water service.

If respondents live in an urban portion of the Indianapolis city limits (Indianapolis city limits include all of Marion County so there are many suburban areas), they were found to be less likely to support water-rate increases in order to improve the reliability of the water service. The marginal effect indicates that the probability of urban residents supporting water-rate increases to improve the reliability of water service was 0.128 lower (on average) than their suburban counterparts. This reflects a potential problem for aging urban water systems with customers being less willing to pay for improved reliability.

Estimation results also show that respondents who used bottled water and ground water as their primary source of water were less likely to support a water-rate increase in order to improve the reliability of the water service. The marginal effect indicates that such respondents have a 0.359 lower probability (on average) of supporting a rate increase relative to those who rely on tap water as their drinking source.

Finally, people who were originally from the Midwestern region of the U.S. were found to be less likely to support a water-rate increase in order to improve the reliability of water service. The marginal effect for this variable indicates that by having a respondent who was originally from Midwest, the probability of supporting a water-rate increase to improve water reliability decreased by 0.128 on average. This may be because respondents from Midwestern regions of the U.S. have generally not been under drought-related water crises, and thus have less experience with water supply-related issues relative to residents of other areas of the country who have been found to be more willing to pay for reliability (Thorvaldson et al. 2010; Gage and Cooper 2015; Seyranian et al. 2015).

Regarding respondents' decreasing their consumption in response to a doubling of water-rates, respondents who had large water-consuming features (such as swimming pool) were less likely to decrease their water consumption pattern if water-rates doubled. This variable reflects the fact that the households with large water use tend to be less concerned with water-rate increases, and this finding is consistent with past research (Morote et al. 2016).

As the number of people living in the household increased, the likelihood of decreasing consumption increased if the water-rate were doubled. The marginal effect for this variable indicates that an increase in household size by one member will increase the probability of decreasing water consumption by 0.121 on average. This finding is supported by past research by Mini et al. (2015).

Estimation results also indicate that female respondents were more likely to decrease their water consumption pattern if water-rates doubled relative to their male counterparts. Gender-related issues and water consumption were also a common theme in several prior studies (Kontokosta and Jian 2015; Hussien et al. 2016; Fuentes and Salom 2018). For instance, Hussien et al. (2016) assessed the influence of household characteristics on the average per capita daily water using data from the Iraqi city of Duhok and found that per capita water consumption increased with the number of female members in the household in that city (Hussien et al. 2016). In other work, Kontokosta and Jian (2015) evaluated the water consumption patterns of 2300 multi-family households located in New York City and explained that number of females in the population has an inverse relationship with water consumption in the central part of the city; however, for the outer boroughs of the city, an increase in the female population equated to an increase in water consumption. These results emphasized that socio-demographic factors and spatial patterns might have prominent effects on water consumption patterns, and subsequently reflect the relationship between price increases and consumption.

Respondents who indicated that tap water was their primary source of drinking water were found to be more likely to decrease their water consumption if water-rates doubled. The marginal effect of this variable is quite high, with tap-drinking respondents having a 0.357 higher probability (on average) of decreasing consumption if water-rates were doubled relative to their non-tap drinking counterparts. This understandably reflects the fact that households, who rely on tap water as a primary source, are more likely (than their non-tap drinking counterparts) to try to adjust and reduce water consumption rates in order to reduce their water bills because of rate increases.

Finally, estimation results indicate that if the average monthly water bill is between $21 and $51, respondents were less likely to decrease their water consumption if the water utility doubles the water-rate, relative to respondents with water bills higher and lower than this amount. The marginal effect is modest with such respondents having just a 0.057 lower probability of decreasing their consumption if rates were doubled (on average), reflecting the relative inelasticity of price/consumption relationship for these people.

4.5 Conclusion

As water utilities attempt to be financially self-sufficient, understanding the water consumption patterns of residential customers in response to water-rate increases is extremely important. This study sought to address this issue by not only assessing households' attitudes toward water-rate increases, but also to simultaneously consider perceptions toward water service reliability and quality through multivariate binary probit approach. The methodological approach described in this chapter shows that a wide variety of factors influence the likelihood that respondents will support water-rate increases.

Results indicate that people respond to rate increases based on their socio-demographic characteristics (such as family size, educational background, and gender) as well as the reliability of water service and the quality of supplied water by water utility. The socio-demographic and other findings of this study provide initial insights for water utilities to evaluate consumer perceptions of water-rate increases, and to set up educational and informational campaigns to deal with potential opposition toward water-rate increases. For instance, respondents with large water usage (such as swimming pool and house garden) tended to indicate that they would not decrease their water consumption pattern if water-rates doubled. In such cases, water utility policy makers could implement public campaign programs for educating and informing consumers on water-pricing structures and how their water use habits could be modified.

Although the findings of this chapter provide important insights for water-pricing policy, future analyses can improve model estimation results further by considering different geographic regions (for example, western regions of the U.S which experience significant water shortages.), different population densities, and the potential effect of word-of-mouth communication among water consumers to support/oppose water-rate increases.

5. ANALYSIS OF COUPLED HUMAN AND WATER INFRASTRUCTURE SYSTEMS UNDER EVENTS OF WATER MAIN BREAKS AND WATER-RATE INCREASES EVENTS

According to the more recent 2018 EPA report on Drinking Water Infrastructure Assessment, over \$472.6 billion is needed over the next 20 years for the replacement and rehabilitation of deteriorated water infrastructure asset including distribution and transmission pipelines, treatment plants, and storage tanks. The deterioration of the physical water infrastructure negatively affects the economics of water utilities and can lead to increases in water-rates for consumers, so that utilities can recover the financial losses. Selecting appropriate water-rates is a critical step for a water utility not only to pursue its financial goal but also to improve customer service. This chapter discusses the evaluation of the dynamic interactions of the human-water infrastructure systems under the event of water main breaks and water-rate increases as a means to explore water demand, utility revenues, consumer behavior, and payoff periods for implementing proactive maintenance strategies. To do this, a hybrid model was developed incorporating system dynamics and agent-based modeling to explore uncertainties, interdependencies, and emergent behaviors arising from unknown relationships between a physical water infrastructure and stakeholders. Different components of the water infrastructure system were integrated in the study. These components include the pipeline network, with the water and associated energy losses, water utility revenues, and consumer behaviors. The physical and economic impacts of water main breaks and water-rate increases on the coupled human-water infrastructure system were quantified. The model is demonstrated over the 2001–2010 period on a case study city with a large water distribution system that includes 4,000 miles of pipeline and nine water treatment plants serving a population of 863,000. The model uses a range of pipeline characteristics, climate, hydrological, and socio-economic data. The model's results highlight the importance of a proactive and targeted asset management approach for a utility's financial health. Furthermore, the model provides new understanding of consumers' water consumption patterns and communication mechanisms among consumers during rate increase events.

5.1 Introduction

As urban systems continue to mature and evolve, the issue of aging infrastructures and how to retrofit and sustain these built systems becomes increasingly important. Perhaps no example more clearly highlights the gravity of the issue than aging water pipeline systems and non-revenue water (NRW) in urban areas. Over 16% of the water pipeline system in the U.S., which is comprised of 880,000 miles of pipelines, is beyond its service life (average service life is reported to be 84 years) (Folkman 2018). Aging and leaking pipes increase the likelihood of water main breaks. Up to 50% of the drinking water in the U.S. is lost in the water distribution system due to leaking and aging pipes (GAO 2011). To compensate for the water loss, utilities have to use more energy for additional extraction, treatment, and distribution of water, which increases their overall operating costs. About four percent of all electricity generated in the U.S. is used to move and treat drinking water and wastewater (EPA 2015). Approximately 80% of urban water supply operating costs are based on electricity consumption (Ghimire and Barkdoll 2007). These negative spillover effects of main breaks, namely non-revenue water, leakage repair, and additional use of energy, undermine the economics of the water utilities and can lead to increases in water-rates for cost recovery. However, there remains a lack of understanding of the dynamics emerging from the interplay among changes in water-rates, consumer behavioral response, water utility economics, and water infrastructure. As a result, it is often unclear how a change in water- rates will affect this interplay and, hence, the aggregate behavioral response of consumers and overall states of water utilities and their infrastructure quality (Hensher et al. 2005).

The main challenge facing water utilities is finding a solution to reduce operation and maintenance expenses while maintaining/growing revenue to improve financial resiliency. Although the issues related to infrastructure aging have been examined in prior studies (e.g., Gat 2014; Mazumder et al. 2018), insufficient work has been carried out to analyze the consequences of an aging pipeline system on water utilities and consumers in ways that explicitly capture NRW, leakage repair, additional use of energy, and water service disruption. In particular, the dynamics emerging from the interplay among pipeline characteristics, temperature, the timing of maintenance, water, and associated energy losses, and utility revenues needs to be investigated further. Pipes of different materials, diameters, and ages perform differently in a water distribution system. The performance of water pipes also varies under various conditions such as different operating pressures, precipitation, and temperatures (Kleiner and Rajani 2002). These variations pose challenges to identifying and implementing cost-effective maintenance strategies. Furthermore, empirical analyses that have examined NRW and its associated energy use in water distribution have been focused on the energy and water demands related to population growth, drought conditions, development of technologies to reduce water and energy footprints of the water and wastewater treatment processes, optimizing energy consumption during construction, renewal, and maintenance of pipeline networks, alternative water supply assessments, and improvement of the energy optimization for water supply and distribution systems (American Water Works Association Research Foundation systems (EPA 2013; WaterRF 2013; Bauer et al. 2014). However, existing systems models of urban water supply are typically lacking in the examination of the dynamic interactions of water loss, energy loss, and utility revenue losses, making long-term planning and management difficult.

In addition, previous studies on the impact of water-rates mainly relied on econometric methods, regression, and time series analyses to estimate water consumption patterns under various tariffs (Howe and Linaweaver 1967; Renwick and Archibald 1998; Troy and Holloway 2004; Gaudin 2006; Inman and Jeffrey 2006; Worthington and Hoffman 2008). Although these studies have provided much insight, a more dynamic 'systems' approach could further improve our understanding by revealing emergent outcomes of water-rate increases. The amount and frequency of water-rate increases are unknown factors in the long-range planning and management of urban water systems (Curtis 2014). Although water demand is generally inelastic, increasing the water-rates can affect both the short-term and long-term trends of water consumption. The long-term trends of declining water consumption are more apparent than the short-term fluctuations and have a significant impact on water utility revenues. Understanding the behavior of consumers under different rate conditions is an important factor to consider when water utilities conduct long-term and short-term financial analyses. Public attitudes and behaviors in response to water-rate increases are highly correlated with the level of water service reliability (uninterrupted service, adequate pressure) and the supplied water quality (color of the water, odor of the water, particles in the water) (Pipe 2003; Bilgic 2010).

The objective of chapter is to address the aforementioned research gaps by explicitly analyzing the interactive effects of features of the physical water infrastructure (pipeline characteristics, water and associated energy losses, and the revenue loss for water utilities) and the behavior of stakeholders (water utilities and consumers). In approaching this aim, a hybrid model was developed that combines system dynamics (SD) and an agent-based model (ABM). The effects of pipeline characteristics, water losses, and water consumption on the dynamics of urban water supply systems, was examined in two stages. First, the system dynamics model was constructed to explore the dynamic behaviors of the water infrastructure components due to water main breaks. This research component focused on the interactions between the pipeline characteristics, water and energy losses, and water consumption that affected the future trajectories of these interrelationships and ultimately the revenue loss for water utilities from water and energy losses. Second, the ABM model was developed to analyze the emergent behavior outcomes due to interactions between the stakeholders (water utilities and communities) in response to water main break events and water-rate increases. This research component was used to represent the stakeholders as autonomous agents to understand their behavioral responses to water service reliability and water-rate increases. It is important to understand consumers' behavior under different rate conditions because revenues generated from consumers form the backbone of water utilities' financial model (Hughes et al. 2014). In addition, individual consumer's decisions regarding water consumption can collectively impact the community in which they live. As consumers receive input from their community and are influenced by factors (such as water service reliability, disruption to water and other infrastructure services, etc.) impacting their environment, they are prone to changing their water consumption patterns and changing their attitudes toward water-rate changes (Athanasiadis et al. 2005; Kandiaha et al. 2019). Thus, long-term water consumption prediction under rates increase events has proven to be quite challenging for utilities since consumers are capable of making both independent and interdependent decisions. In the ABM model, we varied the parameters of the water-rates and levels of agent connectivity during the simulation period to explore how these conditions affect the future possibility space of water consumption.

5.2 Review of Methodological Approaches

Traditionally, research efforts in urban water management research have been on physical infrastructure planning and policy prescription (Ward et al., 2006; Srinivasan 2015). Researchers have used statistical modeling to predict the frequency of pipe failures in water distribution systems (e.g., Kleiner and Rajani 2010; Zamenian et al. 2017), hydraulic modeling and integral equations to optimize the water leakages in water distribution systems (e.g. Pelli and Hitz 2000; Cabera et al. 2010), Life Cycle Energy Analysis (LCEA) to quantify the operational costs of maintaining water distribution systems (e.g. Filion et al. 2004), and optimization techniques to minimize failure costs in water distribution systems (e.g. Wu et al. 2010; Piratla and Ariaratnam 2012). These methodological approaches provided important guidance to asset managers in their efforts to maintain their water distribution systems when the problems were static and defined, the underlying relationships between variables were known, the level of uncertainty was zero, and the goal was to manage a well-understood system. However, such methods could not capture uncertainties, interdependencies, and emergent behaviors of the system, when the problem was dynamic, and system's components (such as consumers) were capable of making independent/interdependent decisions. Modeling methods that are typically used for analyzing systems with dynamic and uncertain characteristics included agent-based modeling, game theory, system dynamics, and discrete event simulations. Application of any of these methods depends on the level of abstraction in the modeling of the problem statement. To explore the interactions between different urban water systems components including pipeline characteristics, water and associated energy losses, maintenance activity, break repair costs, and ultimately the revenue loss for water utilities, a system dynamics model was selected in this study.

Prior assessments of residential water consumption typically used projections of demand based on population growth, system capacity, assuming homogeneous populations of the customers (Ali et al. 2017). However, the existence of multiple interactions between physical water infrastructure (pipeline characteristics, water and associated energy losses, and the revenue loss for water utilities) and stakeholders (water utilities and consumers) create uncertainties on human-water infrastructure systems that may not be predictable using traditional models such as econometric methods, regression, and time series. There is a long history of simulation approaches in representing engineering, hydrological, environmental, socio-technical, and socio-economic aspects of water infrastructure systems. An ABM is a simulation technique that facilitates understanding the probable macro patterns of a system based on the micro-behaviors of adaptive components (Pfeffer and Salancik 2003). This simulation method provides useful information for decision-makers by understanding the activities and interactions between components of a system. ABM has been used for a number of applications in urban water management including adoption of water-efficient technologies (e.g.; Kotz and Hiessl 2005; Rixon et al. 2007), adoption of green infrastructure for controlling runoff (Montalto et al. 2013), setting policies for allocation of water within communities (e.g. Tillman et al. 2005; Lopez-Paredes et al. 2005; Srinivasan et al. 2010), water quality issues associated with water supply systems (e.g. Shafiee and Zechman 2013; Zhang et al. 2013), water availability and satisfaction for agricultural water use (Berger et al. 2007; Ng et al. 2011), decision-making on decommissioning and downsizing of physical water infrastructure systems (Faust et al. 2017), and adoption of water reuse and reclaimed water within communities (Kandiaha et al. 2019).

Existing literature on the analysis of human behavior toward water-rate increase has often considered different econometric modeling approaches including the use of utility-theory frameworks (Alcubilla and Lund, 2006; Olmstead et al., 2007), stated-choice analyses (Yoo et al., 2014; Castro et al., 2016), and contingent valuation methods (Vasquez, 2014; Tanellari et al., 2015). Yoo et al. (2014) utilized stated-choice models to assess the price elasticity of residential water demand, and concluded that water demand could be elastic depending on factors such as temperature, precipitation, and having large water usage (for instance, having a pool in the household). They also found the price elasticity of water demand to be higher among lower-income water consumers than in higher-income water consumers. Castro et al. (2016) used stated-choice to assess how social perceptions and willingness to pay for preserving ecosystems varied among stakeholder groups including people residing in watersheds, tourists, business visitors, and potential water users. The results indicated that individuals who were socially or politically active in the community were more likely to be willing to pay for watershed conservation. Vasquez (2014) used contingent valuation to investigate households' willingness to pay and willingness to work for improvements in the water services in Guatemala. His study showed that households in Guatemala that were serviced by the local water utility were willing to pay a substantial increase (approximately 200%) in their water bill for reliable water service (consistent and safe supply of drinking water). Although prior literature assessed human behaviors by exploring the impacts of demographic characteristics, water quality and service performance, household income, and water quality, the theoretical approaches do not consider dynamic interactions and uncertain characteristics of household responses toward water-rates increase, as well as water service reliability and quality. Therefore, empirical data collected from the residential customers in a case study city was used to develop decision rules (related to water consumption) during events of water-rate increases. In this study, residential customers consist of heterogeneous households who differ from one another in various aspects such as demographic characteristics, level of income, experiences related to water service reliability and quality, consumption attitudes under water-rate increase events, etc. Also, dynamic interactions between water consumers were simulated via word-of-mouth communication based on empirical data collected through a survey of households that was conducted in 2015 in the case study city. Methodologically, the proposed hybrid system dynamics and agent-based model (SD-ABM) examines interdependencies between the physical water infrastructure, the water utility, and the water consumers to explore possible emergent behavior patterns of water users during water-rate increases over time.

5.3 Structure of the Hybrid SD-ABM Model

A hybrid SD-ABM was used in this study to explore the interactions between different system components of the coupled human and water infrastructure systems (see Figure 5.1), including pipeline characteristics, water and associated energy losses, and ultimately the revenue loss for water utilities. The hybrid model was developed to understand the collective response of water users to water-rate increases.

