ASSESSMENT OF URBAN WATER INFRASTRUCTURE SYSTEM RESILIENCE

A Dissertation

by

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ABSTRACT

Urban water infrastructure systems are exposed to the impacts of various chronic and acute stressors such as climate change, population growth/decline, aging infrastructure, and extreme events (e.g., natural disasters). The ability and capacity of infrastructure systems to cope with the impacts of these stressors is characterized as resilience. Water utility agencies and infrastructure managers face significant challenges (due to deep uncertainty, funding constraints, lack of knowledge, etc.) to enhance the long-term resilience of their urban water infrastructure systems under the impacts of external stressors. To enable informed resilience planning and adaptation decisions, the present study adopted a complex system perspective to comprehensively assess the long-term resilience of water infrastructure systems. Through this perspective, different components of water infrastructure systems (i.e., physical infrastructures, human actors, external stressors) were captured, modeled, and analyzed using a simulation method for theory development and exploratory assessment.

This research conducted four interrelated studies focused on both supply and demand sides of the water infrastructure resilience. As aging water distribution infrastructures near the end of their useful lifespan, first two studies focused on the resilience of water distribution systems. The third study was prompted to deal with the impacts of climate change on coastal water supply infrastructures. The last study evaluated demand-side solutions to enhance the resilience of urban water infrastructure systems, where due to population growth, climate change, and other factors making water scarcer, the supply-side solutions may no longer be sufficient.

Accordingly, four sets of important theoretical constructs related to the long-term resilience of water infrastructure systems were identified: (i) performance regimes of water distribution

infrastructure system are shaped by the internal dynamics in stressors-humans-infrastructure nexus; (ii) implementation of dual water distribution systems would improve the long-term infrastructure performance, but will have three times higher life-cycle costs; (iii) an adaptive planning approach can improve the resilience of coastal water supply infrastructure systems under climate change impacts; and (iv) household water conservation technology adoption is driven mostly by income level and water pricing structure. The results highlighted the importance and capabilities of the proposed frameworks in better understanding of the water infrastructure resilience. The insights of this research would benefit water utilities, city planners, municipalities, and other stakeholders endeavoring to strengthen the resilience performance of water infrastructure systems.

DEDICATION

In the name of GOD, the most gracious, the most merciful

This work is dedicated to the three pillars of my life:

My Father, Reza

My Mother, Sakineh, and

My love, Nikoo.

"The secrets eternal neither you know nor I

And answers to the riddle neither you know nor I

Behind the veil there is much talk about us, why

When the veil falls, neither you remain nor I."

— Omar Khayyam

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1. INTRODUCTION

1.1. Background

Globalization and large-scale urban development in the latter half of the 20th century have precipitated massive demographic shifts in regions across the world, a trend which is expected to continue in the near future. In a bid to cater to these burgeoning developments, the demand for water infrastructure has grown disproportionately to the supply that is currently made available by urban bodies. The American Water Works Association (AWWA) estimates that an additional $1 trillion is required, merely to keep up with the increasing rate of demand for water infrastructure over the next 25 years (ASCE 2017a).

An important factor affecting the demand-supply economics of urban water infrastructure is the longevity and utility of said infrastructure over a given period of time. External factors such as inclement weather directly affect the performance of physical assets, a statement which is of greater importance today than ever before owing to climate change (IPCC 2014). More generally, urban water infrastructure systems composed of water supply resources, treatment plants, storages, and distribution networks, are exposed to various stressors (Figure 1-1) which are broadly classified into two major groups: chronic and acute stressors. Chronic stressors are gradual, low-impact, and high-probability phenomena which affect water infrastructures over a period of time, such as climate change, population growth/decline, and funding limitations, to name a few. On the other hand, acute stressors are abrupt, high-impact, and low-probability events that are mainly caused by extreme event disturbances. Acute stressors include, but are not limited to, natural and man-made disasters such as flooding, earthquakes, terrorism attacks, which would result in extreme events.

These external stressors not only affect the physical infrastructure, but also change the response behaviors of human actors who are either managing or using the infrastructure. Hence, both chronic (e.g., saltwater intrusion due to sea-level rise) and acute stressors (e.g., flooding) affect the long-term behaviors of water infrastructure systems (e.g., network condition, service reliability). Coupled with the aging of the nation's water infrastructure systems (ASCE 2017b), the impacts of chronic and acute stressors pose major challenges to scientists and policy-makers to identify and implement strategies and measures for reducing adverse impacts of the external stressors on urban water infrastructure systems.

Figure 1-1. Urban Water Infrastructure System Exposure to External Stressors

The ability of infrastructure systems to cope with the impacts of the stressors is characterized as resilience, which is an emerging topic in the field of infrastructure sustainability. Resilience, in the context of this study, is defined as the capacity of infrastructure to experience the impact induced by various types of stressors, while retaining the function to provide services required for the socio-economic development and safety of humans (Park et al. 2013). In essence, it serves to inform scientists and policy-makers about ways to cope with the impact of stressors on infrastructure.

An important feature of resilience is that it enables recovery and robustness to unknown and uncertain events (Ganin et al. 2016). The fact that threats are often impossible to foresee and quantify in water infrastructure systems has been one of the main motivations to complement risk-based approaches with resilience analysis (Ganin et al. 2016, 2017). Considering the pivotal role played by water infrastructure systems in sustainable socio-economic development as well as in protecting communities, a better understanding of their resilience under external stressors is a critical step towards enhancing the sustainability and resilience of the communities themselves.

1.2. Problem Statement

Understanding of the long-term resilience is critical because due to the significant physical and institutional inertia in urban water infrastructure systems, undesirable performance regimes are very difficult to reverse. Over the past decade, the literature related to water infrastructure resilience (e.g., Diao et al. 2016; Francis and Bekera 2014; McDaniels et al. 2008; Ouyang et al. 2012) has focused on examining the physical attributes and topological characteristics that affect the attributes of networks under disruption, through the use of engineering-based approaches. The focus of engineering-based approaches is to assess resilience in the presence of acute stressors, while chronic stressors which change the long-term dynamics of infrastructure over a long-time horizon are not fully considered. These approaches to resilience assessment primarily focus on event-based analysis of resilience, considering system dynamics related to loss of function and short-term recovery of infrastructure for a particular disruptive event. Dynamic behaviors of water infrastructure systems are governed by three major factors including (i) physical assets; (ii) human actors; and (iii) chronic and acute stressors, which affect its long-term transformation. The consequence of defining resilience as the final equilibrium state which is a product of the infrastructure's robustness and resistance to acute stressors, is that the engineering-based approach ignores adaptive behavior of human actors (e.g., institutional agencies and water consumers), which is dynamic in nature. However, infrastructure resilience to the external stressors must contend with potential changes in human decision-makers' values and attitudes about the effects of external stressors on their planning strategies (Deyle and Butler 2013). Therefore, the conventional approaches to assessment of resilience do not provide a holistic perspective for understanding the resilience of infrastructure under various chronic and acute stressors. In particular, chronic stressors, which affect infrastructure systems over a long time, necessitate approaches for understanding of long-term resilience in urban water infrastructure systems.

Researchers now argue that a complex system approach to long-term resilience provides a more holistic perspective for assessment of resilience in infrastructure systems (Park et al. 2013). Long-term resilience has been investigated in ecological systems based on understanding of the interactions among human and natural systems in response to stressors such as climate change impact (Folk et al. 2004; 2006). In this context, long-term resilience is defined as the ability of a complex system to adapt and transform internal feedback processes, cope with chronic or "surprise" shocks, and recover from internal/external disturbances (Park et al. 2013). That is, the system does not attempt to maintain status quo (equilibrium) through resistance and robustness.

Urban water infrastructure systems can be considered as complex systems (Francis and Bekera 2014) composed of the facilities and assets associated with the physical infrastructure, the services provided to a community, the people using these services, and the organizations that manage the infrastructure (EPA 2016). The resilience of such systems is a function of their internal and external dynamics (Gao et al. 2016), and their performance depends on the interplay between human actors and the physical assets. Hence, in the context of urban water infrastructure systems, long-term resilience is a property that arises due to stressors-humans-infrastructure interactions (Figure 1-2) and evolves over time.

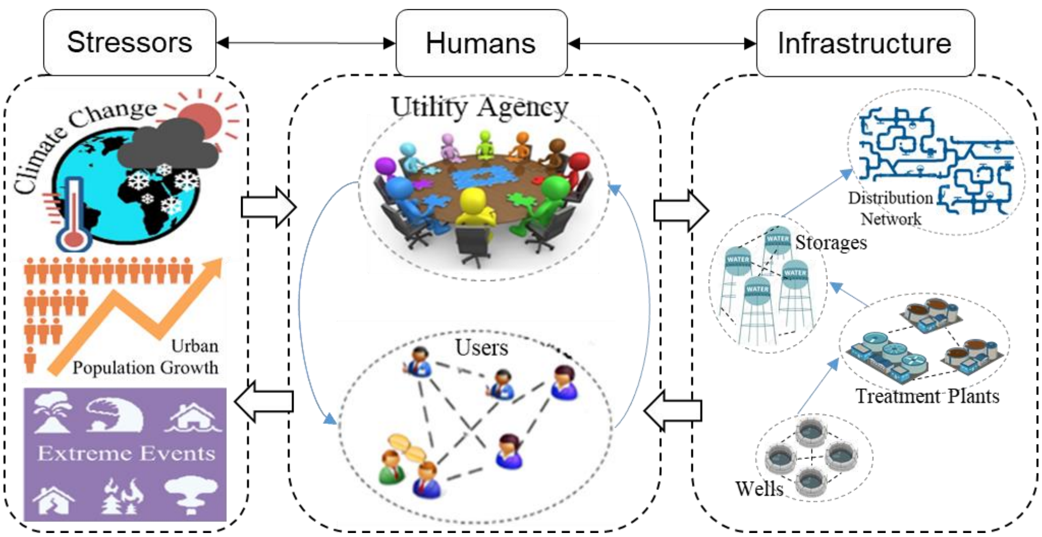

Figure 1-2. Stressors-Humans-Infrastructure Nexus

1.3. Knowledge Gap

A holistic assessment of long-term resilience of urban water infrastructure systems requires a better understanding of human actors (e.g., users and administrative agencies) and their capacity for adaptive decision-making. Surprisingly, fewer numbers of studies have conducted a holistic assessment of the long-term resilience in urban water infrastructure systems (EPA 2015). A review of the literature pertaining to the assessment of long-term resilience of urban water infrastructure systems shows four major gaps in the existing knowledge. The existing approaches (i) fail to examine the long-term resilience of water infrastructure systems under different chronic stressors and renewal strategies; (ii) lack the evaluation of innovative/alternative infrastructure solutions to improve the long-term resilience performance of water infrastructure systems; (iii) do not consider the adaptive behavior of decision makers (i.e., utility agencies) for resilience building in water infrastructure systems under the impacts of external stressors (e.g., climate change); and (iv) miss the incorporation of demand-side strategies in resilience enhancement of urban water infrastructure systems. Each of these four gaps is discussed in further detail in the remainder of Section 1.2.

1.3.1. Long-term Resilience Characterization

Despite the growing literature in the areas of resilience, the characteristics of long-term resilience in urban water infrastructure systems are not fully specified and evaluated. In particular, in the context of chronic stressors, such as population change, funding constraints, and aging infrastructure, specifying and characterizing log-term resilience holds the key for formulating robust investment strategies. However, the fundamental knowledge of long-term resilience and its characteristics are missing in urban water infrastructure systems. For example, performance regime shifts and tipping point behaviors are two of the important characteristics of long-term resilience (Karunanithi et al. 2008). Evaluation and identification of performance regime shifts in water infrastructure systems is very important in light of the negative consequences and limited reversibility of undesirable performance regime shifts. A critical knowledge gap is examining human-infrastructure dynamics affecting the long-term steady state, and hence resilience in water infrastructure systems. While recent developments in the field of complex systems science have addressed some of these concerns (Gao et al. 2016; Ulusan and Ergun 2018), the understanding of dynamics that affect the long-term resilience of water distribution infrastructure systems is rather limited. Addressing this gap would uncover what physical infrastructure attributes and renewal decision-making factors yield long-term resilience in water distribution systems under different scenarios of external stressors.

1.3.2. Alternative Infrastructure Solutions

As aging water infrastructure in larger communities of cities is replaced, there is an opportunity to evaluate new approaches to long-term sustainable goals, such as meeting increased future water demands and quality standards, while using sustainable and resilience-based replacement practices and limiting the impact on the society and environment (Yang et al. 2018b). Dual water distribution infrastructure has been proposed as a more efficient and resilient alternative approach in order to respond to aging water infrastructure, excess treatment energy, and potable quality issues related to oversized distribution piping. Dual distribution systems are comprised of two separate distribution networks: one that delivers potable water for indoors; and another that delivers non-potable water for outdoor uses (e.g., irrigation and fire protection). A number of existing studies have demonstrated the applicability of dual water supply at a city-wide scale (Cole et al. 2018; Fourness 2015; Kang and Lansey 2012). These studies have evaluated the network design for dual water distribution systems and also compared them with the existing singular systems qualitatively using a triple bottom line perspective. However, further analyses are needed to understand the long-term infrastructure performance behavior of dual systems versus the existing singular systems. To evaluate innovative infrastructure strategies, such as dual systems, before investments are made, analysis of long-term outcomes of the strategies as well as their life-cycle costs are needed. In particular, these become more important when rapid deterioration of physical water infrastructure and potable water quality issues along with the funding constraints necessitate resilience-based, cost-effective management of the infrastructure system.

1.3.3. Adaptation Planning under Deep Uncertainty

Urban water supply infrastructure systems located in coastal areas are exposed and susceptible to saltwater intrusion exacerbated by sea-level rise stressors. Majority of coastal cities, such as ones located in Southeast Florida, use underground aquifers as their main source of freshwater supply (Heimlich et al. 2009). Saltwater intrusion into water facilities (e.g., wellfields) would affect the freshwater capacity of water supply infrastructure and thus, the system's service reliability in meeting the potable water demand of service areas. A stream of research has investigated the impact measure of saltwater intrusion on coastal water supply infrastructure systems (Dausman and Langevin 2005; Elsayed and Oumeraci 2017; Park et al. 2011; Prinos et al. 2014), and another stream of research has evaluated the adaptation and resilience of coastal water supply infrastructure systems under these impacts (de Almeida and Mostafavi 2016; Bloetscher et al. 2010; Elsayed and Oumeraci 2018; Heimlich et al. 2009; Schoen et al. 2015). A review of the existing literature shows that the steady-state and ex-post (Mostafavi 2018) analysis approaches fail to provide robust insights for resilient adaptation planning in of coastal water supply infrastructure systems due to the complex, uncertain, and adaptive nature of coastal hazards (Batouli and Mostafavi 2018a; Chappin and van der Lei 2014). In addition, the existing evaluation approaches lack the consideration of the dynamic behaviors and interactions between physical infrastructures and institutional decision-makers. While different factors contributing to the physical damage of saltwater intrusion on of coastal water supply infrastructure systems are well studied, little is known about the impact of adaptive decision-making processes of utility agencies in response to saltwater intrusion. The key to addressing this gap in knowledge is the consideration of uncertainty and complexity in hazards-humans-infrastructure interactions.

1.3.4. Demand-side Strategies

Climate change impacts add further pressure to water resources, and government officials and policy advocates have taken two different approaches to address growing water concerns (Kanta and Zechman 2014): supply-side management and demand-side management. Supply-side solutions (e.g., infrastructure adaptation investments) have been effective historically; however, the dire state of water scarcity has diminished the sufficiency of supply-side management. It will eventually become too difficult to track down additional water sources, or there will simply be no more water left to find. Because of this, more research is needed on demand-side approaches. Demand-side management is based on the idea that lowering a household's (or other users') usage for water will subsequently reduce water demand. While implementing demand-side management to govern a typically inelastic good is controversial among economists and planners, it has been shown in many studies to be effective in alleviating water scarcity (Chen et al. 2005; Inman and Jeffrey 2006; Renwick and Green2 2000; White and Fane 2002). At its core, reducing residential water demand can be done by changing behavior or technology (Inman and Jeffrey 2006). While change in behavior is typically ephemeral, change in technology will be the most permanent, applicable method heading into the coming decades (Lee and Tansel 2013). However, technology's impact on policy implementation and household adoption patterns still needs to be specified and characterized. Governmental policies (e.g., rebate availability, water pricing structures) and household demographic characteristics, as well as external factors (e.g., social networks) are variables that can cause different adoption patterns (Bandiera and Rasul 2006; Baumann 1983; Dolnicar et al. 2012; Po et al. 2003). While some of these influential factors have been researched to promote policy change and growth, there is a deficiency in the existing literature as to how they all intersect and challenge water conservation technology adoption.

1.4. Research Objectives

The overarching objective of this study is to analyze the long-term resilience of urban water infrastructure systems by capturing and evaluating various dynamics of the coupled human-infrastructure system. In particular, this study aims to examine the resilience characteristics that emerge due to stressors-humans-infrastructure interactions in order to devise robust strategies that could mitigate adverse impacts of various stressors, such as climate change, population growth/decline, funding constraints, and aging infrastructure, on urban water infrastructure systems. To attain its overarching objective, this research aims to accomplish four specific objectives:

Objective #1: *Establish a framework for analyzing and understanding dynamics affecting the long-term resilience performance of urban water distribution infrastructure systems.*

As aging water distribution infrastructures (i.e., pipelines) near the end of their useful lifespan, now is a critical time to focus on system resiliency to potential supply and demand changes from climate change and population growth. The first objective of this research is to establish a complex systems-based framework to analyze how the internal dynamics of water distribution infrastructure systems (i.e., infrastructure aging, renewal strategies, funding levels) shape the steady state, and hence the long-term resilience performance of water distribution infrastructure systems under various scenarios. The scientific question of objective 1 is: What decision and infrastructure attributes would influence the occurrence and timing of possible performance regime shifts and tipping point behaviors under different stressor scenarios? What is the sensitivity of long-term performance of water distribution infrastructures to population change scenarios?

Objective #2: *Analyze the long-term performance of dual water distribution systems, as an alternative infrastructure approach, versus the existing singular systems.*

Dual water distribution systems have been proposed as a technological infrastructure solution to enhance the sustainability and resilience of urban water systems by separating the distribution of potable water from non-potable. The second objective of this research is to capture long-term performance measures (e.g., network condition, leakage, breakage, energy consumption, etc.) of water distribution systems, and then evaluate and compare the long-term performance of dual systems versus the existing singular systems under various scenarios of renewal strategies and demand fluctuations. The scientific questions in objective 2 include: Whether or not the implementation of dual water distribution networks would improve the long-term performance of urban water distribution infrastructure systems? To what extent the dual systems would increase the life-cycle costs?

Objective #3: *Investigate the coupled impacts of saltwater intrusion and utility adaptation decision-making processes on the resilience of coastal water supply infrastructure systems.*

Water supply resources are one of the important components of water infrastructure systems, which are specifically susceptible to saltwater intrusion impacts in coastal regions. The third objective of this research is to understand the coupled impacts of saltwater intrusion and adaptation planning of utility agencies on the long-term resilience behavior of water supply infrastructure systems in order to devise robust adaptation strategies that could mitigate subsequent impacts of saltwater intrusion and yield enhanced resilience in the system. The scientific questions in objective 3 are: What are the most important determinants of resilience in coastal water supply infrastructure systems? Would the adaptive planning approach improve the long-term resilience of the system (if yes, to what extent)? How adaptation planning characteristics (e.g., investment levels, decision review intervals, risk attitudes) influence the resilience performance of coastal water supply infrastructure systems under the impacts of saltwater intrusion?

Objective #4: *Understand fundamental phenomena affecting the water conservation technology adoption behavior of residential water consumers.*

As supply-side water management is no longer enough to solve the water resource depletion, there is a growing movement toward the adoption of water conservation technology as a way to improve the resilience and sustainability of urban water systems. The fourth objective of this research is to specify and model the behavior of households regarding the installation of water conservation technology and evaluate strategies that could potentially increase water conservation technology adoption at the household level. Objective 4 seeks answers for the following scientific questions: What are the intersectional influences of household socio-demographics, social networks, and water policies on adoption of water conservation technology? Which mechanisms significantly drive the decision of households regarding the adoption of water conservation technology?

Achieving these research objectives would improve the understanding of the interactions between external stressors, human actors, and physical water infrastructures in shaping the long-term resilience of urban water infrastructure systems. Understanding these interactions and interrelationships also enables creation of integrated theories and decision-making tools to proactively improve resilience in complex water infrastructure systems. Hence, this research addresses a critical step toward improving infrastructure resilience performance in complex, uncertain environments. By achieving the research objectives, new knowledge in the field of infrastructure resilience assessment could be developed. Urban water infrastructure mangers, planners, and decision-makers could use the knowledge to enhance their adaptation strategies, investment decisions, and capital improvement plans to achieve more resilient infrastructure systems under dynamic, complex, and uncertain unfolding of external stressors.

1.5. Research Approach

Urban water infrastructure systems are complex adaptive systems consisting of interconnected simpler systems such as physical networks and human actors who are either managing or using the infrastructure (EPA 2016). The behavior of such complex systems under external stressors (e.g., climate change) depends on the interrelations and interactions among different components of the system. Hence, for evaluating the resilience of water infrastructure under external stressors, different components and their adaptive behaviors and interconnections should be properly characterized. In order to facilitate the characterization of the components and their adaptive mechanisms and interactions in water infrastructure, this research employs a simulation modeling approach.

According to Davis et al. (2007), a simulation approach is an effective method for studying behaviors of complex systems when (i) a theoretical field is new; (ii) the use of empirical data is limited; and (iii) other research methods fail to generate new theories in the field. These traits are consistent with the proposed research. First, the theoretical field related to the transformation of water infrastructure systems under the impacts of external stressors is a new field and is still developing. Second, empirical data related to the impacts of external stressors on the economic, environmental, and social performance of water infrastructure are not available. Third, using a simulation approach in the assessment of long-term water infrastructure resilience facilitates setting various experiments, and thus conducting scenario analysis to answer the research questions. In addition, the simulation approach enables building the computational representations of stressors-humans-infrastructure interactions and conducting experiments based on different scenarios pertaining to external stressors and decision-making attributes to deal with existing uncertainties. This will enable testing the research hypotheses and building propositions that quantitatively link various theoretical constructs to answer the research questions. Figure 1-3 gives an overview of the research steps in the simulation research approach proposed by Davis et al. (2007).

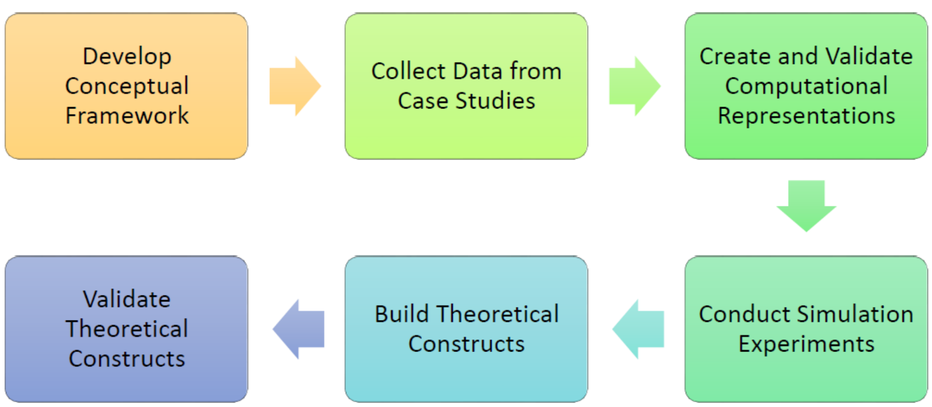

Figure 1-3. Simulation-based Research Tasks

1.5.1. Existing Modeling Approaches

The simulation approach has been extensively utilized in studying complex systems in water infrastructure management. Studies such as Athanasiadis et al. (2005), Galán et al. (2009), Kanta and Zechman (2014), and Rehan et al. (2013) have utilized simulation modeling as a successful tool to analyze water management systems. Galán et al. (2009) demonstrated that simulation modeling is a useful methodological approach to dealing with the complexity derived from multiple factors with influence in the domestic water management in emergent metropolitan areas. Kanta and Zechman (2014) developed a simulation framework for assessing the consumer water demand behavior against different degrees of water supply. Their model incorporated both consumers and policy-makers as agents as they adapted their behaviors to different water supply systems and rainfall patterns. Studies such as these have set a precedent that simulation modeling is a viable research tool for water use and management issues. However, the existing simulation models developed for water infrastructure management do not enable conducting exploratory analysis (Kwakkel and Pruyt 2013). The traditional simulation approaches basically aim to predict the behavior of a system and intend to optimize a system. However, exploratory analysis focuses primarily on considering different policy scenarios based on changes in system behaviors and future uncertainty (Lambert et al. 2004; Mohor et al. 2015). In addition, the existing simulation models in the area of water infrastructure management (e.g., EPANET models) lack the integration of human decision-making processes with the physical components of water infrastructure systems. Therefore, this research adopted a unique simulation approach, System-of-Systems (SoS), that enables capturing the coupled human-infrastructure dynamics under various scenario experiments and thus conducting exploratory analysis.

1.5.2. SoS Modeling Approach

System-of-Systems (SoS) framework is a collection of systems which offers more functionality and performance than simply the sum of the constituent systems (Mostafavi 2018). This modeling approach enables capturing emergent properties of complex systems from interdependencies and interactions among its components. Hence, for the long-term resilience assessment of urban water infrastructure systems, the SoS framework would enable capturing the activities of and interactions among the various institutional actors and physical infrastructure, and thus facilitates examining the transformation of water infrastructure under external stressors. Therefore, to attain the research objectives, the dynamic interrelations among external stressors, physical infrastructure networks, and human actors (i.e., stressors-humans-infrastructure nexus) were captured in a SoS framework based on the theory of complex systems as shown in Figure 1-4.

As an illustration of Figure 1-4, at the top-level of the framework (i.e., SoS level), external stressors lead to different changes in the physical network conditions and behaviors of the social systems (human actors): First, they impose pressures on the physical infrastructure leading to a greater exposure of networks to risks of physical damage. Second, they will affect the priorities of infrastructure agencies to determine an optimum trade-off between normal condition requirements and those targeting the impacts of stressors, given resource limitations and future uncertainties. Accordingly, the mid-level of this framework (i.e., system level) characterizes multiple physical infrastructure systems (e.g., water wells, treatment plants, and distribution networks), as well as social systems consisting of institutional agencies, utilities, and consumers. At the base-level of the framework, water utilities, water users (e.g., households), and physical infrastructure assets (e.g., water distribution pipeline) and their attributes and interactions are captured as agents, each with a set of social capabilities and goals, values, and preferences. There are various attributes and behaviors that affect the internal feedback processes between utilities and physical infrastructure assets. For utilities, the decision-making behaviors such as adaptation actions, resource allocation, network renewal, and capacity expansion are examples of behaviors that may be characterized. An important aspect of SoS approach to urban water infrastructure resilience is the ability to integrate infrastructure degradation, serviceability, and vulnerability with the decision-making processes and adaptation actions of utilities and enable dynamic analysis over a long time (Mostafavi 2018).

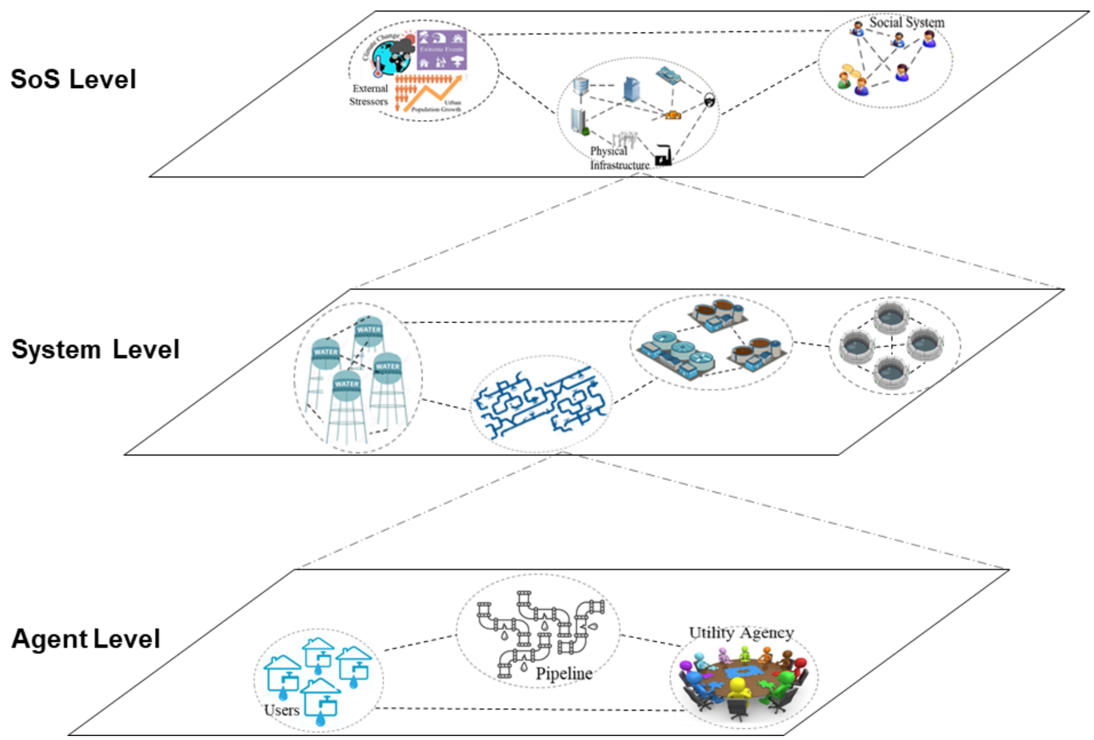

Figure 1-4. System-of-Systems Modeling Approach for Urban Water Infrastructure

In this research, the simulation models are developed based on the SoS modeling approach. The computational representations of the simulation models are implemented in an object-oriented, java-based modeling platform called AnyLogic. Accordingly, Monte Carlo simulation and Classification and Regression Tree (CART) analysis, as well as other statistical analyses are utilized to conduct exploratory analysis to identify likely range of the outcomes under each scenario in order to enable testing the research hypotheses.

1.6. Dissertation Organization

To attain the research objectives and answer the research questions, this research conducted four different studies, each focused on a specific issue pertaining to the long-term resilience of urban water infrastructure systems. This dissertation follows a "multiple publication" format. It includes six chapters, of which chapters 2, 3, 4, and 5 are self-sufficient papers that are published or submitted to be published in peer-reviewed journals. Each of these chapters has its own introduction, methodology, case study, analysis, results, and conclusion sections. Table 1-1 provides an overview of the purpose, focus area, and contents of each chapter.

The current chapter (Chapter 1) provided a background of the problem, the point of departure, the research objectives and questions, and an overview of the research's overarching approach. The organization of dissertation document is also included in this introductory chapter. Chapters 2, 3, and 4 focus on supply side of the urban water infrastructure system. In Chapter 2, a complex systems-based framework was established to analyze the long-term resilience behavior of urban water distribution systems. Chapter 3 evaluates the implementation of dual water distribution networks, as an innovative infrastructure solution, to improve the resilience performance of urban water distribution systems. Chapter 4 examines the coupled impacts of saltwater intrusion and utility agencies' adaptation decision-making processes on the resilience of urban water supply systems. Chapter 5 specifically looks at the demand side of urban water infrastructure systems and evaluates adoption of water conservation technology by residential consumers. Chapter 6 summarizes the findings, contributions, limitations and future work directions of this research. References of each chapter are listed as a whole at the end of this dissertation.

Table 1-1. Overview of Dissertation Chapters

Chapter	System Component	Focus Area	Knowledge Gap	Research Question
2	Water Distribution	Framework for understanding of long-term resilience characteristics	Lack of understanding of emergent properties of long-term resilience in human-infrastructure systems	What decision and infrastructure attributes yield the occurrence of performance regime shifts and tipping point behaviors?
3	Water Distribution	Evaluation of Alternative infrastructure strategy of dual systems	Lack of analysis of long-term performance of alternative infrastructures	Whether dual infrastructure systems would improve the long-term performance of water distribution networks?
4	Water Supply	Adaptation planning for resilience building in coastal areas	Lack of consideration of the dynamic behaviors and interactions between physical infrastructures and institutional decision-makers	How different characteristics of adaptation planning influence the long-term resilience under impacts of saltwater intrusion?
5	Water Demand	Household water conservation technology adoption	Lack of understanding of the influence of different underlying mechanisms on adoption of conservation technology by households	What mechanism primarily drive the decision of households regarding the adoption of water conservation technology?

2. RESILIENCE AS AN EMERGENT PROPERTY OF HUMAN-INFRASTRUCTURE DYNAMICS: A MULTI-AGENT SIMULATION MODEL FOR CHARACTERIZING REGIME SHIFTS AND TIPPING POINT BEHAVIORS IN INFRASTRUCTURE SYSTEMS [†]

The objective of this study is to establish a framework for analyzing infrastructure dynamics affecting the long-term steady state, and hence resilience in civil infrastructure systems. To this end, a multi-agent simulation model was created to capture important phenomena affecting the dynamics of coupled human-infrastructure systems and model the long-term performance regimes of infrastructure. The proposed framework captures the following three factors that shape the dynamics of coupled human-infrastructure systems: (i) engineered physical infrastructure; (ii) human actors; and (iii) chronic and acute stressors. A complex system approach was adopted to examine the long-term resilience of infrastructure based on the understanding of performance regimes, as well as tipping points at which shifts in the performance regime of infrastructure occur under the impact of external stressors and/or change in internal dynamics. The application of the proposed framework is demonstrated in a case of urban water distribution infrastructure using the data from a numerical case study network. The developed multi-agent simulation model was then used in examining the system resilience over a 100-year horizon under stressors such as population change and funding constraints. The results identified the effects of internal dynamics and external

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[†] This chapter is reprinted with permission from "Resilience as an emergent property of human-infrastructure dynamics: A multi-agent simulation model for characterizing regime shifts and tipping point behaviors in infrastructure systems." by Rasoulkhani, K. and Mostafavi, A., 2018. *PLOS ONE*, 13(11), e0207674.

stressors on the resilience landscape of infrastructure systems. Furthermore, the results also showed the capability of the framework in capturing and simulating the underlying mechanisms affecting human-infrastructure dynamics, as well as long-term regime shifts and tipping point behaviors. Therefore, the integrated framework proposed in this paper enables building complex system-based theories for a more advanced understanding of civil infrastructure resilience.