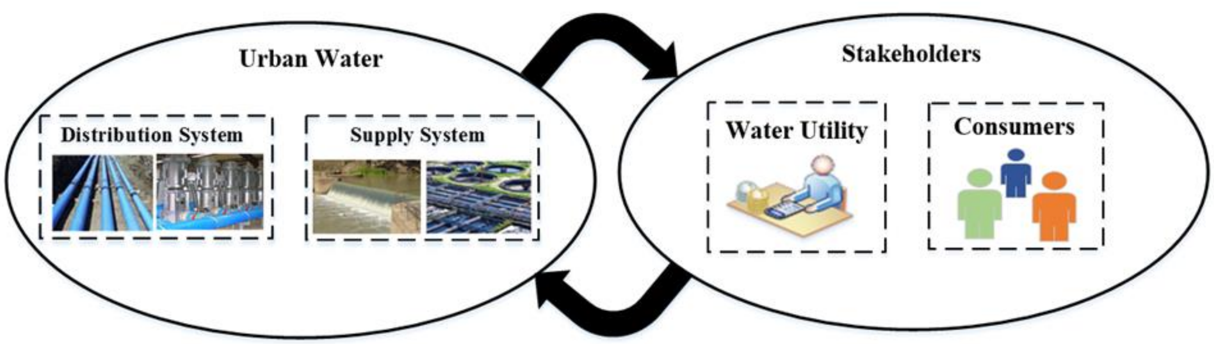

Figure 5.1. Coupled Human and Water Infrastructure Systems

The SD component of the model focuses on the urban water system interactions stemming from main breaks in pipeline networks. Previous studies developed mathematical models to assess the water loss and associated energy loss impact due to water main breaks on the water supply and distribution systems (e.g., Filion et al. 2004; Cabrera et al. 2010; and Hernandez et al. 2011). For example, Filion et al. (2004) conducted a Life Cycle Energy Analysis (LCEA) for the water distribution system by quantifying the energy usage of the pipe fabrication phase, the water usage (during operation maintenance), and the end-of-life phase of the pipes. The LCEA was applied to the New York City water supply system, and showed that the energy expenditure for pipe fabrication and pipe repair is higher than the net energy expenditure for pipe recycling and disposal. Cabrera et al. (2010) applied the Reynolds's transport equation to the integral energy equation by developing a mathematical model to estimate the energy input/output in water distribution systems. The integral energy equation could be used to calculate the energy loss through leakage; however, the equation only measures the energy loss in the closed loop of water distribution and does not consider the energy loss due to extraction and treatment phases. Hernandez et al. (2011) subsequently applied and extended Cabrera et al. 2010 integral energy equation to evaluate the proportion of input energy utilized in pumping and transport (friction, tap and discrete energy losses) for the City of Denia, Spain. The case study demonstrated that the huge amounts of energy losses due to pipes leakage.

In summary, previous studies paid insufficient attention to the dynamic interactions among the water system physical components such as pipeline characteristics and water and associated energy losses over time. To better understand the system behaviors and to examine the range of possible system dynamics, we conducted SD modeling that addresses these gaps. Our model incorporates pipe break frequencies, water and associated energy losses, and water utility revenues. The model is grounded on empirical data, including pipeline characteristics, monthly temperatures, average water pressures, schedule of maintenance activities, leakage rates, duration of pipe repairs, energy consumption rates of water supply components, and pipeline repair costs. The SD model was developed using AnyLogic 8.2.3, an object-oriented program, to demonstrate the modeling and simulation of dynamic interactions. The integrated model is comprised of the following five modules (1) pipe breaks, (2) water and associated energy losses, (3) utility revenues, and (4) the consumer (Figure 5.2). The input variables, transformations, and output variables for each module are explained in Table 5.1.

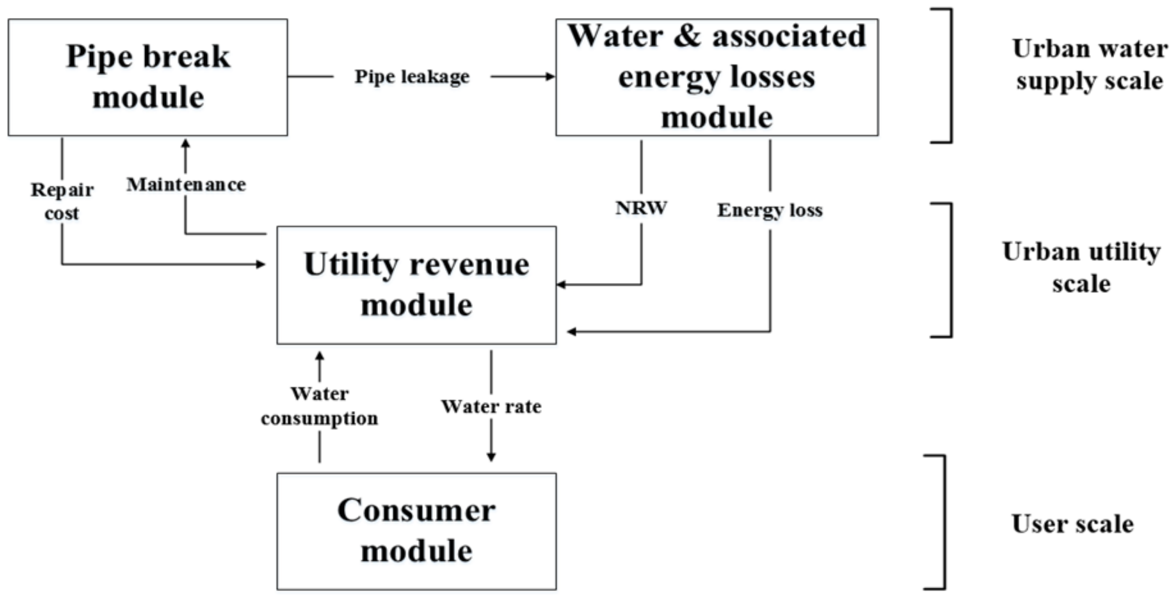

Figure 5.2. Integration of Modules

ABM was used to model the consumers as autonomous agents to understand their behaviors toward water main breaks and potential increases in costs and energy losses that may have been passed on to water consumers. In this simulation, the role of the water utility agent was to send the message of "water-rate increases" to consumer agents and observe various behaviors of consumer agents. The behavior of the water consumer agent was modeled based on data collected from the residential customers in a Midwestern city. The data included information about the household water bill, household's experiences related to water service reliability, water service performance, water quality, and consumption attitudes in response to water-rate increases. Consumer agents and water utility agents have different beliefs, desires, and intentions when pursuing their goals (Figure 4.5 and Figure 5.5). In this study, the consumer agents' goal is to have uninterrupted access to quality water supply. The dynamic environment of the model allows consumer agents to update their decisions about their water consumption based on (1) the influences of neighboring consumer agents through word-of-mouth communication and (2) the level of water service and quality of the water supply.

The emergent behavior captured in this ABM simulation included the impact of increasing consumer water usage rates, the impact of water price elasticity cascading into the water utility revenue, and the impact of consumer agents' water usage on the water utility revenues. Due to water main break events, the water utility agent encounters revenue losses stemming from energy loss, repair costs, and water loss (NRW). To cover the maintenance and rehabilitation of water main breaks when federal and state funding for infrastructure renewal was limited, the only other source of funding was a water-rate increase. In this study, revenue losses were recovered through higher water-rates passed on to the consumer agents.

5.4 Case Study Used for Demonstration

To assess the public attitudes, perceptions, and responses toward increasing the water-rates, a survey was deployed to the residents of the case study city in the U.S. The case study city is located in the Midwestern region of the U.S., and is served by a large water distribution system that includes 4,000 miles of pipeline and nine water treatment plants serving a population of 863,000. Typical water-rates increases between 8% -20% occur every three years with approval of the State regulatory agency. The responses from this survey were used in the simulation to (1) assess the public attitudes towards an increase in the water-rate, (2) quantify the differences in the consumption rates of drinking water after the consumer agents adapted to the new rate, and (3) evaluate the effects of word-of-mouth communication between agents on changing their water consumption rates.

5.1. Function of Individual Modules

Module	Object Classes (Type)	Function	Parameter and variables	Examples of decision rules and formulas
Pipe Break Module	Pipe break (SD)	Simulation of main breaks frequency in water distribution system	Pipe length, Pipe age Pipe material, Maintenance (city databased) Temperature (National Oceanic and Atmospheric Administration 2015)	Equation generated using statistical modeling for number of breaks occurring per month based on pipe characteristics, month, and average temperature
Water and Associated Energy Loss Module	Water losses (SD)	Simulation of water losses produced due to pipe break in water distribution system	Number of breaks (from pipe break module), Average pressure, flow rate average duration (city databased)	Equation generated using hydraulic modeling for amount of water loss based on member of breaks, pressure, flow rates, and response time
	Energy losses (SD)	Simulation of associated energy losses from water losses produced due to pipe break in water supply and distribution system	Amount of water losses (water losses module), Energy consumption rates (WaterRF 2013)	Increase in the amount of water loss, increases the amount of energy losses from water supply and distribution systems
Utility Revenue Module	Utility Revenue (SD)	Simulation of revenue generated from water sales and financial losses due to pipe breaks	Total water consumption city wide (consumer module)	Generated revenue from water sales is based on volumetric pricing of water consumption per household
			Repair cost (Grigg 2013), NRW, Associated energy loss (water and associated energy loss module)	Increase in number of breaks, increases operations costs (repair cost and energy losses), as well as amount of non-revenue water (NRW) for water utility
Consumer Module	Agent (ABM)	Simulation of the residential consumer water consumption during rates increases events	Household water consumption pattern (water consumption distribution based on the survey of case study city)	Willingness to increase/ decrease water consumption determined based on the survey of households in case study city
		Simulation of word-of-mouth communication among residential consumers during rates increases events	Word-of-mouth communication (custom distribution based on survey of households in case study city)	Percentage of agents changing their decision based on word-of-mouth communication determined through pre-define custom distribution based on the survey of households in case study city

5.5 Model Development

This section presents the model development and calibration of the different component modules that comprise the model. Most of the relevant data needed for model development were readily available from information provided by the water utility in the case study city online databases including USGS, annual reports from the water utility during 1990-2010, and other open-access resources such as AWWA, WaterRF, and EPA. Figure 5.3 shows the components of the SD-ABM model.

5.5.1 Pipe Breaks Module

The purpose of using the Pipe Break Module was to estimate the number of breaks occurring in the case study city. The main break module estimated the quantity of water main breaks in four pipe diameter units (6”, 8”, 12”, and 16”). Data on pipeline characteristics and other information were gathered from the water utility GIS database. Econometric modeling was used to simulate the number of water main breaks monthly (Zamenian et al. 2017).

5.5.2 Water and Associated Energy Losses Module

The Water Loss Module simulated the total water loss from water main breaks based on the AWWA M36 Manual (AWWA 2016). Water loss is a function of the number of breaks in a distribution system, the average flow rates of the leaks, the duration of the leaks, and the average pressure in a distribution system. The number of breaks was calculated using the Pipe Breaks Module. The total duration of water loss (awareness duration + repair duration) was retrieved from the GIS database in the case study city. “Awareness duration” as defined by the AWWA Manual (2016) the duration/time that water utility will receive report on main breaks/leakage until the maintenance crew reaches job site to fix the break. The average pressure was assumed to be 70 psi for the entire water distribution system due to the limited data availability of the pressure at each breakpoint. The average flow rate for water main breaks was estimated using the pipe diameter and the AWWA M36 Manual (AWWA 2016). The amount of water loss from water main breaks in the water distribution system was translated into an extra water demand, which affected what the water supply system needed to extract, transport, treat, and pump additional amounts of water to customers. Two primary sources were available for extracting drinking water in a water supply system, (1) groundwater (wells) and (2) surface water (reservoirs).

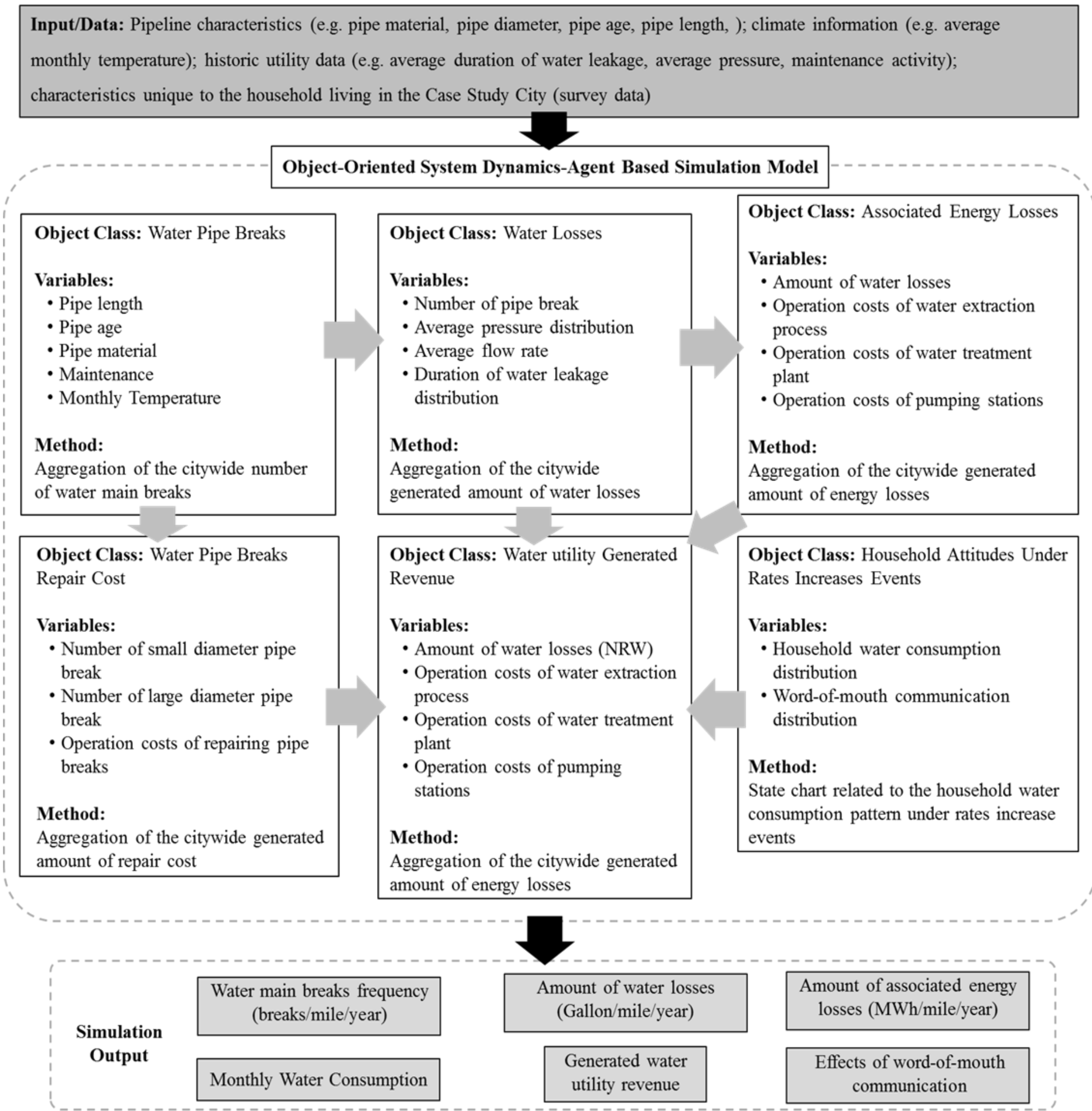

Figure 5.3. Components of the SD-ABM model

The energy consumption (electricity usage) of a pumping system was the function of the flow, an assumed distribution system pressure head, and an assumed wire-to-water efficiency (overall efficiency of the pump and motor combination). The average flow rate for a pumping system was considered to be 20 million gallons per day (MGD), based on the current capacity of the water treatment plant in the case study city. The electricity usage for the groundwater pumping system was calculated with an average head of 150 feet as a common practice (AWWA 2009). According to the WaterRF and EPRI (2013), the wire-to-water efficiency for the pumped water depended on the quality and characteristics of the pump. The wire-to-water efficiency for this study was assumed to be 65% based on the commonly observed practices in the water industry (AWWA 2009; WaterRF and EPRI 2013).

The amount of energy used for the water treatment process depended on the quality of raw water and the quality standard required for drinking water. Drinking water quality regulations have become more stringent in recent years, requiring advanced energy-intensive water treatment processes. The type of treatment plant needs to be considered for an energy loss analysis because a traditional water treatment process is different from a more advanced water treatment process making the energy consumption of each process unique. This study considered three types of treatment plant processes (1) conventional treatment, (2) advanced treatment, and (3) desalination treatment. The conventional water treatment plant for raw surface water consisted of treating raw water through rapid mixing, flocculation, sedimentation, filtration, and chlorine stages with an approximate energy intensity of 1,420 kWh/MG (WaterRF 2013). Conventional water treatment plants for raw groundwater consisted of treating raw water through aeration, filtration, and UV disinfection stages with the approximate energy intensity of 2,260 kWh/MG (WaterRF 2013). The groundwater treatment plant process was energy-intensive due to the pumping and involved aeration to remove iron and manganese. The advanced treatment of raw surface water consisted of treating raw water through rapid mixing, chemical feed systems, dissolved air flotation, ultrafiltration, UV disinfection, and chlorine stages with an approximate energy intensity of 2,510 kWh/MG (WaterRF 2013).

Desalination water treatment of raw surface water consisted of treating raw water through media filtration, chemical addition, reverse osmosis, and chlorine disinfection stages with an approximate energy intensity of 13,600 kWh/MG (WaterRF 2013). "The greatest energy use was associated with the reverse osmosis membranes, but the brine must be disposed of so there is energy required for backwashing and residuals pumping" (WaterRF 2013).