2.1. Introduction

Globalization and large-scale urban development in the latter half of the 20th century have precipitated massive demographic shifts in regions across the world, a trend which is expected to continue in the near future. In a bid to cater to these burgeoning developments, the demand for civil infrastructure has grown disproportionately to the supply that is currently made available by civic bodies. For instance, the American Society of Civil Engineers estimates that an additional 3.6 trillion dollars are required, merely to keep up with the increasing rate of demand for infrastructure (ASCE 2017b).

An important factor affecting the demand-supply economics of civil infrastructure is the longevity and utility of said infrastructure over a given period of time. External factors such as inclement weather directly affect the performance of physical assets, a statement which is of greater importance today than ever before owing to climate change. In fact, climate change is expected to affect the performance of physical assets, both directly and indirectly (IPCC 2014) as evidenced by the following example. Climate change-induced increase in the number of freeze-thaw cycles directly affects the physical condition of pavements. In addition to this, climate change stimulates changes in the behavior of both users and administrative agencies responsible for the upkeep of pavements, which in turn also affects their physical condition (Batouli and Mostafavi

2014). More generally, civil infrastructure systems such as those catering to transport, power grids, water supply and sewage networks are exposed to various stressors which are broadly classified into two major groups: acute and chronic stressors. Acute stressors are extreme events such as natural and man-made disasters, whereas chronic stressors are gradual, low impact-high probability phenomena which affect infrastructure over a period of time, such as climate change, population growth and decline, and funding limitations, to name a few. Coupled with the aforementioned increase in demand and usage, the impact of these stressors poses a major challenge to scientists and policy-makers concerned with the sustainability of civil infrastructure.

The ability of civil infrastructure to cope with the impact of these stressors is characterized as resilience, which is an emerging topic in the field of infrastructure sustainability. Resilience, in this context, is defined as the capacity of civil infrastructure to experience the impact induced by various types of stressors, while retaining the function to provide services required for the socio-economic development and safety of humans (Park et al. 2013). In essence, it serves to inform scientists and policy-makers about ways to cope with the impact of stressors on infrastructure.

Considering the pivotal role played by civil infrastructure in sustainable socio-economic development as well as in protecting communities, a better understanding of the long-term transformation of infrastructure under external stressors is a critical step towards enhancing the sustainability and resilience of the communities themselves. Over the last decade, literature pertaining to infrastructure resilience (Diao et al. 2016; Francis and Bekera 2014; McDaniels et al. 2008; Ouyang et al. 2012) has centered on examining the physical attributes and topological characteristics that affect the behavior of infrastructure systems under disruption, through the use of an engineering-based approach. The focus of engineering-based approaches is to assess resilience in the presence of acute stressors, while chronic stressors which change the long-term dynamics of infrastructure over a long-time horizon are not fully considered. Engineering resilience approaches primarily focus on event-based analysis of resilience considering system dynamics related to loss of function and short-term recovery of infrastructure for a particular disruptive event. Dynamic behavior of infrastructure is governed by three major factors including (i) physical assets; (ii) human actors; and (iii) chronic and acute stressors, which affect its long-term transformation. The consequence of defining resilience as the final equilibrium state which is a product of the infrastructure's robustness and resistance to acute stressors, is that the engineering-based approach ignores adaptive behavior seen in its human actors (users, administrative agencies and policy-makers), which is dynamic in nature. However, planning for long-term adaptation to evolving external stressors (e.g., climate change) must contend with potential changes in human decision-maker values and attitudes about the effects of external stressors on hazards and tradeoffs among adaptation options (Deyle and Butler 2013). However, despite the growing literature in the areas of resilience, the characteristics of long-term resilience in civil infrastructure systems are not specified and evaluated. In particular, in the context of chronic stressors (e.g., population change), understanding of long-term resilience characteristics holds the key for robust adaptation planning. For example, performance regime shift is one of the important characteristics of long-term resilience (Karunanithi et al. 2008). Evaluation of performance regime shifts in infrastructure systems is very important for long-term adaptation planning and investment decision-making; due to the significant physical and institutional inertia in infrastructure systems, undesirable performance regime shifts are very difficult to reverse (Rasoulkhani et al. 2017b). A critical knowledge gap is examining what attributes and relationships in stressor-human-infrastructure nexus would yield long-term resilience that will mitigate the potential impacts of evolving external stressors under different scenarios (Aerts et al. 2014). Recent developments in the field of complex systems science have addressed some of these concerns (Gao et al. 2016; Ulusan and Ergun 2018).

Civil infrastructure systems can be considered as complex systems (Francis and Bekera 2014) composed of facilities and assets associated with the physical infrastructure, the services they provide to a community, people using these services and the organizations that manage the infrastructure (EPA 2016). The resilience of such systems is a function of their internal and external dynamics (Gao et al. 2016), and their performance depends on the interplay between human actors and the physical assets. Thus, developing a holistic framework for assessing resilience of civil infrastructure requires a better understanding of human actors (users and administrative agencies) and their capacity for adaptive decision-making. Going one step further, under the complex systems approach, resilience of civil infrastructure itself needs to be redefined to account for its dynamic nature. Consequently, resilience may be defined as the ability of a complex system to adapt and transform internal feedback processes, to cope with chronic or "surprise" shocks, recover from internal/external disturbances (Park et al. 2013). That is, the system does not attempt to maintain status quo (equilibrium) through resistance and robustness, rather, the system evolves and improves with non-stationary conditions, through flexibility, diversity and adaptability, which makes resilience as an emergent property of complex systems (Park et al. 2013). An important feature of resilience is that it enables recovery and robustness to unknown and uncertain events (Ganin et al. 2016). The fact that in complex systems, threats are often impossible to foresee and quantify was one of the main motivations to complement risk-based approaches with resilience analysis (Ganin et al. 2016, 2017). Although the proposed approach in this study is not particular threat-diagnostic, it can be used in the presence of "threats". Essentially, the impact of a threat (i.e., acute stressor) on a system over time would depend on the steady state performance of the system, which is governed by the internal dynamics and chronic stressors.

A complex systems approach holds the key to addressing knowledge gaps in the development of a holistic framework that is capable of conceptualizing and assessing the long-term resilience of civil infrastructure. Under this approach, resilience of civil infrastructure is characterized using three mechanisms: (i) external stressors; (ii) internal dynamics; and (iii) regime shifts. (Gao et al. 2016) theorized that the resilience of complex systems can be described based on their topology and dynamics. However, the understanding of dynamics that affect infrastructure resilience is rather limited. To address this inadequacy, this paper proposes a framework to capture important phenomena that affect the dynamics, model the long-term performance regimes of infrastructure using a complex systems approach, and analyze the resilience of civil infrastructure in a long-term horizon based on the performance regime shifts and tipping points of external stressors. The components and application of the proposed framework are presented in the context of urban water distribution infrastructure. To this end, a Multi-Agent Simulation (MAS) model was developed to integrate the institutional agencies' renewal decision-making processes with physical components in order to simulate the transformations, capture the dynamics, and model the performance regimes of water distribution infrastructure system under the impact of external stressors such as population change and funding fluctuations. Using the developed simulation model, various experiments were designed to measure the long-term resilience based on the visual detection of regime shifts and identification of the threshold values (i.e., tipping points) associated with infrastructure performance regimes. That is to say, the long-term resilience of the water distribution infrastructure was evaluated in the presence of stressors using the proposed framework. Accordingly, the effectiveness of different renewal strategies was assessed in light of improving the resiliency of the infrastructure for various scenarios.

2.2. Long-term Resilience Theoretical Framework

This study utilized a complex system-theoretic approach for the civil infrastructure long-term resilience investment. The literature related to ecological sciences has made significant advancements in adopting a complex systems perspective for understanding the long-term resilience in ecological systems. According to (Folke 2006; Folke et al. 2004; Holling 1996), resilience in complex ecological systems can be defined based on their ability to cope with the changes in the surrounding environment. In fact, complex systems frequently do not return to their prior state of performance following the impact of stressors. Instead a new equilibrium state is attained, as seen in other fields such as ecology and economics which inspired developments in the engineering resilience field (Holling 1996). In the proposed study, grounded theories, measures, and methods related to resilience in complex systems (Batouli and Mostafavi 2018b; Folke 2006; Folke et al. 2004; Gao et al. 2016; Holling 1996; Karunanithi et al. 2008; Mostafavi 2018) were utilized to build a long-term resilience framework (Figure 2-1) for civil infrastructure systems under external stressors. The resilience of civil infrastructure system is contingent upon its transformation and adaptation to evolving conditions in the social and environmental sphere (Mostafavi 2018). Complex systems approach addresses this need by considering the ability of the system to reach a stable state after a certain threshold (critical or tipping point) has been reached.

2.2.1. Long-term Resilience Landscape

Using a complex systems approach, the long-term resilience landscape of civil infrastructure systems can be investigated based on stable states and regimes that determine the performance behavior of the system (Karunanithi et al. 2008). Changes in internal dynamics and external disturbances can cause shifts from the current stable state to a new stable state (better or worse) (Karunanithi et al. 2008). Accordingly, long-term resilience is defined as the ability of an infrastructure system to maintain its performance regime or transform to a better regime in response to internal and external disturbances. The performance regime of infrastructure system is the state related to the system's long-term performance in terms of the environmental, social, economic, functionality, and vulnerability parameters, which is maintained by internal dynamics pertaining to stressors-human-infrastructure interactions (Figure 2-1). The regime shifts occur when a change in the stressor-human-infrastructure interaction triggers a different behavior in the performance of infrastructure system (Lade et al. 2013; Scheffer et al. 2001). The occurrence of regime shifts is specified based on the detection of steady state transitions in infrastructure system performance behavior (Lade et al. 2013; Scheffer et al. 2001). Accordingly, the system resilience is evaluated using two methods (Folke 2006): (i) examination of steady state transitions in infrastructure behavior over time; and (ii) sensitivity analysis of infrastructure cumulative performance with respect to input parameters (i.e., external stressors).

Based on the existing evidence related to resilience in complex systems (Batouli and Mostafavi 2018b; Folke 2006; Folke et al. 2004; Gao et al. 2016; Holling 1996; Karunanithi et al. 2008; Mostafavi 2018) this study, as shown in Figure 2-1, identified three important characteristics related to long-term resilience of civil infrastructure systems: (i) external stressors, (ii) internal dynamics, and (ii) performance regime shifts. The following sub-sections explain the three mechanisms which characterize the resilience of complex infrastructure systems.

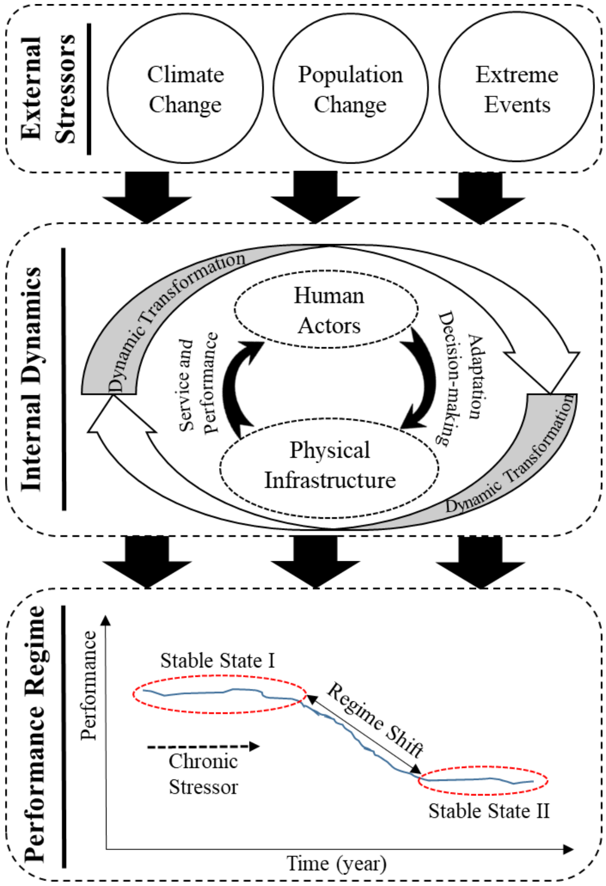

Figure 2-1. Long-term Infrastructure Resilience Framework Using a Complex-Systems Approach

2.2.1.1. External Stressors

External stressors can be chronic or acute in nature. Chronic stressors are gradual, low impact-high probability events that are caused by changes in the internal feedback processes and the external environment. Acute stressors are abrupt, high impact-low probability events that are mainly caused by extreme events. Both chronic (e.g. accelerated erosion due to climate change) and acute stressors (e.g. flooding) affect the dynamics of the infrastructure and as a consequence, its resilience. For instance, climate change (chronic stressor) is a major driver of changes in the socio-environmental conditions surrounding civil infrastructure (European Commission 2013; The World Bank 2017). Climate change impacts the sustainability and resilience of civil infrastructure in various ways such as (i) changes in temperature and precipitation which affect the erosion of the networks; (ii) population displacement which affects the demand on the networks; (iii) changes in the priorities of agencies which affects allocation of resources; and (iv) increased frequency and magnitude of extreme events (e.g. floods), leading to greater exposure of the networks to risks (Chappin and Lei 2014; Koetse and Rietveld 2009). Hence, changes in decision and physical infrastructure attributes and relationship would change the sensitivity of civil infrastructure system to external stressors. The Threshold values of these attributes at which the sensitivity of infrastructure system to stressors varies can be examined as tipping points. Tipping points occur in complex systems when "a small smooth change made to the parameter values of a system causes a sudden qualitative or topological change in its behavior". The parameter value at which state transition occurs is referred to as the tipping point or threshold point. Understanding tipping points is essential in describing long-term resilience in complex systems. In the context of civil infrastructure system resilience, regime shifts describe the extent to which the infrastructure system performance regime is sensitive to changes in external stressors magnitudes (e.g., population growth rate). On the other hand, tipping points, explain the critical values related to decision and physical infrastructure attributes (e.g., funding level and network age) that drastically increase or decrease the infrastructure system sensitivity to a certain scenario and stressor magnitude.

2.2.1.2. Internal Dynamics

Civil infrastructure as a complex system is composed of various components which are connected by a complex set of direct and indirect interactions and controlled by not one micro-behavior, but by a host of drivers. The observable collective behavior (overall performance) of civil infrastructure emerges from the underlying internal interactions and feedback among the system's components (internal dynamics), as well as through the impact of external stressors. The internal dynamics of civil infrastructure are determined based on the interaction between human actors (i.e. agencies and users) and physical networks. The dynamics of each component (i.e. human actors and physical networks) are determined by two factors: (i) interaction between the components, which is governed by dynamic rules that impose the activity or decision on the human actors and distribute the condition (performance) to the physical networks; and (ii) global fluctuations in the overall performance of the infrastructure system (de Menezes and Barabasi 2004). Figure 2-2 depicts the internal dynamics of civil infrastructure through the lens of a complex systems approach. This figure illustrates the couplings between human activities and engineered infrastructure. On the human actor side, two distinct decision-making processes of institutional actors (i.e., infrastructure agencies) can affect the long-term transformation of physical infrastructure. First, actor's decisions on maintenance, rehabilitation, or reconstruction of assets (referred to as preservation decisions) (Batouli and Mostafavi 2018b) influence transformation of physical infrastructure by affecting the degradation rates and renewal of assets. Second, the adaptation decisions of actors affect the vulnerability of assets to external stressors. As demonstrated in Figure 2-2, the decision-making processes of institutional actors affect the expansion, maintenance, and rehabilitation of physical infrastructure. In making their operational and strategic decisions, agencies adopt certain heuristics related to performance (functionality) requirements. These decision-making heuristics are affected by the demand and expectations of the users (consumer actors) as well as by the risks posed by external stressors (acute and chronic stressors). In addition to the decision-making processes of agencies, the functionality of infrastructure networks is affected by attributes (e.g. design, material and age) of physical assets in the network, behavior of its users (e.g. demand) and physical deterioration induced by aging of assets. These internal interactions between human actors and the physical infrastructure, both of which in turn are influenced by external stressors, lead to a certain performance regime for the infrastructure system as a whole. System and policy changes which affect interactions between human actors and physical networks can lead to shifts in the performance regime of the infrastructure. Hence, evaluation of such changes in the performance regime of infrastructure is a key aspect of resilience assessment from a complex systems perspective.

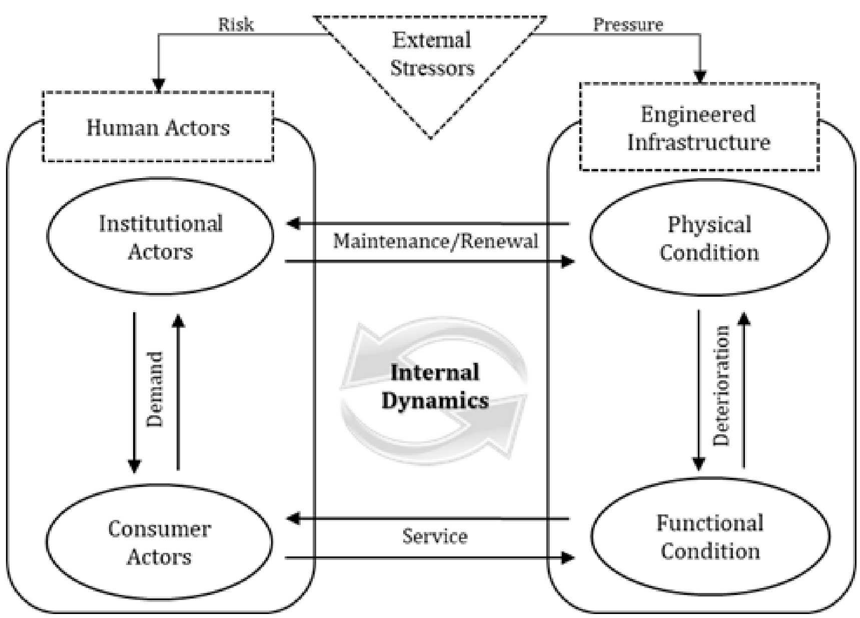

Figure 2-2. Internal Dynamics in Complex System of Civil Infrastructure

2.2.1.3. Performance Regime Shifts

The performance regime of infrastructure is defined as the steady state related to the system's performance, which is maintained by internal dynamics associated with the interactions between human actors and physical infrastructure affected by different stressors. A regime is a characteristic behavior of a system which is maintained by mutually reinforced processes or internal dynamics (Scheffer et al. 2001). A change of regime (regime shift) occurs when a change in an internal process (dynamics) or external disturbance triggers a completely different system performance behavior (Folke et al. 2004). Regime shifts are large, abrupt, persistent changes in the performance behavior of a system (Biggs et al. 2009). The regime shifts occur at tipping points (critical points), where an external stressor interrupts the steady state of the system performance. Evaluation of performance regime shifts is critical for long-term decision-making. Due to significant physical and institutional inertia that is prevalent in civil infrastructure, undesirable performance regime shifts are very difficult to reverse. Identification and adoption of the critical points would facilitate early detection of regime shifts, prior to their occurrence. The occurrence of shifts in the performance regime of an infrastructure system can be detected using different methods such as (i) plotting mean and standard deviation values of the system performance parameters against socio-environmental parameters (e.g. population change, temperature change, and level of funding); and (ii) using time-series data related to different system performance measures in non-parametric methods. To this end, a visual investigation of system performance parameter values under different scenarios can be conducted to identify the non-linear trends and long-term regime shifts.

In the next step of this study, a dynamic (time-dependent) multi-agent simulation model was created and validated to capture and explain the complex dynamics of stressor-human-infrastructure nexus. The elements of the multi-agent model are explained in the following section.

2.3. Multi-Agent Simulation Model

Further to identifying different components of a complex system, capturing mechanisms that dictate dynamic interactions between them is a necessary step towards assessing the long-term resilience performance of the system as a whole. To this end, a Multi-Agent Simulation (MAS) method was adopted in order to capture the coupled human-infrastructure dynamics. MAS enables modeling complex and real-world systems through the adoption of influential concepts such as adaptation, emergence, and self-organization (Al-Zinati et al. 2013). This method is routinely employed for analyzing problems which require distributed problem-solving capabilities in the absence of a centralized solution (Bousquet and Page 2004). In this method, agents of a complex system are structured such that they are independent entities which function concurrently in the presence of specific relationships that govern the complex system. In MAS, an agent has several essential characteristics: active–initiating actions, reactive–responding to external stimulus, and autonomy (Grignard et al. 2014). MAS has been shown as an effective simulation approach for analyzing complex processes and interactions in civil infrastructure systems (Batouli and Mostafavi 2018b; Bhamidipati 2015; Rasoulkhani et al. 2017a, 2018). Many entities within an infrastructure system (e.g., users, human-decision makers, and physical infrastructure) can be viewed and modeled as an agent. Given that human actors and physical assets of an infrastructure system interact in unique ways at different levels, the MAS method enables capturing such behaviors (i.e., internal dynamics, performance regime, and regime shifts) in a comprehensive framework to assess the long-term resilience of complex systems. Indeed, through developing a MAS model of a water distribution network the proposed framework was tested and used for long-term resilience assessment of this complex infrastructure system. The following section describes the conceptual framework of MAS created for capturing internal dynamics and modeling the impact of external stressors on the performance regime of civil infrastructure, in the context of an urban water distribution system.

2.3.1. Conceptual Model for Simulation

Water distribution infrastructure is a vital part of urban water supply systems, comprising of expensive and often complex physical assets. When thought of as a complex system, it includes physical pipeline networks delivering water to users, the municipality or private company as an institution that manages the infrastructure and the organizations and individuals who consume the water (EPA 2015). In water distribution networks, aging pipelines accelerate the effects produced on the infrastructure by external stressors, leading to a faster decay in the performance of this complex system as a whole. The three important drivers of dynamic interactions between agents of a water distribution are shown in Figure 2-3 below. They include (i) physical degradation of the infrastructure network and its components, which is a function of several factors such as aging, erosion and environmental conditions (ii) renewal decision-making processes and adaptive behavior of institutional actors (Mostafavi et al. 2015) (iii) external stressors such as population change and fluctuations in funding, which either exacerbate physical degradation of the system or affect the response behavior/decision-making processes of its institutional actors.

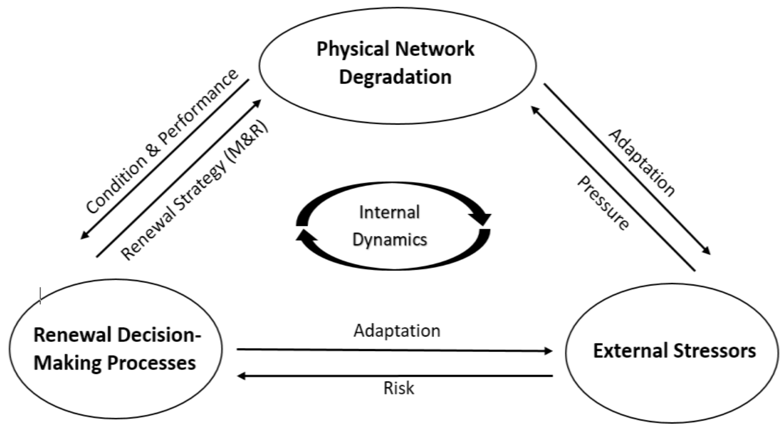

Figure 2-3. Conceptual Modeling Framework for Water Distribution Infrastructure Systems

2.3.1.1. Physical Network Degradation

The physical condition of an infrastructure asset denotes its structural capacity and ability to withstand different types of stressors. On the other hand, the functionality of infrastructure indicates its ability to serve its intended function at the desired level of service. The approach to modeling the mechanisms of physical degradation varies for different infrastructure (e.g., roadways vs. water systems) (Brownjohn 2007). However, the modeling of infrastructure degradation essentially involves identifying indicators of physical and functional conditions of an asset and then integrating them into a unified performance measure (Ben-Akiva and Gopinath 1995). A unified performance measure quantifies the state of an infrastructure asset at any given time based on variables such as design characteristics of the asset, asset's age, ambient climate, and service load of the asset in that period (Ben-Akiva and Gopinath 1995). Typical physical attributes of a water distribution network are pipeline age, materials used, length of pipes, fluid pressure and flow rate. The deterioration of physical assets in a network decreases the reliability of the infrastructure and affects the system as a whole in terms of maintenance and operation costs, rehabilitation needs and exposure of actors in the system to risks. Therefore, a complex system model of water distribution infrastructure needs to account for degradation and the effect that it has on service life, condition states, future maintenance and rehabilitation expenses. The physical degradation process of pipework is not clearly understood, with published literature citing several factors such as age, material and network pressure as driving mechanisms, meaning, different functions may be implemented to capture the process (Tabesh et al. 2009). However, several deterioration model studies have correlated age with condition thereby establishing that the process is age-dependent (Younis and Knight 2010). From a system perspective, age-based deterioration can be used as a criterion to sort various sections (lengths) of piping in the network into discrete age groups based on pre-defined age ranges. As a consequence, aging sections would move from one age group to the next during the process of deterioration. Thus, modeling degradation as a dynamic process would capture long-term transformation effects in the network which would lend greater accuracy to the assessment of the system's resilience.

2.3.1.2. Renewal Decision-Making Processes

In addition to physical network degradation, human actors (users and administrative agencies) play an important role in the long-term dynamics of water distribution infrastructure. For instance, expectation of and demands placed by users determine the actual quantity of water supplied by the network, while municipalities and private institutions (administrative agencies) which manage the decision-making processes related to renewal and restoration, affect the ability of the network to maintain the required supply. Consider the following scenario which illustrates the interplay of human behavior in the network. The demand placed on the network fluctuates with changes to the user population. These fluctuations drive the price of water, which in turn affects the revenue generated by administrative agencies. Since revenue drives renewal decision processes as well as regular maintenance work, a direct consequence of this interplay is the degradation rate of physical assets in the water distribution network. In response to the various factors which affect the decision-making process, administrative agencies often identify strategy targets to pursue when maintaining large infrastructure networks. A strategy target may be defined as that indicator of network performance (e.g. average condition and break frequency) which is deemed acceptable by the administrative agency. Thus, any strategy target is a combination of various factors in the behavior spectrum of its human actors. The proposed model captures various behavioral factors affecting the decision-making process such as capital and operational expenses, revenue, water price and capital improvement funds, which are uniquely combined to create three heuristic renewal strategy targets for the network: (i) controlling the average break frequency (ii) controlling average condition of network and (iii) regular renewal based on age of pipes. When the agency adopts a break-control strategy, the motive is to keep the frequency of breaks below a certain target threshold. The annual pipe renewal process would be maintained until the desired average annual break frequency over a five-year horizon is reached. If the target is average condition control, the agency strives to maintain the condition of the network below the required threshold through the renewal process. In either of these strategies, renewal costs exceeding the base allotment are met through the activation of a surplus called the capital improvement fund. This fund is allocated based on a 5-year budget from which 20% can be used annually towards the renewal process if expected costs are exceeded. In the case of an age-based (regular) renewal strategy, the agency performs maintenance work only on sections of the pipeline which are older than 100 years (100 years is the average service life of water pipes as reported by (Rehan et al. 2011)). The capital improvement fund is unavailable when an age-based strategy target is adopted. Therefore, when faced with a deficit, the agency performs renewal based on the amount of available revenue. It is apparent that renewal decision-making processes of the utility agency and other adaptive actions affect the dynamic variables of the infrastructure, resulting in different performance regimes. Hence, a long-term resilience assessment of the water distribution infrastructure system would be incomplete in their absence.

2.3.1.3. External Stressors

The impact of stressors on civil infrastructure systems has been highlighted in the previous sections. The impact of chronic stressors in particular, has greater bearing when the long-term dynamics of a water distribution infrastructure are being investigated. The proposed model framework considers the impact of population change and funding fluctuations as external stressors. Accordingly, different levels of capital improvement fund and various rates of population change are accounted for, to investigate its influence on the dynamics of the infrastructure. Together, water demand fluctuations arising from population change, and availability of funds for renewal, produce critical points which lead to shifts in performance regimes of the water distribution network.

The following section presents the methodology and estimation procedures required to parameterize the MAS model and develop its computational components for a numerical case study of water distribution infrastructure system.

2.3.2. Computational Simulation Model

The MAS model in this study was created based on the conceptual logic and principals representing the real-world behaviors of an urban water distribution infrastructure system. The creation of a computation representation for all the input and output parameters of the conceptual model entails constructing mathematical algorithms to match the conceptual logic representing the behaviors of water distribution infrastructure. The computational representation of the MAS model was developed in an object-oriented programming platform (i.e., AnyLogic 7). It integrates the institutional actors' renewal decision-making processes with the physical infrastructure performance in order to assess the long-term resilience behavior of water distribution infrastructure system under different stressors (e.g., user population changes) and various scenarios (e.g., renewal strategies). A numerical case of a water distribution network composed of 180 miles of pipes with different materials and age categories was used to create the computational simulation model that captures the dynamics of the system to examine its resilience. The population in the service area of this case is 113,000 (60,000 households). This MAS model of the water distribution infrastructure system includes three classes of agents: water pipeline network, water users, and utility agency, each of which is simulated in the model as an object (i.e., function, variable, or data structure that has memory in the computational model). Figure 2-4 depicts the Unified Modeling Language (UML) class diagram of the computational MAS model and summarizes the information regarding the attributes and functions implemented.

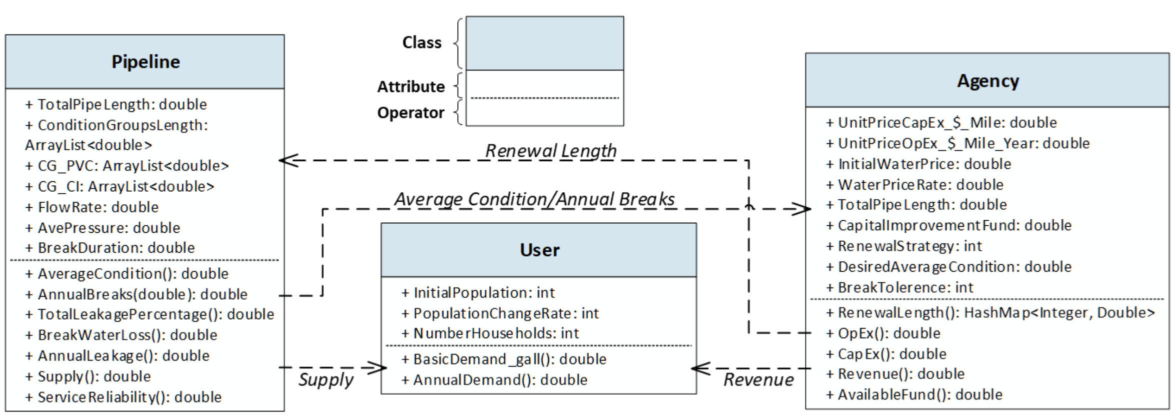

Figure 2-4. Unified Modeling Language (UML) Class Diagram of the Model

The relationships among agent classes and their attributes are based on the existing literature and empirical information. Figure 2-4 shows the attributes, functions, and relationships among different agent classes. The following subsections represent the mathematical implementation for the model agents and their attributes.

2.3.2.1. Pipeline Network Agent

The pipeline network agent includes different pipe classes with a defined total length (in miles) divided into 5 condition (age) group states ($i = 20, 40, 60, 80, 100$). For each group, which represents a certain condition level, there is a defined material (e.g., percentage of PVC and CIP type). Deterioration of pipes is modeled based on their age. As pipes age, their condition group may change; every year, 5 percent of pipes in each condition group (except condition group 100) moves to the next condition group. Another mechanism that affects the transition of pipes into different condition group states is pipe renewal. Based on the renewal decision-making outcomes of the agency agent (which is explained later), a certain percentage of pipes is renewed and moves from condition group 100 to condition group 20, annually. Figure 2-5 depicts the modeling deterioration mechanism of pipes in the model.

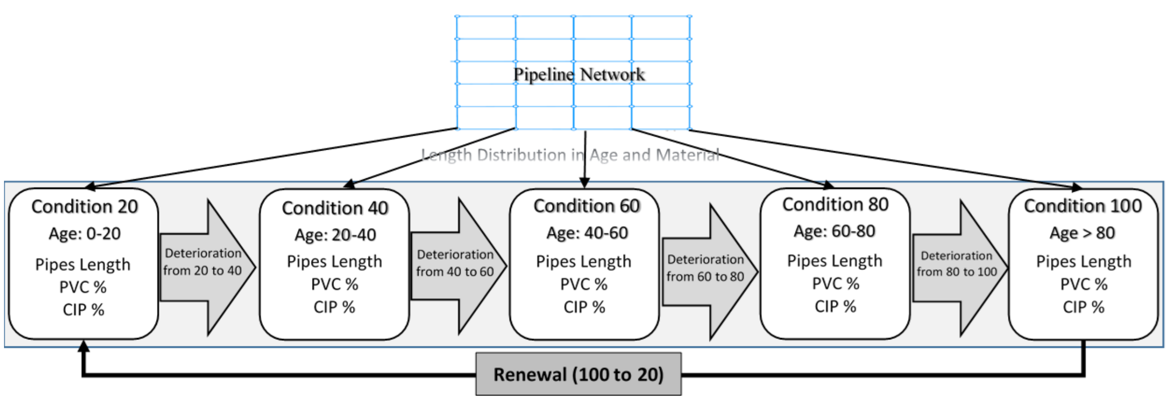

Figure 2-5. Modeling Physical Pipeline Deterioration Process

The aging of the pipes is also reflected in the changes in the percentage of materials for each group. At the beginning of simulation, the model starts with a defined percentage of PVC and CIP pipes for each group. As pipes age, these percentages change (because renewal is by PVC). Based on the portion of pipe length in each condition group, the model computes the network average condition ($\bar{C}$) using Equation 1 (Rehan et al. 2011):

$$\bar{C} = \frac{\sum_i (l_i * i)}{L_N} \qquad (i = 20,40,60,\ 80,100) \tag{1}$$

where l_i and L_N are the total length of pipes (mile) in condition group i and in the network, respectively. The other attributes of the pipeline network agent include breakage, leakage, and service reliability. Breakage is modeled using a stochastic process that determines the frequency of pipe breaks during one year. The frequency of breaks for each mile of pipes is a function of pipe's material and age. The model uses a Poisson Process with a mean rate of break (λ) (shown in Equation 2) to calculate the annual frequency of pipe breaks per each mile of pipeline. In Equation 2, the Lambda (λ) represents the mean rate of break per mile per year (Shamir and Howard 1979):

$$\lambda = N_0 . e^{g(i-10)} \tag{2}$$

where N_0 is the initial number of breaks per mile per year in a new pipe, g is the growth rate which is 0.07 for PVC and 0.078 for CIP pipes (Kleiner and Rajani 2000), and i is the pipe's condition group. The total number of breaks in the network per year (N_B) would be sum of the breaks in each mile of the entire network pipes. The annual water loss due to network breaks is calculated using Equation 3 (Zamenian et al. 2015):

$$WL_B = 1440 * N_B * \bar{F} * d * \sqrt{\bar{P}/70} \quad \textbf{(3)}$$

where, WL_B is the annual water loss due to network breaks (gallon), N_B is the total number of annual breaks, $\bar{F}$ is the network average flow rate (gallon per minute), d is the total duration of disruption due to break (day), and $\bar{P}$ is the network average pressure (psi). $\bar{F}, \bar{P}$, and d are user-defined input parameters into the model. Similarly, network leakage is determined as total water volume lost in the network, which is a fraction of annual water demand. Leakage rate (LR), which is a unitless variable, depends on network average condition ($\bar{C}$) and is calculated using Equation 4 (Rehan et al. 2015):

$$LR = 0.00075 * e^{\bar{C}(0.07PVC+0.078CIP)} \quad \textbf{(4)}$$

where PVC and CIP are the fractions of pipeline network with each material type. Accordingly, the annual water loss due to network leakage is determined by Equation 5:

$$WL_L = LR * D \quad \textbf{(5)}$$

where WL_L and D denote the annual water loss due to network leakage (gallon) and the annual water demand (gallon), respectively. Considering the total water loss in the network due to both breakage and leakage, annual water supply (S), which represents the delivered water to users (gallon per year), is calculated using Equation 6:

$$S = D - (WL_B + WL_L) \quad \textbf{(6)}$$

In order to determine whether the supply of water transported by the pipes can meet the given demand, a service reliability (SR) parameter is defined. This parameter represents the extent to which the supplied water through the network met the demand. To determine SR, in each year (t)

the cumulative supply is divided by the cumulative demand and this gives the service reliability until that year (SR_t) based on Equation 7:

$$SR_t = \frac{\sum_{j=1}^{t} S_j}{\sum_{j=1}^{t} D_j} \quad \textbf{(7)}$$

where S_j and D_j are delivered water and water demand (gallon) in year j, respectively.

2.3.2.2. Users Agent

The agent of users represents population (P) and number of households (N_h) consuming water from the given pipeline network, which determine the amount of water (gallons) demanded from the network. In each year, water demand (D_t) is assumed to be the average indoor water demand (gallon/year) which is calculated using Equation 8 (Reichel et al. 2016):

$$D_t = 87.4(\frac{P_t}{N_h})^{0.69} * N_h * 365 \quad \textbf{(8)}$$

Population (P_t) is changed in each year based on the user-defined values of growth/decline rate (r) and base population (P_0). Population in each year (t) is computed based on Equation 9:

$$P_t = P_0 * e^{t.r} \quad \textbf{(9)}$$

2.3.2.3. Utility Agency Agent

The utility agency agent models the decision-making processes of the agency. The renewal decision-making process is affected by revenue, operational and capital expenditures, and capital improvement fund. The initial water price (WP_0) in the model is user-defined ($/gallon). Water price ($WP_t$) can hike annually over the simulation period with a price hike rate (w) based on

Equation 10. Accordingly, annual revenue (Rev_t) is determined based on that year's projected water demand (gallon/year) and water price ($/gallon) using Equation 11.

$$WP_t = WP_0 * (1 + w)^t \tag{10}$$

$$Rev_t = D_t * WP_t \tag{11}$$

The annual operational expenditure ($OpEx$), which increases exponentially based on the network average condition ($\bar{C}$), is determined using Equation 12 (Rehan et al. 2015):

$$OpEx = U_{OpEx} * L_N * [1 + \left(1.4877e^{(0.0449\bar{C})}\right)/100] \tag{12}$$

where U_{OpEx} is the unit cost (dollar per mile) for operating and maintaining the network (which is $0.06 million per mile per year based on (Rehan et al. 2011)). The renewal rate depends on the availability of funding for the capital expenditures. The available funding for the pipes renewal equals to the annual revenue minus the operational expenditures. The required funding for capital expenditures of renewing pipes is determined using Equation 13.

$$CapEx = U_{CapEx} * RL \tag{13}$$

where, U_{CapEx} is the cost of rehabilitation of one mile of pipes with PVC ($1.2 million), and RL is the length of pipes (mile) with age 100 or more (5% of pipes in condition group 100). If the available funding for capital expenditures is less than the required capital expenditures, the renewal length would be equal to the available funding divided by the unit cost of rehabilitation. For additional renewal in order to keep the network's performance in terms of break frequency or average condition below the user-defined threshold (i.e., strategy target), the agency would use the capital improvement fund (CIF) in addition to the revenue. In the model, CIF ($ Million) is a user-defined input parameter, 20 percent of which can be used annually by the utility to conduct more pipe renewals in the network. Figure 2-6 shows the action chart of renewal process under the strategy of controlling network average condition. Based on this action chart, the model identifies to what extent (i.e., mile) the renewal process should be conducted (as much as the CIF allows) in order for the network to reach the strategy target (i.e., desired average condition). That is, similarly, for the strategy of break control, the model determines to what extent the renewal process should be conducted in order for the network to reach the desired number of breaks.

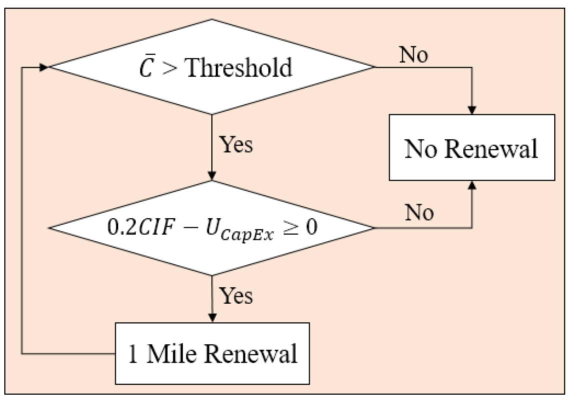

Figure 2-6. Action Chart of Renewal Strategy for Controlling Network Average Condition

2.3.3. Verification and Validation

Verification and validation techniques focus on verifying the data, rules, logic and computational algorithms (Bankes and Gillogly 1994). They could be as simple as tracking variables at intermediate levels in simulation and running the simulation with extreme values of constructs (Davis et al. 2007). Typically, attempts are made to replicate the outcomes seen in theory, failing which, systematic checks are carried out to identify errors in the code. In this study, a gradual, systemic, and iterative procedure was employed to conduct a thorough verification of the computational model. In addition, the validation of the model was ensured through the use of grounded theories, logic and equations utilized by previous studies in modeling the performance of water distribution networks such as (Ganjidoost et al. 2015; Younis and Knight 2010).

Various internal and external validation techniques (e.g., predictive and face validation) were employed to verify the data, logic, and computational algorithms related to the simulation model. First, the initial conditions and the ranges of the parameters were compared to the existing empirical data to ensure the reliability of the parameters in the model (Werker and Brenner 2004). For example, the parameters related to the physical network, such as pipes' age, length, and material, were compared to the actual water distribution data related to another network (in Ontario, Canada). Second, the behaviors of model entities (e.g., network average condition) were followed so as to identify unusual model behaviors. Whenever an unusual behavior was observed, the model logic was checked to ensure that the behavior was not due to unreasonable assumptions or imperfect logic. Third, extreme value analyses were performed, where the model was run at different extreme conditions (for each component) to observe its response and verify its functionality under these scenarios. Fourth, several random replications (more than one thousand runs) of the model were compared to check for the consistency of the results (Xiang et al. 2005). Fifth, predictive validation of the model was conducted. In predictive validation, the model is used to predict the system's behavior, and then the model's forecast is compared with actual system's behavior obtained, for example, from data related to behaviors of an operational system (Sargent 2010). To conduct the predictive validation, the outputs related to each model specification were compared to the existing data related to the water distribution networks in Fort Collins, CO. For example, the simulated annual leakage and breakage rates of the network were compared to the real values based on historical data. Accordingly, most of the observed errors pertained to incorrect implementation of the algorithm (the algorithm itself proved robust) in the code and were rectified easily. Finally, a face validation was pursued by research team through examining the simulated behaviors of the model (output results) to ensure that they are reasonable for a real case. Following this, the quality of the model components was ensured for completeness, coherence, consistency and correctness (Mostafavi et al. 2015) based on the performance of the model outputs.

2.4. Simulation Experiments

After using different internal verification and external validation techniques to ensure the model quality, the simulation model was used for building various experiments based on all possible scenarios. Various simulation experiments were conducted through the change of model input parameter values and logics in the computational model. The possible scenarios were established based on different combinations of the input variables (parameters) in the model, shown in Table 2-1. The combinations of these scenarios reflect changes in population growth rate, capital improvement fund level, water price hike, renewal strategy, and strategy target. Accordingly, under each specific scenario, one thousand runs of Monte-Carlo experiments were conducted to determine the mean value of the model output parameters (e.g., service reliability).

Two sets of simulation experiments were conducted to evaluate the long-term resilience of the water distribution infrastructure system. First, the impacts of decision and physical infrastructure attributes were examined in order to explore the significant attributes and their critical threshold value that could lead to the occurrence of tipping point behaviors. To this end, time-series results related to the network average condition were visualized to investigate the existence of non-linear increase or decline trends in the simulated long-term performance measure.

Accordingly, the threshold values related to decision and infrastructure attributes (e.g., level of capital improvement funding and desired network average condition), at which the steady state of infrastructure performance is disrupted were examined as tipping points. The results related to regime shifts and tipping points were used to evaluate the long-term resilience of the case study network under different adaptation strategy scenarios (i.e., funding allocation and renewal strategies). Second, the impacts of population changes and funding fluctuations on the network performance parameters and its ultimate effects on network service reliability over the analysis period (e.g., 100 years) were investigated. To this end, the mean values of the infrastructure service reliability were plotted against different values of population change rate and capital improvement funding level to visually examine the occurrence of shifts in the service reliability performance of the infrastructure system. Accordingly, the occurrence of regime shifts and tipping points were detected and used to analyze the sensitivity of long-term infrastructure system performance to external stressors.

Table 2-1. Model Input Variables

Input Variable	Variable Value(s)
Base Population	113000
Number of Households	6000
Population Change Rate (%)	-2, -1.5, -1, -0.5, 0, 0.5, 1, 1.5, 2
Pipeline Renewal Strategy	1. Regular Renewal 2. Controlling Network Average Condition at 40, 45, and 50 3. Controlling Average Break Frequency at 20, and 25
Initial Water Price ($/gallon)	0.005
Water Price Hike Rate (%)	0, 4, 8
Capital Improvement Fund ($ Million)	0, 10, 15, 20, 25, 30

2.5. Results

The MAS model of water distribution infrastructure system was used to extract, animate and visualize the long-term regimes of different performance and condition measures in the case study water distribution network. For instance, the simulation model was run for a scenario of 1% population growth, 4% water price hike, and regular renewal strategy. Figure 21 shows a screenshot of the graphical output dashboard of the simulation model under this scenario. As can be seen in Figure 2-7, this dashboard displays the 100-year regimes of the network average condition (age), the network leakage, the network annual breaks, and the system service reliability. Also, age-material distribution of the pipes of the network in each year is observable in this dashboard.

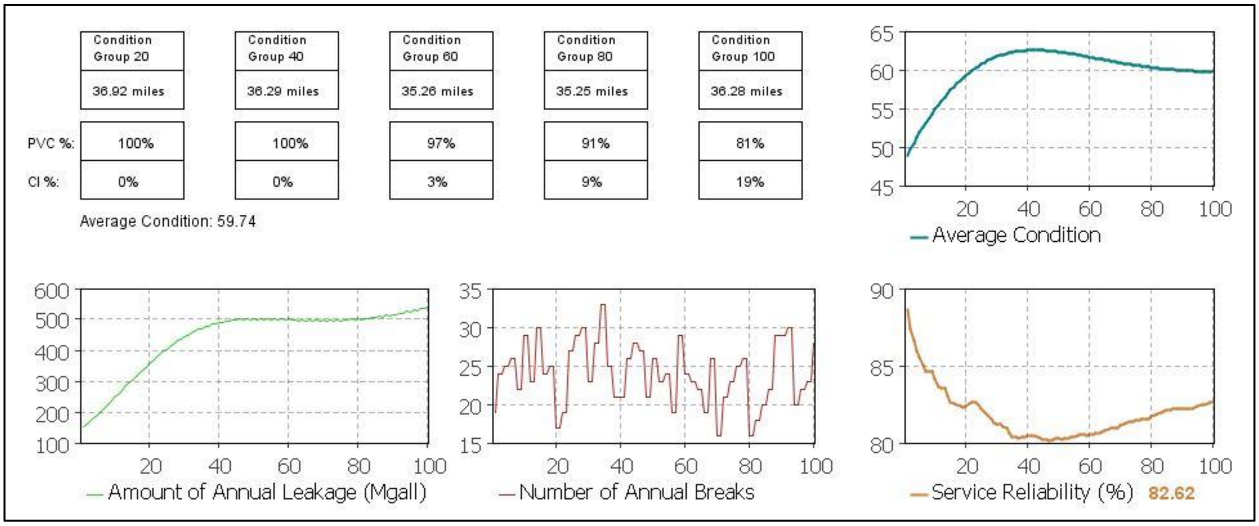

Figure 2-7. Simulation Output Dashboard: Visualized Long-Term Performance Regimes

These visualized long-term performance regimes of the water distribution infrastructure are utilized to detect the occurrence of regime shifts, visually (as discussed before, a visual investigation of system performance parameter values under different scenarios could be used to identify long-term performance regime shifts); and accordingly, the long-term resilience of the system is evaluated. Thanks to the analysis results, two sets of theoretical constructs related to complex systems approach to infrastructure resilience were examined: (i) the performance regime of infrastructure is shaped by its internal dynamics; and (ii) the effective performance of infrastructure is sensitive to external chronic stressors.

2.5.1. Internal Dynamics and Performance Regime

The simulation model was used to examine how infrastructure dynamics shape performance regimes. To this end, the effect of renewal strategies (as an element affecting infrastructure dynamics) on the performance regime of the network was evaluated. Two renewal strategies (i.e., condition and break control) were considered. For each renewal strategy, different required performance targets and capital funding levels were assessed. In total, 25 scenarios of renewal strategy were simulated. Each scenario represents a unique state of infrastructure dynamics in the case study. Figure 2-8 shows network average conditions over a 100-year horizon under 1% population growth rate for all the scenarios. In Figure 2-8, each column represents a certain renewal strategy and each row represents a certain level of capital improvement fund (CIF). As can see in Figure 2-8, the state of infrastructure dynamics in each scenario leads to a certain regime in the performance of the network. For example, under scenarios A1-A4, the behavior (regime) of the network performance follows a similar trend; however, under scenario A5, the dynamics of the system changes (because of change in renewal strategy target), and hence the infrastructure performance changes.

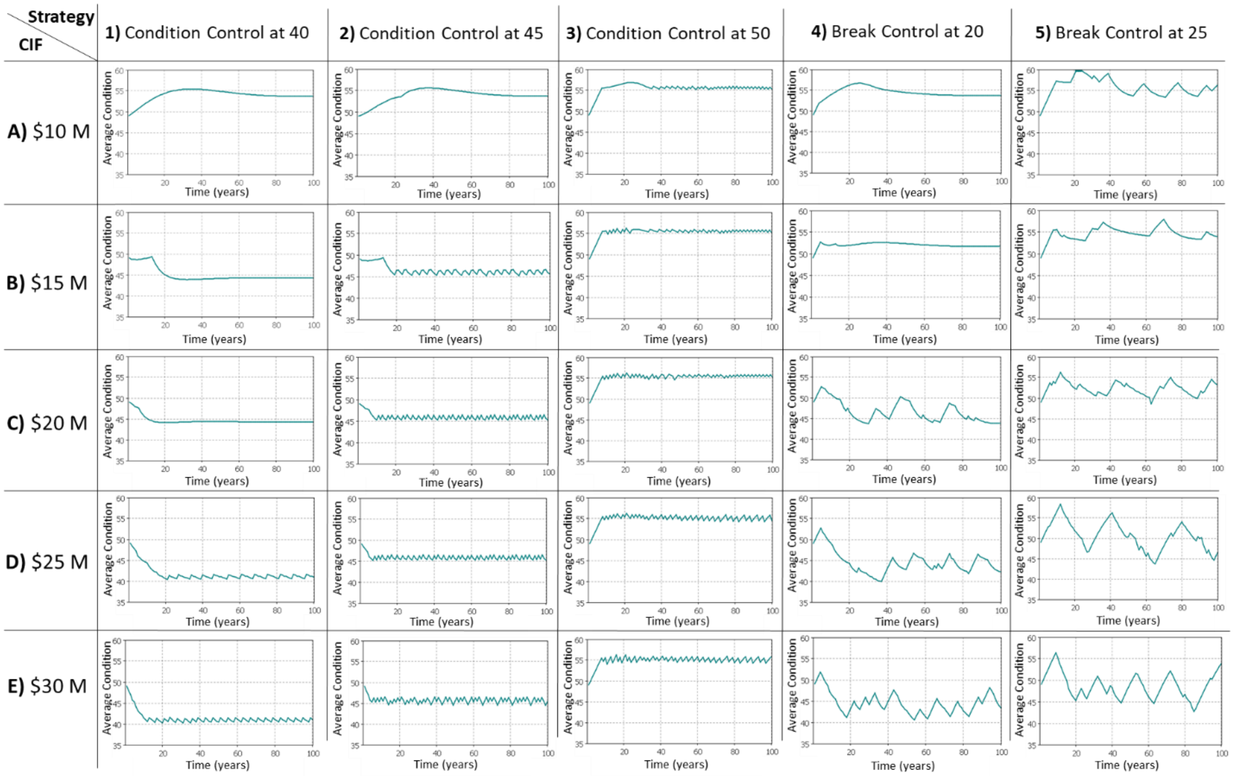

Figure 2-8. Modeling Regimes of Network Average Condition Under Various Scenarios

The change in the performance regime of infrastructure is a significant phenomenon and can be characterized as a critical point or tipping point. Critical or tipping points represent values related to the internal dynamics of infrastructure or external stressor in which a small change in the parameter value leads to a significant change in the performance of infrastructure. For example, Figure 2-8 shows that under a fix capital improvement funding (e.g., $20 Million), a change in the renewal strategy from condition control to break control will lead to a shift in the performance regime of the network (compare scenarios C1-C3 with C4-C5). Under each renewal strategy, there is a certain value of capital improvement funding that leads the infrastructure system to a resilient behavior (i.e., the network meets the desired target with a stable regime). This value, accordingly, is specified as a tipping or critical point. For instance, under the renewal strategies of controlling average condition at 40, 45, and 50, any capital improvement funding below $25 million, $20 million, and $15 million, respectively, wouldn't lead the system to a resilient behavior (compare D1 with C1, C2 with B2, and B3 with A3). These results show that internal dynamics shape the performance regime of infrastructure and how the changes in these internal dynamics affect the long-term performance regimes and cause the regime shifts.

2.5.2. Impact of Chronic Stressors

The simulation model was also used to examine the impact of external chronic stressors on the performance regime of the case study infrastructure. To this end, the effect of population changes and funding fluctuations were considered. Various scenarios of population change rates and levels of capital improvement fund were defined; and then for each scenario, one thousand runs of Monte-Carlo experiments were implemented to determine the mean value of the water distribution infrastructure's service reliability. Service reliablity indicator measures how reliable the network is in successfully delivering the demanded water to users. Figures 23 and 24 show the simulation results for these scenarios. Figure 2-9 shows that, under regular renewal strategy, without any changes in the water price, the service reliability of system drops significantly when the system faces a decline in the population of the service area. However, if the water price grows 4% or greater annually, the sensitivity of the network performance to population change decreases. Based on the results, implementing a plan of 4% water price hike annually, will lead this water distribution infrastructure system to a resilient behavior against the population decline over the 100-year horizon. However, a 4% annual price hike might be greater than the inflation rate or the average rate of household income increase, which makes the implementation of this plan impossible (Mack and Wrase 2017).

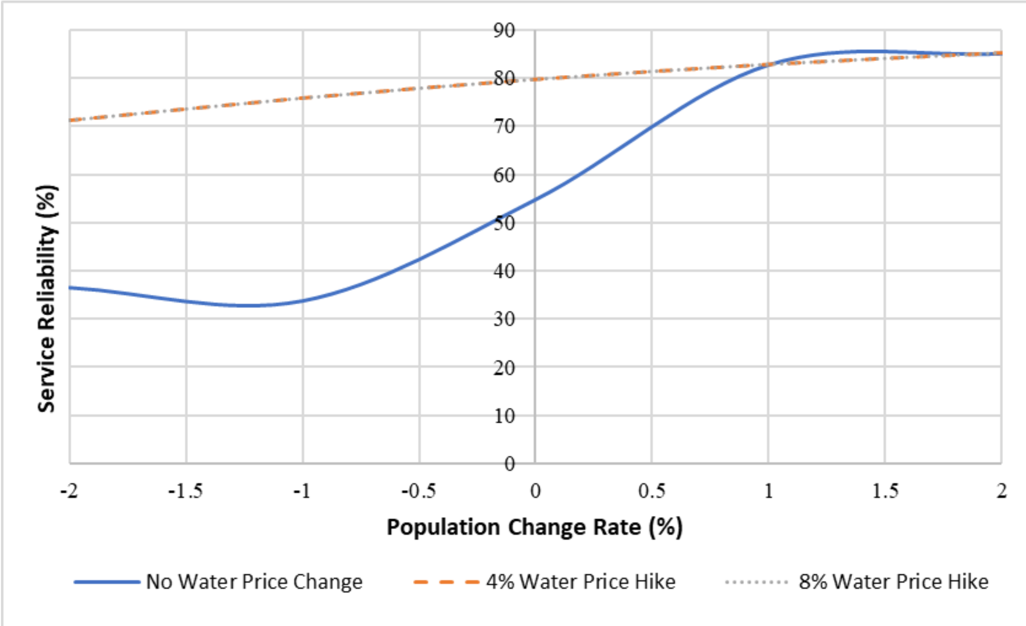

Figure 2-9. Impact of Population Change (Chronic Stressor) on System Service Reliability

Since for two other renewal strategies the extent of renewal processes prominently depends on the capital improvement fund, the impact of this external stressor (funding fluctuations) on the system effective performance was examined under different renewal scenarios. Figure 2-10 shows the sensitivity of five different scenarios of renewal strategy to the level of capital improvement fund. It is seen that, renewal scenario of 3 and 4 have a roughly steady-state trend within different levels of the capital improvement fund. However, for three other renewal scenarios, there are two different phases over the trend of service reliability, which indicates a critical point for capital funding level. Critical point means the threshold level of funding, around which the service reliability of system significantly changes from the previous phase. As shown in Figure 24, for the renewal scenarios 1 and 2, \$20 Million and \$15 Million are the critical points of capital improvement fund, respectively. Hence, it seems for the case study water distribution network, if strategically implemented, renewing the pipes at a rate to keep the network average condition at 40 will lead the infrastructure system towards a more resilient behavior over the long-term horizon.

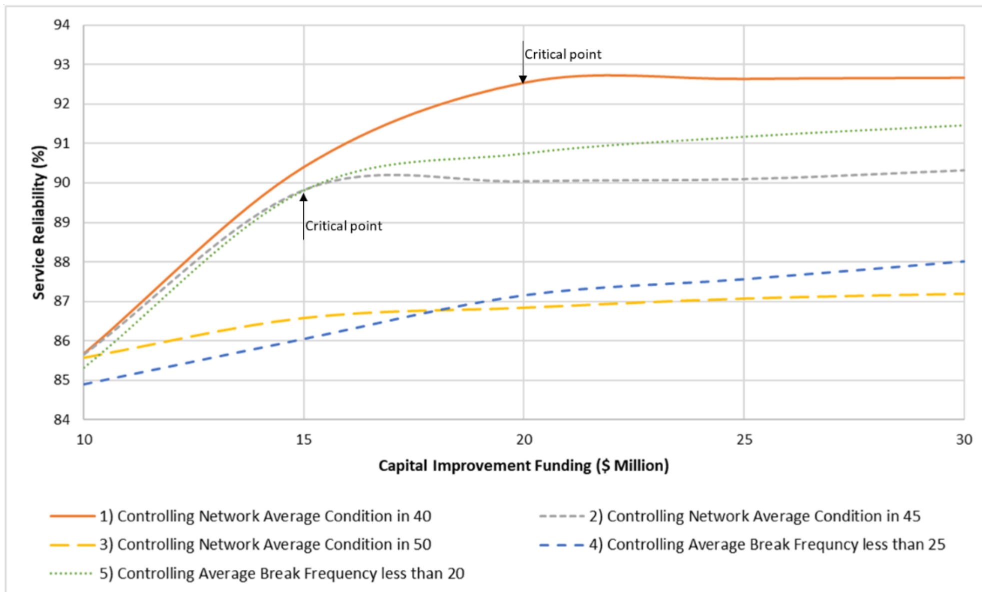

Figure 2-10. Impact of Funding Fluctuations on System Service Reliability

These example results show the sensitivity of infrastructure system performance to external stressors and to what extent they affect the effective performance indicator of infrastructure system.

2.6. Concluding Remarks

This study was conducted with the objective of capturing internal dynamic behaviors which influence the long-term resilience of civil infrastructure systems in the presence of external stressors. The proposed framework characterizes the object of study (a water distribution network) as a complex system and offers a multi-agent simulation (MAS) model to quantify its components, dynamic processes, and external stressors acting on it. The output of the model depicts the performance regime of the system over an extended horizon which enables the detection of regime shifts to evaluate the long-term resilience.

Different performance regimes were observed in response to changes in the renewal decision-making process of the administrative agency, which is an expected outcome owing to the fact that availability of funding is a function of revenue, which in turn depends on the demand generated by the user population. The model also identified tipping points in the performance regime when specific renewal strategy targets were adopted by the administrative agency. For instance, when a renewal strategy of average condition controlling at 45 was adopted in conjunction with a capital improvement fund of $15 Million, the infrastructure satisfied the target by exhibiting long-term performance. Any decrease to the fund however, caused a regime shift if the agency continued to maintain the same strategy target. These results show that the performance regime of an infrastructure system is shaped by its internal dynamics, which reinforces the premise that changes in internal dynamics would lead to regime shifts in long-term behavior of the system. The model also adequately captured the long-term response of infrastructure when subjected to external stressors. For instance, a positive correlation between decline in user population and the long-term service reliability of the infrastructure was observed. The model showed that a price hike of 4% annually would maintain the service reliability of the case study water distribution infrastructure system in a stable state, despite changes to its user population.

2.6.1. Contribution and Significance

The contributions of this study are threefold: theoretical, computational, and practical contributions. From theoretical perspective, this study proposed a complex system-based framework for infrastructure resilience assessment through a better understanding of internal dynamics and tipping point behaviors. Accordingly, it proves that (i) the performance regimes of infrastructure are shaped by their internal dynamics and (ii) chronic stressors affect the effective performance of infrastructure system. In terms of computational contribution, this study developed a MAS model of a water distribution network that adequately captures and quantifies the dynamic behaviors and performance regimes of the infrastructure system in the presence of external stressors. Practically speaking, through the quantifying the impacts of external stressors, internal dynamics and performance regime shifts, researchers can predict the resilience of civil infrastructure systems with greater accuracy. This in turn would help decision-makers formulate policies (e.g., renewal strategy) that enhance the sustainability and resilience of these systems.

2.6.2. Future Studies

The simulation model presented in this study doesn't include all the dynamic mechanisms affecting the long-term resilience of a coupled human-infrastructure system. Depending on the objective of a study, additional dynamics can be captured and modeled using the proposed framework. For example, in the analysis shown in this paper, the influence of user behaviors was not within the study objectives. Hence, in this model, the influence of consumer actors was modeled exogenously with a prescribed rate of population growth and water demand. Future studies can examine the dynamics of consumer behaviors in evaluating the long-term resilience of infrastructure systems by evaluating individual consumer's response to water price (Mack and Wrase 2017) and other incentives (such as rebate).

3. RESILIENCE-BASED INFRASTRUCTURE PLANNING AND ASSET MANAGEMENT: STUDY OF DUAL AND SINGULAR WATER DISTRIBUTION INFRASTRUCTURE PERFORMANCE USING A SIMULATION APPROACH‡

Dual water distribution systems have been proposed as a technological infrastructure solution to enhance the sustainability and resilience of urban water systems by improving performance and decreasing energy consumption. The dual system separately distributes non-potable water for outdoor demand and potable water for indoor demand. The objective of this study was to evaluate the long-term performance of dual water distribution systems versus singular systems under various scenarios of renewal strategies and demand fluctuations. To this end, a dynamic (time-dependent) simulation model was developed to capture long-term dynamics of water distribution infrastructure systems using empirical relationships. The model integrates utility agency's renewal decision-making processes with the physical infrastructure degradation to simulate the long-term transformation of the pipeline network. Various system performance measures, including breakage, leakage, energy loss, level of service, and life-cycle costs, were simulated over a 50-year horizon. The simulation model was implemented using data from the City of Fort Collins, CO, and used to examine the long-term performance of the dual and singular water distribution systems. The analysis results enabled: (i) understanding the long-term transformation of water distribution systems; (ii) comparing different performance measures of

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dual and singular systems; and (iii) exploring the sensitivity of both systems to demand fluctuations.

3.1. Introduction

In the United States, the current conventional approach for public water systems is to treat a raw water source at a central facility and distribute potable water to consumers through a singular distribution system. Water is treated to an increasingly stringent potable drinking standard in preparation for all domestic uses. Only 1% of potable water is used for direct human consumption, including drinking and cooking (Cotruvo 2003). Other varieties of human contact account for roughly 25% of total consumption leaving nearly 75% to activities such as toilet flushing, lawn irrigation, fire protection, and exterior use (Cotruvo 2003). Differing water quality requirements for these uses suggests that not all domestic water consumption requires potable quality supply and thus requires adoption of alternative approaches that would lead towards resilient water supply systems and thus sustainable cities in the future (Fraga et al. 2017).

The motivation for the adoption of alternative approaches to conventional water treatment and singular distribution is related to the costs of excess treatment for a large percentage of treated water and deteriorating water quality due to oversized distribution networks (Bischel et al. 2012; Grigg et al. 2013). The production and delivery of potable drinking water is highly energy intensive. Energy consumption in the water sector is approximately 3-4% of national energy consumption in the United States and 30-40% of municipal energy use (Plappally and Lienhard V 2012). Treating the entire domestic demand to potable quality requires a substantial amount of energy and operating cost (Plappally and Lienhard V 2012). The 2011 Drinking Water Infrastructure Needs Survey and Assessment (EPA 2013) reported that 18.9% of the U.S. total investments in water infrastructure system are for raw water treatment (Figure 3-1). This equates to an estimated $4 billion in annual expenditures nationally. In addition, singular distribution networks must be sized for peak day water use in addition to fire demand, resulting in longer residence times which allow water quality to deteriorate during delivery and lower flows to deposit sediment (Hickey 2008).

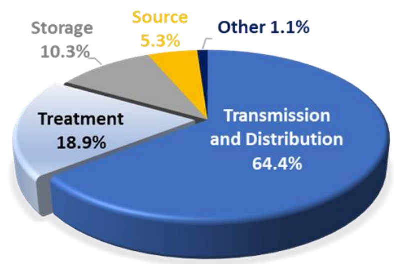

Figure 3-1. Water Infrastructure System Investment Need in the USA (EPA 2013)

As aging water infrastructure in larger communities of cities is replaced, there is an opportunity to evaluate new approaches to long-term sustainable goals, such as meeting increased future water demands and quality standards while using sustainable and resilience-based replacement practices and limiting the impact on the society and environment (Yang et al. 2018b). Dual water distribution systems have been proposed as a more efficient and resilient alternative approach in order to respond to aging water infrastructure, excess treatment energy, and potable quality issues related to oversized distribution piping. Dual distribution systems are configured to separate the distribution of potable water from non-potable. They are comprised of two separate distribution networks: one that delivers potable water for indoors; and another that delivers non-potable water for outdoor uses (e.g., irrigation and fire protection). In dual systems, raw, reclaimed or lightly-treated water is delivered through a distribution system running parallel to a potable delivery system (Okun 1997). That is, the dual system offers increased resiliency through multiple distribution paths in case of pipe failure and provides an infrastructure that can also be used toward implementation of alternative urban water management strategies in the future (Cole et al. 2015).

Integration of non-potable water distribution within the existing water supply system introduces new complexities in infrastructure and water management beyond challenges associated with traditional water planning (Kandiah et al. 2019). Some studies have demonstrated societal support and public acceptance of water reuse for non-potable purposes through dual distribution systems (Garcia-Cuerva et al. 2016; Kandiah et al. 2019). In addition to the social factors (e.g., community acceptance), the performance of dual systems relies on the development of new infrastructure. The replacement of aging water infrastructure provides an opportunity to evaluate the sustainability and applicability of dual distribution alternatives in comparison to the existing conventional system (i.e., singular distribution). The purpose of an alternative approach, such as dual distribution systems, is to meet future water demands and quality standards which can be achieved by treating less water through the separation of supply for outdoor irrigation and fire flow from potable demand. Dual distribution systems provide the opportunity to deliver a variety of alternative water sources for different purposes not necessarily motivated by water shortages and irrigation needs (Fourness 2015). Separate distribution of raw water can provide fire flow and irrigation demands while reducing the overall volume of treated water for domestic uses. Additionally, smaller diameter potable networks reduce water age, improving water quality (Cole et al. 2018). The absence of case studies related to raw water distribution reflects that this is not currently a common practice, likely due to a lack of urgency to invest in new infrastructure and regulatory and policy barriers.

In the United States, however, the prevalence of dual distribution systems is increasing due to water scarcity and the need to address wastewater treatment issues (Grigg et al. 2013). This flexibility is a key benefit in response to increasing source water scarcity due to climate change, population growth, and unsustainable water usage. There are more than 330 dual distribution systems in place in the United States (Grigg et al. 2013). Dual distribution systems are commonly applied to independently distribute reclaimed water due to source water shortages instead of the separation of raw water for fire flow and irrigation demand. A large number of these systems can be found in California and Florida (Grigg et al. 2013).