After the treatment, water must be pumped to the distribution system. The water pipeline network in this case study relied on pumping stations to provide an appropriate level of service and adequate pressure at the tap for the customer. The energy consumption of pumping stations was a function of the flow, an assumed distribution system pressure head, and an assumed wire-to-water efficiency. In the study, the average pressure of the distribution system was assumed to be 70 psi, and the efficiency of the pump was assumed to be 65% based on the commonly observed practices in the water industry (AWWA 2009). Based on these values, the approximate energy consumption of pumping treated water with the pumping efficiency of the medium was 32,344 kWh/MG (WaterRF 2013).

5.5.3 Consumer Model

The Consumer Module simulated the behavior of the consumer agents toward water-rate increases. Each consumer agent represented a consumer group (household) having a common goal. As shown in Figure 5.5, the goal of consumer agent is to having uninterrupted access to quality water supply. To develop behavior rules for consumer agents' attitudes toward water-rate increases and to provide a realistic representation of water service reliability and quality of the water supplied by water utility, a survey was distributed to the population of residents of a Midwestern city (used as a case study for demonstrating the models developed in this study). The respondents were filtered using four questions/statements listed at the beginning of the survey including: (1) I am living in the City, (2) I am above 18 years old, (3) Are you responsible for paying your water bill or a portion of your water bill, and (4) Do you have access to the water service provided by water utility. Only respondents who satisfied all these criteria were included in the survey. To obtain a confidence level of 95% with a confidence interval of 5%, 400 complete surveys were found adequate to represent the sample population. Consumer agents are defined in this study as the 400 residential users (281 males and 119 females) of drinking water in the case study city who provided responses regarding water service reliability and quality of water supplied by the water utility in that city.

The revenue of the water utilities was tied to water consumption. To fund improvement projects, operate effectively, and maintain the water infrastructure, utilities considered increasing water-rates. Historically, over the past 10 years, the water-rate has increased every three years between

15-25% in the case study city (CEG 2014; CEG 2016). Therefore, this range of water-rate increase was used as an assumption in this simulation. When consumer agents were modeled, water-rates were doubled, so that rate increases could be readily understood by survey respondents. In addition, this level of increase would be sufficient to generate a feasible rate-increase response given the low price elasticity of water demand. When modeling the utility agent, the water-rates increases (typically 15% - 25%) employed by the water utility are used to estimate the generated revenue for the utility.

Consumer agents made decisions based on quality, reliability, and the cost of water available from a water utility. Upon receiving a rate increase notice from the water utility, consumer agents were likely to review their current water consumption patterns based on their beliefs, knowledge, and information (BKI) (Figure 5.5), and made one of these decisions to (1) increased consumption, (2) decreased consumption, and 3) decided that their habits would not change. The water bill for the customers in the case study city is structured based on unit-used charges based on the volume of water usage. Therefore, when water consumption is increased or decreased, the water bill increases or decreases proportionally. Consumer's decisions can be affected due to two aspects:

1. Each consumer agent is capable of making an independent decision to decrease/increase/not change its water consumption. Consumer agents made decisions to transition between these states based on their demographic characteristics (income, age, gender, number in household) and the quality of service they received from the water utility agent (as defined by the number of and duration of disruptions due to water main breaks). This change in consumption is modeled in the study using the custom distribution of consumers' behavior, as represented in the survey of 400 residents in the case study city. Based on the survey results, when the water utility doubled the water-rate at any time, six consumer agents increased their water consumption, 296 consumer agents decreased consumption, and 98 consumer agents did not change their water consumption. Out of 296 consumer agents who decreased their water consumption levels, 61 agents decreased their consumption by 1-5%, 105 agents decreased their consumption by 6-10%, 75 agents decreased their consumption by 11-15%, and 55 agents decreased their consumption by 16-20%. These water consumption changes are assigned to the consumer agents until the next water-rate increase event.

2. There are also decisions which are interdependent since consumers can influence the behavior of an agent regarding consumption pattern through rules that respond to new information. This may cause one agent to change its previously independent consumption pattern. Consumer agents' behaviors toward water-rate increases are likely to be affected by word-of-mouth communication among consumer agents within the community and hence, influence their decisions about water consumption. The communication mechanism among consumer agents was simulated using the cellular automata (adjacency neighbor relationships) framework (Couclelis et al. 1997; Steven and Dragicevic 2007). Consumer agents were randomly placed on a square grid. Each square grid was assumed to be a typical house in the Midwest region of the U.S. with an average size of 2000SF (based on the average SF area houses in the Midwest).

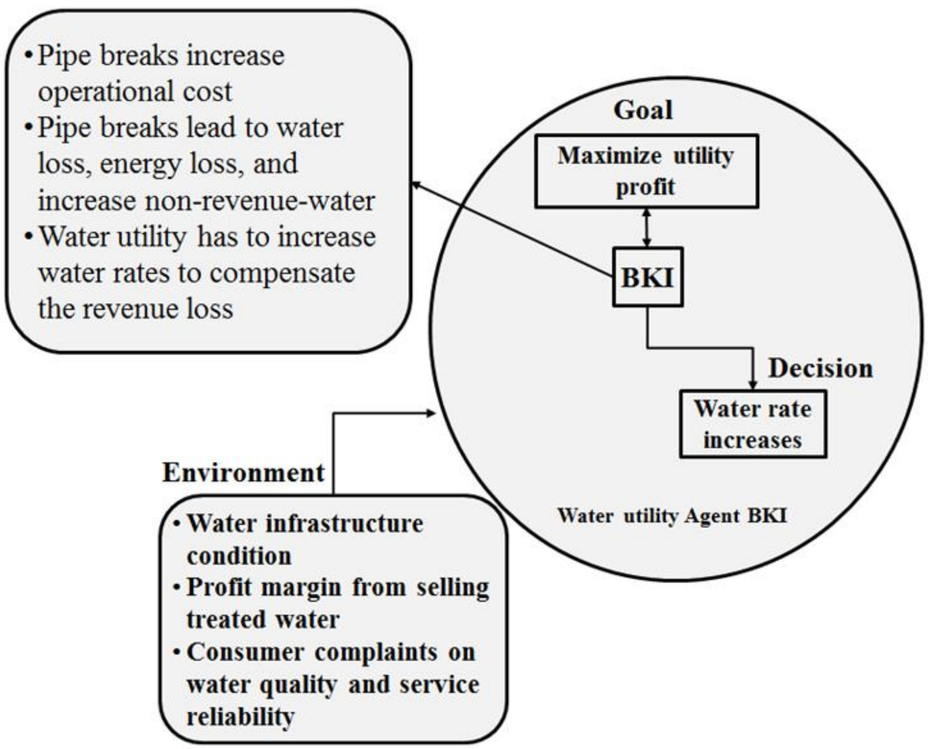

Figure 5.4. BKI Diagram for Water Utility Agent

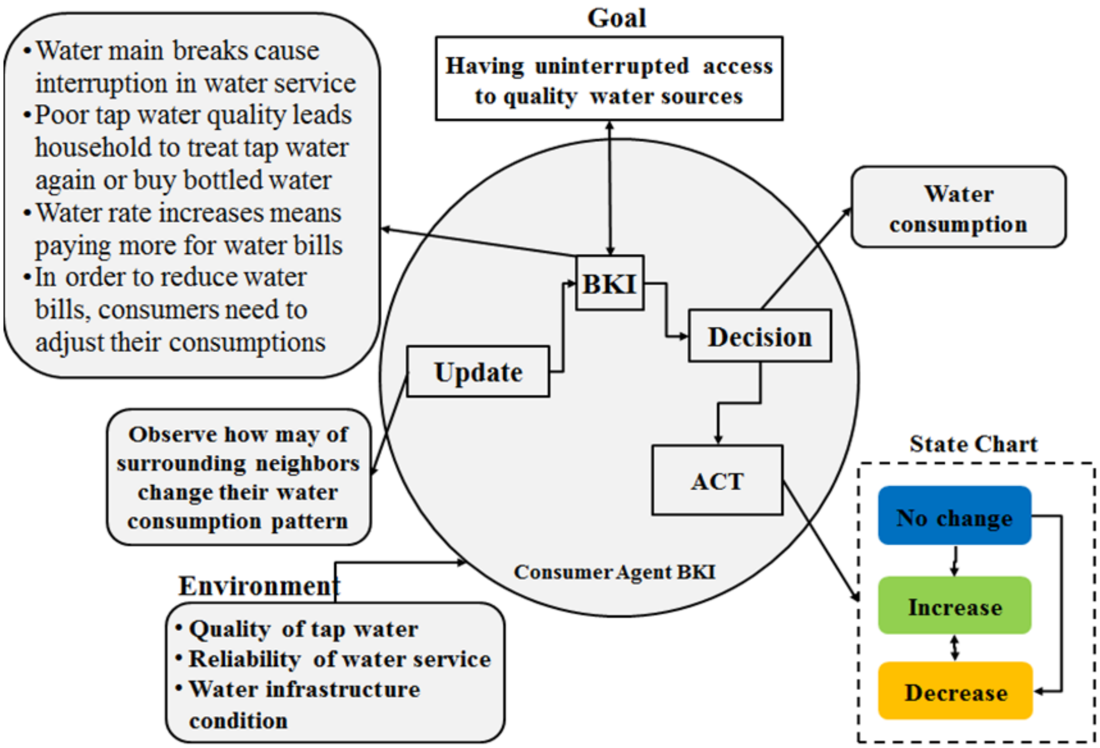

Figure 5.5. BKI Diagram for Consumer Agent

Some consumer agents may interact with a large number of surrounding neighbors and some agents may interact with a limited number of neighboring agents or may remain isolated. Interactions between consumer agents were limited to surrounding neighbors (Figure 5.6), based on the Moore definition of a neighborhood (Weisstein 2019). Thus, each consumer in a square grid was linked up to its eight neighboring agents and could only exchange information among each other. As an example, in the 2-D grid of 5×5 (Figure 5.6), the consumer agent A was placed at the center of the grid where the agent A could interact up to eight neighboring agents. The consumer agent (A) only communicated and received information with the immediate neighboring agents. At the start of the simulation, each consumer agent sent messages reporting its state based on the state chart: (1) decrease consumption, (2) increase consumption, (3) no-change to the neighboring agents. At each step, the transition between the state's (decrease, increase, no-change) occurred based on the grid weight, which represented the number of the influenced neighboring agents using a pre-defined threshold.

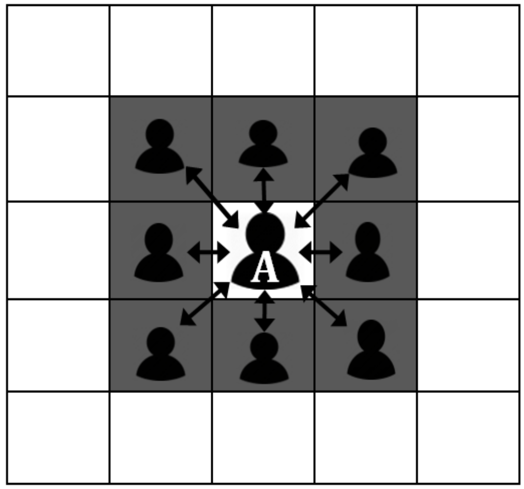

Figure 5.6. Flow of Communication for a Consumer Agent

To assess neighboring agents' influences, each consumer agent (A_x) summed that all grid weights (GW) received the same time from its neighbors at each time step using Equation 5.1.

$$GW(x,t) = \sum_{y=1}^{n} A(y,t) \times CP(y,t) \qquad (5.1)$$

Where $GW(x,t)$ is the total number of messages that each consumer agent received from neighbors in grid x at time *t*. $A(y,t)$ represents the existence of a consumer agent (A) in neighboring grid y at time *t*. If there was an agent in neighboring grid y, then $A(y,t)$ was equal to 1. If there were no agents in the neighboring grid, the value A was equal to zero. $CP(y,t)$ was the consumption pattern of consumer agents in the neighboring grids y at time *t*. If an agent consumption pattern was assigned to decrease, the value CP was equal to 1. If an agent consumption pattern was assigned to no-change or increase, the value was equal to 0.

The effect of communication on a consumer agent decision was represented using a threshold rule, which simulates consumer agent adopting a new decision on water consumption after it communicates with its neighboring agents. At each time step, each consumer agent (A_x) updates its decision about water consumption based on its grid weight (GW) value using pre-defined threshold as shown in Equations 5.2, 5.3, and 5.4. These pre-defined thresholds and responses were defined during the survey of households in the Case Study City. Equation 5.2 explains that if the number of neighboring agents intending to decrease their water consumption is less or equal to three neighbors, the agent (A_x) decreases its water consumption pattern. Equation 5.3 describes that if the number of neighboring agents intending to decrease their water consumption is between four to six neighbors, the agent (A_x) decreases its water consumption pattern. Equation 5.4 defines that if the number of neighboring agents intending to decrease their water consumption is more than seven neighbors, the agent (Ax) decreases its water consumption pattern. N_D Represents the number of consumer agents who decreased their water consumption pattern.

$$\textbf{IF} \quad GW(x,t) \leq 3 \ \textbf{ THEN } \ N_D = N_D + 1 \ \textbf{ AND } \ CP(x,t+1) = 1 \tag{5.2}$$

$$\textbf{IF} \quad 4 \leq GW(x,t) \leq 6 \ \textbf{ THEN } \ N_D = N_D + 1 \ \textbf{ AND } \ CP(x,t+1) = 1 \tag{5.3}$$

$$\textbf{IF} \quad GW(x,t) \geq 7 \ \textbf{ THEN } \ N_D = N_D + 1 \ \textbf{ AND } \ CP(x,t+1) = 1 \tag{5.4}$$

The simulation was performed based on five main steps as shown in Figure 5.7. (1) The water utility agent sends a water-rate increase message to consumer agents. (2) Each consumer agent determines its water consumption. (3) Consumer agents communicate with other agents regarding the water-rates increase. (4) The water consumption of the individual consumer agent is calculated. (5) The total water consumption in the neighborhood is estimated.

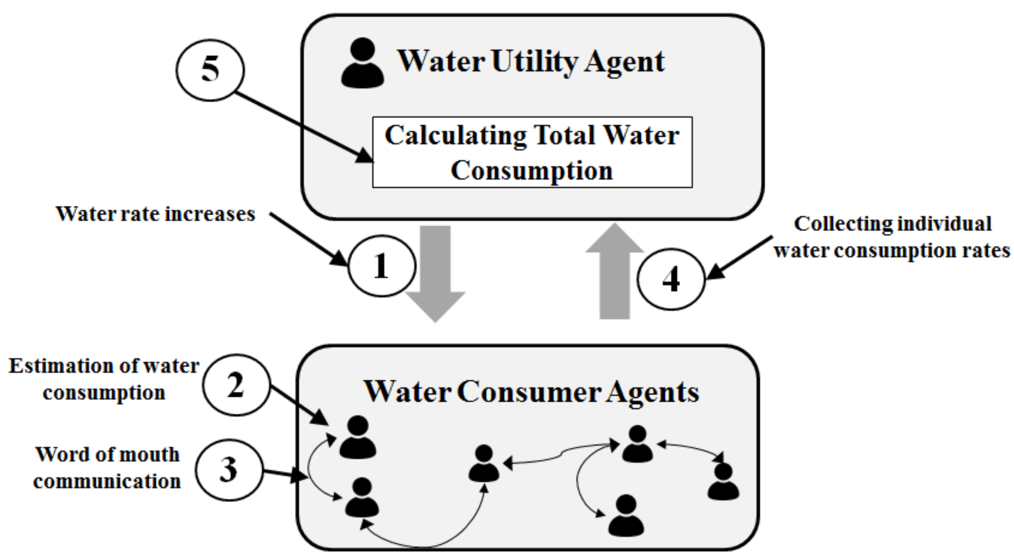

Figure 5.7. ABM Simulation Procedure

5.5.4 Utility Revenue Module

The Utility Revenue Module estimated the generated revenue by the utility company from selling water to residential customers and the revenue losses stemming from water loss (NRW), energy loss (additional use of energy due to NRW), and repair costs of main breaks. Figure 5.8 explains the interactions among the system components. Typically, water utilities in North America are structured to be self-sufficient, such that revenues collected by the utility company from its customers are expected to cover all of the expenses, without the need to obtain additional revenue from taxes, federal funds, or other enterprises (WaterRF 2014). Hence, the majority of water utilities' revenue was derived from customer sales. The water consumption rate (from Consumer Module) was multiplied by the current water-rate ($3.67/CCF) in the case study city to estimate utility revenue. According to Water Audit and Loss Control Programs Manual-M36 (AWWA 2009), NRW is comprised of three components including leakages and overflow at the utility's storage tanks, leakage at transmission and distribution mains, and leakage at service connection pipelines. However, for this study, NRW from leakage at transmission and distribution mains was calculated as explained in the Water Loss Module. The amount of NRW was calculated by multiplying the volume of water losses (from Water Loss Module) by the current water-rate in the case study city.