A number of existing studies have demonstrated the applicability of dual water supply at a city-wide scale (Cole et al. 2018; Fourness 2015; Kang and Lansey 2012). For instance, Kang and Lansey (2012) have evaluated the costs, system reliability, and greenhouse gas production of single and several dual system scenarios. In addition, studies conducted by Cole et al. (2018), Cole et al. (2015), and Fourness (2015) focused on the separate distribution of raw water through dual supply opportunities to address energy and water quality considerations in Fort Collins, Colorado. These studies have proposed that the use of the existing central water treatment facility is maintained for treatment of indoor demand while a city-wide dual distribution system delivers raw and potable water separately. Raw water demand is distributed through the existing network to meet irrigation demand and fire flow requirements. A newly constructed potable distribution network will supply potable water for indoor use.

The aforementioned studies showed that the dual distribution strategy could lead to benefits to the water utility agencies. These studies have evaluated the network design for dual water distribution systems and also compared them with the existing singular systems qualitatively using a triple bottom line perspective. Indeed, these studies created a Multi-Criterion Decision Analysis (MCDA) incorporating eleven main criteria each evaluated from an economic, social and environmental standpoint using a triple bottom line perspective. Their results suggested that in a city-wide application, separating potable water from irrigation and fire flow is a practical solution that may be competitive with conventional water distribution. However, further analyses are needed to understand the long-term infrastructure performance behavior of dual systems versus the existing singular systems.

To evaluate innovative water strategies, such as dual systems, before investments are made, analysis of long-term outcomes of the strategies as well as their life-cycle costs are needed. In particular, these become more important when rapid deterioration of physical water infrastructure and potable water quality issues along with the funding constraints necessitate resilience-based, cost-effective management of the infrastructure system. To address this, the present study adopted a simulation approach to capture the long-term transformation of water distribution infrastructures and then examine the performance measures of dual water distribution systems (Figure 3-2). The simulation model captures the long-term dynamics and components of dual water distribution systems as well as singular ones. A set of model parameters and variables that varies for dual and singular distribution infrastructures based on the system attributes, such as pipe characteristics (length, material, and diameter), energy intensity, water demand, water price, average pressure and flow rate, as well as capital, operational and maintenance expenditures, were considered in the simulation model. Accordingly, the model simulates the long-term network performance measures, such as network condition, annual break frequency, annual leakage, energy loss and level of service under various scenarios of pipe renewal strategies and water demands. Based on these performance measures, the model also captures the annual network costs, including capital costs, reconstruction costs, renewal expenditures, operational and maintenance expenditures, treatment expenditures, break costs, water loss costs, and energy loss costs. These cost items were used to conduct a network-level life-cycle cost analysis of the dual and singular systems. Eventually, the simulation model results were used to compare the dual and singular water distribution systems in terms of the network performance measures as well as the present worth value (PWV) of the network costs in a long-term horizon (i.e., 50 years).

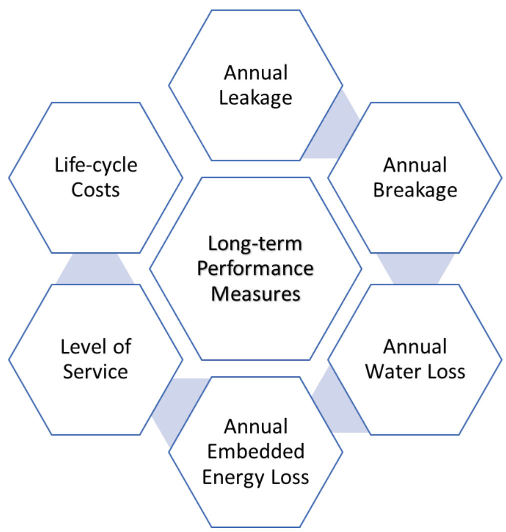

Figure 3-2. Long-term Performance Measures of Urban Water Distribution Infrastructure Systems

The following section explains the simulation model development process. It includes the conceptual and computational representations of the developed simulation model of dual and singular water distribution infrastructures.

3.2. Methodology

To compare the long-term performance of singular and dual distribution systems, a dynamic (time-dependent) simulation approach was employed. Dynamic simulation models facilitate ex-ante analysis to understand the probable macro patterns of complex systems (Mostafavi et al. 2013). Such models facilitate considering various probabilities and possibilities to provide a set of robust solutions across different parameter values, scenarios, and model representations (Bankes 2002a). This approach has been used for the analysis of plans and policies in infrastructure systems (Mostafavi et al. 2013, 2015; Rinaldi et al. 2001; Silva et al. 2018). For instance, Mostasfavi et al. (2015) proposed a simulation model for exploratory analysis of financing policies in highway transportation infrastructure in the United States.

Because there is no real dual system implemented in the case study area (i.e., Fort Collins Utilities service area), empirical data related to the dual distribution infrastructure are not available. Understanding benefits and challenges associated with alternative distribution networks, such as dual systems, usually needs detailed analysis of a utility's existing system and there is no availability of necessary data, time or indeed resources to enable such a study (Ambrose et al. 2008). In addition, using a dynamic simulation approach in the assessment of dual and singular water distribution systems facilitates conducting scenario analysis and thus examines the system's resilience behavior over a long time. The dynamic simulation approach enables building the computational representations of utility-infrastructure interactions and conducting experiments based on different scenarios related to network renewal strategies. This would also enable testing the sensitivity of these systems to external dynamics (e.g., demand fluctuations and water price changes) and building propositions that quantitatively compare the long-term infrastructure performance of dual versus singular water distribution systems. For these reasons, this study adopted a dynamic simulation approach to capturing the long-term dynamics of urban water distribution infrastructure systems.

The developed simulation model integrates the utility agency's renewal decision-making process with the degradation of physical pipeline infrastructure to simulate the long-term transformation of the network. Based on the network's transformation, the model determines the condition and performance of the system. Figure 3-3 represents the dynamic mechanisms underlying the transformation and performance of water distribution infrastructure systems, which all play a role in shaping the emergent behavior of the system such as its level of service index and life-cycle costs. This figure maps out the causalities between different variables of water distribution infrastructure systems. The causality relationships between variables are shown by causal links with a polarity, where positive and negative signs indicate a direct and inverse relationships, respectively. As illustrations, an increase (decrease) in the number of network breakage, would increase (decrease) the maintenance expenditures; or as the water loss increases, the level of service decreases. These dynamic variables are categorized into three mechanisms as shown in Figure 3-3.

The remainder of this section explains the characterization of water distribution system components and their interactions and relationships with each other through the simulation model. The computational representation of the simulation model was implemented through an object-oriented programming platform (i.e., AnyLogic 8).

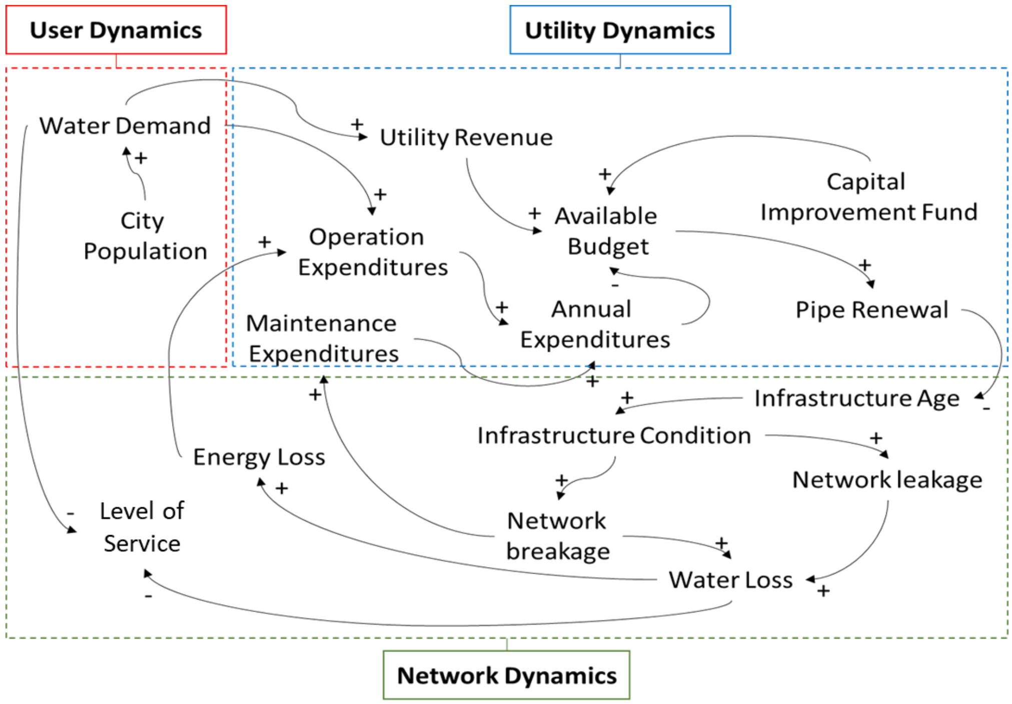

Figure 3-3. Dynamics of Urban Water Distribution Infrastructure Systems

3.2.1. Network Transformation

To capture the transformation of the pipeline network, the simulation model integrates the renewal actions of the utility agency with the physical deterioration (i.e., aging) of the pipelines. In the singular distribution system, treated potable water is delivered through a single distribution network which is already constructed and comprised of cast iron pipe (CIP), ductile iron pipe (DIP) and polyvinyl chloride (PVC). In the dual distribution system, raw and potable water are delivered separately. Raw water is distributed through the existing network (which is already constructed and used in the singular system) to meet irrigation demand and fire flow requirements. A newly constructed potable distribution network transports potable water for indoor use. The pipes of the existing network were classified into five condition groups (i=1,2,3,4,5) based on their age (Figure 3-4). For instance, the condition group 1 contains the pipes with age 0 to 20 years. For each group, which represents a certain condition level (i.e., 20i), there is a distribution of defined materials (e.g., percentage of PVC and DIP&CIP type). Because of similar characteristics of DIP and CIP in terms of their degradation and break behavior, these two types of pipe material were considered identical in the modeling. The degradation of pipes was modeled based on their age; and as pipes age, their condition group can change. To model this process, each year, 5% of pipes in each condition group (except group 5) transitions into the next group. As a result, the length of pipes in each condition group would change every year. Another mechanism that affects the transition of pipes into different condition groups is pipe renewal. Per Rehan et al. (2011) the average life of water pipes was assumed to be 80 years. Therefore, based on the renewal decision-making outcomes of the utility agency, in each year, a percentage of pipes in condition group 5 (i.e., older than 80) can be renewed and move from group 5 to group 1 (more details about the utility's renewal decision-making process are discussed in the remaining of this section). The aging of the pipes is also reflected in the changes in the percentage of materials for each group. At the beginning of simulation, the model starts with a defined percentage of PVC and CIP&DIP pipes for each group. As pipes age and get renewed by new material (i.e. PVC), these percentage values change every year.

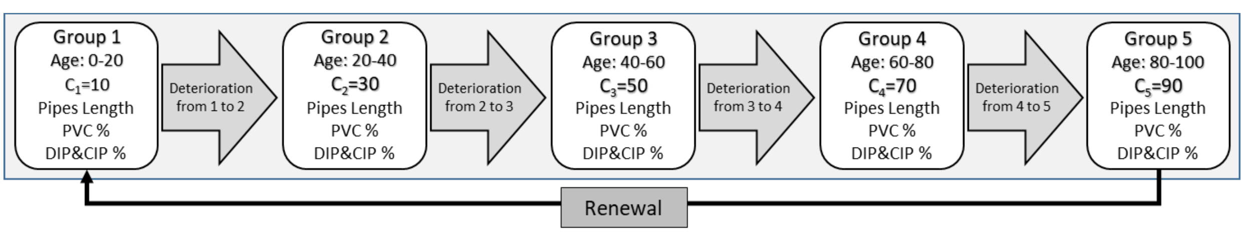

Figure 3-4. Modeling Pipeline Transformation Process in the Existing Network

In the dual system, the transformation of the potable network was modeled as follows: the entire potable network contains pipes with the material type of PVC, which start with an average

age of one year. No renewal happens for this network as there would not be pipes older than 80 years in this network during the simulation period (i.e., 50 years).

3.2.2. Network Condition

Network condition is defined as collectively representing the physical condition state of all water pipes in the network. Since a simple age-based degradation was implemented in the model, the age of pipelines is representative of their condition. Therefore, it was assumed that network condition can be expressed numerically such that higher values represent a highly deteriorated state of the pipes and vice versa (Rehan et al. 2011). Accordingly, condition values (C_i) of 10, 30, 50, 70, and 90 were assigned to pipes in group 1, 2, 3, 4, and 5, respectively. Based on the portion of pipe length in each condition group (l_i), the model computes the condition of the existing network ($\bar{C}_E$) every year using Equation 14. So the annual network condition of the singular system would be equal to $\bar{C}_E$ (the unit for $\bar{C}_E$ is year).

$$\bar{C}_E = \frac{\sum_{i=1}^{5}(l_i * C_i)}{L_N} \quad \textbf{(14)}$$

where l_i and L_N are the total length of pipes in group i, and in the network, respectively. Similarly, the model computes the annual network condition of the dual system ($\bar{C}_D$) using Equation 15:

$$\bar{C}_D = 0.5 * (\bar{C}_E + T) \quad \textbf{(15)}$$

where T is the average age of all pipelines in the potable network which is newly constructed and starts with the age of one year. In this equation, both networks (i.e., potable and non-potable networks) have the same weight in determining the dual network condition because they have the same total length of pipes in the system. In the remaining of this paper, $\bar{C}$ represents the annual network condition for either the singular system and the dual system.

3.2.3. Network Renewal Process

In addition to the physical network degradation (i.e., aging), the pipe renewal decision-making process of utility agency underlies the long-term transformation of the water distribution infrastructure. The renewal decision-making process is affected by the utility's revenue and the network's annual expenditures. The utility's annual revenue (Rev) is determined based on the multiplication of annual water demand and water unit price using Equation 16.

$$Rev = \begin{cases} \left(D_p + D_{np}\right) * WP_p \,, \; System = Singular \\ D_p * WP_p + D_{np} * WP_{np} \,, \; System = Dual \end{cases} \tag{16}$$

where D_p and D_{np} denote annual potable and non-potable water demand (gallon/yerar), respectively. Also, WP_p and WP_{np} are unit prices of potable and non-potable water ($/gallon). The annual operational and maintenance expenditures ($OpEx$), that increase exponentially based on the network condition ($\bar{C}$), is determined using Equation 17 (Rehan et al. 2011).

$$OpEx = U_{OpEx} * [1 + \left(1.4877e^{(0.0449\bar{C})}\right)/100] \tag{17}$$

where U_{OpEx} is the base cost ($/year) of the annual network operation and maintenance including chemicals, media, filters, flushing, and repairs.

To accurately capture the energy consumption expenditure of dual and singular systems, the energy expenditure has been excluded from the operational and maintenance cost (U_{OpEx}) as it directly depends on the amount of water treated ever year. The dual and singular systems would differ in energy consumption for the treatment process as they require different amount of water to be treat ed. Hence, the annual energy expenditure ($EnEx$) is separately calculated based on Equation 18:

$$EnEx = U_{EnEx} * EI * TW \tag{18}$$

where U_{EnEx} is the unit cost ($/kWh) of energy used for treating raw water and EI is the average energy intensity of water treatment (kWh/gallon) for potable purposes (energy used to treat raw water for non-potable purposes was assumed to be insignificant). Also, TW denotes the annual amount of treated water (gallon/year), which equals to the total demand in the singular system and the potable demand in the dual system. In this model, the distribution networks were assumed to have ignorable, insignificant energy consumption for pumping as the majority of the service area is served by a gravity-fed distribution system.

The available funding for renewal (AF) equals to the annual revenue deducted by expenditures of network operation, maintenance and water treatment (Equation 19). In this model, the utility agency can follow two distinct renewal strategies. The first renewal strategy, which is called regular renewal, is based on the collected revenue from the water end-users. Under this strategy, the utility agency wants to renew the pipes older than 80 (condition group 5) every year and hence, the required funding (RF) for this renewal is calculated based on Equation 20:

$$AF = Rev - (OpEx + EnEx) \quad \textbf{(19)}$$

$$RF = U_{RenEx} * l_5 \quad \textbf{(20)}$$

where, U_{RenEx} is the unit cost of pipe renewal with PVC ($/mile), and l_5 is the length of pipes in condition group 5 in each year. However, the annual renewal rate (i.e., the length of pipes that get renewed in a year) can be less than l_5 if the available funding isn't sufficient. Therefore, if the available funding for renewal (AF) is less than the required fund for renewal expenditures (RF), the renewal rate (RR) would be equal to the available funding divided by the unit cost of pipe renewal (U_{RenEx}); otherwise, it is equal to the length of pipes in condition group 5 (l_5) (Equation 21).

$$RR = \begin{cases} l_5 , & AF \geq RF \\ AF/U_{RenEx} , & AF < RF \end{cases} \quad \textbf{(21)}$$

The second renewal strategy that the model can capture is called network condition controlling. Under this strategy, to keep the network condition ($\bar{C}$) below a certain threshold (i.e., strategy target), the utility would use additional improvement funds (AIF) aside from the revenue. To do so, the model computes to what extent (i.e., mile) the renewal process should be conducted in order for the network to reach the desired condition (Figure 3-5). Figure 3-5 depicts the flowchart of the implemented algorithm to model the renewal process under the strategy of network condition controlling.

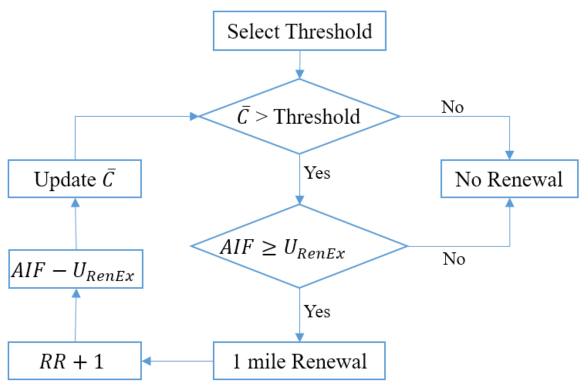

Figure 3-5. Modeling Renewal Process for Network Condition Controlling

After determining the annual renewal rate (RR), the model calculates the renewal expenditures ($RenEx$) using Equation 22:

$$RenEx = U_{RenEx} * RR \quad \textbf{(22)}$$

where $RenEx$ is the annual renewal expenditures (\$), U_{RenEx} is the unit cost of pipe renewal with PVC (\$/mile), and RR denotes the annual renewal rate (mile).

3.2.4. Network Break Frequency

The number of breaks is an important indicator of water distribution network's service performance (Rehan et al. 2013). In this study, breakage was modeled using a stochastic process that determines the frequency of pipe breaks during each year. The frequency of breaks for each mile of pipes is a function of pipe's material and age (Shamir and Howard 1979). The model uses a Poisson Process with a mean rate of break (calculated based on Equation 23) to determine the annual frequency of pipe breaks per each mile of pipeline. In Equation 23, the Lambda (λ) represents the mean rate of break per mile per year (Shamir and Howard 1979):

$$\lambda = N_0 . e^{g.a} \tag{23}$$

where N_0 is the initial number of breaks per mile per year in a new pipe, g is the growth rate which is 0.07 for PVC and 0.078 for CIP&DIP pipes (Kleiner and Rajani 2000). Also, *a* represents the condition (i.e., age) of pipe, which equals to T in the new potable network and C_i for the existing network. The total number of breaks in the network per year (N_B) would be the sum of breaks in the entire pipelines network. Accordingly, the break rate is determined by dividing the annual number of breaks (N_B) by the network length (mile).

After specifying the annual break frequency, the model calculates annual water loss due to network breaks based on Equation 24 (AWWA 2009; Zamenian et al. 2015)

$$WL_B = 1440 * N_B * \bar{F} * d * \sqrt{\bar{P}/70} \tag{24}$$

where, WL_B is the annual water loss due to network breaks (gallon), N_B is the total number of annual breaks, $\bar{F}$ is the network average flow rate (gallon per minute), *d* is the total duration of disruption due to break (day), and $\bar{P}$ is the network average pressure (psi). $\bar{F}, \bar{P}$, and *d* are user-defined input parameters into the model.

3.2.5. Network Annual Leakage

Another indicator of a water distribution network performance is network leakage. The network leakage is determined as the total water volume lost in the network, which is a fraction of the annual water demand (D). Leakage rate (LR), which is a unitless variable, represents the fraction of the water demand that gets lost due to network leakage. This variable depends on network condition ($\bar{C}$) and is calculated using Equation 25 (Rehan et al. 2015):

$$LR = 0.00075 * e^{\bar{C}(0.07pvc+0.078(cip+dip))} \quad \textbf{(25)}$$

where pvc, cip, and dip are the fractions of pipeline network with each material type. Accordingly, the annual water loss due to network leakage is determined by Equation 26:

$$WL_L = LR * D \quad \textbf{(26)}$$

where WL_L and D denote the annual water loss due to network leakage (gallon) and the annual total water demand (including potable and non-potable) imposed to the network, respectively.

3.2.6. Embedded Energy Loss

The amount of energy used for the water treatment process (embedded energy consumption) depends on the quality of raw water and the quality standard required for drinking water. The type of treatment plant needs to be considered for energy footprint analysis because traditional treatment plants energy consumption is different from advanced treatment plans (Zamenian et al. 2015). To capture this, average energy intensity (EI) of potable water treatment was considered in this model. The embedded energy loss depends on the amount of water lost in networks. The network's annual water loss (WL) is the total water loss due to both breakage and leakage in the network (Equation 27). Accordingly, the model computes the network's annual embedded energy loss (EL) using Equation 28:

$$WL = WL_B + WL_L \quad \textbf{(27)}$$

$$EL = EI * WL/1000 \quad \textbf{(28)}$$

where EL and EI represent the annual embedded energy loss (MWh/year) and average treatment energy intensity of potable water (kWh/gallon), respectively.

3.2.7. Level of Service

To determine whether the supply of water transported by the pipes can meet the given demand, a level of service (LoS) parameter was defined (Asefa et al. 2015). This parameter represents the extent to which the supplied water through the network met the demand over the long time. To determine LoS, the cumulative amount of delivered water is divided by the cumulative demand and this gives the level of service in the system until year t based on Equation 29:

$$LoS_t = \frac{\sum_1^t (S_t - WL_t)}{\sum_1^t D_t} * 100 \quad \textbf{(29)}$$

where D_t, S_t, and WL_t are annual total demand, supply and water loss (gallon/year), respectively.

3.2.8. Network-level Life-Cycle Costs

The cost variables considered in the simulation model as life-cycle costs of water distribution networks include: initial capital expenditures ($CapEx$), reconstruction expenditures ($RecEx$), renewal expenditures ($RenEx$), operational and maintenance expenditures ($OpEx$), energy expenditures ($EnEx$), break costs, water loss costs, and energy loss costs, as well as the remaining value (i.e., salvage value) of the network infrastructure at the end of analysis period. All these variables, except $CapEx$ and $RecEx$, would be dynamic over the 50-year analysis period, and can change annually based on the network condition and performance (e.g., network condition, break frequency, leakage amount), as well as the renewal decision of the utility agency. Equation

30 calculates the present worth value (PWV) of the network costs over the simulation period (i.e., 50 years):

$$PWV = CapEx + RecEx * (1 + i)^{-n} + \sum_{t=1}^{50} AnCo_t * (1 + i)^{-t} - RemVal * (1 + i)^{-50} \quad \textbf{(30)}$$

where i denotes the real discount rate which is 2.75% in infrastructure life-cycle cost analysis (Reclamation Bureau 2018). $CapEx$ includes initial capital costs of development of new infrastructure in the dual system, such as potable distribution pipeline, raw water filtration, non-potable water meters, and backflow prevention devices for potable service lines which add a layer of protection that the existing system doesn't have. Raw water was assumed to be treated by 80 μm filtration at the existing water treatment facility prior to distribution for non-potable purposes. There is no initial capital expenditure in the existing singular system as the network is already developed and existed in both the dual system and the singular system.

However, the existing water treatment facility requires expenditures for replacement (reconstruction) of old infrastructure or components that have reached their lifetime ($RecEx$). The existing water treatment facility's anticipated lifetime is 50 years with 15 years remaining ($n = 15$). This cost item (i.e., $RecEx$) would differ in the dual system than the singular system because their required treatment capacities are different.

In Equation 30, $AnCo_t$ denotes the total annual costs in every year (t), which is determined based on Equation 31:

$$AnCo_t = RenEx + OpEx + EnEx + \mathrm{BrC} + \mathrm{WLC} + \mathrm{ELC} \quad \textbf{(31)}$$

where BrC, WLC, and ELC are the dollar value of the costs imposed on the utility due to break repairs, network water loss, and network energy loss, respectively. These costs are obtained using the Equations 32 (Sherali et al. 1996), 33, and 34:

$$\mathrm{BrC} = N_B * 600d^{0.4} \tag{32}$$

$$\mathrm{WLC} = WL * WP \tag{33}$$

$$\mathrm{ELC} = EL * U_{EnEx} \tag{34}$$

where N_B is the annual number of network breaks and d denotes the average diameter of the network pipes. Finally, $RemVal$ which denotes the remaining value (salvage value) of the entire network is calculated using Equation 35:

$$RemVal = \frac{UL - \bar{C}_{50}}{UL} (U_{RenEx} * \ L) \tag{35}$$

where UL denotes the expected useful life of a new water pipeline, which is assumed to be 80 years (Rehan et al. 2011), $\bar{C}_{50}$ is the network condition (age) at year 50 (i.e., the end of analysis period), and L is the total length of pipes in the network.

3.3. Case Study

This study was implemented in the case of Fort Collins, Colorado, as water managers from this city recognized the planned renewal of their water supply infrastructure as an opportunity to reevaluate their long-term urban water management strategy and also previous studies examined the applicability of dual water distribution systems in this city. Three sample neighborhoods representative of the service area of the City of Fort Collins Utilities were selected to be modeled. Further details on the neighborhood selection and supporting data are provided in Cole et al. (2018).

3.3.1. System Overview

Currently, residents of Fort Collins receive their water supply via two main surface water sources that are blended and treated at a centralized conventional water treatment facility where finished water is then distributed to the end user via a predominately gravity-fed potable water distribution system for all municipal uses (Cole et al. 2018). Initially comprised of cast iron pipe (CIP) prior to 1976, the network is now additionally composed of ductile iron pipe (DIP) used through 2005 and more recently polyvinyl chloride (PVC). In the proposed dual system, drinking water treatment continues at the central facility, the existing distribution system is used to distribute non-potable raw water for fire and irrigation demand, and a new potable distribution system is used to distribute drinking water for indoor use. Both distribution systems remain gravity-fed. The existing distribution network would still need some pipe renewals as about 25% of existing pipes are older than 80 years (Figure 6) and this network will deliver non-potable water which is about 40%-50% of the annual water demand (Cole et al. 2018).

3.3.2. Model Calibration

The developed simulation model for water distribution infrastructure was calibrated using data and information from three neighborhoods in Fort Collins to capture the dynamics of dual and singular distribution systems over an extended 50-year horizon. The data and information related to water distribution infrastructure networks of these neighborhoods, which are composed of 57.21 miles of pipeline were collected mainly from scientific research and reports provided by the City of Fort Collins Utilities (CFCU). The CFCU has dedicated numerous studies to understand the challenges and benefits associated with the implementation of dual distribution systems. As shown in Table 3-1, the information related to hydraulic parameters and configuration of the distribution networks were extracted from an EPANET model developed by Cole et al. (2015; 2018).

In addition, the information about the attributes of the existing (singular) distribution pipeline was provided by the CFCU and summarized in Figure 3-6. This figure shows the length-material distribution of pipes in five age categories used in the simulation model. Regarding the dual system, it was assumed that the potable network will be built in the first year of the analysis period using only the PVC type of material. Hence, in the dual system modeling, all pipes of the potable network are PVC starting with an average age of one year.

Table 3-1. Parameters of Water Distribution Networks

Network Parameter	Dual System		Existing Singular Network
	Potable Network	Non-potable Network	
Average Flow (gpm)	35.3	27.2	27.2
Average Pressure (psi)	86.7	88.9	88.6
Annual Demand (MGall)	398	341	739
Average Diameter (inch)	4	10	10
Number of Service Connections	4,469	4,542	4,469

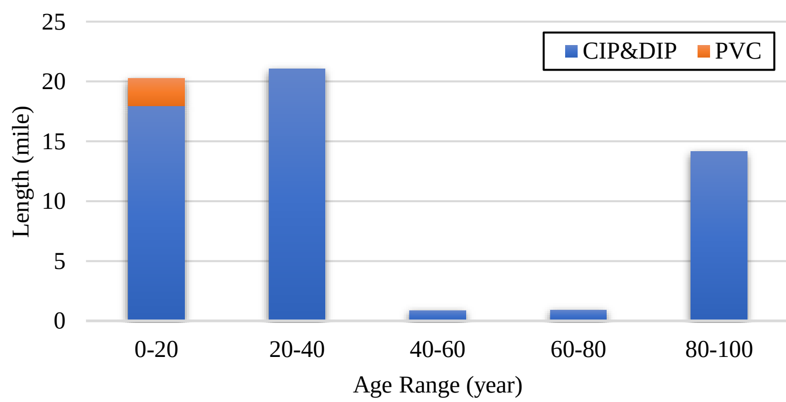

Figure 3-6. Pipeline Information of the Existing (Singular) Network

Information about the cost items and their values were also collected from the CFCU reports (Cole et al. 2015; 2018) and online resources (e.g., websites of Denver and Fort Collins Utilities). This data includes the unit costs of network operation and maintenance (O&M), pipeline renewal, treatment energy consumption, treatment facility reconstruction, and capital expenditures. This information as well as the energy consumption of water treatment are provided in Table 3-2. In addition, based on the utilities' suggestion, the initial prices for potable and non-potable water were assumed to be $3 and $1 per 1000 gallons, respectively. Some other information needed for model parameters' values (such as discount rate) were assumed based on the literature as mentioned in the previous section.

Table 3-2. Unit Costs and Energy Consumption of Singular and Dual Water Systems

Cost Category	Expenditures	Singular	Dual
Capital	Non-potable Water Filtration ($/connection)	0	48
	Non-potable Water Meter ($/connection)	0	120
	Backflow Prevention Device ($/connection)	0	707
	Potable Pipeline Network (M$/mile)	0	1.2
Reconstruction	Treatment Facility Replacement (M$)	9.2	3.9
Annual	Base Cost of O&M (Chemicals, Media, Filters, Flushing, and Repairs) (M$/yr)	0.86	0.91
	Pipeline Renewal (M$/mile)	1.2	1.2
	Treatment Energy Use (MWh/yr)	228	183
	Potable Water Energy Intensity (MWh/MG)	0.321	0.321
	Energy Price ($/MWh)	90	90

All these data and information were input in the simulation model as values for either internal variables (e.g., unit costs, initial break rate) or input parameters (e.g., water demand). For instance, the initial break rate for new pipes (N_0) was calibrated based on the break history data provided by the CFCU and was set to 0.01 per mile per year. The model user is asked to specify the values related to each of the input parameters in an interactive user interface. As an illustration, a snapshot of the model input interface for the dual system, which captures the input parameters and their values, is shown in Figure 3-7. By changing the value of input parameters such as water demand change rate, renewal strategy (regular renewal and network condition controlling), water price growth rate and so forth, the created simulation model enables conducting scenario analysis.

After inserting the input information, the simulation model can be run and the simulated long-term performance measures of the distribution system would be displayed in the output interface of the model. A snapshot of the output dashboard of a specific scenario related to the dual system is shown in Figure 3-8. In this screen, the annual values of network condition and performance measures, as well as the annual expenditures and available funding are represented over the 50-year horizon. Based on these output graphs under various scenarios and multiple runs, the overall (cumulative) value of each performance measure (e.g., leakage, breakage, water and energy loss) and the 50-year average value of the network condition, as well as the final present worth value of network costs were extracted and then used to conduct comparisons between the dual and singular systems for the case study of Fort Collins.