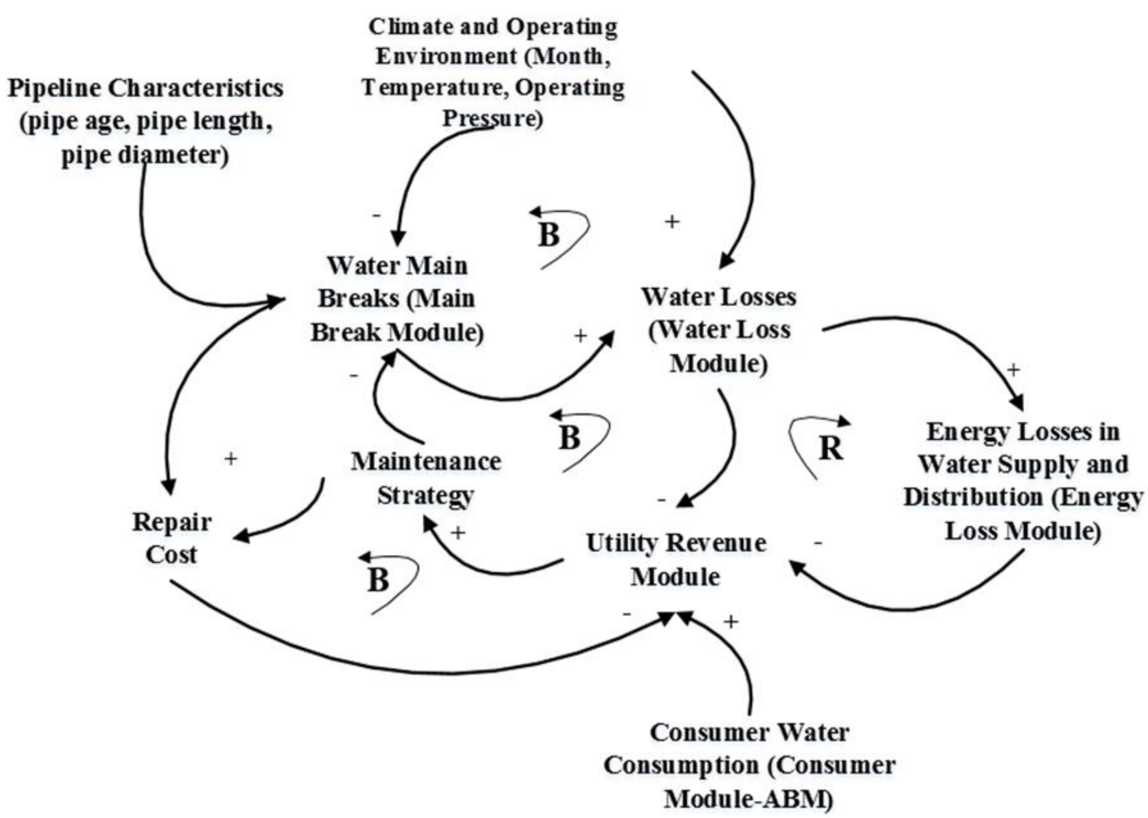

Figure 5.8. Interactions among the System Components

Calculations of the additional use of energy for extraction, treatment, and distribution due to main breaks in the distribution system were computed by multiplying the overall energy losses by the average industrial electricity rate in the case study city. Repair costs for water main breaks included (1) indirect costs for construction materials, equipment, and labor; (2) direct costs, which were paid by the owner or contractor; and (3) social costs, which usually accounted for inconveniences, disturbances, and damages to the environment to the consumer agents. Since the costs of inspection and repair were not available from the utility in the case study city, this doctoral research assumed total direct and indirect costs of $10,000 for a water main break occurring in small diameter pipes (6" and 8"), and total direct and indirect costs of $50,000 for a water main break occurring in large diameter pipes (12" and 16") based on Grigg (2013).

5.6 Analysis and Results

The SD-ABM framework is used to simulate (1) water main breaks frequency, (2) water and associated energy losses from main breaks, (3) water consumption projection (within three scenarios), (4) level of connectivity between consumer agents and water consumption, and (5) generated revenue from water-rates increase (within three scenario). The time-step of the simulation is one month. Thus, the main break frequency is calculated on number of breaks per month, and the estimated water consumption is based on a monthly-step, since this data was available on a monthly basis. Predictions of water main breaks and water loss and associated energy losses were done for a 20-year period. The data related to water and energy losses are reported on an annual basis to capture the entirety of water and energy loss analyses. However, for water consumption and revenue calculation, the prediction was done for a 10-year period, since the relevant data was available was only available for this period of time.

5.6.1 Dynamics of Water Main Breaks

By running the SD simulation in AnyLogic for 20 years, the estimated numbers of breaks based on the input data from the case study city were generated. Figure 5.9 shows the estimated number of breaks/miles/year during the simulation period. According to the 2018 WaterRF survey, the average water main break rate for water utilities in North America varies between 0.21 to 0.27 breaks per mile of pipeline per year (WaterRF 2018). The WaterRF study estimated the break frequency for the city-wide pipeline network. However, this study conducted a detailed analysis to explore break frequency for different pipe diameter cohorts. To minimize the frequency of main breaks and implement cost-effective strategies, understanding the physical conditions of a water pipeline system was inevitable. The simulation showed a clear distinction between small diameter pipes and large diameter pipes in terms of pipe breaks. Even though larger diameter water main breaks have larger failure consequences in terms of their impact on the water system, the higher number of breaks often experienced with smaller diameter pipes could have made the total cost comparable (Zamenian et al. 2017). As shown in Figure 5.9, the 6" diameter pipes experienced higher rates of main breaks compared to the other diameter cohorts. Generally, small diameter water pipes (6" and 8") were the most common type of pipes in the water distribution system. Due to their smaller pipe wall thicknesses and greater number of joints and connections that maybe prone to more planes of weaknesses, compared to large diameter pipes, the failure rates in small diameter pipes (6" and 8") are higher.

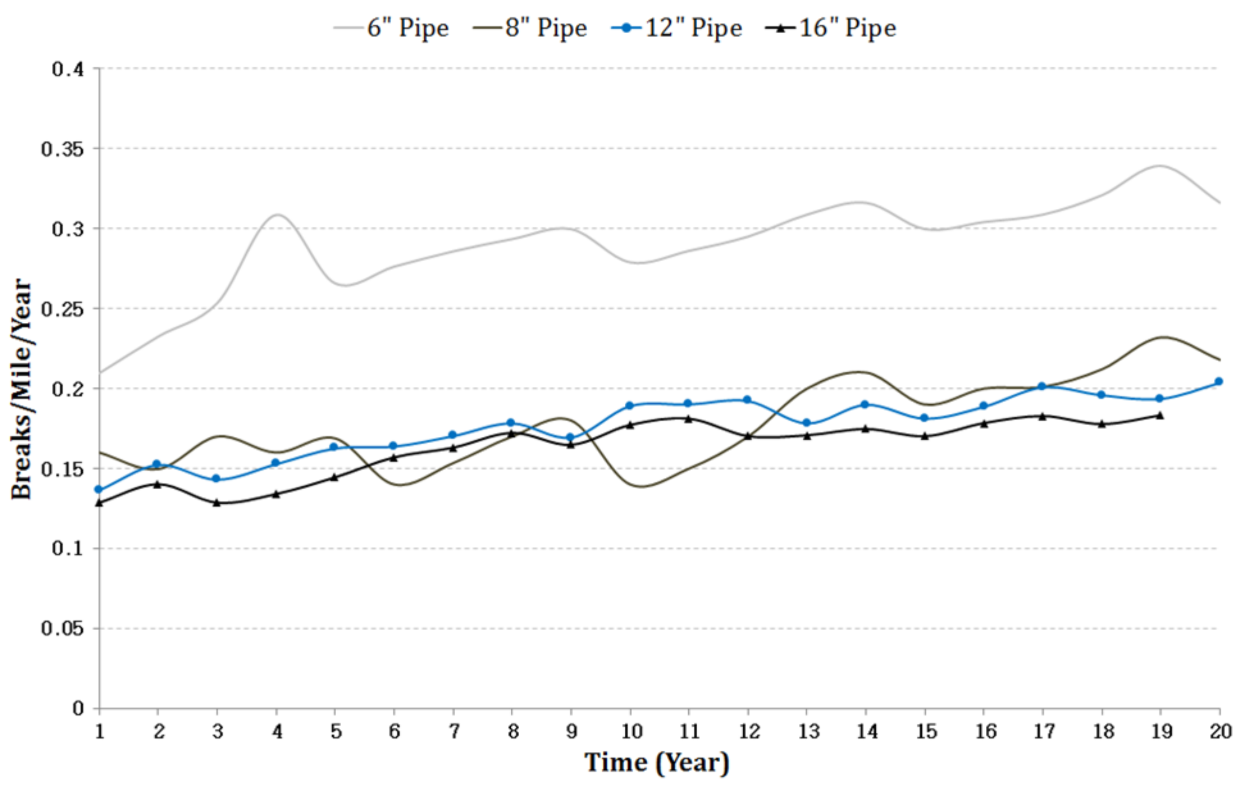

Figure 5.9. Estimated Number of Breaks for the Period of Simulation

5.6.2 Water and Associated Energy Losses Dynamics

By running the SD simulation for the same period, the amount of water and associated energy losses based on the input data from the case study city and the Main Break Module were generated. It is clear that the energy loss from pipe breaks followed the same pattern as the water loss. As shown in Figure 5.10, the 6" diameter pipes had higher rates of water and associated energy losses in water distribution systems, mainly due to the higher frequency of breaks occurring in this diameter cohort. Although the numbers of breaks for the 8" diameter pipes were higher than for the 12" diameter pipes (Figure 5.9), the amount of water and associated energy losses of the 12" diameter pipes (Figure 5.10) was higher by 43% and 11% on average respectively than for the 8" diameter pipe. This can be explained by the higher leakage rate of the 12" diameter pipes compared to the leakage rate in the 8" pipes and other operational factors such as the higher water pressure and the response time to fix the breaks by the water utility company. The simulation results indicate that the decision-making procedures regarding replacement and rehabilitation of water pipes should not be limited to the number of main breaks, but should also consider other consequences such as water and associated energy losses to make more informed decisions regarding budget allocations for water pipeline renewal. For instance, although the frequency of failure on the 8" diameter pipes had an 8% higher average compared to the frequency of failure of the 16" diameter pipes, the amount of water loss and associated energy losses in the 16" diameter pipes were higher by 38% and 45% on average respectively.

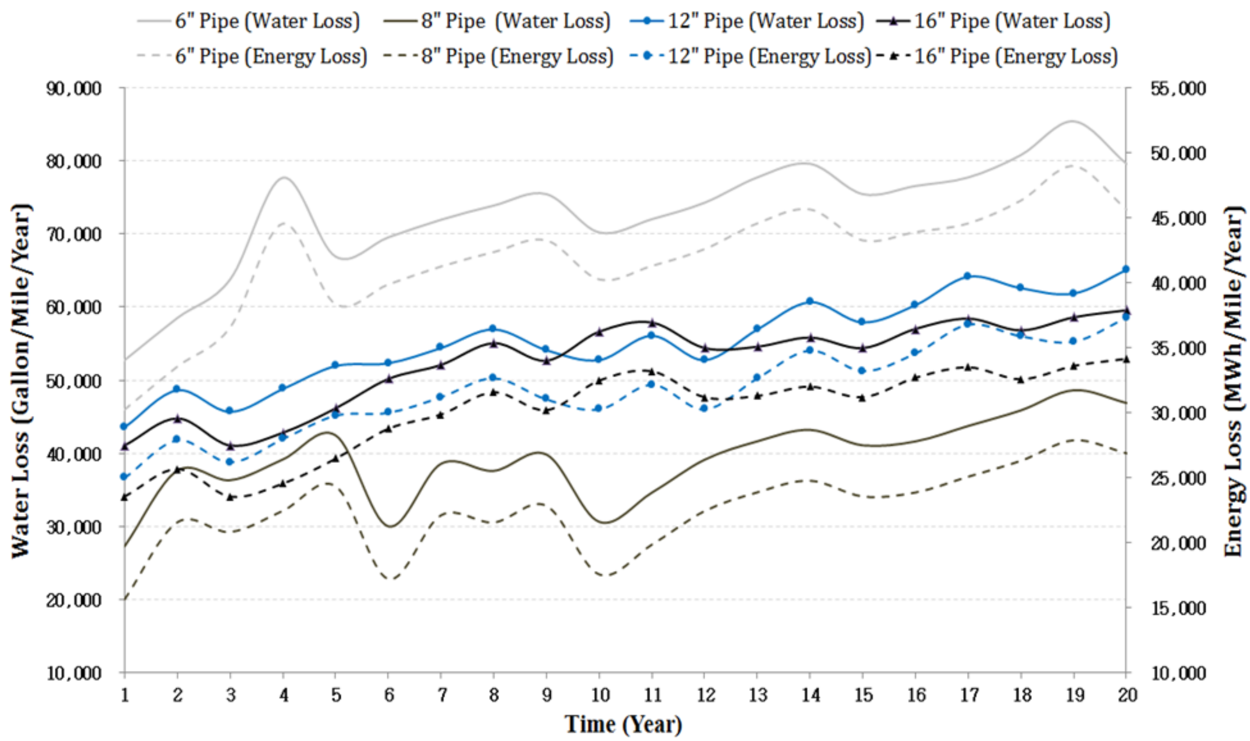

Figure 5.10. Estimated Amount of Water and Associated Energy Losses for the Period of Simulation

The water and associated energy losses presented significant challenges to the utility manager and manifested major revenue losses (because of NRW, energy loss, repair cost) and consequences of failure due to the criticality of large diameter pipes in the water distribution system. The consequences of large diameter pipe failure have social and operational impacts. Social impacts in the affected communities include massive flooding, major disruptions of service, and city or neighborhood orders to boil water. The operational impacts of large diameter pipes create undesirable conditions due to the water pressure drops in the system.

5.6.3 Consumer Behavior Dynamics

A total of 400 consumers, located in five subdivisions in the case study city were considered for the simulation. The ABM was used to explore three water consumption trajectories that water utility could have followed regarding its water charges to the customers. Scenario (A) was the baseline scenario, in which the water utility company does not increase water-rates for 10 years. Scenario (B) simulated water consumption patterns after rate increases with no communication among consumer agents. Scenario (C) simulated water consumption patterns after rate increases by allowing consumer agents to communicate with their neighboring agents. AnyLogic 8.2.3 was used to estimate water consumption per month based on the 400 consumer agents for 10 years (Figure 5.11).

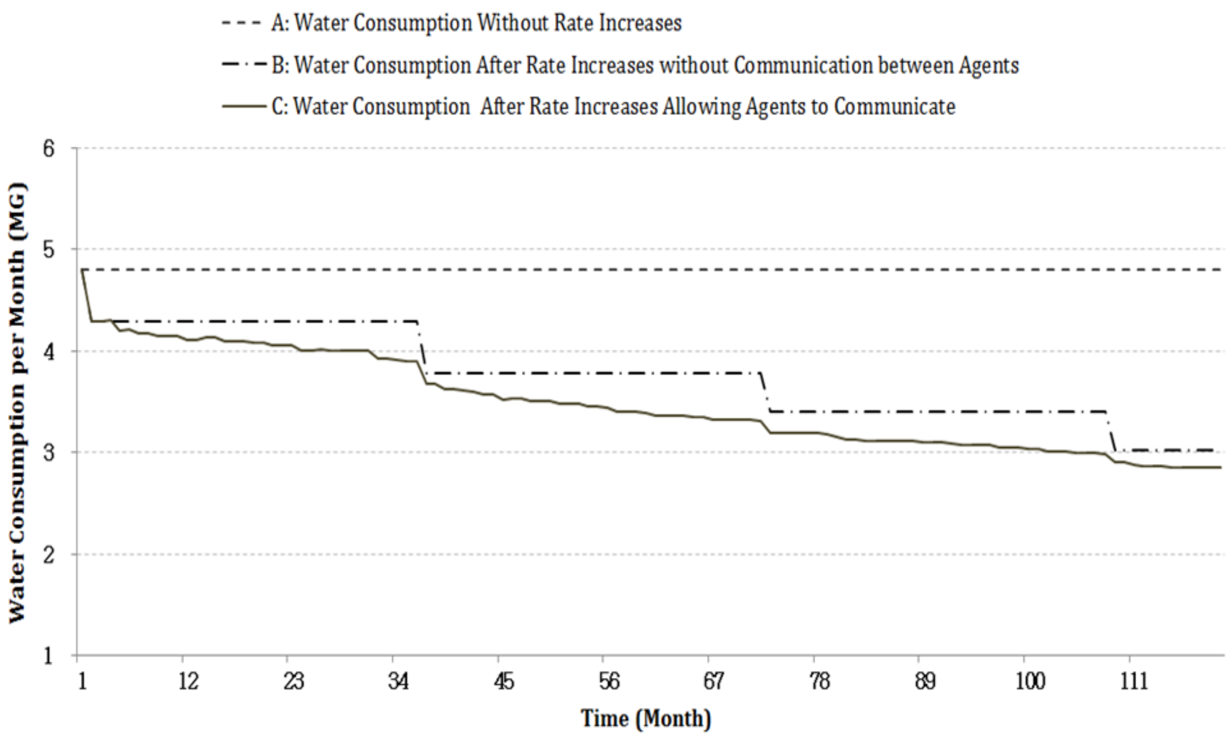

Figure 5.11. Water Consumption per Month Based on 400 Consumer Agents for the Period of the Simulation

(1) Scenario A: Water Consumption with No Water-Rate Increases (baseline)

In this scenario, the water utility company did not increase water-rates for 10 years. This assumption was the benchmark for assessing the different outcomes, such as the consumption patterns and generated revenues. The analysis for this case was based on a 12,000-gallon water consumption pattern for a typical family of four in the U.S. (EPA 2018). The water-rate during the simulation period was constant and was based on the current water rate ($3.67/CCF) in the case study city.

(2) Scenario B: Water Consumption after Rate Increases with No Communication between Consumer Agents

In this case, the water utility agent increased water-rates every three years. Therefore, every three years, consumer agents had to make decisions about their water consumption patterns. In this scenario, the consumer agent was assumed to be isolated and was not allowed to communicate with neighboring agents during the simulation period. However, consumer agents perceived their environment (water service reliability and quality) and responded in a realistic time frame to a new environmental condition (water-rate increases event). This attribute was captured through a survey of households in the case study city. As shown in Figure 5.11, the water consumption rate dropped in months 39, 73, and 109 due to the sudden increase in the water-rates in those particular months. It was also observed that the total water consumption of consumer agents decreased by 37% at the end of the simulation (Line B) compared to the water consumption without rate increases (Line A). The constant consumption patterns between the months of 1-38, 39-72, 73-108, and 109-120 were mainly due to the consumer agents not communicating with their neighboring agents about the water-rate increases. Once the consumer agents adjusted their water consumption based on the water-rate increases, they continued that particular consumption pattern until they received notice of another rate increase. For example, the consumer agents who reduced their water consumption in week 39 continued the same consumption pattern until week 73 until they were made aware of another rate increase by the utility agent.

(3) Scenario C: Water Consumption after Rate Increases Allowing Agents to Communicate

A conventional water demand simulation (Scenario B) typically ignored the effects of consumer communications or was treated as a single parameter describing the community as a whole (Athanasiadis et al. 2005). To overcome this shortcoming, in Scenario C, the water utility increased the water-rate every three years during the simulation period, and consumer agents communicated with neighboring agents about water-rate increases. Then, they updated their decisions to increase/decrease their water consumption. As shown in Figure 5.11, the water consumption dynamically changed each month based on the consumer agents' awareness about the water-rate increases. It was also observed that the total water consumption of consumer agents decreased by 6% at the end of the simulation (Line C) compared to the water consumption with rate increases when there was no communication between consumer agents (Line B). Although an initial drop in water consumption was observed in Year 1 of the simulation along with water-rate increase events, the process of adapting water consumption (in response to the rate change) slowed over the 10 years of the simulation. As shown in Figure 5.11, communication among consumer agents (Scenario C) caused a reduction in total water consumption by 15% during the same 10 years, compared to the situation when consumer agents were not allowed to communicate with neighboring agents (Scenario B). However, near the end of the simulation, the water consumption pattern in Scenarios B and C approach steady rates. This trend can be explained by the fact that the total population of the case study city was assumed to be constant during the simulation period.

Within the ABM, the simulated water consumption pattern showed that the level of connectivity and communications between consumer agents had a significant impact on overall water consumption. To observe consumer agents' behaviors under price increases during the simulation period, sixty agents were selected randomly. Each agent's behavior related to water consumption was assessed based on two factors 1) the level of connectivity to its neighboring agents and 2) the amount of water consumption at the end of Year 1, Year 5 and Years 11-13. Figure 5.12 depicts an individual agent and its water consumption at the end of Year 1. During this year, agents who encountered water-rate increases attempted to adjust their consumption (increase/decrease/no-change) based on the reliability of their water service and the quality of water provided by the water utility. In Scenarios 1 and 3, consumer agents communicated with their neighboring agents during the simulation period and influenced the neighboring agents regarding water consumption. Figure 5.14 shows consumer agents' consumption patterns in response to water-rate increases at the end of Year 10. As shown in Figure 5.14, those agents with a higher level of connectivity with neighboring agents tended to decrease their water consumption compared to agents with a lower level of connectivity during the simulation. When exploring each agent's water consumption changes during the simulation period (as shown in Figures 5.12, 5.13, 5.14, 5.15), a consumer agent with a zero level of connectivity barely changed its water consumption pattern, If the agent's level of connectivity varied between one and four, the consumption rates decreased between 1.2% to 3%.

Interestingly, the level of connectivity higher than four appeared to have a higher impact on reducing water consumptions, typically between 9% to 13%. A major shift in water consumption was identified between the level of connectivity of four and five when the consumption rates declined by 7%. The simulation results highlighted the influence of word-of-mouth communication on water consumption patterns.

Many water utility companies conduct public water conservation programs for educating and informing consumers on water-rate structures, and on modifying consumer water use habits to subsequently reduce water consumption (Syme et al. 2000; Athanasiadis 2005; Inman and Jeffrey 2006). Not only do such public water conservation programs have a direct impact on communities who participate in such programs, but there can also be an indirect impact realized by the participants who publicize the message of rates increases, water conservation, etc., to their neighbors.

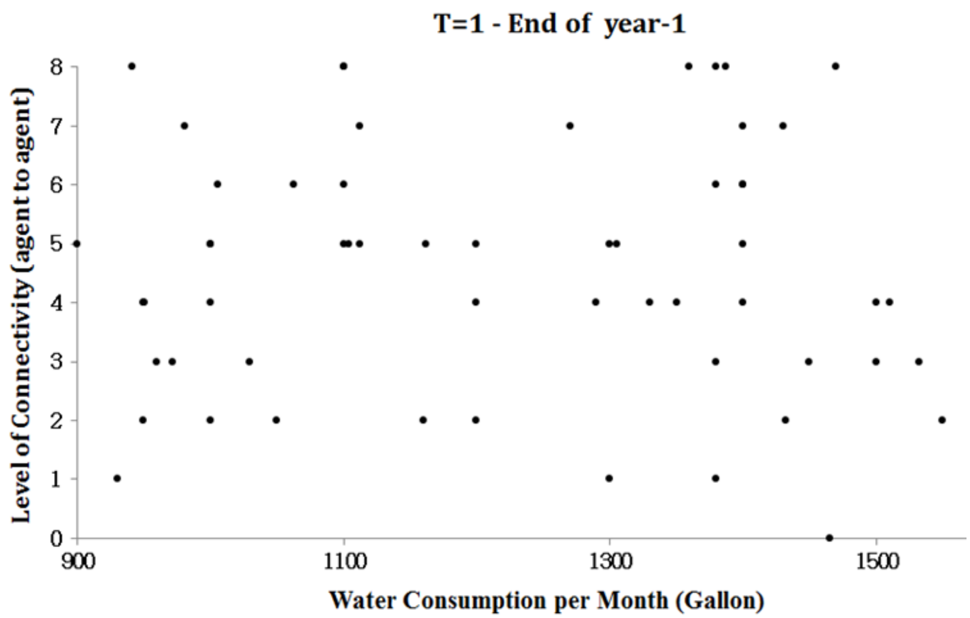

Figure 5.12. Level of Connectivity vs. Water Consumption at the End of Year-1

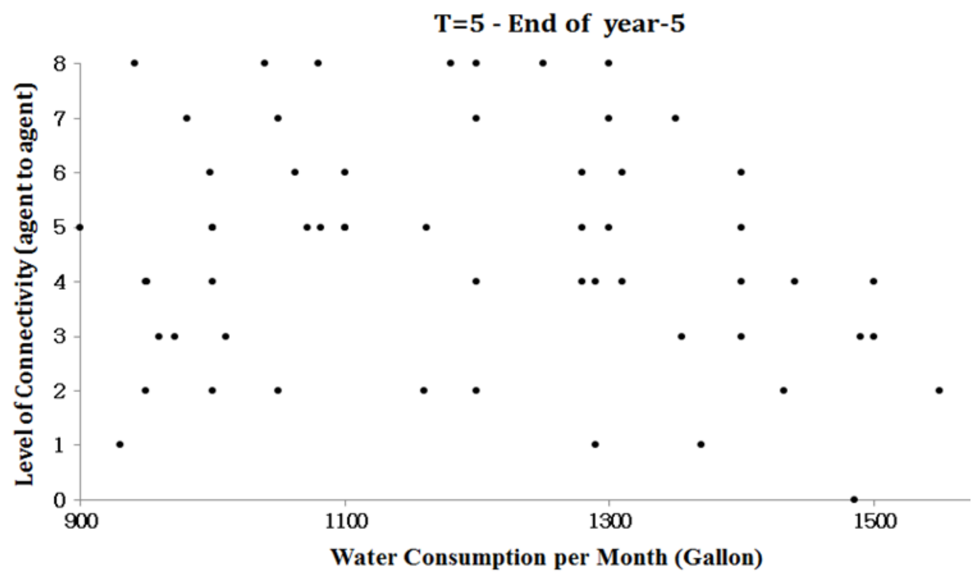

Figure 5.13. Level of Connectivity vs. Water Consumption at the End of Year-5

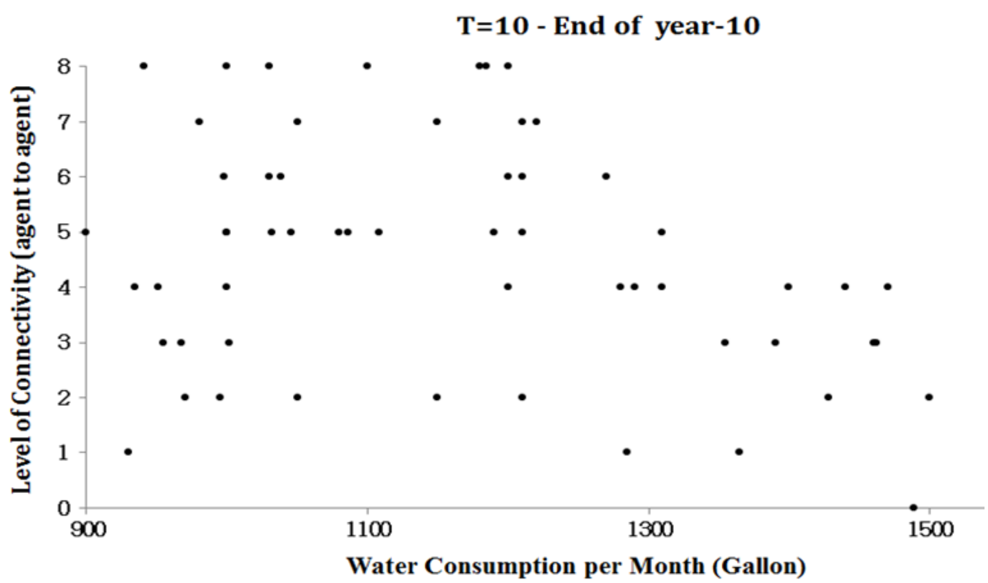

Figure 5.14. Level of Connectivity vs. Water Consumption at the End of Year-10

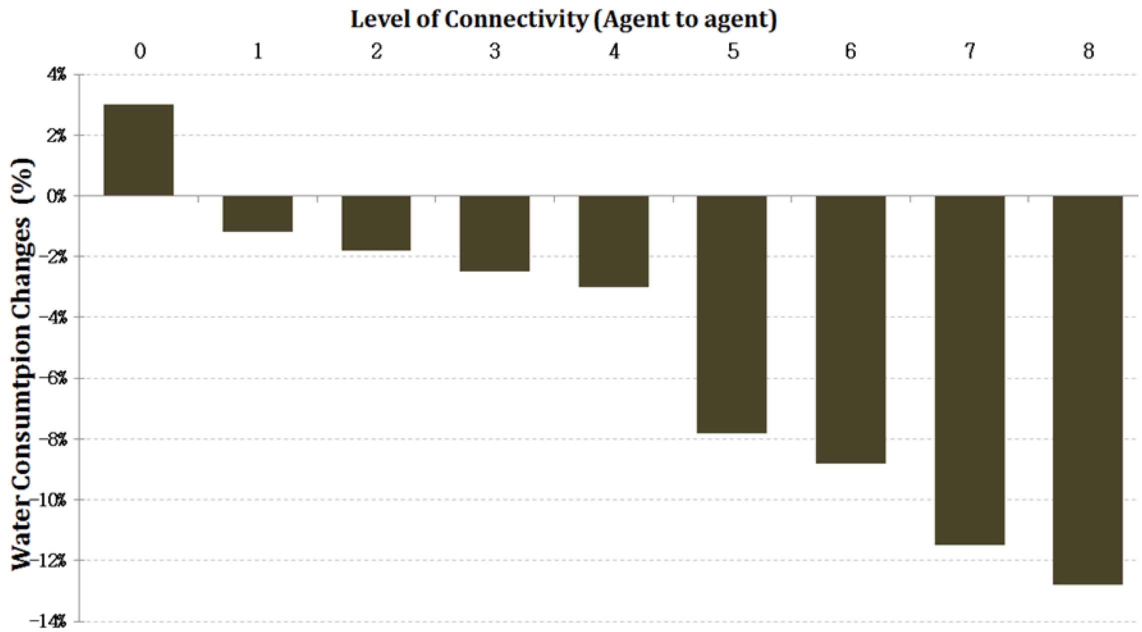

Figure 5.15. Level of Connectivity vs. Water Consumption Changes

5.6.4 Utility Revenue Dynamics

Long-term financial planning was crucial for the water utilities to cover operational and maintenance expenses, and to implement capital improvement projects. The water utilities collected revenues from various sources, including service charges to customers, fees, and grants. However, the largest component of water utility revenues was generated from customer sales based on water consumption (Hughes et al. 2014). Selecting an appropriate water-rate for water services was a critical step for the water utility not only to keep revenues consistent with rising costs but also to improve customer service. The extent of the water-rate increases by water utilities in North America varies widely from 5% to 45% (Hughes et al. 2014).

By running the SD simulation using AnyLogic for 10 years in one-month implements, Figure 5.16 shows the total revenue generated from residential customer sales by considering changes in water consumption under four different rates increase scenarios including: (I) without rate increases (baseline), (II) 15% water-rate increases every three years, (III) 20% water rate increases every three years, and (IV) 25% water-rate increases every three years. As shown in Figure 5.16, the total amount of revenue generated without rate increases (baseline case) is constant since there are no rate increases and consumer agents' water consumption is fixed.

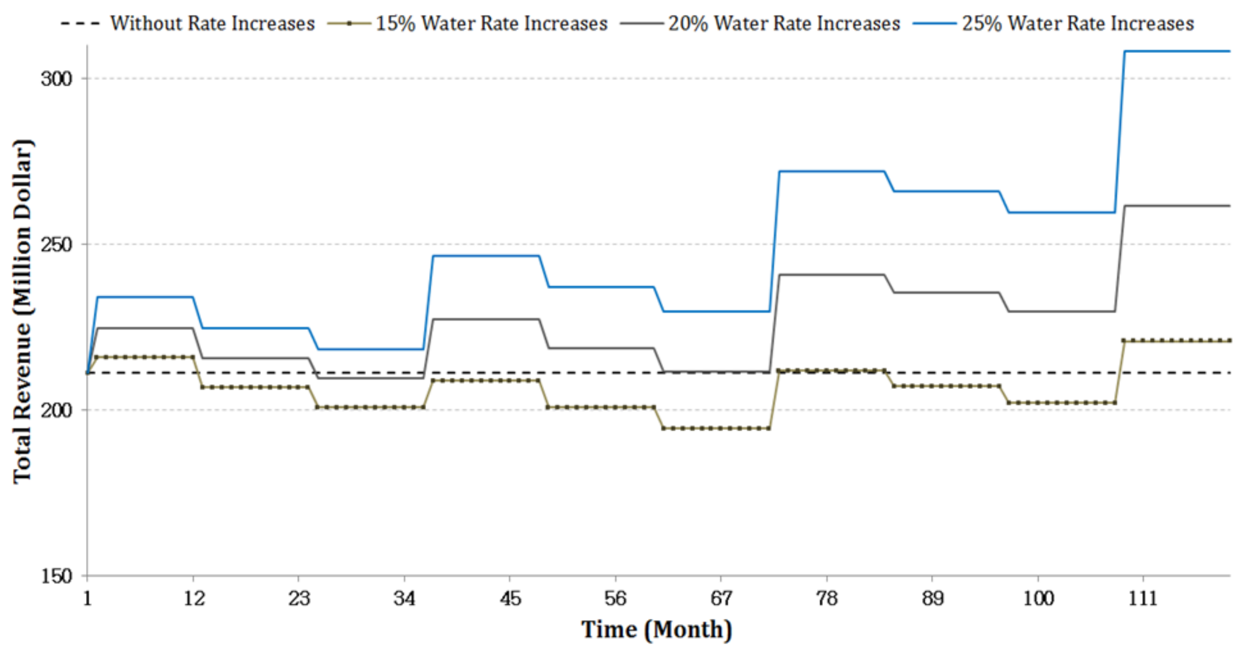

Figure 5.16. Total Revenue from Different Water Rates Increase

The revenue generated from water-rate increases was estimated (Figure 5.17) to compare three different water-rates increases (15%, 20%, and 25%). The generated revenue refers to the total amount of water sales under each pricing structure minus total revenue generated in baseline scenario (without rate increases). In scenario (1), where water utility increases water-rate by 15%, consumer agents respond to this event through changing their water consumption patterns. The water utility encountered 2.1% revenue losses when implementing a 15% water-rate increase every three years compared the baseline scenario (without rate increases). This finding can be explained by the fact that the water price is elastic, and residential consumers respond to rate increases by lowering their water consumption as explained in the Consumer Module.

In scenario (2), water utility tries to implement 20% water-rate increase every three years. Although implementing a 20% water-rate increase causes a 0.5% revenue loss at Year 3, the additional generated revenue during the 10 year period is $162 million compared to the baseline scenario (without rate increase). As shown in Figure 5.16 and 5.17, increasing water-rates by 25% provided higher revenues during the simulation period. However, implementing higher rates poses hardship to low-income customers, since the monthly water bill represents a higher portion of their monthly expenditures. In addition, most public water utilities are financially regulated by the

State’s Public Service Commission and must request state approval for rate increases. This approval process requires additional resources such as a proactive asset management plan. In many cases, the State’s Public Service Commission conducts public hearings regarding the amount of water-rate increases and the water service reliability and quality, and based on these hearings, evaluates proposed rate changes. Hence, having rates higher than 20% may need additional effort and documentation (i.e., utility’s financial plan, plans for capital improvement projects, revenue allocation plan, and rate design) from the utility for review by the State’s Public Service Commission.