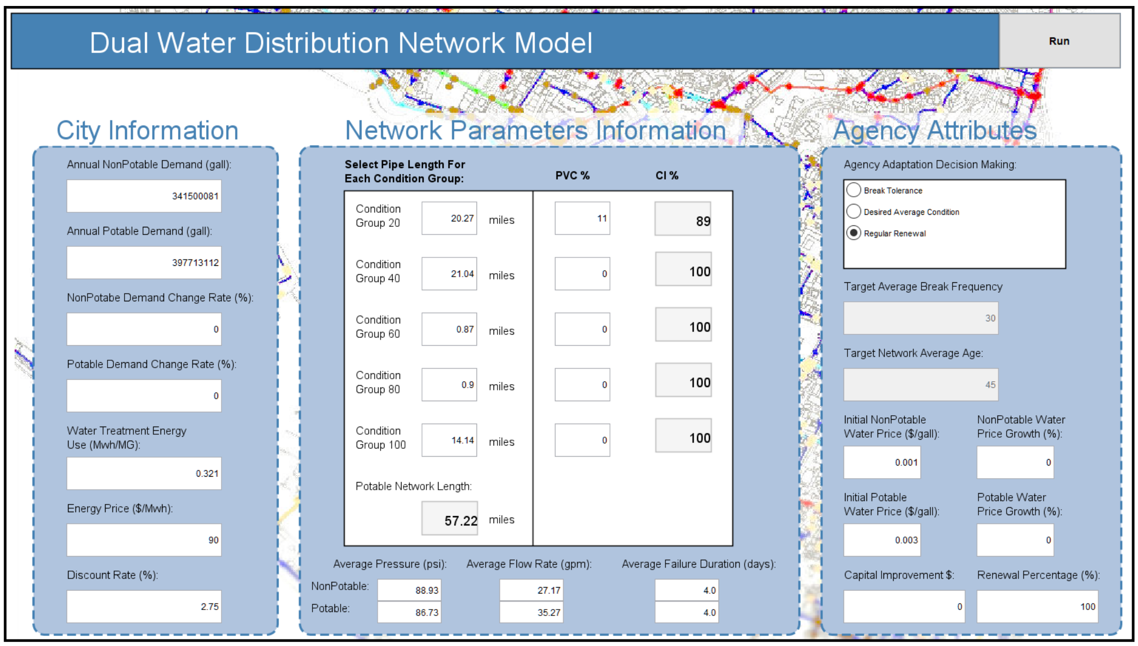

Figure 3-7. Input Interface of the Model

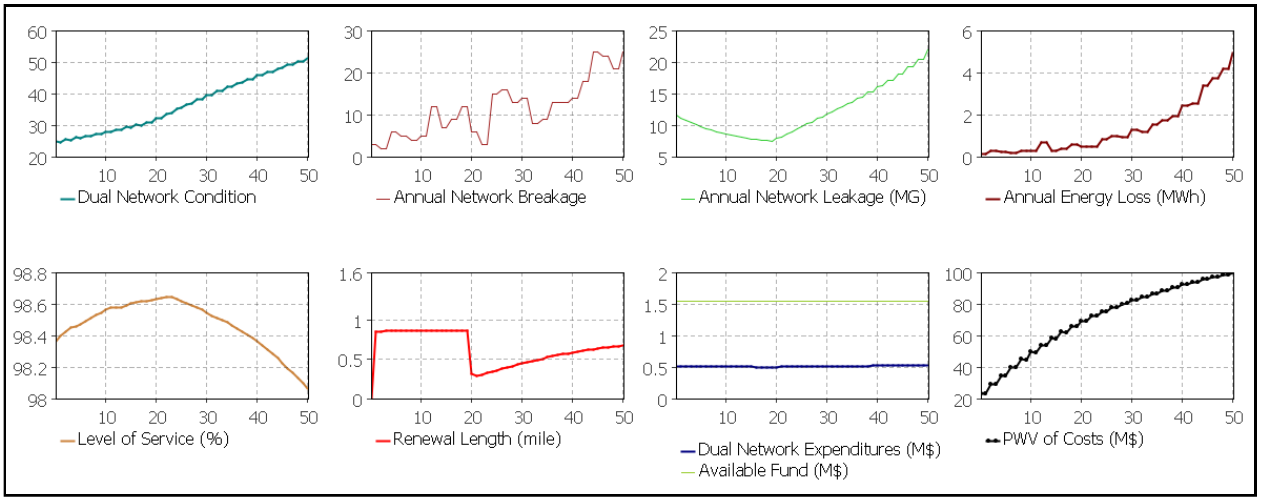

Figure 3-8. Output Dashboard of the Model

3.4. Verification and Validation

To ensure the quality of the developed simulation model, verification and validation processes were conducted. Indeed, the verification and validation methods focus on verifying the data, rules, logic and computational algorithms (Bankes and Gillogly 1994). In this study, a gradual, systemic and iterative procedure was employed to conduct a thorough verification and validation of the simulation model. The different techniques used for verification and validation of the model and its components are described as following.

3.4.1. Internal and External Verification

Various internal and external verification techniques were employed to verify the data, logic, and computational algorithms related to the simulation model. First, the initial conditions and the ranges of the parameters were compared to the existing empirical data to ensure the reliability of the parameters in the model (Werker and Brenner 2004). For example, the parameters related to the physical network, such as pipes' age, length, and material, were compared to the actual water distribution data related to a network (in Fort Collins) to ensure values were reasonable. Second, the behaviors of model entities (e.g., network condition) were followed so as to identify unusual model behaviors. Whenever an unusual behavior was observed, the model logic was checked to ensure that the behavior was not due to unreasonable assumptions or imperfect logic (Batouli and Mostafavi 2018b). Third, extreme value analysis was performed, where the model was run at different extreme conditions (for some input parameters) to observe its response and verify its functionality under these scenarios. Fourth, several random replications (more than one thousand runs) of the model were compared to check for the consistency of the results (Xiang et al. 2005).

3.4.2. Face Validation

A face validation approach was used to facilitate triangulation and thus validation and testing process (Love et al. 2002). Per Carson (2002), a simulation model that has face validity appears to be a "reasonable imitation of a real-world system to people who are knowledgeable of the real world system." Face validity is conducted by having users and people knowledgeable with the system examine the model logic and output for reasonableness (Mostafavi et al. 2015). In this study, face validity was conducted in two phases. In the first phase, through multiple teleconferences, the simulation model and its preliminary results were presented to an expert panel composed of a specialist from the CFCU and a seasoned academic in the area of water distribution systems. During the teleconferences, the components of the model, including conceptual model, logics, rules, data, assumptions and preliminary results, were demonstrated to the expert panel in detail. Accordingly, model modifications were made on the basis of input from the expert panel.

In the second phase of the face validation, the simulation model, its components, and the results were presented to seven verified subject matter experts (SMEs) in a face-to-face meeting at CFCU. All the SMEs involved in the validation process were from different units of the CFCU with an average experience of 18 years (Table 3-3). After the presentation, the SMEs were asked to evaluate whether the simulation model components (i.e., conceptual model, logics, rules, data, assumptions, and results) were reasonable for the assessment of dual and singular water distribution systems.

Table 3-3. Information of Participants in the Face Validation Process

ID	SME Role	Years of Experience
1	Water Plant Superintendent	31
2	Water Resources Manager	20
3	Project Manager	23
4	Water Conservation Specialist	3
5	Civil Engineer – Water Operations	12
6	Superintendent – Water Field Operations	39
7	GIS Data Analyst (Water Conservation)	2

The SMEs evaluated 12 features related to the four components of model (Figure 3-9). In the validation of the conceptual model, three features were evaluated to ensure that the conceptual model was complete in terms of capturing the important components and processes. In the validation of the computational model, three features were evaluated to ensure that the mathematical equations and logics used for capturing the dynamics of the networks were reasonable and correct. In the validation of the data, two features were evaluated to confirm that the assumptions related to different parameters and variables in the model were reasonable. Finally, in the validation of the results (i.e., output validity), four features were evaluated to ensure that the simulated behavior of the system and the results of the model were reasonable.

Based on the evaluation forms, all the SMEs asserted that the behavior of the model is consistent with the real world and the relationships between different components of the model are realistic. They also indicated that the simulation and visualization component of the model provides a useful tool for scenario analysis and decision making. Following this, the quality of the developed simulation model was ensured for completeness, coherence, consistency, and correctness (4Cs) (Mostafavi et al. 2015) based on the performance of the model outputs.

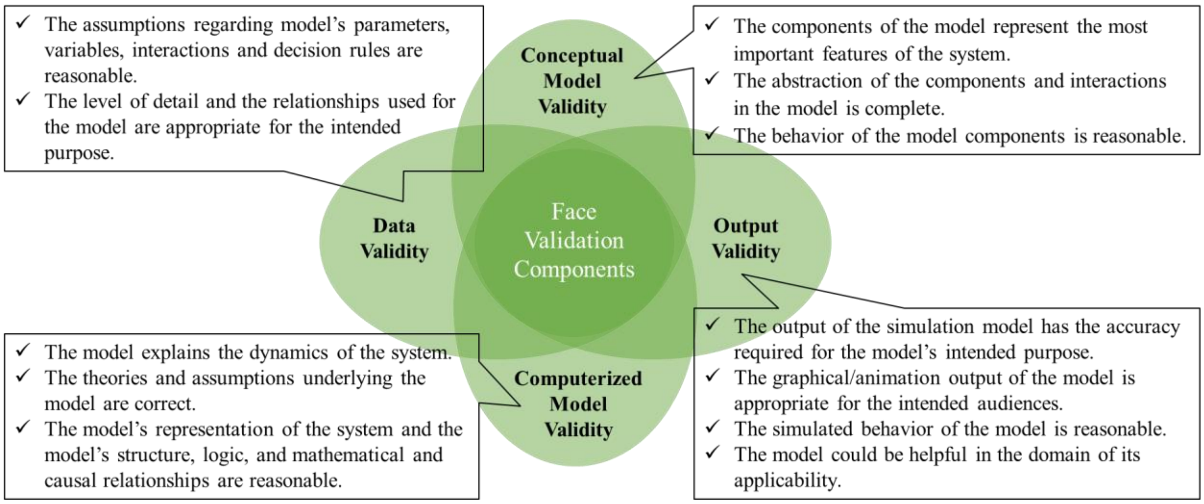

Figure 3-9. Validation and Assessment of Model Features

3.5. Simulation Experiments and Results

After the verification and validation of the simulation model, it was used for experiment design and analysis. Various scenarios of renewal strategies and demand fluctuations were defined, and then Monte-Carlo experiments were conducted to determine the mean value of the model outputs (e.g., break frequency) under each scenario. Based on the Monte-Carlo experiments, it was observed that the mean values and the distribution of outputs did not change significantly with larger replications. Therefore, each scenario was replicated 1000 times and the mean values of outputs were determined based on a 90% confidence interval. Accordingly, the dual and singular water distribution systems were analyzed and compared under these experiment scenarios. The analysis results include: (i) performance comparison of the dual system with the existing singular system under the same renewal strategy (i.e., regular revenue-based renewal strategy); (ii) whether the existing singular system can perform similar to the dual system? (iii) assessment of the dual and singular systems sensitivity to demand changes.

3.5.1. Long-term Performance Comparison

In the first set of simulation experiments, this study analyzed the long-term performance measures of dual and singular systems under the same renewal strategy which is a regular renewal strategy. Under this strategy, based on the availability of funding (i.e., revenue minus network expenditures), the pipes older than 80 years get renewed. Figure 3-10 depicts the annual network renewal rates for the dual and singular systems under the regular renewal strategy. As seen from the graphs, the singular system should start with a higher rate of renewal compared to the dual system. The results showed that the total renewal length over the 50 years would be 32 miles for the singular system and 30 miles for the dual system.

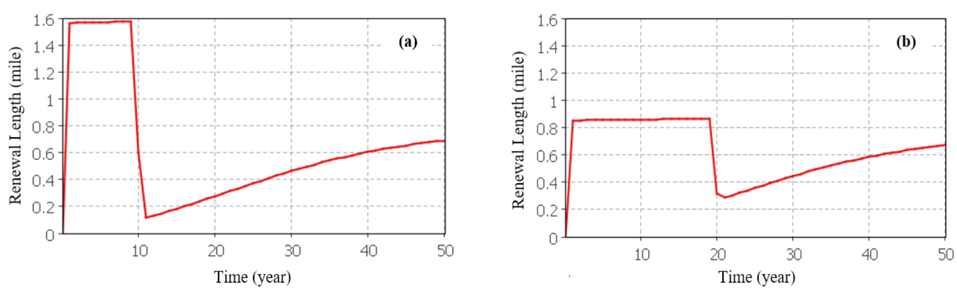

Figure 3-10. Long-term Renewal Patterns for (a) Singular System and (b) Dual System

Under this renewal strategy, the annual condition, performance, and cost measures of both systems were simulated. Accordingly, the long-term (accumulated) values of these measures were determined and documented in Table 3-4. As an illustration, the long-term average condition represents the 50-year average of annual network conditions; also, the total number of breaks represents the cumulative number of breaks in 50 years (i.e., analysis period). As shown in Table

3-4, for the case of Fort Collins, the dual system would have 22% better long-term average condition, 20% lower break rate, 35% less leakage, 28% less water loss, 80% less energy loss, and 1% higher level of service, but 61% more total number of breaks. Therefore, since most of the long-term performance measures in the dual system are better than the singular system, it can be concluded that the dual system would improve the long-term performance of the system. However, the dual system has 206% higher life-cycle costs than the singular system (see the present worth value of life-cycle costs of the dual and singular systems in Table 3-4).

Table 3-4. Long-term Measures of Network Performances and Parameters

Long-term Measure	Dual System	Singular System	Difference (%)
Long-term Average Condition (year)	36	46	-22%
Total Number of Breaks	559	348	+61
Total Break Rate (#/mile)	4.9	6.1	-20
Overall Network Leakage (MG)	603	930	-35
Overall Water Loss (MG)	713	992	-28
Overall Energy Loss (MWh)	63	318	-80
Level of Service (%)	98.1	97.3	+1
PWV of Life-cycle Costs (M$)	106	34.6	+206

3.5.2. Singular System Alternatives

The study also examined whether or not the existing singular system could perform similar to the dual system if the utility renews the pipes of the singular network at a rate to keep its annual condition below a certain threshold. As explained in the methodology section, the developed model is able to implement a renewal strategy called network condition controlling. Under this strategy, different scenarios were tested on the singular system to find what renewal pattern would lead this system to have a similar long-term performance to the dual system. To this end, in addition to the regular renewal strategy, three different renewal alternatives were considered and tested for the singular system. Renewal alternatives for the singular system included: (i) regular revenue-based strategy (Alt 1); (ii) controlling network condition at 40 years (Alt 2); (iii) controlling network condition at 45 years (Alt 3); and (iv) controlling network condition at 50 years (Alt 4). Accordingly, long-term performance measures of the singular system under each of these renewal alternatives were determined and compared to the dual system (which is under the regular revenue-based strategy). The results were depicted in a radar chart that compares four alternatives of the singular system to the dual system in terms of multiple long-term performance measures (Figure 3-11).

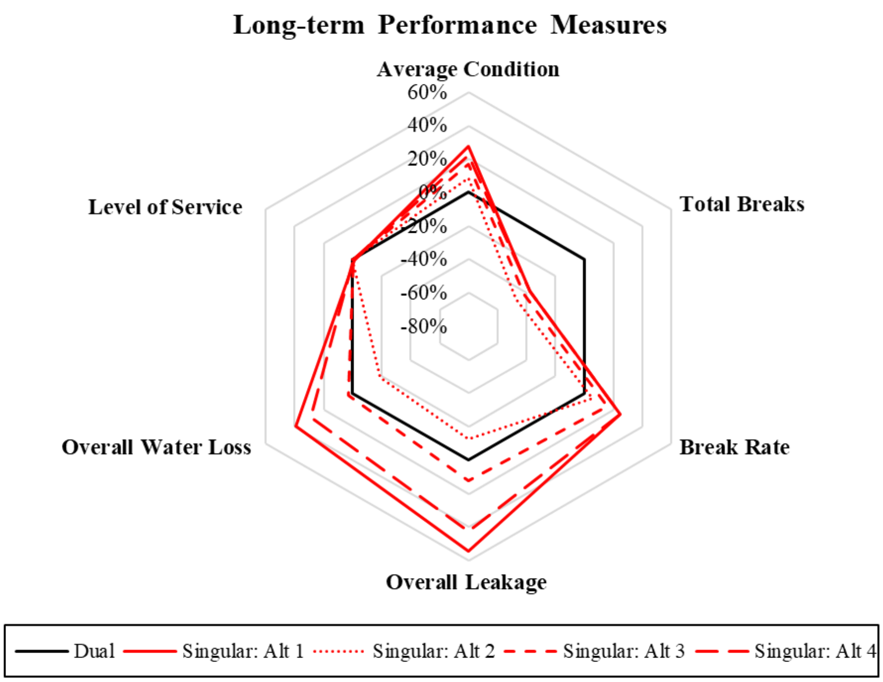

Figure 3-11. Multivariate Comparison of Singular System Alternatives to the Dual System

In Figure 3-11, the results for Alt 2 show that under the renewal strategy of controlling network condition at 40 (which means the utility keeps the network condition at 40 years), the singular system would have the most similar (or even better) performance compared to the dual system. The simulation results showed that, under this strategy, the singular system, in comparison with the dual system, would have the same level of service, 19% less water loss, 12% less leakage, 47% fewer breaks, and just 8% and 6% higher values of network condition and break rate, respectively. This strategy in the singular system resulted in 41% less energy loss compared to the regular strategy; however, it still has 197% more energy loss than the dual system (this performance measure was excluded from the radar chart to prevent the chart skew). In addition, although extra funding was needed to implement the strategy of Alt 2 in the singular system, the present worth value of life-cycle costs of the singular system under this strategy was found to be 42.6 million dollars, which is 60% less than the dual system.

The results suggested that if the existing singular network gets renewed with an annual rate to keep the network condition at 40, it would lead the system to have almost similar performance to the dual system over the long term. Figure 3-12 shows the renewal pattern that the agency should follow for the network to achieve this level of condition and thus performance measures. This renewal pattern requires 48 miles of pipe renewal in total, which is 50% more than the regular revenue-based renewal strategy.

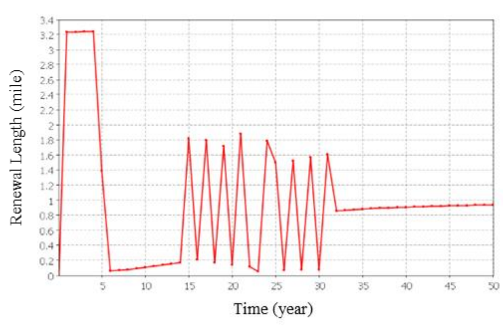

Figure 3-12. Renewal Pattern for Controlling Network Condition at 40 in Singular System

3.5.3. System Sensitivity Assessment

In the last set of simulation experiments, the impacts of water demand changes on the long-term performance of the distribution systems were assessed. To this end, the sensitivity of the level of service of dual and singular systems was examined in response to different rates of annual demand growth/decline. Based on the results (Figure 3-13), when the system faces demand shrinkages (i.e., negative rates), the level of service in the dual system drops more than the singular system. This is mainly because, in the dual system, the agency's revenue is collected separately from potable and non-potable water distributions. However, the non-potable water price is assumed to be less than the potable water price, which causes the dual system to have less revenue compared to the singular system. Hence, when the demand decreases in the dual system, the agency's revenue might no longer meet the required renewal rates. It would subsequently result in the dual system's performance drop. Therefore, the dual system performance seems to be more sensitive to demand decline than the singular system. In addition, it can be observed that in demand growth cases as well as when demand declines less than 2% annually, the dual system performs better than the singular system in terms of level of service (Figure 3-13). However, the singular system has higher level of service than the dual system when demand declines more than 2% annually. Another insight here is that the tipping point of demand change for the dual and singular systems is 0% and -1.5%, respectively. These values indicate the thresholds where any rates below them would result in a significant drop in the system performance. Overall, this study discovered that the dual system is less sensitive to demand increase while the singular system is less sensitive to demand shrinkage, which is accordingly translated as the systems' resilience behavior to these situations (i.e., less sensitivity is translated as higher resilience).

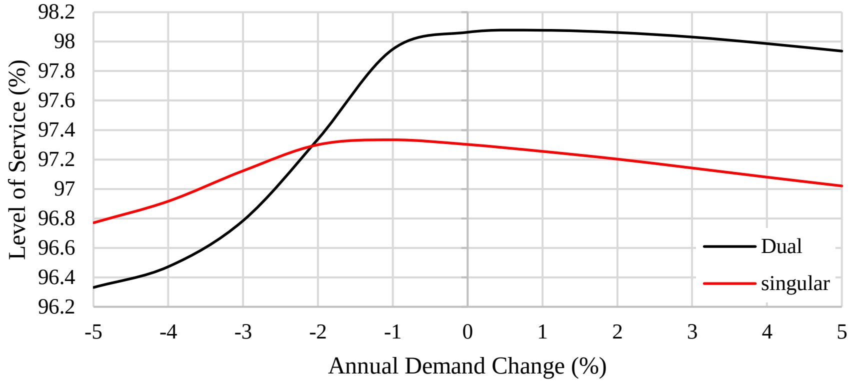

Figure 3-13. Sensitivity of Level of Service to Demand Changes

Furthermore, the sensitivity of both systems' long-term average condition was evaluated against demand fluctuations (Figure 3-14). Regardless of demand changes, the dual system always has better average condition than the singular system. Another observation here was that when both systems face demand shrinkage up to -5% annually, the average condition gets worse up to 9% and 19% in the singular system and the dual system, respectively. This result further demonstrates that the singular system's average condition has less sensitivity to demand shrinkage in comparison with the dual system.

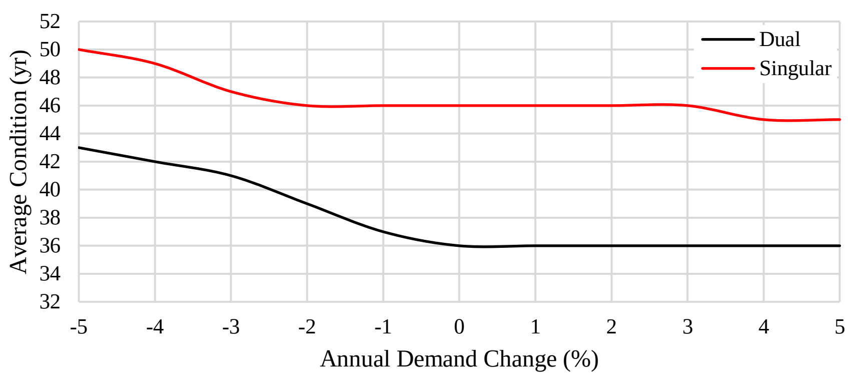

Figure 3-14. Sensitivity of Average Condition to Demand Changes

3.6. Discussion

This study developed a simulation model to quantify the deterministic and stochastic infrastructure performance behavior of the dual and singular water distribution systems. The results of this study showed that the dual infrastructure system, overall, has better long-term performance, especially in terms of the embedded energy loss reduction, in comparison with the existing singular system. However, the dual network would increase the life-cycle costs of the system substantially (more than three times), as it needs huge capital investments for installing a new pipeline network. Therefore, from a financial perspective, implementation of dual systems may not be feasible. However, taking the social and environmental benefits into account might allocate more value to the dual system implementation which can potentially decrease its life-cycle costs. Cole et al. (2015; 2018) qualitatively evaluated the dual and singular systems from social and environmental standpoints as well as the economic perspective. Their study used a Multi-Criterion Decision Analysis (MCDA) to achieve a triple bottom line score for dual and singular systems. Their comparisons were based on a set of criteria, including impact of new infrastructure, energy use, routine maintenance, staffing, consumer water quality, use of city water corridors, risk of limited supply, risk of rate changes, opportunity for new water management, revenue opportunities, regulatory/political risk, with input from city stakeholders. Their results showed that the dual system outperforms the singular system in social and environmental performance, substantially (from economic bottom line both systems had an almost similar score).

The quantitative findings of our study can be integrated with the qualitative and indirect quantitative findings of Cole et al. (2015; 2018) to provide a better understanding of challenges and benefits associated with the implementation of dual system for water utility managers. In addition, based on the quantitative and qualitative performance indicators developed in these two studies, future work can expand the simulation model presented in this paper to incorporate social and environmental factors in the life-cycle analysis of dual and singular water distribution systems. For instance, future work should capture benefits of carbon footprint reduction (induced by the decrease in treatment energy consumption) (Kang and Lansey 2012) and add it to the network life-cycle cost analysis.

3.7. Concluding Remarks

Conventional delivery of potable water (i.e., singular distribution system) in the United States is under pressure to adapt to aging infrastructure now more than ever. Production of potable water consumes a substantial amount of energy and cost. Sizing distribution networks to meet peak demand and fire flow requirements extends water age and delivery time producing deteriorating water quality concerns. Interrelated concerns such as these have motivated the consideration of alternative approaches. One of the proposed approaches is to implement a dual distribution system while it is time to replace the existing old distribution infrastructure. An investigation into the competitiveness of dual distribution systems at a municipal scale was formed based on the application of these approaches in Fort Collins, CO. This study was prompted by the previous studies that have reported the potential benefits of a new paradigm in water provision through approaches in which a smaller volume of potable quality water is delivered to the end-users for direct human consumption while separating the supply for other domestic uses such as outdoor irrigation and fire flow. However, further evaluations, such as quantitative, long-term, and infrastructure performance examinations, were needed to better inform the utilities to understand the benefits and challenges associated with the implementation of dual distribution systems in a city-wide scale. To this end, the present study developed a time-dependent simulation model that captured the long-term dynamic behavior of both dual and singular distribution systems. The model simulated various performance measures, of dual and singular systems, including network condition, leakage, breakage, water loss, embedded energy loss, and level of service, under different scenarios. It also captured the networks' life-cycle costs over the 50-year analysis period and examined to what extent the life-cycle costs of the implementation of a dual system could differ from the existing singular system's life-cycle costs.

3.7.1. Summary of Findings

This study concluded that the dual infrastructure system would improve the network condition and reduce water loss and energy consumption in the network. It was observed that through the implementation of the dual network, the system reliability would be slightly enhanced, which in line with the findings of Kang and Lansey (2012). However, the dual system will have more than three times higher life-cycle costs due to huge capital investments in installing a new pipeline network. Hence, in addition, this study identified to what extent the existing singular system needs to be renewed for the network to have almost similar performance to the proposed dual system over the long term. It was found that this goal can be achieved by controlling the existing network condition at 40 (years). Furthermore, the impacts of annual water demand fluctuations were explored on both dual and singular systems. The results showed that the dual system is better (less sensitive) under water demand growth, which is the case in cities facing rapid population growth (such as Fort Collins). However, for shrinking cities in which water demand is going to decline over time, the singular system would have better performance behavior than a dual system.

3.7.2. Significance of the Study

This study compared the dual and singular water distribution systems primarily from pipeline network infrastructure perspective. However, it is recognized that there might be some other factors, such as water storage considerations, that could influence the decision of dual system implementation. The simulation model presented in this paper didn't capture the new reservoir infrastructure required for non-potable water storage. Therefore, future works willing to study the dual systems can expand the current model to capture all of these system-wide factors and then compare the dual and singular systems more holistically. Hence, this paper provides a basis for future studies to further investigate the emergent properties of water distribution networks and also more holistically compare the dual and singular systems. The contributions of this study are threefold: first, this study developed a dynamic simulation model capable of characterizing and visualizing the long-term transformation of water distribution systems; second, it captured the long-term performance measures such as leakage and breakage to compare the dual and singular distribution systems under various scenarios (e.g., renewal strategies); third, it explored the sensitivity of dual and singular systems to demand fluctuations. From a practical perspective, the findings of this study will help municipalities and water utilities better understand the long-term infrastructure transformation, performance measures, and life-cycle costs associated with the dual systems. This study, along with previous studies, can provide a clear course of action for the future development of urban water distribution infrastructure systems and enhance institutional capacity for implementing more sustainable and resilient alternative urban water strategies.

4. MULTI-AGENT SIMULATION MODEL FOR EXPLORATORY ASSESSMENT OF ADAPTATION PLANNING IN COASTAL WATER SUPPLY INFRASTRUCTURE UNDER SEA-LEVEL RISE[§]

Urban water supply infrastructure systems in coastal areas are exposed to saltwater intrusion exacerbated by sea-level rise stressors. To enable assessing the long-term resilience of water supply infrastructure to such chronic impacts of sea-level rise, this study developed a novel hazards-humans-infrastructure nexus framework that enables the integration of: (i) stochastic processes of hazard scenarios based on the data obtained from previous studies pertaining to future projections of saltwater intrusion and storm surge events; (ii) decision-theoretic elements of adaptation planning processes of utility agencies based on theories of bounded rationality and regret aversion; and (iii) dynamic processes of water supply infrastructure performance. Using the proposed framework and data collected from South Miami-Dade service area, a multi-agent simulation model was created to conduct exploratory assessments of long-term resilience of water supply infrastructure under various sea-level rise scenarios and adaptation approaches. The results showed the capability of the proposed simulation model for adaptation planning and scenario landscape generation to discover robust adaptation pathways for enhanced resilience in urban coastal water supply infrastructure systems under uncertainty. The analysis results could provide

[§] This chapter is submitted to the Journal of "Environmental Modeling and Software" as an individual paper and is under review (Rasoulkhani, K.; Mostafavi, A.; Presa, M.; Batouli, M., Resilience Planning in Hazards-Humans-Infrastructure Nexus: Simulation-based Exploratory Assessment of Coastal Water Supply Infrastructure Adaptation to Sea-level Rise, 2020).

actionable scientific information to coastal water infrastructure mangers, planners and decision-makers to enhance their adaptation planning and investment decision-making processes.

4.1. Introduction

Coastal states in the United States of America are faced with evolving stressors and hazards exacerbated by climate change impacts. Evolving coastal hazards create significant challenges to U.S. public safety (U.S. Geological Survey 2014) because, of the 25 most densely populated and rapidly growing U.S. counties, 23 are along a coastline (Wilson and Fischetti 2010).

One of the most pressing coastal stressors is sea-level rise. There is clear scientific evidence that sea level is rising due to melting of glaciers and thermal expansion of oceans caused by global warming (IPCC 2007). The fifth assessment report of the Intergovernmental Panel on Climate Change (IPCC) reported that there has been an unequivocal upward trend in average global sea levels (IPCC 2013). In fact, global sea level has risen at an average rate of 1.7 mm per year since 1901 and projections show that it will continue to rise with an accelerated rate for the projected future (IPCC 2013). Sea-level rise (SLR) impacts in coastal areas have been studied intensively over the last decades (de Almeida and Mostafavi 2016). SLR has significant impacts on built infrastructure systems in coastal communities. It increases the frequency, duration, and magnitude of extreme weather events (e.g., storm surge, heavy precipitation, flooding) leading to greater exposure of coastal infrastructure systems to chronic and acute stressors. SLR, in general, exacerbates the severity of four coastal hazards including coastal erosion, flooding, land subsidence, and saltwater intrusion (de Almeida and Mostafavi 2016), each leads to specific impacts on infrastructure systems across different sectors (e.g., water, wastewater, energy, transportation). In particular, coastal water supply infrastructure systems, including water wellfields, treatment plants, and distribution networks, located in coastal regions are susceptible to SLR impacts. SLR affects water infrastructure in various ways, including: accelerated degradation of underground utility, inundation of low-lying facilities, contamination of groundwater through saltwater intrusion. Most water infrastructure systems are not designed to account for SLR impacts, and hence, could not operate under these conditions.

One of the most serious impacts of SLR on the coastal water supply infrastructure is saltwater intrusion (Werner and Simmons 2009). Majority of coastal cities, such as ones located in Southeast Florida, use underground aquifers as their main source of freshwater supply (Heimlich et al. 2009). With a constant discharge rate from groundwater wells and after a certain rise in sea levels, saltwater would start to flow into the wells from the shores. As saltwater intrusion (SWI) moves inland due to rising sea levels, the risk of freshwater contamination increases. SWI would happen in two ways: (i) chronic SWI into groundwater aquifer due to SLR; and (ii) storm-induced SWI due to storm surge events exacerbated by SLR. Chronic SWI occurs when the ocean hydraulic static pressure is higher than the underground aquifer's pressure, which causes the saltwater-freshwater interface zone (salinity line) located beneath the surface move inland over a long time (Werner and Simmons 2009). The rise in sea levels is expected to increase the inland movement of the salinity line because as sea level continues to rise at faster rates, the hydraulic pressure exerted by the seawater will also increase, resulting in a higher lateral push that drives the salinity line inland (Werner and Simmons 2009). Storm-induced SWI often starts with overtopping of a coastal barrier followed by hinterland inundation and subsequent vertical seawater intrusion (Elsayed and Oumeraci 2018). Hurricanes and extreme storm events can cause storm surges that result in SWI into coastal aquifers through vertical infiltration of saltwater (Elsayed and Oumeraci

2017; Yang et al. 2013). In either way, SWI would affect the freshwater capacity of water supply infrastructure and thus, the system's service reliability in meeting the potable water demand of service areas. Hence, SWI increases the groundwater salinity that either results in abandonment of contaminated wellfields or requires desalination of the saline water. Many cities such as Miami and Hallandale Beach in Florida have closed a number of their water wellfields due to the contamination of saltwater (MDWASD 2014).

Several studies have investigated the impact measure of SWI on coastal water supply infrastructure systems (CWSIS) (Dausman and Langevin 2005; Elsayed and Oumeraci 2017; Park et al. 2011; Prinos et al. 2014) and many other studies have evaluated the adaptation and resilience of CWSIS under these impacts (de Almeida and Mostafavi 2016; Bloetscher et al. 2010; Elsayed and Oumeraci 2018; Heimlich et al. 2009; Schoen et al. 2015). A review of the existing literature shows that the steady-state and ex-post (Mostafavi 2018) analysis approaches do not provide robust insights for resilient adaptation planning in CWSIS due to the uncertain nature of SLR and SWI impacts requiring more adaptive approaches to planning and decision making (Batouli and Mostafavi 2018a; Chappin and van der Lei 2014). In addition, the existing approaches for evaluation of SWI impacts on CWSIS do not consider adaptation decision-making behaviors of human actors (e.g., agencies and users). While different factors contributing to the physical impacts of SWI on CWSIS are well studied, little is known about effective adaptation approaches in response to SWI impacts. Such assessment would require consideration of uncertainty and complex interactions in hazards-humans-infrastructure nexus. To this end, the present study utilized model-based exploratory analysis to understand the coupled effects of the uncertain unfolding of SWI and adaptation decision-making processes of utility agencies on CWSIS performance. Accordingly, the study examined the long-term scenarios emerging from interactions in hazards-humans-infrastructure nexus to devise robust adaptation strategies that could mitigate subsequent impacts of SWI and improve resilience in CWSIS.

4.2. Resilience in Hazards-Humans-Infrastructure Nexus

An important step towards formulating robust adaptation plans and investment strategies is to specify and characterize the long-term scenarios related to CWSIS performance under impacts of coastal hazards. Understanding of long-term performance and resilience is essential because, due to the significant physical and institutional inertia in water supply infrastructure systems, undesirable performance regimes resulting from maladaptation are very difficult to reverse (Rasoulkhani and Mostafavi 2018).

In the context of complex infrastructure systems, such as CWSIS, long-term resilience is defined as the ability to transform and adapt to changes in internal feedbacks (Park et al. 2013) to cope with chronic or "surprise" hazards and thus sustain performance suitable for the social and economic development of communities (Rasoulkhani et al. 2017b). Long-term resilience is an emergent property that arises due to hazards-humans-infrastructure interactions and evolves over time (Rasoulkhani and Mostafavi 2018). The present study adopts a hazards-humans-infrastructure nexus framework (Figure 4-1) to specify and characterize the underlying mechanisms and their attributes and relationships that all shape and influence the long-term resilience landscape of CWSIS under SWI impacts. This framework, which is based on a complex system approach, captures three mechanisms underlying the long-term resilience (Figure 4-1): (i) *climatic hazards*: uncertain unfolding of evolving coastal hazards (e.g., SWI); (ii) *human actor decision-making* *processes*: adaptation planning processes of utility agencies; and (iii) *physical infrastructure performance*: water supply infrastructure condition and performance.