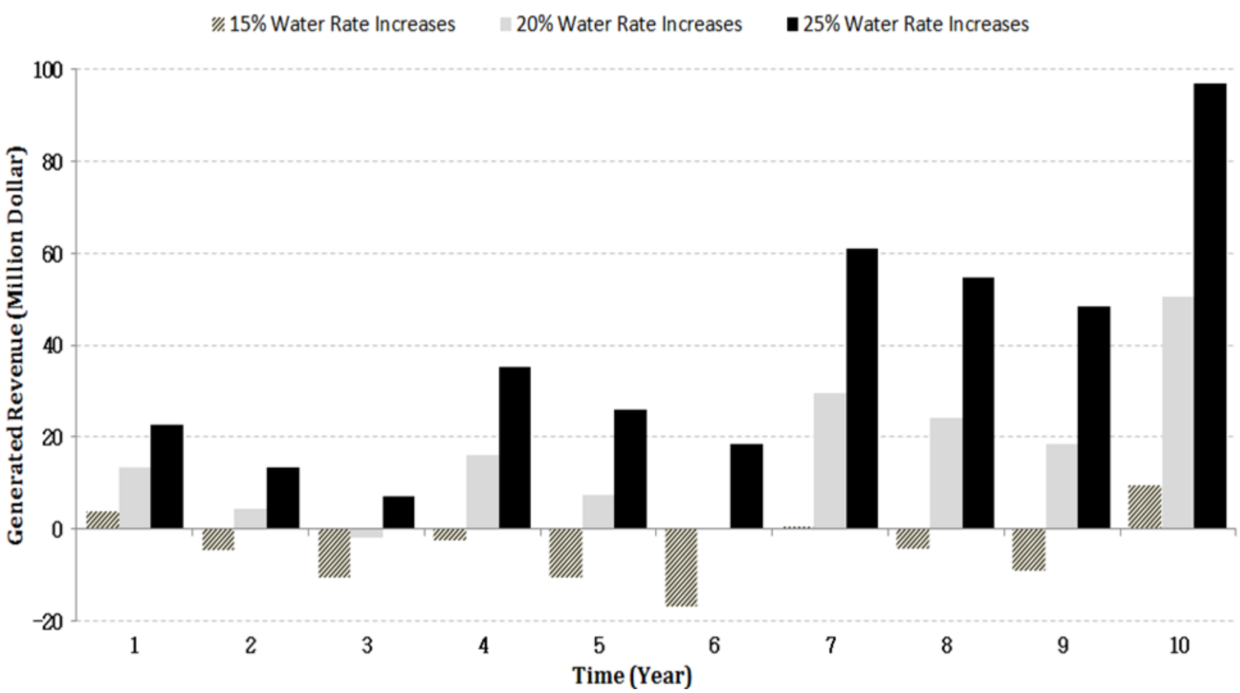

Figure 5.17. Generated Revenue from Water-Rate Increases

The Utility Revenue Module simulated the revenue losses from operational expenses stemming from main water breaks in the distribution system. This revenue loss was comprised of the following (1) additional uses of energy, (2) leakage repair costs, and (3) NRW. Based on the estimated results, NRW comprised 6% of the utility revenue losses, while the repair costs and the energy losses were 48% and 46% of revenue loss respectively.

The majority of water losses occurred in the small diameter pipes (6” and 8”), highlighting the higher their break frequency, as well as the lower maintenance activity allocated for these pipe diameter cohorts. In addition, small diameter pipe failures had a lower social cost compared to the large diameter pipes. Typically, small diameter pipes are located in residential or less-congested areas. Therefore, when water pipe breaks occur in the smaller diameter pipes, the pipes can be fixed while the water system is in operation, causing minimal impact to consumers and businesses. In a case where a specific area had to be shut down to allow for small diameters pipe repairs, the affected areas were often more limited than that associated repairs with a large diameter pipe break. Large diameter pipes have higher costs for repairs and are more important for utilities to maintain due to their criticality and the consequences of failures. Conducting a targeted asset management approach can reduce utility revenue losses. For instance, this approach can be initiated by conducting a proactive maintenance strategy for a specific pipe diameter cohort.

In order to assess the effects of a proactive maintenance strategy on water utility's revenue, a maintenance strategy with the goal of reduction in pipe breaks was considered for a specific pipe diameter cohort (Table 5.2). The maintenance program was assumed to include a proactive inspection program for 40 miles of the 6" diameter pipes (which constituted a significant portion the pipeline network in the case study city and exhibited higher rates of failure) using remote field eddy current technology at a cost of $2/feet, 40 miles of the 8" diameter pipe (which exhibited the second highest number of failures); using remote field eddy current technology at a cost of $2/feet, 20 miles of the 12" diameter pipes; using acoustic leak detection technology at the cost of $7.80/feet; and 20 miles of the 16" diameter pipes using acoustic leak detection technology at the cost of $7.80/feet. Also, $50,000 in indirect costs, including traffic control, mobilization, etc. was considered. After inspecting the pipes, the identified leaks were assumed to be repaired at the cost of $10,000 for the small diameter pipes (6" and 8") and $50,000 for large diameter pipes (12" and 16") based on Grigg (2013).

By implementing a proactive maintenance program, there should be an increase in revenue for water utilities due to reduction in the number of main breaks and hence, reduction in the repair costs, NRW, and additional use of energy.

Table 5.2. Yearly Proactive Maintenance Program

Diameter	Length of pipe need to be inspected (Miles)	Inspection techniques (WaterRF 2018)	Direct cost of inspection ($/feet). (WaterRF 2018)	Indirect cost of inspection ($/year) (WaterRF 2018)	Cost of repair ($/leak) (Grigg 2013)
6”	40	RFEC[1]	2	50,000	10,000
8”	30	RFEC[1]	2	50,000	10,000
12”	20	ALD[2]	7.8	50,000	50,000
16”	20	ALD[2]	7.8	50,000	50,000

1. RFEC= Remote field eddy current technology 2. ALD= Acoustic leak detection technology

Figure 5.18 estimates the economic trade-off for conducting a proactive maintenance strategy. In Figure 5.18, the lower light-gray portion of columns represents the expenditures associated with implementing a proactive maintenance program, including inspection and rehabilitation (Table 5.2). The upper dark-gray portion of each column shows the cost savings through repairing pipe breaks, reducing water and associated energy losses, and reduction in repair costs by implementing a proactive maintenance program.

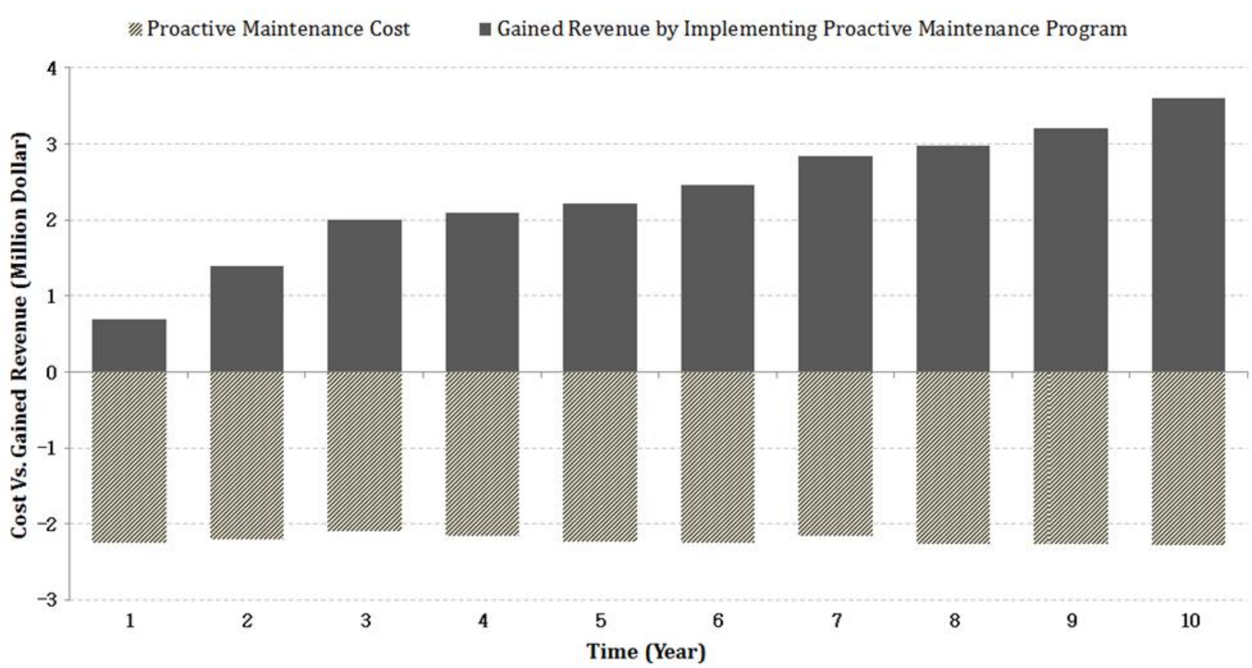

Figure 5.18. Cost vs. Gained Revenue by Implementing a Proactive Maintenance Program

Quantifying these trade-offs (between proactive maintenance and reactive maintenance program) is vital to determine the desired asset management strategy. Figure 5.19 shows that the estimated net revenue under different water-rate increase scenarios during the simulation period. In this model, net revenues were calculated by subtracting the cost of the services (Proactive Maintenance Program) from the generated revenue (sales of water to the customer). Comparison of the generated revenue (Figure 5.17) and net revenue (Figure 5.19) under the 20% water-rate increase scenario, indicated that conducting a proactive maintenance program could not only eliminate the losses in year 3 of simulation, but also boosts the net revenue by 0.5% due to decrease in the water utility's expenditures (fewer pipe repairs and reduced non-revenue water). These results show strong financial incentive for water utilities to reduce water main breaks because this action translates into higher revenues and lower operating costs.

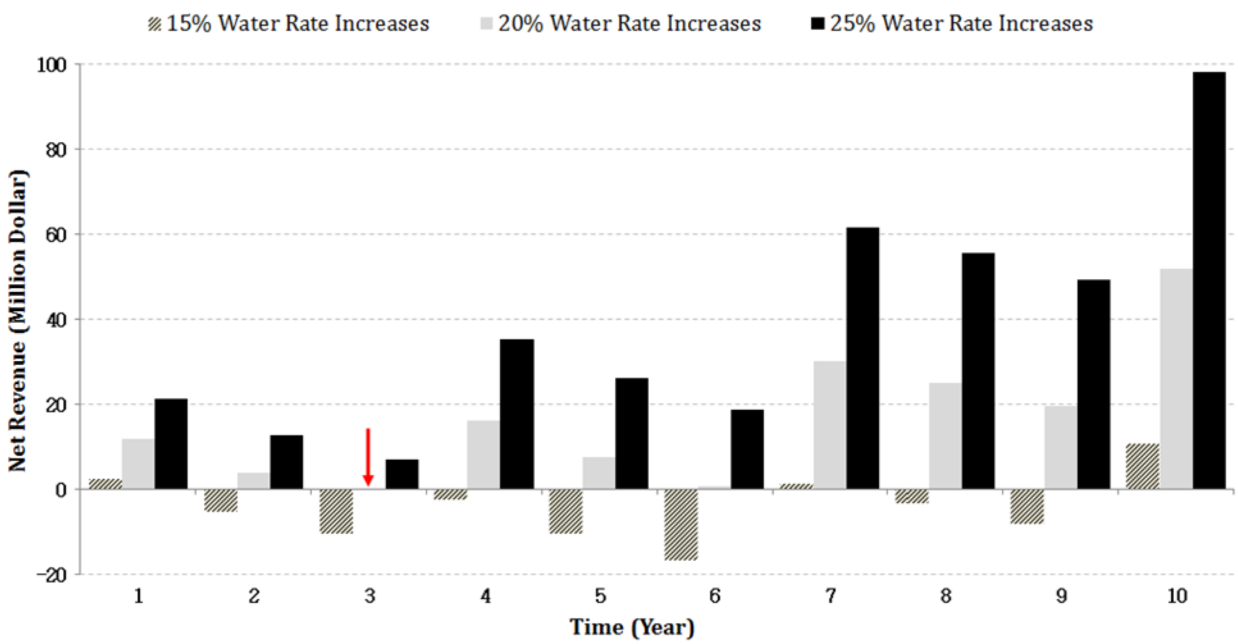

Figure 5.19. Net Revenue for Water Utility in the Case Study City

5.7 Validation and Verification

Verification is defined as a process of determining that the model implementation accurately represents the developers' conceptual description, while validation is the process of determining the degree to which a model is an accurate representation of the real world from the perspective of the intended user of the model (Thacker et al. 2004). In this study, validation and verification was conducted throughout the development of simulation models discussed in this chapter, and included the following steps: 1) data validity, 2) conceptual model validity, 3) computerized model validity, and 4) operational validity. Data validity refers to ensuring that the data used for developing a model is correct, reliable, and able to sufficiently represent a population sample (Sargent 2011). Data used in the SD-ABM analysis were provided by the water utility in the case study city, and obtained from online databases including USGS, annual reports from the water utility during 1990-2010, and other open-access resources such as AWWA, WaterRF, and EPA. Conceptual model validity determines the correctness of the theories and assumptions of the conceptual model and representation of the systems within the model were reasonable. The conceptual model verification occurred during the development of model system dynamics causal loop diagrams and the development of survey of water consumers' attitudes toward water-rate increases face-to-face meetings in September 2015 with three Subject Matter Experts (SMEs) in three Midwestern water utilities, as well as meetings in February 2016 with two different SMEs at the Indiana Office of Utility Consumer Counselor (OUCC) and the Indiana Utility Regulatory Commission (IURC). These SMEs have between 10-15 years of experience in either water assets management or regulatory issues related to water assets The SMEs were shown components of the conceptual model to determine if the theories, assumptions and data incorporated into the model, and representation of the systems within the model were reasonable and representative of the water distribution, water utility, and water customers. The SMEs confirmed the appropriateness of the data and assumptions used, and that the model representations were valid.

Computerized model validity ensures that the computer programming of the model and implementation of the conceptual model are correct and appropriate. Sargent (2011) recommended deploying the model in different scenarios to ensure the consistency of the outcomes from computer programming. In this study, the evolution of SD-ABM model was examined through two set of scenarios to confirm the consistency of the outcomes from computer programming. The first scenario was considered to assess consumers' water consumption patterns under different cases: (Case A) the baseline scenario without water-rates increases, (Case B) water-rate increases with no communication among consumer agents, and (Case C) water-rate increases by allowing consumer agents to communicate with the neighboring agents. The second scenario was implemented to evaluate revenue generated from residential customer sales by considering changes in water consumption under four different cases including: (Case I) without rate increases (baseline), (Case II) 15% water-rate increases every three years, (Case III) 20% water-rate increases every three years, and (Case IV) 25% water-rate increases every three years. Also, face validity was conducted in June-July 2019 with three different subject matter experts (SMEs) from the three Midwestern water utilities to review the computerized model components, logic, and scenarios to ensure that the SD-ABM model accurately represented the conceptual model, and that the SD-ABM model's behavior represented the system accurately. The three SMEs agreed that the model's representation of the system and the model's structure, logic, mathematical and causal relationships, and pre-defined scenarios are reasonable in the context of water distribution system.

Operational validity determines that the model's outcome has sufficient accuracy for the model's intended purpose over the domain of the model's intended applicability (Sargent 2011). This can be verified by the data that are used to determine whether the model behaves as the system does, and validated by the SMEs to examine if the behavior of the model accurately represents the system. In this study, operational validity was assessed by examining the model stability over multiple simulation runs and logic correctness, and the appropriateness of model responses. The logic correctness and the appropriateness of model responses were assessed through face-to-face meetings with SMEs with average experience of 15 years in the management of water assets (either in water utilities or in regulatory agencies). In the face-to-face meeting with the SMEs at the water utility in the case study city in July 2019, the hybrid SD-ABM computerized model (Anylogic 8.2.3) was presented and several simulation runs were conducted with the actual pipeline characteristics data and maintenance activities data in a city-wide water distribution system. The SMEs at the water utility in the case study city agreed that the simulated behavior of the model was reasonable and the output of the simulation model regrading water main break frequency, amount of water and associated energy losses, generated revenue, and payoff periods for implementing proactive maintenance strategies had the accuracy required for the model's intended purpose. They have also suggested simulating the model with actual price-elasticity of water in the case study city instead of survey responses from water consumers. Since the price-elasticity data was not available at that time at the water utility, this suggestion will be implemented in the future as the utility collects the data and provides it to the research team. Table 5.3 highlights studies with similar discussions and findings related to this study.

Table 5.3. External Validation of Findings

Aspect of model	Findings within model	Other studies with similar findings/discussion
Relationship of failure rates and pipe diameters	Small diameter pipes have higher rates of failures	Bernardi et al. (2008)
Relationship of water main breaks and water and associated energy losses	Positive correlation between water main breaks and amount of water and associated energy losses in water supply and distribution systems	Cabrera et al. (2010); Hernandez et al. (2011); Cabrera et al. (2015)
Impacts of water-rates increases on residential water consumption patterns	Water-rates have a direct impact on the residential water consumption patterns	Yoo et al. (2014); Vasquez (2014); Tanellari et al. (2015)
Relationship of word-of-mouth communication among residents of the city and residential water consumption patterns	Incorporating social network in modeling will impact the community's perceptions toward water usage and also change residential water consumption patterns	Athanasiadis et al. (2005); Ali et al. 92017); Kandiaha et al. (2019)
Relationship of proactive maintenance on water utility revenue	Implementing proactive maintenance (inspection and rehabilitation) will increase water utility revenue in the long-term	Morimoto (2010); Tsakiris et al. (2011); Baird (2018)

5.8 Conclusion

As water infrastructure systems continue to age and deteriorate, water utilities cannot afford to replace all deteriorated components due to the high costs for replacement and limited funds. Hence, it is crucial to implement innovative strategies to reduce operational and maintenance expenses while maintaining/growing revenues to improve financial resiliency. This chapter presented a hybrid SD-ABM model to capture the dynamics of the physical water infrastructure components, water utility, and water consumers.

The research presented here generated new insights about the physical water infrastructures as dynamic systems to explore complex behaviors as they changed over time. Although the break frequencies for the 8" diameter pipes were higher than for the 12" diameter, it was observed that the operational costs (water and associated energy losses) of the 12" diameter pipes were higher than the 8" diameter pipes. The simulation approach that was developed can benefit utility managers in making more informed decisions regarding budget allocations for water pipeline renewals.

The results highlight the importance of consumers adapting their water consumption during water-rates increase events. Analyses conducted in this research revealed a new understanding of consumers' behaviors and communication mechanisms. Although the process of adapting water consumption rates was slow over the 10-year period, the initial drop on water consumption patterns was significant compared to the subsequent years, mainly because the consumers were experiencing their first water-rate increase. By implementing a word-of-mouth communication mechanism, the analysis demonstrated that consumers with higher levels of connectivity to their neighbors tended to adapt quickly and decreased their water consumption during the simulation period. It was also observed that a major shift in reducing water consumption rates occurred while the numbers of influential neighbors reached five. Future research may investigate the extent to which social networks and public education campaigns can better inform consumers on water-rate structures, and on modifying their water use habits. Finally, this research investigated the trade-offs between operational costs and gained revenues by implementing a proactive maintenance program. This cost-benefit analysis of implementing a proactive maintenance program can help in evaluating the effectiveness of different water pricing to select the most beneficial strategy. This integrated model assisted asset managers in understanding their systems, identified pathways for growing revenue through increasing water-rates, and implemented a proactive asset management program.

5.9 Significance of the Study

This chapter presents a model of coupled human-water infrastructure that simulates the feedbacks between human, physical water infrastructure, and water utility system, and demonstrates the model in the context of a case study city in the U.S. over a 10-year period. Previous research has tried to address the issue of aging water distribution system by implementing (1) hydraulic modeling to evaluate the performance of pipeline network, (2) statistical modeling to predict the frequency of pipe failures, (3) life cycle analysis to improve the performance of pipeline network, and (4) optimization techniques to minimize the failures of physical assets in water distribution system. However, analyzing the interactive effects of features of the physical water infrastructure to water utilities (due to non-revenue water, leakage repair, and additional use of energy) and consumers (due to water service disruption) had not been explored. This study differs from and complements the prior research by incorporating dynamic interactions of physical water infrastructure components including pipeline characteristics, water and associated energy losses, and the revenue loss for water utilities, while considering consumers' behavior toward water-rates increases.

Prior simulations of the human–water infrastructure interactions were focused on adoption of water-efficient technologies, adoption of green infrastructure for controlling runoff, setting policies for allocation of water within communities, water quality issues associated with water supply systems, water availability and satisfaction for agricultural water use, decision-making on decommissioning and downsizing of physical water infrastructure systems, and adoption of water reuse and reclaimed water within communities. However, the behavior of water consumers and their interactions to analyze water consumption pattern under water-rate increase events has not been assessed. The proposed framework brings in an additional dimension to water infrastructure interdependency modeling by considering human (consumers) sector and their interactions to quantify water consumption under water-rate increase events. Methodologically, this chapter illustrates how a hybrid SD-ABM simulation can analyze bi-directional feedbacks between societal, economic, and engineered components of urban water systems to gain insight about financing, both short-term (to cover operational and maintenance expenses) and long-term (to implement capital improvement projects).

Any simulation framework of a real-world system, including this study, is likely to suffer from limitations. In setting boundaries and scales for analysis (e.g., population size, water infrastructure systems at the city scale), possible relevant factors may have been omitted. The assessment of dynamic interactions of the human-water infrastructure systems under the event of water main breaks and water-rate increases was demonstrated in the context of a large city (over 500,000 residents); thus, the applicability of the framework cannot be confirmed for small cities or medium cities. Also, the consumer agent parameters within the model that are unique to the case study city (e.g., water service reliability and quality, household side, water consumption rates) should be varied within the model to reflect the circumstance of different cities. This limitation can be addressed by deploying surveys to the local communities at the time of analysis, to capture context-sensitive data that could impact the values of the consumer agent parameters. Also, the current model does not capture the effect of population growth.

5.10 Future Studies

The proposed framework in this research can be extended and applied to analyze more comprehensive coupled human and water infrastructure systems by incorporating the wastewater collection system within the boundaries of the study, and assessing consumer behaviors toward increases of both water and wastewater-rates. Furthermore, by extending the analysis to other cities, factors such as geographical characteristics (e.g., weather, supplied water service reliability and quality, population growth) and local policies, may lead to further findings on coupled human-water infrastructure issues This study indicated that by implementing a word-of-mouth communication mechanism, consumers with higher levels of connectivity to their neighbors tended to adapt quickly and decreased their water consumption during the simulation period. Future research may investigate the extent to which social networks and public education campaigns can better inform consumers on water-rate structures and pricing, and on modifying their water use habits. As suggested by SMEs during verification and validation process, simulating the model with actual price-elasticity of residential water demand in the case study city could improve model results further, and provide additional insights in household attitudes toward water-rates increase events.

6. CONCLUSION AND RECOMMENDATION

One of the major challenges facing water asset managers is finding solutions to reduce operation and maintenance expenses of physical infrastructure systems while maintaining or increasing revenues to improve the financial resiliency of utilities. The impact of deteriorated pipeline networks negatively affects the economics of water utilities, and can lead to increases in water-rates for consumers that are levied by utilities to recover financial losses due to massive repair, cost of non-revenue water, and operational costs. This research aimed to bridge the gaps in the body of knowledge and the body of practice by developing a hybrid model to capture the interactive effects of features of the physical water infrastructure (pipeline characteristics, water and associated energy losses, and the revenue loss for water utilities) and the behavior of stakeholders (water utilities and consumers) under water main breaks and water-rate increase events. The first two sections of this chapter provide the overview of research approaches and summarize the findings of the doctoral study. The third section of this chapter describes the limitations of this study, while the fourth section of this chapter highlights the contributions of this research to the body of knowledge and the body of practice. Finally, recommendations for future research are presented.

6.1 Summary of the Research

The overarching goal of this dissertation was to assess the dynamic interactions of water utility and water consumers in response to water main breaks and water-rates increase events. Compared to prior studies related to human-water infrastructure interdependencies (such as adoption of water-efficient technologies; adoption of green infrastructure for controlling runoff; policies for allocation of water within communities; water quality issues associated with water supply systems), analysis of the consequences of an aging pipeline system to water utilities (due to non-revenue water, leakage repair, and additional use of energy) and consumers (due to water service disruption) has been less explored. The data and analysis presented in this study are unique in that: (1) it uses empirical data including pipeline characteristics, monthly temperatures, average water pressures, schedule of maintenance activities, leakage rates, duration of pipe repairs, energy consumption rates of water supply components, and pipeline repair costs to simulate the water main breaks frequency, as well as water and associated energy losses due to water main breaks, and (2) it is focused on the coupling between the pipeline infrastructure, water utility, and consumers, to explore possible emergent behavior outcomes of water users during water main breaks and water-rate increase events.

The first component of this dissertation examined the frequency of water main breaks in a water distribution system using readily available water-main data such as diameter, material type, length, and age of pipes. A methodological framework was used to demonstrate the impact of influential factors affecting main breaks in water distribution systems in two cities (used as case studies): Indianapolis, IN (large U.S. city – population over 800,000) and Fort Wayne, IN (mid-size U.S city – population between 200,000-800,000). These cases studies demonstrated the applicability of random-parameters negative binomial regression that utilities can apply to forecast monthly breaks in their pipeline networks.

Although the first reaction to the high number of water main breaks is to attribute them to older and deteriorated pipeline networks, previous research (Folkman 2012; Folkman 2018) based on a survey of 188 water utilities in North America showed that more recently installed pipes, such as PVC pipes also contribute to the number of breaks in water distribution system. However, the current literature is limited to macro-level analysis of PVC pipe failures in water distribution due to limited historic data about PVC pipe failures. Therefore, in the second component of this study, a random parameters negative binomial and a latent class negative binomial regression is used to identify possible unobserved heterogeneity in the data and to assess the system wide monthly frequency of PVC pipe breaks. Using PVC pipe-break data for a 21-year period from the water distribution system in Indianapolis, Indiana, the results demonstrated that methodological approach presented can provide new insights into the identification of PVC pipe failures.

The third component of this dissertation evaluated household attitudes towards water-rate increases based on perceptions of water service reliability and quality, using econometric analyses. The analysis in this section not only assessed households' attitudes toward water-rate increases, but also simultaneously considered perceptions toward water service reliability and quality using a multivariate binary probit approach. For this purpose, a survey was deployed to the residents of Indianapolis, Indiana, who were above 18 years of age, had access to the water service provided by local water utility, and were responsible for paying their water bill or a portion of the water bill. The probabilities of supporting/opposing water-rate increases based on perceptions of water service reliability and quality were calculated.

In the fourth and final component of this dissertation, a hybrid system dynamics and agent-based model was developed to explore uncertainties, interdependencies, and emergent behaviors arising from unknown relationships between the physical water infrastructure components, the water utility, and water consumers. The model used a range of pipeline characteristics, climate, hydrological, and socio-economic data over the 2001–2010 period on a case study city with a large water distribution system. The physical and economic impacts of water main breaks and water-rate increases on the coupled human-water infrastructure system were demonstrated through this component.

6.2 Summary of the Results

The analysis described in this dissertation answers the research questions that were outlined in Chapter 1. Table 6.1 summarizes the models that were developed, the link to the research questions, and findings from the analyses.

Table 6.1. Models and link to research questions

Analyses component	**Analyses performed**	**Summary of the findings**
Modeling the frequency of water main breaks in water distribution systems	Random parameter negative binomial regression, and demonstration within the context of a large water utility and a medium-sized water utility in the U.S.	• During cold winter months (December –March) the number of main breaks increases compared to other months of the year, due to thermal stresses created by temperature differences between the soil and water inside the pipe • Transferability of statistical models from one city to another is not possible because the effect of specific variables is clearly dependent on specific system characteristics (e.g., Indianapolis and Fort Wayne are Midwestern cities that share similar climate, soil conditions, and other factors, their water pipeline networks are different in terms of constructed facilities and operations, and this could explain the many substantive differences in findings when comparing the model-estimation results of the data from Fort Wayne and Indianapolis.

Table 6.1 continued

Assessment of PVC failure in water distribution systems	Random parameter negative binomial and random parameter latent class regressions	• Negative binomial and latent class models with random parameters captured the heterogeneity of the data on PVC pipeline characteristics • As PVC pipes aged in a water distribution system (pipes installed more than 10 years before), the rates of failure generally decreased. Most failures in PVC pipes occurred in the early stages (typically right after pipe installation) because of poor installation, damage during excavation, and the effects of ultraviolet light. • Small diameters (6” and 8”) PVC pipes have higher rates of breaks frequency compared to large diameter PVC pipes, mainly because this pipe diameter cohort are used in service connections and are more likely to be affected by poor tapping and poor installation at joints
Evaluation of the household attitudes to support/oppose water-rate increases based on perception of water service reliability and quality	Qualitative analyses and multivariate binary probit regression	• Female respondents, relative to their male counterparts, were found to be sensitive to water-rate increase, suggesting that water utilities could implement targeted public campaign programs to educate female water users to further disseminate their ideas of water conservation to their circles of influence • Households respond to rate increases based on their socio-demographic characteristics (such as family size, educational background, and gender) as well as the reliability of water service and the quality of supplied water by the water utility • Understanding the price responsiveness of different households enables water utilities to identify specific groups of households and specific strategies through a proportionate price structure (e.g., the pricing structure for the low-income household group could be different from the high-income household group)
Analyses of the dynamics of human-water infrastructure system systems under water main breaks and water-rates increases events	Hybrid agent based system dynamics model	• Replacement and rehabilitation of water pipes should not only be limited only to pipes that have experienced breaks. Asset managers should consider other consequences such as water and associated energy losses to make more informed decisions regarding budget allocations for water pipeline renewal • Consumers with higher levels of connectivity to their neighbors tend to adapt quickly to change their water consumption during water-rate increases • A major shift in reducing water consumption rates occurs while the numbers of influential neighbors reached five during the simulation period in the case study city

6.3 Limitations of the Study

The statistical significance of random parameters in the pipe-diameter models (presented in Chapters 2 and 3) underscores the importance of unobserved heterogeneity in the data. The source of this unobserved heterogeneity likely relates to unobserved variations in soil types and conditions (water saturation levels and soil temperatures), pipe/water temperatures, water pressure, tapping and joint installation quality, and other factors that are not typically available in databases, and hence were not considered in this study. Applying random-parameters negative-binomial modeling approach using extended databases that include data on soil types, temperature extremes, water pressures, etc., could improve statistical modeling of water main breaks frequency, and provide additional insights into the factors that affect break frequencies in specific cities.

The survey of household attitudes to support/oppose water-rate increases based on perception of water service reliability and quality was conducted within the context of the Midwestern region of the U.S. As mentioned in Chapter 4, socio-demographic variables (such as gender, level of income, level of education, etc.) may affect water consumer's attitudes toward water-related issues. Therefore, considering households that were most affected by drought and water restrictions (in areas such as Southern California) would undoubtedly provide additional insights into the factors that affect water pricing policy in other regions of the U.S. Another limitation to this research is that the analysis of household attitudes toward water-rates increases did not consider dynamic changes in the nature of households' behavior. Russell and Fielding (2010) stated that communication among households affects water using behaviors, and that when one family member starts conserving water, other family members are more likely to adopt similar conservation behaviors. Thus, considering household dynamics in residential water consumption could improve model estimation results. This doctoral study was able to obtain demographic information and households' characteristics for 405 households in 2015 from the City of Indianapolis; however, omitted variables may bias the coefficient estimates of the model. Additional detailed data such as years living in current housing, house ownership, age of the house, sewer bill, etc., could be useful information in the analysis, and also enhance the explanatory power of the model.

Finally, in the analysis of coupled human-water infrastructure systems under water main breaks and water rates increases events, the applicability of the proposed framework is limited to large cities (populations greater than 800,000), and cannot be confirmed for mid-size cities (population between 250,000 – 800,000) small cities (population lower than 250,000). Also, the consumer agent parameters within the model are unique to the case study city (e.g., household side, water consumption rates). This limitation can be addressed by deploying surveys to the local communities at the time of analysis, and data from such surveys can be applied within the model to reflect the characteristics of different cities.

6.4 Contributions of the Research

This doctoral study makes various contributions to the body of knowledge and the body of practice in the area of water infrastructure management. The methodological framework incorporates a mixed-method qualitative and quantitative approach to highlight the importance of a proactive and targeted asset management approach for a utility's operation management and financial health. The methodological framework can also be applied to assess the dynamic interaction of human-infrastructure systems under water main breaks and water-rate increase events.

6.4.1 Contributions to the Body of Knowledge

Different models (Shamir and Howard 1979; Andreou et al. 1987; Watson et al. 2004; Bernardi et al. 2008; Wang et al. 2009; Kleiner and Rajani 2010; Singh and Adachi 2012; Gat 2014) have been developed to estimate the frequency of pipe failures using the limited available pipeline and main break data. However, existing water main break models listed above use the restrictive assumption with regard to the impact of specific explanatory variables that parameters are constrained to be the same across observations. In addition, some of these models (Shamir and Howard 1979; Andreou et al. 1987; Watson et al. 2004) are restricted to predict the break frequency based on the failure characteristics of a single pipe segment and cannot be applied to estimate the number of breaks for a city-wide water system using currently available data such as diameter, material type, length, and age of pipes. The methodological approach in Chapter 2 addresses a critical concern with past research on this subject (the assumption that the effect of any explanatory variable is the same for all observations) by applying a random-parameters negative binomial model that utilities can apply to predict monthly breaks in their water system.

Prior literature (Wang et al. 2009; Folkman 2012; Folkman 2018) on the analysis of PVC pipe failures has often been limited to the comparison of PVC pipe failures with those of cast iron and ductile iron pipes. In addition, analysis of past studies (Davis et al. 2007; Wang et al. 2009; Folkman 2012; Folkman 2018) on PVC pipe failure did not address issues relating to the possibility that the effect of explanatory variables may vary across observations. The research framework in Chapter 3 contributes to the body of knowledge by developing models that allow estimated parameters (including commonly collected factors such as the length and age of the PVC pipes, and possible environmental observations (such as monthly temperature, precipitation, snow depth) to vary among monthly failure-frequency observations in response to potential unobserved effects as opposed to traditional statistical approaches that estimate a fixed effect for each variable across all observations.

Prior research on the analysis of human behavior toward water rate increase has often considered different econometric modeling approaches including the use of utility-theory frameworks to estimate the price elasticity of water demand based on household-level data such as household income, age of home, area of lot, etc. (Alcubilla and Lund, 2006; Olmstead et al., 2007), stated-choice analyses to assess willingness to pay for preserving ecosystems varied among stakeholder groups including people residing in watersheds, tourists, business visitors, and potential water users (Yoo et al., 2014; Castro et al., 2016), and contingent valuation methods to investigate households' willingness to pay for improvements in the water services (Vasquez, 2014; Tanellari et al., 2015). In contrast to past research that evaluated responses to single questions; the multivariate binary probit approach developed in Chapter 4 advances past research by modeling three interrelated questions simultaneously: (1) if the water service provider proposes to increase the water-rate in order to improve the quality of water, would the respondent support a rate increase? (2) if the water service provider proposes to increase the water-rate in order to improve the reliability of the water service, would the respondent support a rate increase?, and (3) if the water service provider doubles the water-rate, how would the respondent change his/her water consumption pattern? Using multivariate binary probit model, this chapter demonstrated the application of an appropriate econometric methodology to enable the exploration of cross-equation correlation, thus allowing additional inferences and more precise parameter estimates of the model.

Traditionally, researchers have proposed different methodological approaches to address the issue of aging water distribution system including (1) hydraulic modeling to evaluate the performance of pipeline network, (2) statistical modeling to predict the frequency of pipe failures, (3) life cycle analysis to improve the performance of pipeline network, and (4) optimization techniques to minimize the failures of physical assets in water distribution system. The existence of multiple interactions between physical water infrastructure (pipeline characteristics, water and associated energy losses, and the revenue loss for water utilities) and stakeholders (water utilities and consumers) create uncertainties on human-water infrastructure systems. However, the impacts of these uncertainties were not analyzed in previous studies. The proposed hybrid system dynamics and agent-based model (SD-ABM) in Chapter 5 addresses the gaps in prior literature by developing and testing a modeling framework that can evaluate the impact of dynamic interactions of physical water infrastructure components including pipeline characteristics, water and associated energy losses, and the revenue loss for water utilities, while considering consumers' behavior toward water-rates increases.