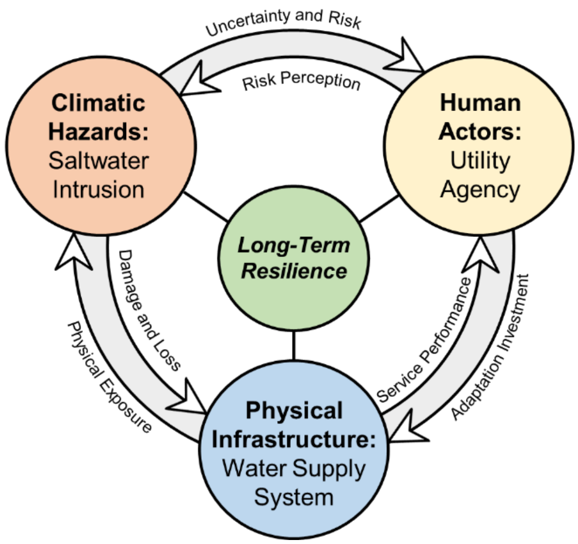

Figure 4-1. Hazards-Humans-Infrastructure Nexus Framework

The three mechanisms underlying the long-term resilience of water supply infrastructure interact with each other. In the context of this study, SLR increases the rate of chronic SWI into water supply infrastructures and also exacerbates the frequency and magnitude of storm surges, which both lead to damages and losses in freshwater aquifers. In addition, the risk of SWI would change decision-making behaviors and priorities of utility agencies. The uncertainty associated with SWI affects the priorities of utility agencies to determine an optimal balance between adaptation investments and perception of potential future SWI risks. Given resource limitations and future uncertainty, adaptation investments of utility agencies would influence the exposure of physical infrastructure to SWI threats. Accordingly, these coupled impacts would determine the performance of water supply system and its ability to serve the intended demand at the desired level of service. The specification and modeling of these mechanisms and their interactions would enable simulating various SLR and SWI future scenarios to examine the effectiveness of adaptation strategies.

4.3. Robust Adaptation Decision-Making and Planning

To moderate the potential impacts of coastal hazards (e.g., SWI) on CWSIS, planning and implementation of effective adaptation strategies is essential (Aerts et al. 2014). Adaptation involves anticipating the adverse effects of hazards and implementing appropriate strategies and measures to reduce the adverse impacts of hazards on coastal communities (IPCC 2013). Understanding the characteristics of robust adaptation planning holds the key to avoid maladaptation in CWSIS. Maladaptation refers to failure to change behaviors and undertake appropriate strategies such that the infrastructure systems on which a society is depended become unable to provide the required service (Aerts et al. 2014). Maladaptation may occur due to failure to take timely actions or taking actions that would be difficult to reverse.

Devising robust adaptation plans and investments is contingent upon evaluation of the long-term resilience of infrastructure systems under different adaptation strategies and hazard scenarios (Batouli and Mostafavi 2018a). Although the existing literature related to robust decision-making involves frameworks (e.g., Haasnoot et al. 2013; Kwakkel et al. 2016; Lempert et al. 2006; Shortridge et al. 2017; Shortridge and Zaitchik 2018) for adaptation planning and evaluation of climate change impacts, the existing frameworks are not developed specifically to specify and evaluate the characteristics of robust adaptation planning and investment decision-making in CWSIS under SWI impacts. Examples of various characteristics of adaptation planning that would yield long-term resilience in infrastructure systems include: (i) *robustness*— mitigating impacts across various future uncertain scenarios (rather than optimizing for the most-likely scenario or no-regret scenario) (Lempert et al. 2006; Mostafavi 2018); (ii) *flexibility*— accommodating short time horizons that require periodic updates and adjustments upon the availability of new information (Aerts et al. 2014); (iii) *decision intervals*— setting time intervals at which the updated information is used to make new adaptation investment decisions (Deyle and Butler 2013); and (iv) *signposts*— tracking signposts and specifying triggers to determine whether the implementation of adaptation decisions is needed (Haasnoot et al. 2013). To provide insights for robust adaptation strategies in the context of CWSIS, this study employed an exploratory analysis approach to examine different adaptation decision-making attributes, such as hazard perceptions, risk attitudes, decision intervals, investment levels, and signposts (thresholds for SWI proximity).

Exploratory analysis is an effective approach for dealing with uncertainty and complexity in climate change adaptation (Bankes 1993; Kwakkel and Pruyt 2013b). Exploratory analysis involves analytical, model-based methods for decision-making under uncertainty. Model-based exploratory analysis uses computational models and simulation experiments to conduct scenario analysis and evaluate the behavior patterns in complex systems such as CWSIS (Agusdinata 2008; Bankes 2002b; Mostafavi 2018; Mostafavi et al. 2013). Unlike traditional simulation approaches, exploratory analysis does not aim to predict the behavior of a system for optimizing the system. Instead, exploratory analysis focuses primarily on considering different scenarios based on changes in system behavior and future uncertainty to evaluate the robustness of different pathways of actions under deep uncertainty.

This study utilized a model-based exploratory analysis approach to describe how fundamental decision-making attributes, risk response behaviors, and physical infrastructure realities affect the adaptation pathways in response to SWI impacts. To this end, a dynamic (time-dependent) multi-agent simulation model was created to capture the attributes and interactions among costal hazards (SLR and SWI), adaptation decision-making processes (risk attitudes, investment levels, decision intervals), and water supply infrastructures (exposure, condition, performance). The following section explains the abstraction and modeling processes.

4.4. Multi-agent Simulation Model

Multi-agent simulation is an effective simulation approach for analyzing complex processes and interactions in coupled human-infrastructure systems (Batouli and Mostafavi 2018a; Bhamidipati 2015; Davidsson 2001; Pahl-Wostl 2002; Rasoulkhani and Mostafavi 2018; Sanford Bernhardt and McNeil 2008). Multi-agent simulation enables modeling complex and real-world systems through the adoption of influential concepts such as adaptation, emergence, and self-organization (Al-Zinati et al. 2013; Rasoulkhani et al. 2018). In multi-agent simulation, an agent has several essential characteristics: active—initiating actions, reactive—responding to external stimulus, and autonomy—freedom from intervention by any other agents (Grignard et al. 2014). Many entities within an infrastructure system can be viewed and modeled as an agent. Hence, multi-agent simulation is suitable approach to model entities and their interactions in hazards-human-infrastructure nexus. The created multi-agent simulation model integrates: (i) stochastic processes related to SLR stressors (i.e., SWI and storm surge); (ii) decision-theoretic elements of utility agency's adaptation decision-making processes; and (iii) dynamic processes of water supply infrastructure exposure and performance.

The components of the multi-agent simulation model are explained in the remainder of this section. The computational representation of the simulation model was developed in an object-oriented, java-based simulation platform (i.e., AnyLogic 8). The relationships among agent classes and their attributes are based on the empirical information and grounded theories (e.g., bounded rationality, regret aversion). The agent classes and their attributes and functions are shown in the unified modeling language (UML) diagram (Figure 4-2). The model contains three main classes of agents: Hazard agent, Human Actor agent, and Infrastructure agent. The mathematical representation of each agent, their attributes and relationships are discussed below.

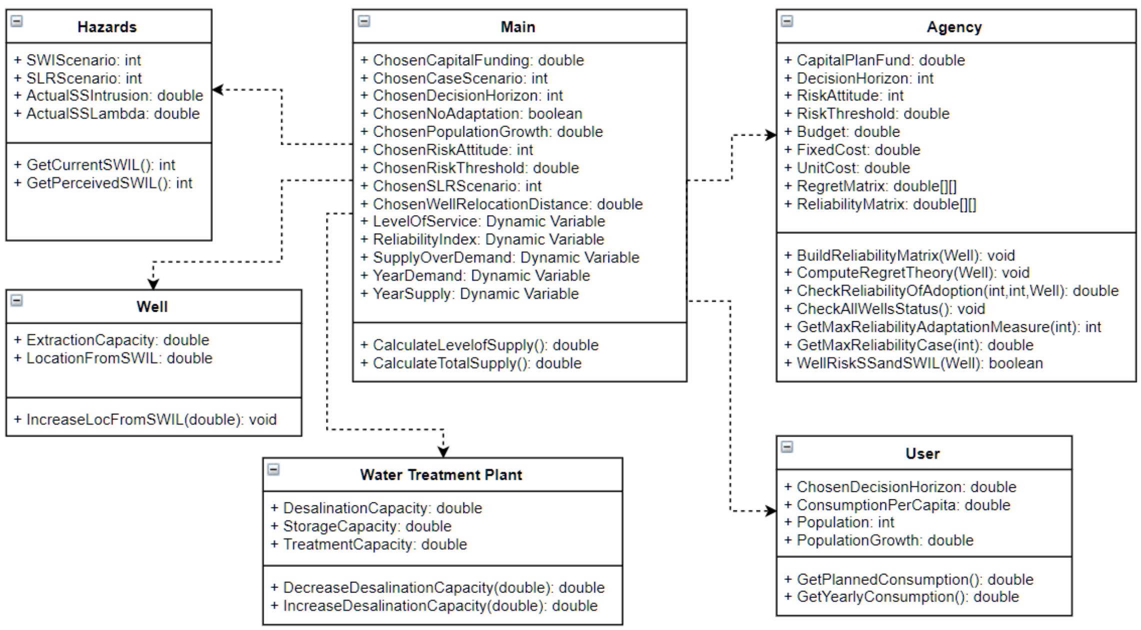

Figure 4-2. UML Class Diagram of the Multi-agent Simulation Model

4.4.1. Hazard Agent

The Hazard agent represents the stochastic processes related to two coastal hazards induced by SLR, including SWI and storm surges, both of which evolve and are exacerbated due to SLR. The higher the sea level rises, the greater the likelihood of storm surge occurrence and the faster the chronic SWI rates. Due to a great deal of uncertainty in projection of future SLR, the Intergovernmental Panel on Climate Change (IPCC) and the Southeast Florida Regional Climate

Change Compact have recommended consideration of a number of alternative scenarios for different trajectories of future SLR (Compact 2015; IPCC 2013). Based on their recommendations, three scenarios (i.e., low, medium, and high sea levels) were considered in this model. Based on the IPCC (2013) and the Compact (2015), the agencies in Southeast Florida are utilizing these three scenarios for adaptation planning and decision making.

In order to evaluate the long-term chronic SWI, it is important to understand how different scenarios of SLR lead to SWI. However, the extent of SWI not only is affected by SLR severity, but also depends on a large number of physical and hydraulic parameters such as recharge (water-table fluctuations), hydraulic conductivity, soil porosity, and mixing properties (La Licata et al. 2011). Hence, three different possible rates of chronic SWI were considered under each SLR scenario: (i) fast SWI; moderate SWI; and (iii) slow SWI. Simulation of contaminant transport such as SWI in coastal aquifers is intrinsically complex and computationally expensive because of the complex flow patterns that develop when freshwater mixes with saline groundwater (Elsayed and Oumeraci 2018; La Licata et al. 2011). However, several numerical models have been specifically developed to evaluate the effect of sea-level fluctuations on SWI. In this study, the results obtained from the existing numerical groundwater models in Southeast Florida were used to determine the rate of SWI into the wellfields (Figure 4-3) (Dausman and Langevin 2005; Fitterman 2014; Prinos et al. 2014). The information related to different SWI scenarios are summarized in Figure 4-3. With this information, the salinity line movement (chronic SWI) in the coastal aquifer was determined and then used to compute the year in which each wellfield gets exposed under different SLR and SWI scenarios over an extended 100 years of the simulation period.

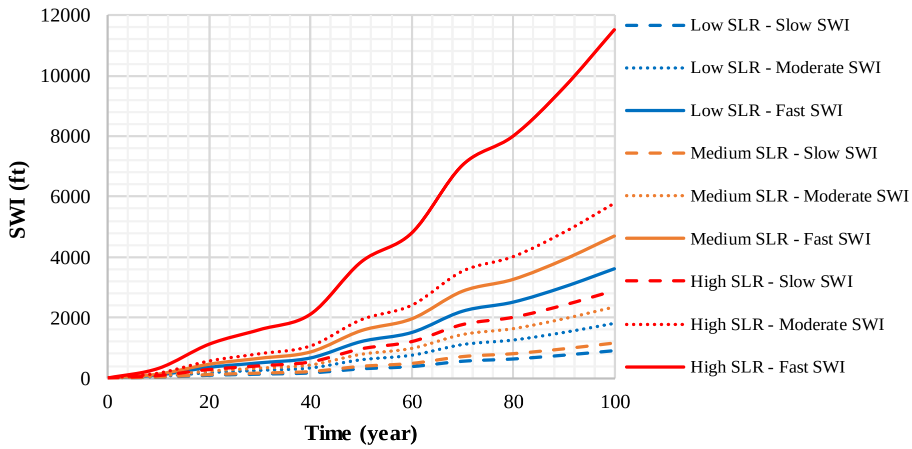

Figure 4-3. Salinity Line Movement under Different SLR Scenarios and SWI Rates

The chronic SWI could be exacerbated due to storm surges (SS). In fact, SS events can accelerate SWI and as a result, temporarily, further push the salinity line towards aquifers (Park et al. 2011). Therefore, in the Hazard agent, the occurrence of SS events and the magnitude of their immediate impact on SWI (which is called secondary or immediate impact) were incorporated during the analysis period (e.g., 100 years). The likelihood and magnitude of SS occurrence vary based on the severity of SLR. The occurrence of SS events was modeled through the use of a homogenous stochastic process, Poisson model, as shown in Equation 36. Per Katz (2010), the Poisson process is an effective statistical technique used for analysis of the frequency of occurrence of an extreme event such as hurricanes. This technique assumes a linear trend in the logarithm of the rate parameter of the Poisson distribution (Katz 2010).

$$P(SS) = P(SS \mid SLR\ Scenario) = \frac{\lambda^k e^{-\lambda}}{k!} = \lambda \times e^{-\lambda} \qquad \textbf{(36)}$$

where λ is the mean rate of SS per year (likelihood of having one SS event at each year). The λ values were determined based on the available data existing in published studies (Park et al. 2011; Tebaldi et al. 2012; Zhang et al. 2013) pertaining to the increased frequency and magnitude of surge events in Southeast Florida. Accordingly, the values of 0.15, 0.20, and 0.25 were assigned to λ under low, medium, and high SLR scenarios, respectively.

The mechanics of storm-induced SWI through surface infiltration or open pits is highly complex and non-linear due to the unsteady nature of the stratification (denser seawater over less dense freshwater) and the significant spatial and geologic inhomogeneities (Park et al. 2011). Due to the complexity and high diversity of the involved processes and interactions (Gingerich et al. 2017), the extents of SWI caused by SS have not been precisely quantified (Miami-Dade County 2016a). Hence, in this study, the results and insights of existing models that couple the surge statistics with SWI to predict the extent of saline infiltration (Elsayed and Oumeraci 2018; La Licata et al. 2011; Yang et al. 2013, 2018a; Yu et al. 2016) were utilized to approximate the possible extents of secondary SWI induced by SS. Accordingly, the following stochastic uniform distributions were defined for the extents of storm-induced SWI (ft) under different SLR scenarios (Equation 37).

$$Secondary\ SWI = \begin{cases} Uniform(100, 200); & SLR = low \\ Uniform(200, 300); & SLR = med \\ Uniform(300, 400); & SLR = high \end{cases} \tag{37}$$

Finally, the processes represented in the Hazard agent enable integrating the storm-induced SWI with the chronic SWI (obtained from Figure 4-3) and calculating the total SWI. Accordingly, every year (i.e., the model time-step), the proximity of the salinity line to each wellfield is determined based on the wellfield's initial distance from the salinity line and the total SWI happened until that year (Equation 38).

$$Proximity_t = Initial\ Distance - Total\ SWI_t \tag{38}$$

Subsequently, the actual and perceived exposure of wellfields to the risk of SWI are determined in the Human Actor agent as explained in the following subsection.

4.4.2. Human Actor Agent

The Human Actor agent captures the underlying behavioral factors and decision rules that influence adaptation decision-making processes of the utility agency (which manages and operates the water wellfields and treatment plants). Two planning approaches were considered: (i) adaptive approach, in which the decisions related to management of the infrastructure are made based on consideration of the future impacts of SWI, and the agency implements adaptation actions before SWI affects the infrastructure; and (ii) reactive approach (or no-adaptation), in which the decisions would be non-adaptive and are made without considering the uncertain SWI impacts. In this approach, the agency waits until an infrastructure is affected by SWI and then would implement recovery actions (such as well relocation or desalination facility installation). The adaptation and recovery decision-making behaviors of the utility agency were modeled using the action chart shown in Figure 4-4. The details about the processes related to these two planning approaches are discussed in the remainder of this section.

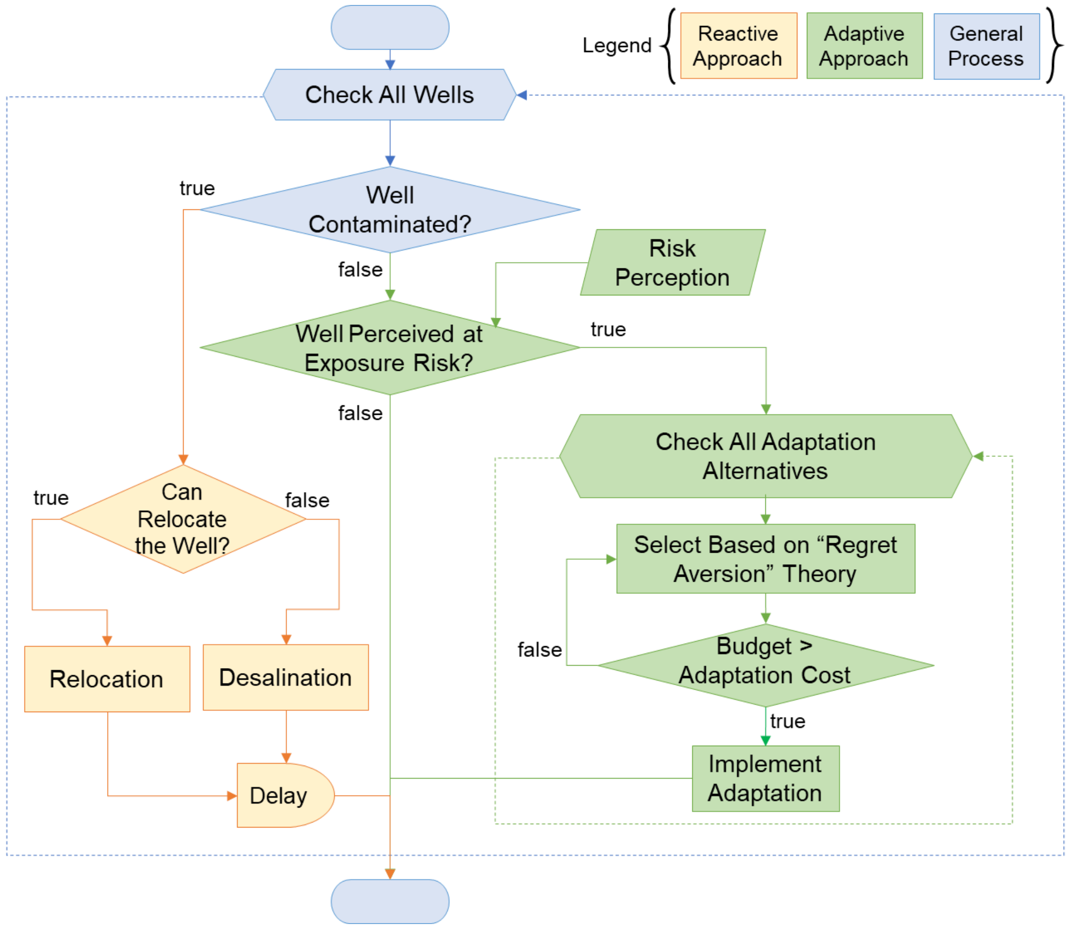

Figure 4-4. Action Chart for Modeling of Planning Processes

4.4.2.1. Adaptive Approach

This study adopted the theory of bounded rationality to model the rational behavior of individuals under certain limitations. Based the theory of bounded rationality, decision makers who are bounded by imperfect information, confined time, and limited capacity seek satisfactory solutions rather than optimal solutions (Simon 1972). The adaptation decision-making processes of utility agencies represent all the traits of bounded rational decision-making. First, there is a significant level of uncertainty in the available information about future SLR and its impacts. Second, utility agencies are bounded to taking adaptation actions at certain points of time (known as decision points) when a multiyear capital improvement program is devised (Wooldridge et al. 2002). Third, all adaptation actions of a utility agency are contingent upon availability of capital improvement funding (Batouli and Mostafavi 2018a).

Decision intervals: The adaptation decision-making process is adaptive in nature. Figure 4-5 depicts the processes leading to adaptation decisions of the utility agency. The entire period of a capital adaptation plan (which is 100 years in this study) is usually divided into a number of time intervals, and the utility agency makes adaptation decisions at certain decision points. The time period between two successive decision points ($t_{i+1} - t_i$) is referred to as decision interval. After the utility agency implemented the adaptation decision at a decision point (t_i), they would observe the actual changes in the state of nature (i.e., SLR and SWI) before taking actions in the next decision point (t_{i+1}). At the next decision point, the actual SLR and SWI as well as the risk attitude of the agency is updated based on the new information that has become available. The entire process is then repeated for next decision horizons to make new adaptation decisions.

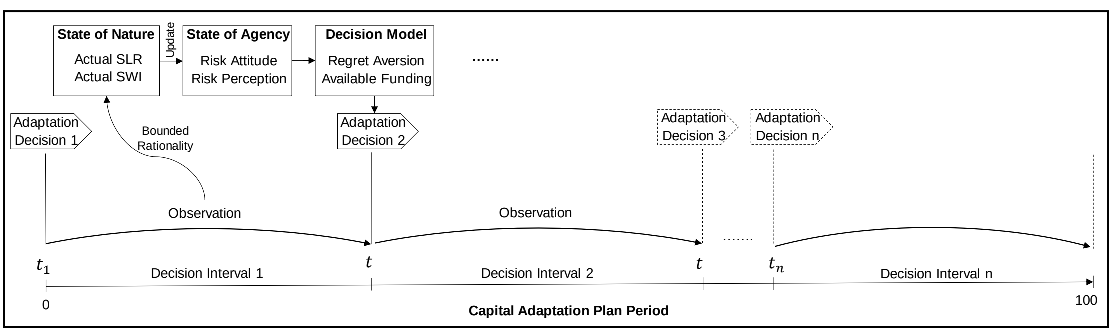

Figure 4-5. Multiyear Adaptation Decision-Making Process

Hazard perception: The imperfect information about future SLR and SWI causes the utility agency to make adaptation decisions based on its perception of the future hazards. The perception of the agency is influenced by its risk attitude towards likely impacts of hazards. Since the agency is unsure what scenario of SLR and SWI would happen in the future, they rely on their own perception to perceive the SWI among the alternative SWI projections. Hence, the perceived SWI (PSWI) of the utility agency may be different from the actual SWI (ASWI). To model this, three different hazard perceptions (h), including optimistic (O), most likely (M), and pessimistic (P), were defined as shown in Equation 39.

$$h = \begin{cases} O = \{(Slow\ SWI \mid Low\ SLR), (SS \mid Low\ SLR)\} \\ M = \{(Mod\ SWI \mid Med\ SLR), (SS \mid Med\ SLR)\} \\ P = \{(Fast\ SWI \mid High\ SLR), (SS \mid High\ SLR)\} \end{cases} \quad \textbf{(39)}$$

Risk attitude: The agency's hazard perception for a decision horizon (from t_i to t_{i+1}) is determined based on its risk attitude at the beginning of the decision horizon (i.e., at decision point t_i). The agency's risk attitude determines the decision-maker's preference among uncertain outcomes of adaptation decisions. The agency could be either risk seeker, risk neutral, or risk averse at the beginning of the adaptation planning period; however, its risk attitude may change at each decision point and get updated for the following decision interval. This is because risk attitude is formed based on past experience (reference point) and observation rather than being based on fully rational analytical models (Leiserowitz 2006). Equation 40 summarizes the representation of the agency's risk attitude in the model at each decision point. In fact, based on the agency's observation during the past decision interval ($i-1$), more updated information becomes available at decision point t_i; and then the agency would become more (less) risk seeking if the perceived SWI for the past decision horizon is greater (lower) than the maximum (minimum) actual SWI happened during that decision horizon (Equation 40).

$$\text{if}\begin{cases} PSWI_{i-1} < ASWI_{i-1,min}\,; & then\ become\ more\ risk\ averse\ at\ t_i\ (Message\ 1) \\ PSWI_{i-1} > ASWI_{i-1,max}\,; & then\ become\ more\ risk\ seeker\ at\ t_i\ (Message\ 2) \\ PSWI_{i-1} \in [ASWI_{i-1,min}, ASWI_{i-1,max}]; & then\ keep\ the\ current\ attitude\ at\ t_i \end{cases} \quad \textbf{(40)}$$

where $PSWI_{i-1}$ and $ASWI_{i-1}$ denote the perceived SWI and the actual SWI during the decision horizon of $i-1$. Accordingly, prior to each decision point, the utility agency transitions between the risk attitude states based on the message received from Equation 40. For example, if the agency was risk seeker at the previous decision point (t_{i-1}) and observes that the perceived SWI is lower than the minimum actual SWI happened during the following decision interval ($i-1$), then the agency's risk attitude would change to risk neutral at decision point t_i.

Signposts: Signposts specify information that should be tracked in order to determine whether the adaptation action implementation is needed (Haasnoot et al. 2013). The critical values of signpost variables are called triggers beyond which adaptation actions should be implemented (Haasnoot et al. 2013). In this model, the distance of SWI from wellfields is the signpost based on which the adaptation implementation is determined. As shown in the agency's action chart (Figure 4-4), if a well has not been contaminated yet, its exposure to SWI is being evaluated. Once the risk attitude of the agency and the hazard perception were specified at a decision point, the exposure of each wellfield to the perceived SWI (PSWI) scenario (during the following decision horizon) is determined using Equation 41. To determine the exposure of wellfields, the utility agency performs conditional logic testing based on the PSWI proximity calculated in Equation 38. The agency would consider a proximity threshold (as a trigger value) which is the minimum distance of SWI from the well that the agency would tolerate. If a well is located at a distance greater than the proximity threshold from the perceived salinity line, it won't be considered at risk for the following decision horizon. However, if the distance is equal or less than the threshold for the following decision horizon, then the well is considered at risk. The utility agency can adopt different values of proximity threshold. For example, if the agency's proximity threshold is 100 ft, then the agency would consider a well at exposure when the proximity of PSWI to the well is less than 100 ft.

$$Exposure_t = Proximity_t - Threshold \quad \textbf{(41)}$$

Adaptation actions: Based on consideration of the exposure of wells to PSWI, if no wells are identified to get exposed to PSWI, the agency does not implement any adaptation actions and proceeds to the next decision point. If one or more wells are identified to potentially get exposed to SWI, the next step of adaptation decision-making is to select appropriate adaptation actions. In this model, four different adaptation actions were considered. The adaptation action space includes the following adaptation actions: (i) aquifer recharge, implementing deep-well injection to control groundwater levels; (ii) salinity barrier, installing seepage barrier to protect wellfields; (iii) well relocation, closing an exposed/contaminated wellfield and exploiting new wellfield farther from the salinity interface location; and (iv) desalination facility, adding desalination capacity to the treatment plant. Each adaptation action has different cost and effect on the water supply system as summarized in Table 4-1. Since there is uncertainty related to cost of SWI adaptation actions, Pert probability distributions are defined based on the min, most likely, and max values reported in previous studies and reports (see the last column of Table 4-1).

Choice modeling: The agency's choice among different adaptation alternatives was modeled based on the theory of regret aversion (Bell 1982). Recent research in behavioral psychology and judgement under uncertainty reveals that regret aversion provides a better model of human choice under uncertainty compared to the standard utility theory. Since regret can be anticipated prior to choice, it can lead to regret-minimizing decisions (Humphrey 2004).

According to this theory, the risk attitude of the decision-maker determines what adaptation action to be selected (Batouli and Mostafavi 2018a). As shown in Figure 4-6, a risk-seeking agency feels optimistic about the climatic hazard scenario and would select the alternative that results in highest performance under the best-case scenario of hazard. On the other hand, a risk-averse agency would want to maximize the system performance under the pessimistic hazard perception (worst-case scenario). Finally, a risk-neutral agency would anticipate the possibility of feeling regret after the uncertainty of future hazards is resolved. Hence, a risk-neutral agency would select the alternative that yields the least regret across all hazard scenarios (i.e., optimistic, most likely, and pessimistic perception).

Table 4-1. Attributes of Adaptation Actions

Action	Cost Function ($ Million)	Efficacy	Source of Information
Aquifer recharge (deep-well injection)	Pert (100, 200, 300)	Pushes back the salinity interface	Walsh and Price (2010); Perrone and Merri Rohde (2016); Aerts et al. (2018)
Salinity barrier	Pert (150, 250, 350)	Reduces the SWI rate	Prinos and Valderrama (2015)
Well relocation	Pert (200, 350, 500)	Distances the well from SWI	Groves et al. (2018); (FSDEP 2015)
Desalination facility	Fixed: Pert (200, 400, 600) Unit Cost: Pert (2, 4, 6) ($/1000 gallons)	Desalinates saline water of contaminated wells	Karagiannis and Soldatos (2008); Mishra (2018)

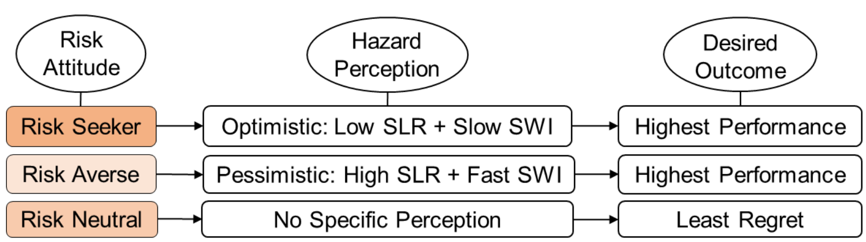

Figure 4-6. Adaptation Alternative Selection Process

To capture the adaptation alternative selection process, at each decision point, the model determines the planned (anticipated) performance of the infrastructure system based on the measure of planned level of service. The planned level of service (PLS_{t_i}) that the agency anticipates at decision point t_i (for the following decision horizon based on the implementation of adaptation actions) is calculated using Equation 42.

$$PLS_{t_i} = \sum_{t_i}^{t_i+d} \frac{Supply\ Capacity\ (t)}{Projected\ Demand\ (t)} \quad \textbf{(42)}$$

where d denotes the duration (years) of decision intervals. Supply capacity and projected demand are parameters driven from the infrastructure agent (explained in next subsection). Accordingly, the model generates a matrix related to the planned level of service resultant of each adaptation action (j) under optimistic, most likely, and pessimistic hazard perceptions (h) as shown in Equation 43.

$$PLS_{j,h} = \begin{bmatrix} PLS_{1,O} & PLS_{1,M} & PLS_{1,P} \\ PLS_{2,O} & PLS_{2,M} & PLS_{2,P} \\ PLS_{3,O} & PLS_{3,M} & PLS_{3,P} \\ PLS_{4,O} & PLS_{4,M} & PLS_{4,P} \end{bmatrix} \quad \textbf{(43)}$$

where rows represent adaptation alternatives and columns represent hazard perceptions. For instance, $PLS_{1,O}$ denotes the planned level of service that the agency anticipates for system if adaptation action 1 is implemented given the optimistic hazard occurrence.

To select an adaptation action to be implemented at each decision point, if necessary (based upon the exposure), the following process is followed: if the agency is risk seeker (risk averse), then the adaptation action A_j that results in $PLS_{max,O}$ ($PLS_{max,P}$) will be selected as shown in Equation 44.

$$Select\ A_j\ if \begin{cases} PLS_{j,O} = \max \{PLS_{1,O}, PLS_{2,O}, PLS_{3,O}, PLS_{4,O}\},\ Risk\ Attitude = Risk\ Seeker \\ PLS_{j,P} = \max \{PLS_{1,P}, PLS_{2,P}, PLS_{3,P}, PLS_{4,P}\},\ Risk\ Attitude = Risk\ Averse \end{cases}$$

(44)

In case the agency is risk neutral, the model also constructs the regret matrix by subtracting the planned level of service achieved under each adaptation action from the maximum possible planned level of service that could be achieved under the adaptation actions (Equation 45). In Equation 45, $Reg_{j,h}$ denotes the regret of selecting adaptation action j if hazard h happens.

$$Reg_{j,h} = \begin{bmatrix} PLS_{max,O} - PLS_{1,O} & PLS_{max,M} - PLS_{1,M} & PLS_{max,P} - PLS_{1,P} \\ PLS_{max,O} - PLS_{2,O} & PLS_{max,M} - PLS_{2,M} & PLS_{max,P} - PLS_{2,P} \\ PLS_{max,O} - PLS_{3,O} & PLS_{max,M} - PLS_{3,M} & PLS_{max,P} - PLS_{3,P} \\ PLS_{max,O} - PLS_{4,O} & PLS_{max,M} - PLS_{4,M} & PLS_{max,P} - PLS_{4,P} \end{bmatrix} \qquad \textbf{(45)}$$

Accordingly, the maximum regret related to selecting adaptation action j ($MaxReg_j$) is determined using Equation 46.

$$MaxReg_j = \max \{Reg_{j,O}, Reg_{j,M}, Reg_{j,P}\} \qquad \textbf{(46)}$$

Finally, the risk neutral agency will select the adaptation action that has the lowest maximum regret (minimax regret) as shown in Equation 47.

$$Select\ A_j\ if MaxReg_j = \min \{MaxReg_1, MaxReg_2, MaxReg_3, MaxReg_4\} \qquad \textbf{(47)}$$

In the adaptation alternative selection process for each risk attitude, if there are more than one adaptation action with the same outcome (i.e., highest performance or least regret), the agency would select the less expensive one. Implementation of the selected adaptation actions is contingent upon sufficiency of the available budget. In this model, the utility agency was assumed to be given a capital improvement fund for the entire 100 years in order to implement adaptation actions (MDWASD 2014). Due to the uncertainty pertaining to climatic hazards, the capital fund should be spent across various decision intervals. In this study, the capital fund is equally distributed among the decision intervals and thus the available budget (B_{t_i}) for the agency at each decision point is determined based on Equation 48.

$$B_{t_i} = B'_{t_{i-1}} + \frac{Capital\ Fund}{100/d} \tag{48}$$

where $B'_{t_{i-1}}$ denotes the reminder of budget from previous decision point and d denotes the duration of adopted decision intervals.

Based on the decision-making and choice processes discussed above, the adaptation decision-making behaviors of the utility agency were captured during a 100-year analysis horizon. It should be noted that in adaptive planning, if a well gets contaminated for any reason, the agency will implement recovery actions as discussed in the remainder of this subsection.