6.4.2 Contributions to the Body of Practice

The research presented in Chapter 2 and Chapter 3 develops a quantitative method to assess the impact of influential factors including pipe characteristics, monthly temperatures, and average water pressures on occurring water pipe failures. A gap in the body of practice identified by SMEs and literature is the lack of knowledge in estimating the number of breaks for city-wide water systems. Prior research (Shamir and Howard 1979; Andreou et al. 1987; Watson et al. 2004) has considered different prediction models (such as times series model, proportional hazards model, Bayesian model, respectively) for future pipe breaks based on characteristics of a single pipe segment such as pipe age. However, detailed information relating to the condition of single pipe can be difficult to obtain due to the lack of pipe-break records for individual pipes (Kleiner and Rajani 2010). In addition, two pipes with similar characteristics, such as two different cast iron pipes with the same diameter in a water distribution system, may have different failure patterns and can be impacted differently by variables not necessarily observed by the analyst such as temperature, soil moisture, traffic load above the pipes, and so on. An effective asset management plan for a water pipeline network typically includes strategies to prioritize water main assets for inspection, utilize condition assessment programs to identify the level of pipe deterioration and the impact of pipe deterioration on the probability of failure, and incorporate the results from condition assessment of the water main asset to prioritize capital planning regarding pipe renewal. Therefore, assessing the physical condition of water pipes in a water distribution system city-wide using historic data relating pipe failures can provide important guidance to asset managers in their efforts to maintain their water distribution system and minimize service disruptions. The proposed random-parameter negative binomial model (Chapter 2) contributes to the body of practice by estimating the number of breaks for city-wide water system using currently available data such as diameter, material type, length and age of pipes.

Chapter 3 provides a methodological approach to assess the PVC pipe failure in a water distribution system using pipe-break data from a 21-year period. Although the first reaction to the high number of water main breaks is to attribute them to aged and deteriorated pipeline networks, current and previous research (Burn et al. 2005; Folkman 2012) show that more recently installed pipes, such as PVC, also contribute to the breaks in a water distribution system. Due to limited recorded failure data for PVC pipes in water utilities, the current state of the practice is limited to macro-level analysis of PVC pipe failures in water distribution system including the comparison of PVC pipe failures with those of cast iron and ductile iron pipes. Assessment of PVC pipe failures considering the pipe diameter, age, and cause of failure was not considered in previous analyses of pipeline failures. The proposed random-parameter negative binomial and latent class negative binomial approaches (Chapter 3) revealed the importance of PVC pipe diameter, length, and age, and environmental conditions, in estimating monthly break frequency. This study contributes to the body of practice by providing insights into the factors that affect PVC break frequencies that can be used as guidance for both maintenance-crew allocations and targeted inspection of PVC pipes.

Chapter 4 provides a qualitative and quantitative methodology for assessing household attitudes toward water-rate increases based on perceptions of water service reliability and quality. As water utilities attempt to be financially self-sufficient, understanding the water consumption patterns of residential customers in response to water-rate increases is extremely important. Using a multivariate binary probit approach, this chapter contributes to the body of practice and address gaps in prior studies by not only assessing households' attitudes toward water-rate increases, but also by simultaneously considering perceptions toward water service reliability and quality. The multivariate binary probit approach used for this analysis shows that a variety of factors (such as types of gender, household level of income, household level of education, amount of water bill, primary source of drinking water, etc.) influence the likelihood that water consumers will support/oppose water-rates increases based on perceptions of water service reliability and quality.

The framework presented in Chapter 5 has the potential to assist water asset managers in assessing water utilities' long-term and short-term financial planning by predicting operational expenses (such as the physical asset (pipe) failure water and associated energy losses, and maintenance costs) and generated revenue from residential customer sales for different scenarios related to amount of water-rates increases. The model is capable of being tailored to different water distribution systems and cities by varying parameters, such as local pipeline characteristics, climate and hydrological data, socio-economic data of residents being served by the utility or water-rate changes, in order to implement strategies to reduce operational and maintenance expenses while maintaining/growing revenues.

6.5 Recommendations for Future Research

There are many avenues that can be undertaken as future research in this area of inquiry. The recommendations for future research fall under three categories of (1) data-driven analysis for pipe failure prediction, (2) spatial transferability of household's responses to water-rate increases, and (3) comprehensive analysis of coupled human and water infrastructure interdependencies.

6.5.1 Data-Driven Analysis for Pipe Failure Prediction

Statistical modeling of water main breaks (discussed in Chapter 2 and Chapter 3) based on historic data relating pipe failures is far less expensive than using direct inspection of the entire pipeline network, could uncover underlying causal effects based on observational data. Therefore, future research studies could use more extensive databases that include expanded data on depth of buried pipe, surrounding soil characteristics, water pressure in the pipe, pipe wall thickness, conditions above the pipe, and construction procedures, etc., to improve the accuracy of statistical modeling and provide additional insights into the factors that affect break frequencies.

In addition, as water utilities attempt to be proactive and implement sustainable asset management programs, a large amount of data on operation and maintenance of water pipeline network is generated and stored; however, a richer set of variables (big data) could increase the statistical model complexity by creating computational constraints (due to the time-consuming convergence process) and challenges in predictive validation (due to potential biases in parameter estimates and estimates of standard errors) (Mannering et al. 2020). Hence, one promising direction for future research would be application of the data-driven methods (such as data mining and machine learning) combined with historic data relating pipe failures and pipe characteristics, to identify the patterns of those pipes that need to be inspected frequently and are most likely to fail.

6.5.2 Spatial Transferability of Household's Responses to Water-Rate Increases

Previous studies (e.g. Dalhuisen et al. 2003; Vasquez 2014; Faust et al. 2018) and this doctoral study reflected the fact that socio-demographic variables (such as family size, educational background, and gender, place of living, etc.) and beliefs (about water service reliability and water quality) may affect household's attitude toward water-related issues. Also, the results of this research (Chapter 4) showed that household's prior experiences related to water service reliability and quality due to their geographic location (in this study Midwestern region of the U.S.) influenced their willingness to support water-rate increases to improve the reliability of water service. Therefore, the geographic location may potentially affect household's attitude toward water-related issues directly or indirectly. Future studies could assess the spatial transferability of household's responses to water-rate increases by considering and comparing different geographic regions (for example, western regions of the U.S which experience significant water shortages).

6.5.3 Comprehensive Analysis of Coupled Human and Water Infrastructure Interdependencies

The proposed coupled human-water infrastructure interdependencies framework (Chapter 5) captured the dynamics of the physical water pipeline components, water utility, and water consumers. The interdependency analysis was conducted under two conditions: (1) water main breaks and (2) water-rate increases. Since the majority of water utilities in the North America are responsible for water and wastewater systems (Hughes et al. 2014), future research can be extended to the other components of water infrastructure system, including the wastewater pipeline network.

A more comprehensive analysis of coupled human- water infrastructure system by incorporating wastewater pipe failure and wastewater-rate increases events into the existing framework can provide important guidance to utility managers in their efforts to improve utility financial resiliency.

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Title	Modeling the Frequency of Water Main Breaks in Water Distribution Systems: Random-Parameters Negative-Binomial Approach	Institution name	Purdue University
		Expected presentation date	2020-03-01
Instructor name	Hamed Zamenian		

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PURDUE UNIVERSITY

HUMAN RESEARCH PROTECTION PROGRAM
INSTITUTIONAL REVIEW BOARDS

To:	DULCY ABRAHAM CIVL 1241
From:	JEANNIE DICLEMENTI, Chair Social Science IRB
Date:	09/10/2015
Committee Action:	**Exemption Granted**
IRB Action Date:	09/10/2015
IRB Protocol #:	1509016456
Study Title:	Socioeconomic Assessment of Water and Energy Losses in Water Supply and Distribution System

The Institutional Review Board (IRB) has reviewed the above-referenced study application and has determined that it meets the criteria for exemption under 45 CFR 46.101(b)(2) .

If you wish to make changes to this study, please refer to our guidance **"Minor Changes Not Requiring Review"** located on our website at http://www.irb.purdue.edu/policies.php. For changes requiring IRB review, please submit an **Amendment to Approved Study** form or **Personnel Amendment to Study** form, whichever is applicable, located on the forms page of our website www.irb.purdue.edu/forms.php. Please contact our office if you have any questions.

Below is a list of best practices that we request you use when conducting your research. The list contains both general items as well as those specific to the different exemption categories.

General

- To recruit from Purdue University classrooms, the instructor and all others associated with conduct of the course (e.g., teaching assistants) must not be present during announcement of the research opportunity or any recruitment activity. This may be accomplished by announcing, in advance, that class will either start later than usual or end earlier than usual so this activity may occur. It should be emphasized that attendance at the announcement and recruitment are voluntary and the student's attendance and enrollment decision will not be shared with those administering the course.
- If students earn extra credit towards their course grade through participation in a research project conducted by someone other than the course instructor(s), such as in the example above, the students participation should only be shared with the course instructor(s) at the end of the semester. Additionally, instructors who allow extra credit to be earned through participation in research must also provide an opportunity for students to earn comparable extra credit through a non-research activity requiring an amount of time and effort comparable to the research option.
- When conducting human subjects research at a non-Purdue college/university, investigators are urged to contact that institution's IRB to determine requirements for conducting research at that institution.
- When human subjects research will be conducted in schools or places of business, investigators must obtain written permission from an appropriate authority within the organization. If the written permission was not

submitted with the study application at the time of IRB review (e.g., the school would not issue the letter without proof of IRB approval, etc.), the investigator must submit the written permission to the IRB prior to engaging in the research activities (e.g., recruitment, study procedures, etc.). This is an institutional requirement.

Category 1

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Categories 2 and 3

- Surveys and questionnaires should indicate
  - only participants 18 years of age and over are eligible to participate in the research; and
  - that participation is voluntary; and
  - that any questions may be skipped; and
  - include the investigator's name and contact information.
- Investigators should explain to participants the amount of time required to participate. Additionally, they should explain to participants how confidentiality will be maintained or if it will not be maintained.
- When conducting focus group research, investigators cannot guarantee that all participants in the focus group will maintain the confidentiality of other group participants. The investigator should make participants aware of this potential for breach of confidentiality.
- When human subjects research will be conducted in schools or places of business, investigators must obtain written permission from an appropriate authority within the organization. If the written permission was not submitted with the study application at the time of IRB review (e.g., the school would not issue the letter without proof of IRB approval, etc.), the investigator must submit the written permission to the IRB prior to engaging in the research activities (e.g., recruitment, study procedures, etc.). This is an institutional requirement.

Category 6

- Surveys and data collection instruments should note that participation is voluntary.
- Surveys and data collection instruments should note that participants may skip any questions.
- When taste testing foods which are highly allergenic (e.g., peanuts, milk, etc.) investigators should disclose the possibility of a reaction to potential subjects.

APPENDIX D. SURVEY QUESTIONNAIRE

Default Question Block

Purdue University is conducting a study investigating public attitudes, perceptions, and responses toward water rate increases for residential water customers. In this study, water rate is defined as the price per unit charged to customers for the use of treated and potable water. We are requesting you to complete this anonymous survey, which includes general questions about your perceptions and attitudes about water rate increases and water service disruptions in your city.

The questionnaire will take about 12 - 15 minutes of your time to complete. The information collected will be kept confidential and it will only be used for academic purposes. You may skip any question you do not wish to answer in the survey. Your participation in this survey is completely voluntary and will remain anonymous.

Thank you for your time!

I am living in the City of Indianapolis or Suburb of Indianapolis (Marion County, Hamilton County, Boone County, Hancock county) :

- Yes
- No

I am above 18 years old:

- Yes
- No

Are you responsible for paying your water bill or a portion of your water bill?

- Yes
- No

Do you have access to the water service provided by water utility:

- Yes
- No

My water service is billed:

- Monthly (12 times per year)
- Every other month (6 times per year)
- Quarterly (4 times per year)
- I do not know

My water service bill includes:

- Water service only
- Water and wastewater service combined
-

I do not know

My average monthly water bill is:

- $0 - $20.99
- $21.00 - $50.99
- $51.00 - $80.99
- Over $81.00
- I do not know

My average monthly water and wastewater bill is:

- $15.00 - $45.99
- $46.00 - $75.99
- $76.00 - $100.99
- Over $101.00
- I do not know

I use water supplied by my local utility for:

- Indoor usage (drinking, cooking, shower and bath, laundry, dishwasher)
- Outdoor usage (lawn, cleaning)
- Both

What is your primary source of drinking water?

- Supplies from my local water utility (tap water)
- Bottled water
- Groundwater wells
- Other (please specify)
- I do not know

Do you have large water uses (for instance, a swimming pool) in your home?

- Yes
- No

Have you experienced any water service disruption (no water service / boil alert / low water pressure) for your home or at your place of employment / work?

- Yes
- No

How many times you have experienced the water service disruption (no water service / boil alert / low water pressure) at your home or at your place of employment/work during the past three years?

- Never
- 1 - 3 times
- 4- 8 times
- 9- 12 times
- More than 12 times

Have you seen any interruptions due to water pipe breaks in your city (flooding / traffic jam / road closure) during the past three years?

- Yes
- No

How many times have you seen interruptions due to water main breaks in your city during the past three years?

- Never
- 1 -3 times
- 4 - 8 times
- 9 - 12 times
- More than 12 times

The service (defined as uninterrupted, at an adequate pressure) of my drinking water is:

- Good
- Fair
- Poor

The quality (defined as color of the water, odor of the water, particles in the water) of my drinking water is:

- Good
- Fair
- Poor

The quality of service (defined as uninterrupted, clean water, at an adequate pressure) from my water provider has changed in the past three years:

- Not applicable, I have lived in the city less than three years
- The quality of service has decreased dramatically
- The quality of service has decreased slightly
- There is no noticeable change in service
- The quality of service has improved slightly
- The quality has improved dramatically

If water service provider proposes to increase the water rate in order to improve the quality of water (such as the color of the water, odor of the water, particles in the water), will you support a rate increase?

- ◯ Yes
- ◯ No

If the water service provider proposes to increases the water rate in order to improve the reliability of the water service (such as uninterrupted, at an adequate pressure), will you support a rate increase?

- ◯ Yes
- ◯ No

If your community (neighbors) is willing to support the water rates increase, will you change your mind about supporting the rate increase?

- ◯ Yes
- ◯ No

If your community (neighbors) is not willing to support the water rates increase, will you change your mind about supporting the rate increase?

- ◯ Yes
- ◯ No

How much more would you be willing to pay per month(dollar amount) for improved reliability of your water service (such as improve water quality and minimized water disruption)? (leave the slider at "0" if you would not be willing to pay more for a more reliable water system)

	0	10	20	30	40	50	60	70	80	90	100
Click to write Choice 1											

How much more would you be willing to pay per month (dollar amount) for improved quality of your water service (such as color of the water, odor of the water, particles in the water)? (leave the slider at "0" if you are not willing to pay more for a more reliable water system.)

	0	10	20	30	40	50	60	70	80	90	100
Click to write Choice 1											

If the water service provider **doubles the water rate**, how would you change your water consumption pattern?

- ◯ I will decrease my water consumption

- I will not change my water consumption
- I will increase my water consumption

How much are you willing to decrease your water consumption:

- 1% - 5%
- 6% - 10%
- 11% - 15%
- More than 15%
- I do not know

I will decrease my water consumption pattern if:

- 1-3 persons from my community (neighbors) reduce their water consumption
- 4-6 persons from my community (neighbors) reduce their water consumption
- 7-9 persons from my community (neighbors) reduce their water consumption
- More than 10 persons from my community (neighbors) reduce their water consumption

How much are you willing to increase your water consumption?

- 1% - 5%
- 6% - 10%
- 11% - 15%
- More than 15%
- I do not know

I will increase my water consumption pattern if:

- If 1-3 persons from my community (neighbors) increase their water consumption
- If 4-6 persons from my community (neighbors) increase their water consumption
- If 7-9 persons from my community (neighbors) increase their water consumption
- Ifmore than 10 persons from my community (neighbors) increase their water consumption

If you implement a water conservation device to reduce the water consumption inside your home, which conservation plan has a higher priority for you? (Please sort it from highest to lowest)

- Water efficient showerhead
- Water efficient faucet for kitchen and bath
- Water efficient dishwasher
- Water efficient washing machine
- Water efficient toilet

- Water efficient lawn sprinklers

Categorize the water consumption components which you will ignore due to a water rate increase? (Please put this list in order from highest to lowest):

- Pool
- Hot tub/ Spa
- Lawn
- Laundry
- Shower

Categorize the water consumption components which you will reduce due to a water rate increase? (Please put this list in order from highest to lowest):

- Pool
- Hot tub / Spa
- Lawn
- Shower

What is your age?

- 18 - 25
- 26 - 35
- 36 - 50
- Above 50

Are you ?

- Female
- Male

Marital status:

- Single
- Married
- Civil Union
- Divorced
- Separated

How would you classify the area in which you grew up?

- Urban
- Suburban
- Rural

How would you classify the area in which you living right now?

- Urban
- Suburban
- Rural

Geographically, would you consider yourself to be originally from:

- Eastern US
- Midwestern US
- Western US
- Southern US
- Non-US

What is your highest completed level of education?

- Some high school
- High school diploma
- Technical college degree
- College degree
- Post graduate degree

What is your employment status (choose all that apply)?

- Employed for wages or salary
- Self-Employed
- Out of work and looking for work
- Out of work but not currently looking for work
- A homemaker
- A student
- Retired
- Unable to work

What is your approximate annual income?

- No income
- Under $19,999
- $20,000 - $34,999

- $35,000 - $49,999
- $50,000 - $74,999
- $75,000 - $99,999
- $100,000 and above

What is the approximate annual household income of the household you are living?

- No income
- Under $19,999
- $20,000 - $34,999
- $35,000 - $49,999
- $50,000 - $74,999
- $75,000 - $99,999
- $100,000 and above

What is your primary source of news (choose all that apply)?

- Newspaper
- Internet
- Television
- Radio
- Social Media
- Friend and family
- Other

Political views:

- Republican
- Democrat
- Independent
- Other

Including you, how many people live in your household?

How many children in your household are under 6?

How many children in your household are between 6 -18 years of age?

How many people living in your home, work outside the home?