4.4.2.2. Reactive Approach

In order to better understand and examine the effectiveness of adaptation planning, a reactive approach was also considered in the model. Reactive approach is based on responding to events after they have happened. In reactive approach, the agency monitors the actual condition of infrastructure systems and implements recovery actions when a failure (or performance drop) happens due to hazards. The reactive behavior of the agency was modeled as shown in the action chart (Figure 4-4).

In reactive approach, two different recovery actions were considered: well relocation and desalination facility. The difference between these two actions in reactive approach with the ones in adaptive planning is that there would be a lag (delay) in recovering from the contaminated wellfield (and thus to retrieve the system's level of service) under reactive approach. When a well is contaminated, the utility agency first examines whether the well relocation can be done based on the relocation limit that each well has (it was assumed that each well could be relocated only for a certain number of times). Accordingly, if the well could be relocated, the agency would close the contaminated wellfield and exploit new wellfield with a farther distance from the saltwater interface location. Otherwise, the agency would install desalination facility to treat the saline water extracted from contaminated wells.

The outcomes of the Human Actor agent include the timing and type of adaptation/recovery actions. These outcomes are used in the Infrastructure agent to model changes in the performance of water supply infrastructure system based on adaptation/recovery actions.

4.4.3. Infrastructure Agent

This agent class captures behaviors of the water supply infrastructure under the coupled impacts of SWI and the utility agency adaptation/recovery actions. This study considered two key components of water supply infrastructure systems: water wellfields and water treatment plants; however, the main focus was on modeling the wellfields. Two sets of processes were captured: (i) *physical condition*, the structural capacity and ability of infrastructure to withstand SWI; and (ii) *functional performance*, the infrastructure ability to provide intended demand at the desired level. To capture these processes, various attributes of wellfields and treatment plants were considered. Attributes of water wellfields included location, distance from the salinity line, source aquifer, number of wells, and installed design capacity. The treatment and desalination capacities of the treatment plants were also considered.

Each year, the simulation model checks all wells based on the proximity of SWI to each well and accordingly, the well contamination status is specified using Equation 49.

$$WCS_{kt} = \begin{cases} 1, \ if \ Proximity_{kt} \leq 0 \\ 0, \ if \ Proximity_{kt} > 0 \end{cases} \quad \textbf{(49)}$$

where WCS_{kt} is the contamination status of well k at year t, and $Proximity_{kt}$ denotes the proximity of SWI interface to well k at year t (which is calculated by Equation 38 in Hazard agent). Once a well is in contaminated status, based on the outcome of utility agency's decision-making process, either the well may be relocated or extra desalination capacity may be added to the system. At the beginning of the simulation, the system does not include any desalination capacity.

Accordingly, the performance of water supply system is evaluated based on the supply capacity which is the amount of water that the system can supply to the service area. The annual water supply capacity of the system is calculated based on the extraction capacity of not-contaminated wells (EC), capacity of treatment plants (TC), and the amount of desalinated water (DW) as shown in Equation 50.

$$Supply\ Capacity_t = \min(\textstyle\sum_{Wells} EC\ , \sum_{Plants} TC) + DW \qquad \textbf{(50)}$$

In equation 50, desalinated water (DW) is the amount of water demand that could not met due to contaminated well(s); so the utility agency would need to desalinate this amount of water (if there is no well contaminated, then $DW$is equal to zero). Also, DW can't be greater than the desalination capacity of the plant. The water demand imposed to the system is projected based on the population of service area. As the population of coastal service areas grow (Wilson and Fischetti 2010), the coastal water supply infrastructure system have to possess the capacity to meet the increasing water demand. Hence, this model captures the dynamic changes in the level of demand imposed to the system over the 100-year analysis period. Equation 51 represents how the projected demand of every year is calculated based on the population of the service area.

$$Projected\ Demand_t = Pop \times \bar{C} \times 365 \times (1 + PopG)^t \qquad \textbf{(51)}$$

where Pop, $\bar{C}$, and $PopG$ denote the base population, the daily per capita water consumption, and the population growth rate, respectively.

The resilience of the water supply infrastructure system was determined based on a measure called level of service, which captures the reliability of water supply to meet the demand. The level of service (LoS_t) is calculated using Equation 52.

$$LoS_t = \frac{Supply\ Capacity_t}{Projected\ Demand_t} \times 100 \quad \textbf{(52)}$$

where LoS_t values between 0-100% as if the supply capacity is greater than the demand, the model equalizes supply with demand. Accordingly, the long-term resilience index (LRI) of the system is computed based on Equation 53.

$$LRI = \frac{1}{100} \sum_{1}^{100} LoS_t \quad \textbf{(53)}$$

The greater LRI indicates less loss in the levels of service in the system over the long period of time (i.e., 100 years).

4.5. Case Study

The application of the proposed framework was illustrated to study the adaptation of coastal water supply infrastructure system to impacts of SLR and SWI in South Miami-Dade County, FL, for over a 100-year analysis horizon. The hydrologic and groundwater conditions in Southeast Florida have been altered significantly due to climate change impacts, that the management and operation of water supply infrastructure has become a complex job for the local utility agencies (SFWMD 2018). South Miami-Dade area (formerly known as the Rex Utility District) is specifically vulnerable to the impacts of SLR as it is located in the lower section of Miami-Dade County. This area has been experiencing SWI in the last couple of decades (Dausman and Langevin 2005; Fitterman 2014; Prinos et al. 2014).

The multi-agent simulation model developed in this study was built using data and information related to the South Miami-Dade water service area. These data and information were collected mainly from the findings of scientific researches (e.g., Dausman and Langevin 2005; Fitterman 2014; Prinos et al. 2014) and reports (e.g., MDWASD 2014) of local institutions and governmental agencies which are in charge of the water utilities of the region. These institutions have conducted numerous studies and resources for understanding of SLR and SWI impacts on their water infrastructure systems.

The water supply infrastructure system located in South Miami-Dade (SMD) area is managed by Miami-Dade Water and Sewer Department (MDWASD) and is serving mainly the southern part of Miami-Dade County. Based on the 20-year Water Supply Facilities Work Plan reported by MDWASD in 2014, this service area has a population of 98690 with a growth rate of 0.88% and an average daily per capita water consumption of 137.2 gallons (MDWASD 2014).

Based on the 20-year Water Supply Facilities Work Plan, MDWASD has planned to consolidate their existing treatment plants and the associated wellfields by construction and operation of South Miami Heights Water Treatment Plant (SMHWTP) in the SMD area. Of the five existing water treatment plants and their individual supplying wellfields in the SMD area, only two plants remain in service on a stand-by-basis after the SMHWTP begins operations (MDWASD 2014). The three anticipated wellfields and their information are summarized in Table 2.

Table 4-2. Information of Case Study Water Wellfields

Wellfields	Aquifer	Installed Design Capacity (mgd)*	Initial Distance from Saltwater (ft)
Roberta Hunter Park	Biscayne	6	3200
Former Plant	Biscayne	4	4400
South Miami Heights	Floridan	24	3200

*mgd: million gallons per day

These three wellfields are responsible for providing all raw water extraction from a combination of Floridan and Biscayne aquifers to the SMHWTP which has a capacity to produce 20 mgd finished water (and more 4 mgd by the stand-by-basis plants). SMHWTP, South Miami Heights Wellfield, and Roberta Hunter Well are located in the same building.

The SWI data was collected from relevant studies (e.g., Dausman and Langevin 2005; Fitterman 2014; Prinos et al. 2014) conducted in various disciplines such as hydrology, hydraulics, geotechnical and environmental sciences. For instance, Dausman and Langevin (2005) have proposed a correlation between SLR severity and SWI rate by analyzing the Biscayne aquifer and the lime rock conditions under the South Floridian continental plate.

4.6. Model Verification and Validation

To ensure the quality and credibility of the developed multi-agent simulation model, verification and validation processes were conducted. Simulation models, especially agent-based models related to human systems, are often criticized for relying on informal and subjective validation or no validation at all. In this study, a gradual, systemic and iterative process was employed to conduct a thorough verification and validation of the simulation model. The different techniques used for verification and validation of the model and its components are described as follows.

4.6.1. Internal and External Verification

Various internal and external verification techniques were employed to verify the data, logic, and computational algorithms related to the simulation model (Bankes and Gillogly 1994). The internal verification of the model was initially ensured through the use of grounded theories (e.g., bounded rationality and regret aversion) for modeling decision and behavioral processes and valid empirical data (e.g., infrastructure attributes, system demand, etc.) for modeling infrastructure condition and performance indicators. In addition, for each component of the model, component verification assessment was conducted to verify the completeness, coherence, consistency, and correctness (4Cs) of the component (Pace 2000). For instance, the model performance was observed under: (i) taking off the function of one component of the model and making sure it influences the outputs to the degree that is specified in the model; and (ii) running the model with extreme values of each component and verifying the functionality of the model under the extreme condition. Also, several random replications of the model were compared to check for the consistency of the outputs. Accordingly, most of the discovered errors had less to do with problems within the theories or empirical rules, and more regarding issues with coding correctly. Thus, most errors in the internal verification process were fixed relatively smoothly and then the aforementioned four features (4Cs) of the model were ensured.

The external verification of the model was ensured by building the model rich in causal factors that were examined to see what leads to particular outcomes (Bharathy and Silverman 2010). Figure 4-7shows a screenshot of the simulation output interface where the behavior regime of various outputs pertaining to different entities of the model can be observed. The behaviors of model entities (e.g., risk attitude, adopted adaptation actions, salinity line movement, etc.) were followed so as to identify unusual patterns. Whenever an unusual pattern was observed, the model logic was checked to ensure that the behavior was not due to unreasonable assumptions or imperfect logics.

Additionally, the range of values of outputs were compared to the existing real data to ensure the reliability of the parameters in the model (Werker and Brenner 2004). For example, the output parameters related to the wells, such as proximity to SWI and extraction capacity, were compared to the actual data related to the wells (in SMD) to ensure values were reasonable.

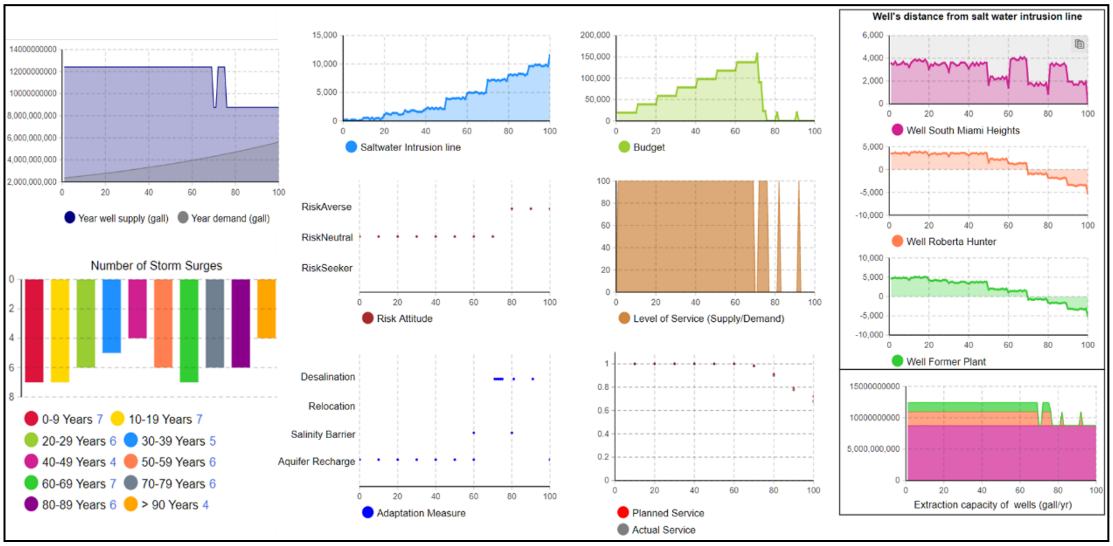

Figure 4-7. Simulation Output Interface

4.6.2. Face Validation

To further ensure the model credibility and defensibility, an iterative participatory face validation was conducted by institutional agencies involved in adaptation processes in the case study region. Face validation is conducted by having users and people knowledgeable with the system examine the model logics and outputs for rationality. Per Carson (2002), a simulation model that has face validity appears to be a "reasonable imitation of a real-world system to people who are knowledgeable of the real-world system." Therefore, the simulation model, its components, and the preliminary results were presented to four verified subject matter experts (SMEs) who are specialist and seasoned in the area of coastal water infrastructure adaptation and resilience. The SMEs involved in the validation process were from different affiliations that are partners of the Resilient Utility Coalition (RUC). The RUC provides leadership in assessing utility operations to address the potential effects of climate change. The RUC seeks to enhance the usefulness of climate science by developing adaptation strategies and improving water management decision-making in the face of climate uncertainty. Table 4-3 provides information of the SMEs participated in the face validation process.

Table 4-3. Information of SMEs in Face Validation Process

SME	Role/Position	Background	Sector	Years of Experience
1	Hydrogeologist and Professor	Hydrogeology	Public Agency	26
2	Hydrogeologist	Geosciences	Public Agency	17
3	Water Resource Manager	Water Resources and Environmental Engineering	Public Agency	15
4	Water Engineer	Civil Engineering	Consulting Firm	6
5	Water Resources Resilience Lead	Civil Engineering	Consulting Firm	12

After each presentation, the SME was asked to evaluate the simulation model elements including conceptual model, computational model, data, and outputs. To this end, a questionnaire survey was completed by the SMEs to evaluate different features of the model (Table 4-4) on a scale of 1 to 5, in which 1 and 5 respectively represented the lowest and highest levels of validity and quality. As shown in Table 4-4, on average, the SMEs evaluated the simulation model with scores above 4. Based on these evaluations, all the SMEs asserted that the behavior of the model is consistent with the real world and the relationships between different components of the model are realistic. They also indicated that the simulation and visualization component of the model provides a useful tool for scenario analysis and decision making in the assessment of coastal water supply infrastructure adaptation and resilience under the impacts of SLR. In addition, some insightful inputs, constructive comments, and minor modifications were suggested by the SMEs and were accordingly addressed on the simulation model.

Table 4-4. Face Validation Results

Component	Model Features	Average Score
Conceptual Model Validity	The components of the model represent the most important features of the system.	4.5
	The behavior of the components of the model is reasonable.	4.5
Computational Model Validity	The model explains the dynamics of the system.	4.5
	The theories and assumptions underlying the model are correct.	4.5
	The model's representation of the system and the model's structure, logic, and mathematical and causal relationships are reasonable.	4.5
Data Validity	The assumptions regarding model's parameters, variables, interactions and decision rules are reasonable.	4
	The level of detail and the relationships used for the model are appropriate for the intended purpose.	4
Output Validity	The output of the simulation model has the accuracy required for the model's intended purpose.	4
	The model could be helpful in the domain of its applicability.	4.5

4.7. Simulation Experiments

After verification and validation, the simulation model was used for experiment design and analysis. Various possible scenarios were determined based on changing the values of input parameters into the model (Figure 4-8). Each of the two planning strategies, adaptive and reactive, was analyzed across different scenarios. Details related to which parameters were used in devising scenarios are presented in Table 4-5. Through the combination of various values of the input parameters, 10,692 and 4,158 scenarios were generated for adaptive and reactive strategies, respectively. For instance, the combinations of the adaptive planning scenarios reflect changes in the actual SLR and SWI as well as in the agency's initial risk attitude, available capital funding, decision interval, and SWI proximity threshold.

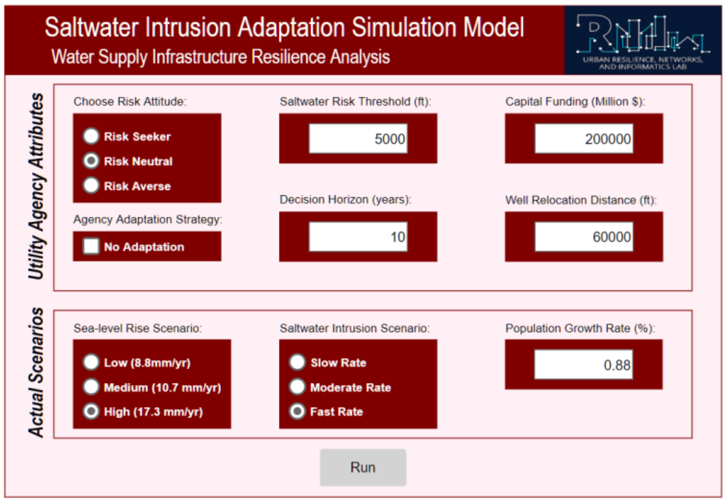

Figure 4-8. Input Dashboard of the Simulation Model

Table 4-5. Variation of Values of Input Parameters for Scenario Setting

Approach	Input Parameter	Parameter Values	Number of Scenarios
Adaptive	Actual SLR	Low; Medium; High	3
	Actual SWI	Slow; Moderate; Fast	3
	Initial Risk Attitude	Risk Averse; Risk Neutral; Risk Seeker	3
	Capital Funding ($ million)	0; 500, 1000; 1500; 2000; 2500; 3000; 3500; 4000; 4500; 5000	11
	Decision Interval (year)	5; 10; 15; 20; 25; 30; 35; 40; 45	9
	Proximity Threshold (ft)	100; 1000; 2000; 3000	4
	Total Scenarios		10,692
Reactive	Actual SLR	Low; Medium; High	3
	Actual SWI	Slow; Moderate; Fast	3
	Capital Funding ($ million)	0; 200, 400; 600; 800; 1000; 1200; 1400; 1600; 1800; 2000; 3000; 4000; 5000	14
	Well Relocation Distance (ft)	500; 1000; 2000; 3000; 4000; 5000; 6000; 7000; 8000; 9000; 10000	11
	Well Relocation Limits	0; 1; 2	3
	Total Scenarios		4,158

Due to the stochastic nature of the simulation model, a Monte-Carlo experiment was conducted for each specific scenario to determine the mean value of the model output variable. The main output variable targeted in this study was the system long-term resilience index (LRI). Each experiment was replicated as many times as the mean value of LRI reached 95% confidence interval.

4.8. Results and Discussion

The simulated output data (i.e., LRI) obtained from the experiment scenarios were used through statistical methods for exploratory analysis of long-term resilience in coastal water supply infrastructure systems (CWSIS) under the coupled impacts of saltwater intrusion and utility agency decision-making processes. The exploratory analysis results are threefold: (i) assessing the significance of underlying determinants of long-term resilience in hazards-humans-infrastructure nexus; (ii) comparing the effectiveness of adaptive and reactive approaches; and (iii) determining the characteristics of robust adaptation decision-making.

4.8.1. Resilience Determinants

The first set of analyses focused on analyzing the scenario landscape to identify the most significant determinants of long-term performance of water supply infrastructure in the study region. To this end, Chi-square Automatic Interaction Detection (CHAID) technique was used for explaining the impact of different system attributes as well as for generating various scenario pathways (i.e., the combination of various attributes leading to a certain outcome). CHAID is a non-parametric data-mining tool used to discover the relationship between variables. Its algorithm incorporates a sequential merge and split procedure based on a chi-square test statistic (Kass G.V 1980). CHAID analysis builds a meta-model to help determine how variables best merge to explain the outcome in the given dependent variable (Magidson and Vermunt 2005). Therefore, CHAID technique was used to identify, among a number of variables, the most important variables in determining the outcome variable (i.e., LRI). Figure 4-9 shows the importance level of different exploratory variables in the simulation model and their effect on the LRI of the CWSIS under adaptive and reactive planning strategies.

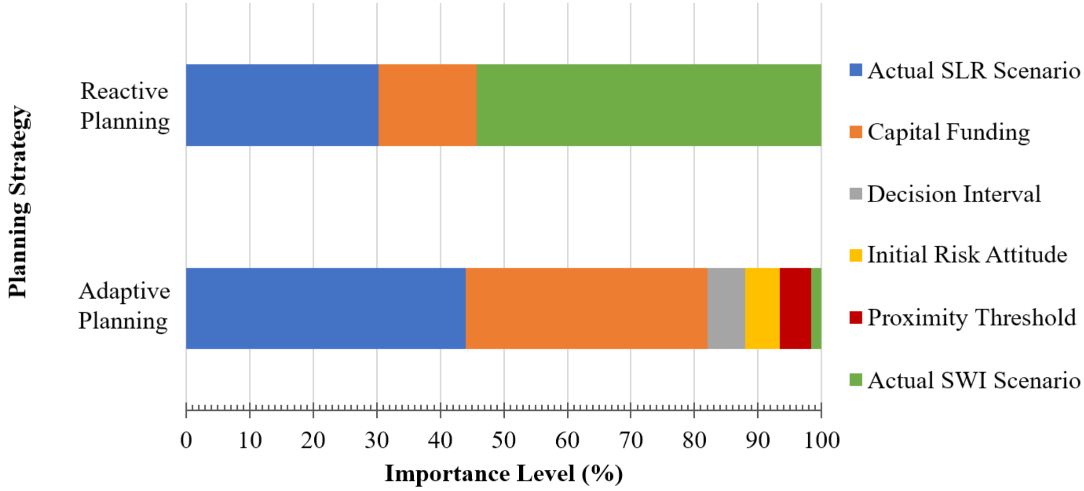

Figure 4-9. Importance Level of Exploratory Variables in LRI Determination

The results presented in Figure 4-9 show that, in reactive approach, the top two determinants of the system LRI were actual SWI and actual SLR. However, under adaptive planning strategy, the top two determinants were actual SLR and capital funding level. Thus, overall, the hazard (i.e., SLR and SWI) was the most significant determinant of the system LRI in both adaptive and reactive approaches. This means that, regardless of the decision-making factors and behavioral attributes of the utility agency, the climatic hazards would significantly influence the long-term resilience in CWSIS. Nevertheless, the adaptive planning strategy was shown to be able to considerably reduce the influence of actual SWI on LRI. This is because, under adaptive planning, the utility agency is able to update the information and make adaptive decisions according to observations of SWI rates and hence select appropriate adaptation actions to mitigate the SWI impacts.

4.8.2. Adaptive vs. Reactive Approach

The second set of analyses examined the effectiveness of adaptation planning approach in enhancing the long-term resilience of CWSIS. The simulated LRI obtained from thousands of scenarios were used to compare the system performance under adaptive and reactive approaches. Using the chi-square goodness of fit test, the best probability distributions were fitted to the simulated LRI values resultant of various scenarios under adaptive and reactive strategies (Figure 4-10). The best probability distribution fitted for LRI values for reactive approach scenarios was Triangular distribution. This is mainly because, under this strategy, the key drivers of LRI were SWI and SLR, which both had three possible values (e.g., slow, moderate, and fast SWI). This result further confirms that in reactive approach, the variables related to climatic hazards are dominant factors influencing LRI. However, the best probability distribution fitted for LRI values under adaptive planning scenarios was Extreme Value Distribution which belongs to the Exponential family (e.g., Normal, Weibull). This type of distribution is frequently encountered in the context of lifetime reliability modeling; this type of probability distribution demonstrates that failures in system LRI could be controlled when adaptation planning was implemented.

As shown in Figure 4-10, the probability of achieving greater LRI in the system varies in adaptive and reactive approaches. The likelihood of achieving LRI greater than 90 is about 94% under adaptive planning approach and 20% under reactive approach. Also, under the reactive strategy, there is a likelihood of 48% that the system LRI would drop below 80; however, this likelihood is about zero in adaptive planning scenarios. Thus, the results show that, if the utility agency implements adaptation actions (i.e., adaptive planning strategy), the chance that the system will achieve a greater LRI is significantly greater than when the agency follows a reactive approach.

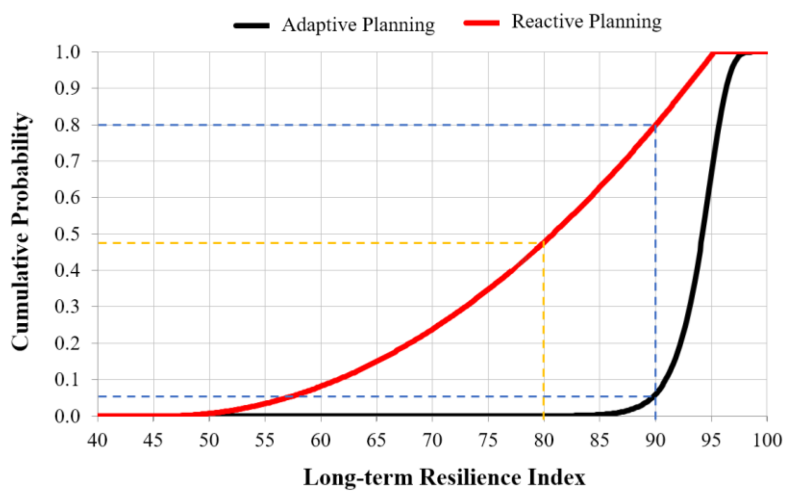

Figure 4-10. System LRI Probability Distribution under Adaptive and Reactive Approaches

As the CHAID analysis results suggested, the level of capital funding was one of the influential determinants of LRI (especially in adaptive planning). Hence, further analysis was conducted to specify the sensitivity and effectiveness of adaptive and reactive approached under different levels of capital funding. Figure 13 depicts the impact of capital funding on the system LRI under various SLR scenarios in the adaptive approach versus the reactive approach. The results presented in Figure 11, first, indicate that the capital funding does not impact the system LRI if low SLR happens; however, the level of capital funding is considerably influential under high SLR. Hence, by increasing the capital funding level, the system LRI could improve under high SLR.

In addition, Figure 4-11demonstrates that there is a critical level of capital funding required to mitigate the impact of high SLR in both adaptive and reactive approaches. Critical capital funding levels are the tipping points after which the system LRI is no longer improved by increasing the capital funding. As shown in Figure 4-11, if a reactive strategy is implemented (upper figure), the capital funding of $1200 million (which is for the entire 100 years and equals to $120 per capita per year) would mitigate the impact imposed by high SLR and would lead to LRI of higher than 85 in average. However, under the adaptive planning strategy (lower figure), the critical level of capital funding that mitigates the impact of high SLR is $2000 million. This amount of capital fund, which is equal to $200 per capita per year, would yield an average LRI above 90 in the system.

Although the critical level of capital funding in reactive strategy is 40% less than the one in adaptive planning, the results indicate that the adaptive planning is more effective due to the following reasons. First, under adaptive planning, the critical capital funding can fully cover the LRI gap induced by SLR uncertainty (the gap is defined as the difference of average LRI under high SLR than average LRI under low SLR). However, the reactive approach is not able to fully mitigate this gap. As shown on Figure 4-11, under the critical level of capital funding (or any amount above that) in reactive approach, there is a gap between the LRI under high SLR and the LRI under low and medium SLR. However, this gap does not exist in adaptive planning where the system can maintain its LRI under high SLR at the same level as low and medium SLR. Second, under lower levels of capital funding (for example, $600 million), the adaptive planning strategy enables achieving greater LRI in comparison with the reactive strategy. Therefore, if the utility agency encounters funding constraints, the adaptive planning approach is more effective as it would lead to greater LRI.

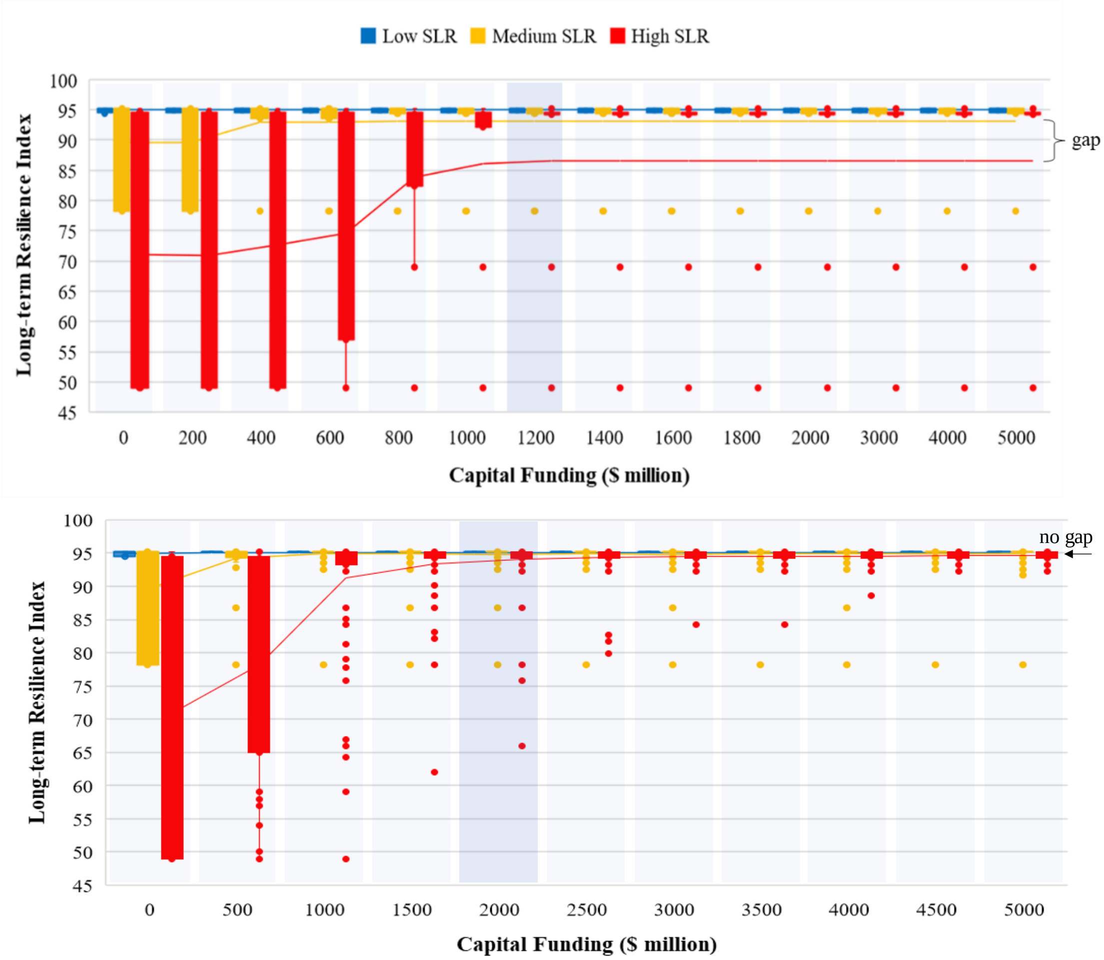

Figure 4-11. System LRI under Different Capital Funding Levels in Reactive Approach (Upper Figure) and Adaptive Approach (Lower Figure)

4.8.3. Characteristics of Robust Adaptation Planning

The third set of analyses evaluated different adaptation decision-making attributes of the utility agency to better understand the characteristics of adaptation pathways that yield in improved long-term resilience of CWSIS. One of these characteristics is the *risk attitude* of utility agencies. Although in adaptive planning approach, the agency was able to update its risk attitude based on observation of the actual SWI happened in the past, the influence of the initial risk attitude on the system LRI was examined. Figure 4-12 shows the influence of initial risk attitude under different SLR scenarios given the critical level of capital funding is available. The results presented in Figure 4-12 indicate that the initial risk attitude of the agency was not influential on changing the system LRI (especially under low and medium SLR). Even under high SLR, the risk-averse attitude improved the LRI very slightly (less than 1 unit). This is because the agency was able to update its risk attitude through the adaptive decision-making process in which periodic updates made at certain decision points throughout the entire period of capital plan. Therefore, the flexibility to adjust upon the updated information mitigates the influence of the agency's initial risk attitude (which might not be a right attitude for planning) on the effectiveness of adaptation pathways.

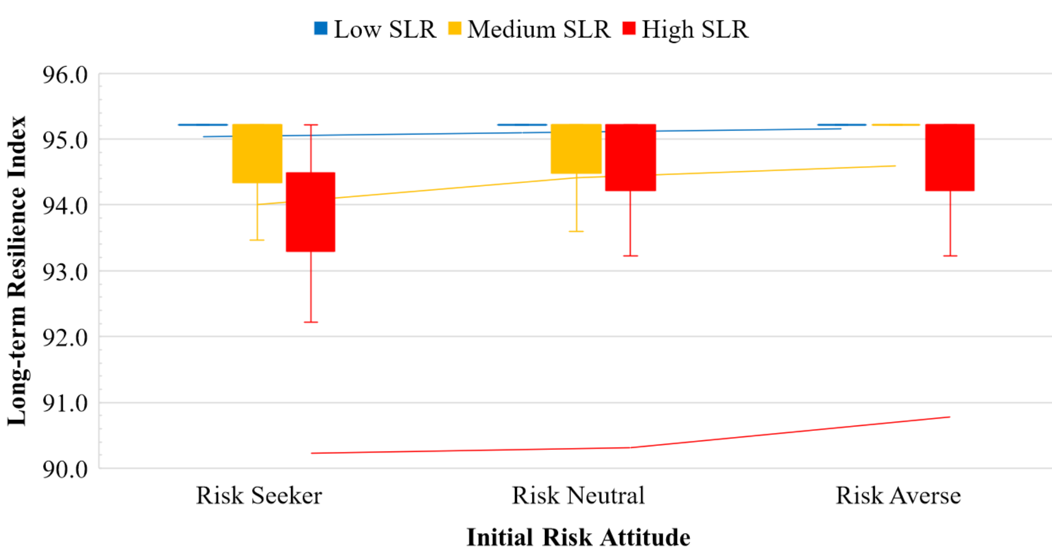

Figure 4-12. Influence of Initial Risk Attitudes on LRI in Adaptation Planning

Another characteristic examined in this study is the duration of decision intervals in adaptation planning. In capital adaptation planning, the entire period of capital plan is divided into a number of decision intervals at which investment decisions are made and implemented. Figure 4-13 depicts the influence of the duration of decision intervals on the system LRI under various ranges of available capital fund (CF). The results show that the duration of decision intervals can be influential when the available capital funding is low (less than $1000 million). When funding is not sufficient, shorter durations (i.e., less than 10 years) would result in decreased LRI in the system; however longer decision intervals (especially 35 years) can result in greater LRI. Since the capital fund is divided equally between decision intervals (based on Equation 48), when a short-term decision interval is followed, the available budget might not be sufficient to implement the selected adaptation measure. In addition, through shorter decision intervals, the agency might not have complete information in selection of right adaptation actions at the earlier decision intervals (it takes time for the agency to observe and obtain updated information on the actual trend of hazards in the past). On the other hand, due to the great deal of uncertainty associated with SLR projections and SWI rates, longer decision intervals (i.e., longer than 45 years) increase the value at risk (VAR) of the capital investment (Batouli and Mostafavi 2018a; Jorion 2000). Thus, the results presented in Figure 4-13 alongside the findings of previous studies (e.g., Batouli and Mostafavi 2018; Jorion 2000) suggest that there is an optimum duration of decision intervals in capital adaptation planning that leads to robust adaptation pathways under insufficient funding.

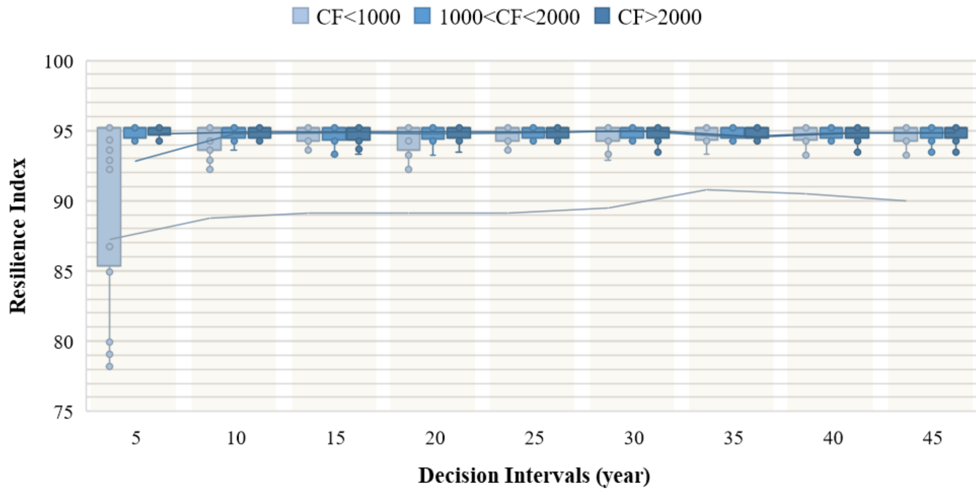

Figure 4-13. Influence of Adaptation Decision Intervals on LRI

The last characteristic evaluated in this study refers to signposts and triggers in adaptation decision-making. In the context of this study, the distance of SWI from wellfields is the signpost based on which the adaptation implementation is determined. The SWI proximity threshold that the agency sets for taking an adaptation action (defined and used in Equation 41) is referred to as a trigger value. Figure 4-14 shows the influence of trigger values (i.e., proximity thresholds) on the system LRI under different decision intervals when the actual SLR is high and sufficient funding is available. The results presented in Figure 4-14 imply that LRI is influenced by the utility agency's proximity threshold. If shorter decision intervals (i.e., less than 10 years) are followed for any reason, smaller proximity thresholds (i.e., less than 1000 ft) would result in improved LRI in the system. Therefore, the smaller proximity thresholds are effective triggers for the implementation of adaptation decisions under short decision intervals and can contribute to the adaptation pathways to yield greater resilience in the system.

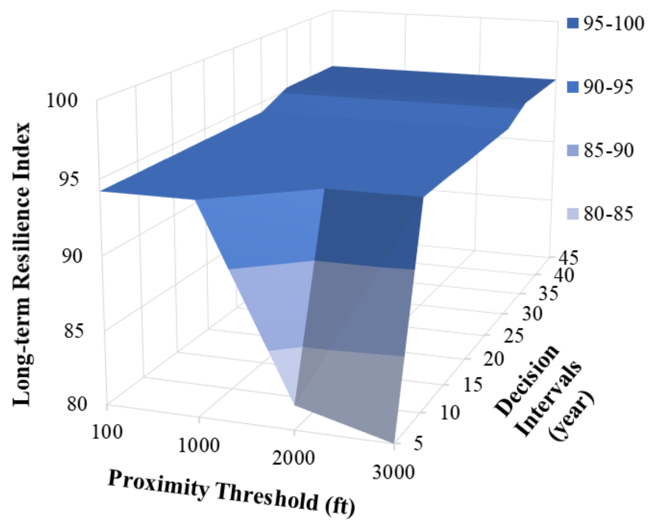

Figure 4-14. Influence of SWI Proximity Threshold on LRI in Adaptation Planning

4.9. Concluding Remarks

The results showed the feasibility and value of the proposed framework and simulation model in integrating various climatic hazard scenarios, human decisions, and infrastructure elements in order to examine the characteristics of robust adaptation planning and long-term resilience in CWSIS. This study discovered fundamental decision-making attributes and risk response behaviors affecting the adaptation decision-making processes of utility agencies in response to coastal hazards. This information is essential in understanding the dynamics of hazards-humans-infrastructure nexus that shape the resilience landscape of CWSIS, and performs as the foundation for modeling and simulating the dynamics of coupled human-infrastructure system of water supply in response to coastal hazards. In addition, identification or estimation of the critical values and tipping points in adaptive pathways has important implications for policy formulation pertaining to the effectiveness of adaptation investments in CWSIS. This study's resultant insights provide actionable scientific information to coastal water infrastructure mangers, planners and decision-makers to enhance their adaptation planning and investment decision-making processes.

This study contributes to the body of knowledge by developing theoretical, computational, and practical foundations needed for assessing the economic, environmental, and social value of SWI adaptation strategies. From a theoretical perspective, this study characterized underlying mechanisms of hazards-humans-infrastructure interactions for a more advanced formulating of robust adaptation decisions and a better understanding of long-term resilience in CWSIS. In terms of computational contribution, based on the abstracted behaviors and interactions among hazards-humans-infrastructure nexus, a computational simulation model was developed that captures the coupled impacts of SLR-induced hazards and adaptation planning processes on the long-term resilience of water supply infrastructures. Practically speaking, this study contributes to more informed decision-making for adaptive design, operation, and management of CWSIS by exploring strategies and indicators that improve the long-term performance of water supply infrastructure under the impacts of SWI. In particular, the outcomes of this study can be disseminated to decision-makers and city planners in Miami-Dade County as they develop adaptation and mitigation plans to improve long-term infrastructure resilience in the aftermath of the recent catastrophic Irma.

One limitation of this research was lack of consideration of the impact of overexploitation of the freshwater aquifers on the movement of salinity interface. Previous studies (e.g., Walsh and Price 2010) have shown that lowering the water head due to intensive groundwater extractions has a significant impact on SWI rates in coastal areas. However, the impact of excessive interaction under different demand scenarios was not captured in the current model. Also, demographic studies (e.g. Neumann et al. 2015) as well as the United Nations Environment Program (UNEP) predict that the percentage of the nearshore population will increase from 60% to 75% in the future, which might lead to an increased extractions from freshwater aquifers (Kalaoun et al. 2016). Therefore, future research should also explore demand-side adaptation solutions, such as household-level adoption of water conservation technology (Rasoulkhani et al. 2017a), to reduce water demands in order to enhance the resilience of water supply infrastructures in coastal communities.

5. UNDERSTANDING FUNDAMENTAL PHENOMENA AFFECTING THE WATER CONSERVATION TECHNOLOGY ADOPTION OF RESIDENTIAL CONSUMERS USING AGENT-BASED MODELING **

The objective of this study is to understand fundamental phenomena affecting the water conservation technology adoption of residential consumers using agent-based modeling. More than one billion people will face water scarcity within the next ten years due to climate change and unsustainable water usage, and this number is only expected to grow exponentially in the future. At current water use rates, supply-side demand management is no longer an effective way to combat water scarcity. Instead, many municipalities and water agencies are looking to demand-side solutions to prevent major water loss. While changing conservation behavior is one demand-based strategy, there is a growing movement toward the adoption of water conservation technology as a way to solve water resource depletion. Installing technology into one's household requires additional costs and motivation, creating a gap between the overall potential households that could adopt this technology, and how many actually do. This study identified and modeled a variety of demographic and household characteristics, social network influence, and external factors such as water price and rebate policy to see their effect on residential water conservation technology adoption. Using Agent-based Modeling and data obtained from the City of Miami Beach, the coupled effects of these factors were evaluated to examine the effectiveness of different pathways

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towards the adoption of more water conservation technologies. The results showed that income growth and water pricing structure, more so than any of the demographic or building characteristics, impacted household adoption of water conservation technologies. The results also revealed that the effectiveness of rebate programs depends on conservation technology cost and the affluence of the community. Rebate allocation did influence expensive technology adoption, with the potential to increase the adoption rate by 50%. Additionally, social network connections were shown to have an impact on the rate of adoption independent of price strategy or rebate status. These findings will lead the way for municipalities and other water agencies to more strategically implement interventions to encourage household technology adoption based on the characteristics of their communities.

5.1. Introduction

Water is undeniably necessary, supporting 7.4 billion people and over 8.7 billion species of life. However, the growing human population and consequences of climate change have created widespread water scarcity that is only expected to worsen in the coming decades. By 2025, 1.8 billion people around the globe will face water scarcity (UN Water 2012). Beyond damaging an individual's quality of life, water scarcity also negatively impacts ecosystem health and political and social stability (Postel 2000). Climate change adds further pressure to water resources, and government officials and policy advocates have taken two different approaches to address growing water concerns: supply-side management and demand-side management (Butler and Memon 2006). Supply-side management focuses more on increasing the availability of water through the development and renewal of water infrastructure systems and identifying new water sources (Kanta and Zechman 2014). This encompasses the creation of reservoirs, water pumps, and irrigation systems to continue to have adequate water supplies. Supply-side solutions have been effective historically; however, it does not influence water use patterns of the consumer, which is the next necessary step in managing demand growth (Kanta and Zechman 2014). Demand-side management is based on the idea that lowering a household's (or other users') usage for water will subsequently reduce water demand. While implementing demand-side management to govern a typically inelastic good is controversial among economists and planners, it has been shown in many studies to be effective in alleviating water scarcity (Chen et al. 2005; Inman and Jeffrey 2006; Renwick and Green2 2000; White and Fane 2002). (Inman and Jeffrey 2006) reviewed different demand-side management tools and explored their potential and effectiveness to save water under varying conditions in developed countries.

At its core, reducing residential water demand can be done by changing behavior or technology (Inman and Jeffrey 2006). Changing someone's behavior, according to (Gilg and Barr 2006; de Young 1993), is a process including incentives and disincentives, the modeling of behaviors, education, and persuasive communication. These techniques work best with mostly-engaged audiences, are adopted infrequently, and are less likely to save water if people do not trust the water authorities (Jorgensen et al. 2009). Despite all of the multifaceted approaches, changing behavior tends to pan out only in the short term while the comprehensive installation of water-efficient appliances in households has been shown to reduce indoor consumption by 35%–50% (Inman and Jeffrey 2006). Change in technology is meant to curb the problems with behavior conservation changes by erecting a more permanent fixture for conservation. In a report of California's water scarcity, (Gleick et al. 2003) found that one-third of the state's water usage could be saved with existing conservation technology. This total equates to more than 2.3 million acre-feet of water. As technology improves, as it has drastically since this report was written in 2003, water savings will only become more prominent. The dire state of water scarcity has diminished the sufficiency of supply-side management. It will eventually become too difficult to track down additional water sources, or there will simply be no more water left to find. Because of this, more research is needed on demand-side approaches. Additionally, although there are two parts to demand-side water management, change in technology will be the most permanent, applicable method heading into the coming decades (Lee and Tansel 2013). Change in behavior is typically ephemeral, while technology is more easily maintained through water policy adoption. However, technology's impact on policy implementation and household adoption patterns still needs to be specified and characterized. Governmental rebate availability, demographic and household characteristics, and external factors are variables that can cause different adoption patterns. Additional costs or potential savings of technology adoption can also be highly variable (Baumann 1983; Dolnicar et al. 2012; Po et al. 2003). In addition, the role of "word of mouth" through social network interactions has been shown to be influential to the adoption processes (Bandiera and Rasul 2006). While some of these influential factors have been researched to promote policy change and growth, there is a deficiency in the existing literature as to how they all intersect and challenge water conservation technology adoption.

To mitigate water scarcity, understanding why—and to what extent—households adopt conservation technology based on the demographic and household characteristic, social interactions, technology cost, water price and other factors is crucial. To this end, the study presented in this paper aimed to investigate the underlying factors and behaviors affecting water technology adoption of residential consumers through the use of Agent-based Modeling (ABM).

In the agent-based model of the current study, households are agents categorized into the three adoption states of non-adopter, potential adopter, and adopter, based on the theory of innovation diffusion (Lee et al. 2011b). The transition of agents between non-adopter and potential adopter is driven by the adoption utility of households, which is determined by their demographic and household characteristics (Boyer et al. 2015). Another mechanism triggering this transition is social interactions which influence households' adoption decision-making based on the theory of peer effect (Friedkin 2001). In addition, per the theory of affordability, if the adoption of a new technology is economically affordable for households (Chu et al. 2009), they would adopt it and thus transition from the potential adopter state to the adopter state.

Unlike studies that focus on residential water use behaviors (Chu et al. 2009), conservation technology effectiveness (Cahill et al. 2013; DeOreo et al. 2011), and demand projection (Athanasiadis et al. 2005; Koutiva and Makropoulos 2016), the current study investigated how changes in different mechanisms (such as water price structure) can affect the adoption rate of conservation technology (rather than residential water demand). Hence, the outputs of the ABM developed in this study are the number and type of adopted water conservation technologies under the influence of various factors (e.g., socio-demographic characteristics, social networks, and water policies). In fact, the outcomes of the model developed in this study can supplement the information from residential water demand projection models in order to incorporate the effects of water conservation technology adoption in projecting future demands under various scenarios.

5.2. Background

Despite there being an immediate need for households to begin conserving water, there is limited knowledge within the scientific community on the reasons people adopt water conservation practices in the first place. Water conservation encompasses both behavioral conservation as well as technology adoption. Because the scope of water conservation is so vast, with both behavioral and technological possibilities, this study focused on water conservation technology adoption conservation as a means of resolving problems with water scarcity. More specifically, we plan to examine the underlying mechanism affecting a household's willingness to adopt water conservation technologies.

Most of the recent literature on residential water conservation management and technology adoption incorporate some of the following features: *water conservation affordability, water price and incentives, education and demographics, household/building attributes,* and *social network influence*. In the following sub-sections, some of the studies on residential water conservation and technology adoption were used for identifying various influencing mechanisms and factors. Although recent studies in this field have contributed thoroughly to water management and the understandings of household influence on water conservation technology, there is currently little to no research assessing all of these mechanisms and factors at once. The remainder of this section summarizes the various mechanisms and factors affecting the water conservation technology adoption of households.

5.2.1. Water Conservation Affordability

Public acceptance of water conservation technology adoption is integral, but also highly variable (Baumann 1983; Po et al. 2003). The characteristics that influence the potential installation of water conservation technologies are not fully understood. According to (Po et al. 2003), cost is one of the largest deterrents or motivations of adopting water-saving technologies. The more expensive a technology, the less likely a household will install it. Income level plays a similar role in influencing the public perception of water-saving technology adoption (Young 1973). (Lutzenhiser 1993) claims that higher-income households are more willing to adopt technologies. Those with less income, conversely, may simply struggle to afford new technologies.

5.2.2. Water Price and Incentives

Directly reflecting cost and income, external factors such as water pricing and rebate programs play a role in water-saving technology adoption (Inman and Jeffrey 2006). In a study of 13 California cities, it was found that certain price-based deterrents of water consumption were more influential on conservation than installing water—saving technology (Olmstead and Stavins 2009). The higher the price of water, the less technology one would adopt; conversely, the lower the price of water, the more technology one would install (Olmstead and Stavins 2009). (Inman and Jeffrey 2006) argue that the comprehensive adoption of water conservation technologies can only be implemented by setting effective regulation and incentives. This sentiment is echoed by another study, which supports the implementation of rebate programs particularly for showerheads and cloth washers (Willis et al. 2013). However, in older studies, government control and assistance were regarded as counterproductive, which caused more grief than environmental pay-off (Lynne et al. 1995). (Stern et al. 1986) assert that households avoid government programs because they cause increased confusion, provide limited choices, take too much time to install, and do not show the direct conservation effects. To solve this, the greater the financial benefit a government entity or utility employs to encourage water-saving technology adoption, the greater the non-financial resources, such as marketing and education, is needed (Lutzenhiser 1993). While there are conflicting perspectives, it is clear that water pricing and other external factors have potential effects on water conservation technology adoption.

5.2.3. Education and Demographics

Education and awareness can be just as influential as government financial incentives. Education correlates positively with public acceptance of water-conserving practices (Baumann 1983; Corral-Verdugo et al. 2003; Po et al. 2003). The development of a greywater reuse program in Barcelona was considered a success due to its awareness efforts and education (Domenech and Sauri 2010). For water conservation in general, the more knowledge a household has on conservation practices—whether through behavior or technology—the more that household conserved water (Corral-Verdugo et al. 2003). Along with education, researchers have found other demographics that influence a household's willingness to adopt water conservation technology. One example is home ownership status; those who own their home are more likely to consider long-term water conservation solutions such as technology (Millock and Nauges 2010; Perret and Stevens 2006). Gender can also make a small impact; since women are commonly heads-of-households, they are more likely to make water conservation technology decisions (Boyer et al. 2015).

5.2.4. Building Attributes

There are studies that show the specific characteristics of a house itself reflect a particular willingness of the household to adopt water conservation infrastructure. Firstly, the age of a household dictates openness to new technology (Mansur and Olmstead 2012). The newer the home, the more likely it is to already have water-saving infrastructure (Mansur and Olmstead 2012). The household size also influences public perception, for those who live in bigger homes may also incur larger water costs and, thus, feel more obliged to invest in water- and cost-saving technology (Corral-Verdugo et al. 2003). Installing water conservation infrastructure outside the home can also restore water supplies. Households with larger open spaces are more willing to incorporate technology since outdoor areas significantly contribute to water usage (Spulber and Sabbaghi 2012).

5.2.5. Social Network Influence

Recent studies have shown that, both in developing and developed countries, social networks and peer effects are important phenomena in human technology adoption behavior (Bandiera and Rasul 2006; Tran 2013). Individual consumer attitudes are modified over time through social influence and interactions (Ramirez 2013). Contextually, households share information and learn from one another. A head-of-household is likely to adopt water-efficient technology based on interactions with someone who has adopted the technology. Technology adopting families educate others on the benefits of technology through their interactions with it. Intuitively, households are more likely to adopt when they know and are connected to other adopters (Anderson et al. 2014). Through community, people are connected through different means—family, work, neighborhoods. Interactions among households depend on the structure of social networks through which they are connected (Rai and Robinson 2015). Scientifically, however, it is difficult to identify all possible connections based on empirical data (Bandiera and Rasul 2006).

5.3. Significance

Understanding the underlying mechanism of water conservation technology adoption patterns is relevant because water scarcity is becoming a worldwide epidemic. There are two ways conservation can combat this problem: changing conservation behavior and changing conservation technology. While changing conservation behavior has made significant strides in water preservation, it is not the only piece of the puzzle (Gleick et al. 2003). It has been discussed that technology improvement is a quicker and more permanent method (Inman and Jeffrey 2006). However, more research is required to understand the full potential that technology has on water conservation for households. Changing conservation technology in conjunction with behavioral changes can help alleviate water scarcity altogether. As technology improves—as it does every day—there will need to be methods for implementing the technology into households of different demographic, household, and external factors. Households are the agents adopting the technology; therefore, knowing their variability in adoption probability is the next big step in improving the status of drought and water scarcity.

There has yet to be research done that can simultaneously analyze all the demographic, household, external factors (i.e., water pricing structure and rebate policy), and social networks that could influence a household's decision to install water conservation technology. Without this information, government agencies will have no starting point for raising awareness or creating proper policies and regulations to encourage technology adoption. Conservation measures will not be grounded in any knowledge of household influences, making them futile. By focusing on these demographic, household, social and external factors, all aspects of demand-side water management can be evaluated together to solve larger societal and political problems regarding water scarcity and climate change.

5.4. Methodology

To implement this research, a simulation approach was used. The simulation approach enables replicating many various types of populations, while other methods (such as conducting surveys and interviews) can only reflect one particular population at a time (Mostafavi et al. 2018).

According to (Davis et al. 2007), simulation is an effective method for theory development when (i) a theoretical field is new, (ii) the use of empirical data is limited, and (iii) other research methods fail to generate new theories in the field. These traits are consistent with the current study of water conservation technology adoption. The chosen simulation technique for this study is agent-based modeling.

5.4.1. Agent-Based Modeling

Agent-based modeling (ABM) is a powerful modeling technique that focuses on the individual active components of a system (Bonabeau 2002). In ABM, active components (e.g., human entities) are characterized as agents, each with a set of social capabilities and goals, values, and preferences. Agents exist in an environment defined by specific rules/micro-behaviors and can inform or evolve their goals or priorities over time (Gilbert 2008). ABM can account for (1) various rational and behavioral decision-making rules for different agents; and (2) an agent's reactions to other agents' decisions. The use of ABM will enable (1) discovering what factors and micro-behaviors result in technology adoption decisions; (2) juxtapose the preferences of various households with the range of conservation technology alternatives to determine the distribution of expected conservation outcomes; and (3) explore effective intervention strategies to enhance water conservation technology adoption. In addition, the use of ABM will enable the construction of a theoretical space that will include a range of community profiles in terms of demographics, water use, social network structures, and other factors. ABM can replicate many different types of populations, and project diverse, tangible scenarios throughout future years (Fang et al. 2016; Mostafavi et al. 2013).

ABM has been successful in studying complex behaviors, policy analysis in infrastructure systems (Mostafavi et al. 2015; Rasoulkhani et al. 2017b), and water demand management. (Athanasiadis et al. 2005; Galán et al. 2009; Kanta and Zechman 2014) have utilized ABM as a successful tool to analyze water management systems. (Galán et al. 2009) demonstrated that the ABM is a useful methodological approach to dealing with the complexity derived from multiple factors with influence in the domestic water management in emergent metropolitan areas. (Kanta and Zechman 2014) developed an ABM framework for assessing the consumer water demand behavior against different degrees of water supply and water supply systems. Their model incorporated both consumers and policy-makers as agents as they adapted their behaviors to different water supply systems and rainfall patterns. Studies such as these have set a precedent that agent-based modeling is a viable research tool for water use and management issues.

ABM has also been successfully adopted in the evaluation of complex phenomena in human-technical systems such as the adoption of environmentally-friendly technologies (Laciana and Rovere 2011; Rai and Robinson 2015; Schwarz and Ernst 2009; Tran 2013). For example, (Rai and Robinson 2015) developed an agent-based model for the adoption of residential solar photovoltaic (PV) systems. In addition, other studies, such as one conducted by (Tran 2013), showed that ABM can be useful in the simulation of the adoption behavior of innovative energy conservation technologies by capturing the underlying mechanisms affecting the decision-making behaviors of households. In another study, (Schwarz and Ernst 2009) adopted ABM to simulate the technology adoption behaviors related to three water-related innovations among households in Southern Germany. This study demonstrated that ABM enables capturing the effects of various factors and attributes (e.g., geographic attributes, heterogeneous agents, and decision processes).

According to the (Schwarz and Ernst 2009), ABM provides a more realistic model of innovation diffusion in comparison with aggregated models such as the Bass model. (Schwarz and Ernst 2009)'s research evaluated the trends of innovation diffusion under several water strategies and policies by developing an empirically-based ABM. However, their model differs from the one in the current study, in which a theoretically-driven ABM was developed that enables the policymakers to test various intervention strategies to diffuse further water-efficient infrastructure in their application area. In particular, the model in the current study captures the effects of social networks in conjunction with several other socio-demographic factors in understanding household behaviors related to water conservation technology adoption.

In addition, ABM provides a useful tool for conducting exploratory analysis. Exploratory analysis (Bankes 1993; Kwakkel and Pruyt 2013a), utilizes computational models and simulation experiments to conduct scenario analysis and evaluate the behavior of complex systems (Bankes 2002a; Mostafavi et al. 2013). Exploratory analysis has been utilized in different studies (e.g., (Lambert et al. 2004; Mohor et al. 2015)) for the evaluation of environmental policies. Unlike traditional simulation approaches, exploratory analysis does not aim to predict the behavior of a system and does not intend to optimize a system. Instead, exploratory analysis focuses primarily on considering different policy scenarios based on changes in system behavior and future uncertainty. To this end, ABM enables capturing the adaptive behaviors and complex interactions that affect the patterns of behaviors in a phenomenon of interest (Azar and Menassa 2012). Hence, ABM was selected in this study to conduct exploratory analysis on the evaluation of the underlying mechanisms affecting water conservation technology adoption by residential consumers.

5.4.2. Theoretical Framework

The ABM in this study was created based on a number of theoretical elements including the theories of Innovation Diffusion, Peer Effect, and Affordability. Demographic and building characteristics, external factors, and social interactions all play a role in whether or not a household adopts water conservation technology. As discussed in Section 2, there have been many studies that analyze the influence of certain demographic, household, and external factors on water conservation technology adoption in isolation; however, theoretically, all of these attributes have the potential to influence a household's willingness to adopt a conservation technology. To this end, the theory of Innovation Diffusion was adopted to capture the coupled effect of income level, education, ownership status, house age, water pricing regimes, rebate availability, technology cost, and social networks concurrently. Based on Innovation Diffusion Theory (IDT), in adopting new technologies, a population can be divided into three groups: *non-adopters*, *potential adopters*, and *adopters* (Lee et al. 2011b). Non-adopters are individuals who do not consider adopting a new technology. In contrast, potential adopters are individuals who do consider adopting new technologies. Different demographic and household attributes can influence whether an individual is a non-adopter or potential adopter. A potential adopter may become an adopter if the adoption of a technology is economically affordable for it. Based on the similar premise, in this study, households were divided into three categories (i.e., non-adopter, potential adopter, and adopter) in terms of their position for water conservation technology adoption. The transitions of households between these categories depend on their demographic characteristics, household attributes, peer influence, as well as water price and technology price factors. The theoretical framework of these transitions is depicted in Figure 5-1. Different components of the ABM framework are explained in the following section.

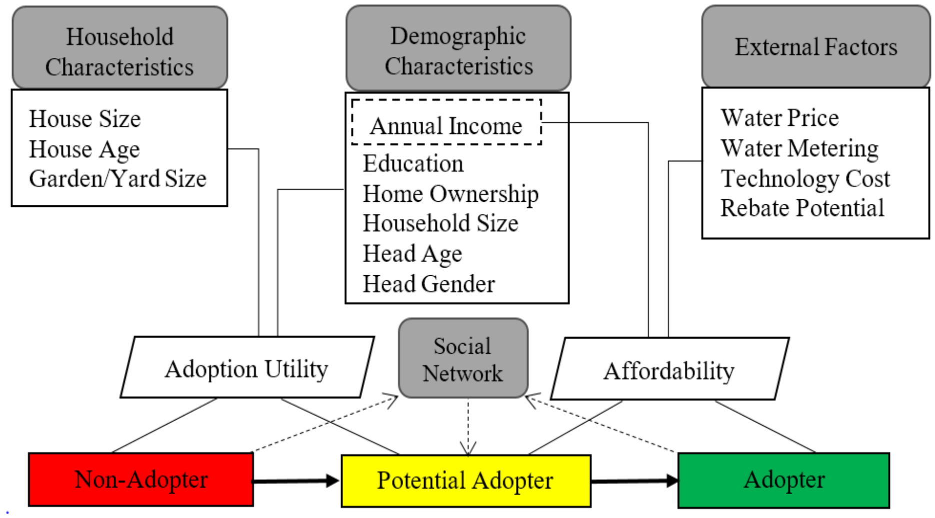

Figure 5-1. The Theoretical Framework for the Simulation

5.4.3. Computational Simulation

The creation of a computational representation for the proposed ABM theoretical framework entails the construction of mathematical models and algorithms to capture the theoretical logic representing the behaviors of households for the adoption of water conservation technology. Anylogic 7.0 was utilized to create a computational ABM. In the ABM framework proposed in this study, an agent (household) is the main target of influence, and the model shows how the agents' behaviors change over a designated period of time. The model incorporates only one agent class, which is the households. The households were divided into three categories (i.e., non-adopter, potential adopter, and adopter), defining their position on water conservation technology adoption. The transitions of households between these categories depend on their demographic and social attributes as well as water price and technology price factors. A household agent, based on its attributes, can transition from one state to another—from non-adopter to potential adopter and from potential adopter to adopter. These transition functions ultimately influence an agent toward or against a particular output. The variables related to the household socio-demographic characteristics, including household income, head education, age and gender, house ownership status, and household size, as well as the household building attributes such as house size and age and garden size, were used to determine one parameter, called Adoption Utility, presented in Equation 54:

$$Adoption\ Utility = \sum_{variable}(Coefficient_{variable} * Value_{variable}) \qquad \textbf{(54)}$$

The variables related to the socio-demographic and building attributes of the households, as well as the coefficients of these variables, were abstracted from the study conducted by (Boyer et al. 2015). The variables and their coefficients are summarized and documented in the Appendix (Table A1). For example, the Adoption Utility of a household whose head is a female college graduate, without other demographics considered, is calculated as follows: $2.91_{education} \times 1_{yes} + 1.21_{gender} \times 1_{female}$. If the utility value is greater than or equal to a user-inputted utility threshold, it then triggers the transition from non-adopter to potential adopter. The threshold indicates a measure of sensitivity. A model user can increase the adoption utility threshold in order to increase the importance placed on the demographic and household characteristics. For this particular model, the lowest possible theoretical threshold is 3000, while the maximum threshold is 60,000. The utility threshold is important because it allows the model to simulate a variety of community profiles. Because the utility value and threshold are based on the demographic characteristics and importance of those characteristics, respectively, variations in the threshold values make it possible to explore a range of community profiles. Communities have varying characteristics (e.g., income, education, or even house size distribution). Through the use of the utility threshold, the difference among communities can be reflected in the analysis.

The function rule that triggers the transition from potential adopter to adopter is based on the *Affordability Theory*. Affordability is defined as the ability of households to pay for their water expenditures (Raftelis 2005). A household's annual water expenditures include the annual water bill plus costs of new water conservation technologies adopted until that year. In this model, household *Affordability Index* is measured by the household's annual water expenditures as a percentage of annual income, as shown in Equation 55 (Chu et al. 2009; Raftelis 2005):

$$Affordability\ Index = 100(B + \sum_T (C_T - R_T) * n_T)/I \tag{55}$$

where, B is the household annual water bill, I is the household annual income, T is the water conservation technology available for adoption, C_T is the average initial cost of purchasing the technology, R_T is the available rebate for the adoption of the technology, and n_T is the number of the technology in the household.

If the Affordability Index of a household agent is less than the user-defined affordability threshold value, the household agent will transition from potential adopter to adopter. If it exceeds the affordability threshold, the adoption of technology is not affordable, and thus the agent will remain as a potential adopter. In other words, a household adopts the offered conservation technologies until the household's Affordability Index exceeds the affordability threshold value. The affordability threshold value is a function of income, water price, and water technology costs. Since water price might be regulated based on the income profile of communities, the affordability threshold can be location-specific. The affordability threshold ranges from 1%–3% according to the studies conducted by the California Department of Public Health, the US Environmental Protection Agency, and United Nations Development Programs (Pacific Institute 2012).

In the affordability measurement process, water price regime is incorporated into the model as an input parameter. Three different water pricing structures were assessed: *fixed price, fixed charge,* and *block prices*. The *fixed price* strategy places a cost on water per unit value. For example, one cubic meter of water costs a household \$1.16. A noteworthy component of this pricing strategy is that the cost directly depends on how much water was used. Conversely, *fixed charge* is a pre-established, flat rate (\$25.25) per month, regardless of how much water was actually consumed. *Block pricing* is similar to fixed pricing in the sense that the unit rate depends on how much water was used—it is a volumetric pricing strategy. However, instead of charging consumers per unit of water with the same rate, block pricing charges households based on the amount of water they consume. Households who typically use more water are charged at a higher rate than those who use less water. More specifically, households using less than 0.65 m^3/day of water will be charged \$0.95 per m^3; households using between 0.65 and 1.5 m^3/day of water will be charged \$1.14 per m^3; and households using more than 1.5 m^3/day of water will be charged \$1.37 per m^3. These water pricing structures are proposed by (Cahill et al. 2013), and the price values are based on the Miami-Dade Water and Sewer Department's rates (MDWSD 2017).

Technology cost was also incorporated into this model as a parameter affecting the affordability index. An agent is able to adopt six main types of water conservation technology: *high-efficiency bathroom faucets, kitchen faucets, shower heads, toilets, washing machines (clothes),* and *dishwashers*. (Cahill et al. 2013) conducted a study on the cost and efficiency of these technologies, which is documented in Table A2 of the Appendix, along with the rebate information that the City of Miami Beach Utility offers for each of these technologies (Miami-Dade County 2016b). Each technology's water-saving capacity is considered a measure of water demand reduction, as the technology is new and more water-efficient. The rebates can affect the technology cost as well—if household agents feel as though they will receive money back, the costs may be perceived as more affordable according to the established affordability index. This, in turn, impacts the model outputs.

Equations (54) and (55) make up the *Adoption Utility* and *Affordability Index*, which define the adoption state of each household agent (i.e., non-adopter, potential adopter, and adopter). There is another phenomenon that can lead a household agent to transition from the non-adopter state to the potential adopter state and that is the *social network influence* from other agents. According to the theory of *Peer Effect*, household agents can have a connection to each other; through this connection between non-adopter and adopter households, non-adopter agents may communicate with adopter agents, and thus get influenced by them into making decisions regarding the adoption of a new technology (Azar and Al Ansari 2017; Friedkin 2001). The model considers and implements five structures of social networks, the description of which are shown in the Appendix (Table A3). Once the model has established a network according to the given structural parameters, it proceeds to simulate the social influence between connected agents. Given a user-defined *likelihood of influence*, if the non-adopter agent is connected to an adopter agent, there is a chance that the non-adopter will transition into the potential adopter state. Further details about social network influence modeling can be found in (Rasoulkhani et al. 2017a).

Figure 5-2 depicts all the transition rules between the three adoption states of the household agents. As shown in Figure 6, each agent, which is in the non-adopter state initially, can become a potential adopter based on its adoption utility or influence from social networks, and then immediately becomes an adopter if the conservation technology is affordable. Hence, it is possible for a non-adopter to become adopter in one time-step of simulation. However, at the same time step, a non-adopter agent should first become a potential adopter before it turns into an adopter. This is because a direct transition from the non-adopter state to the adopter state is not considered in the theory of innovation diffusion.

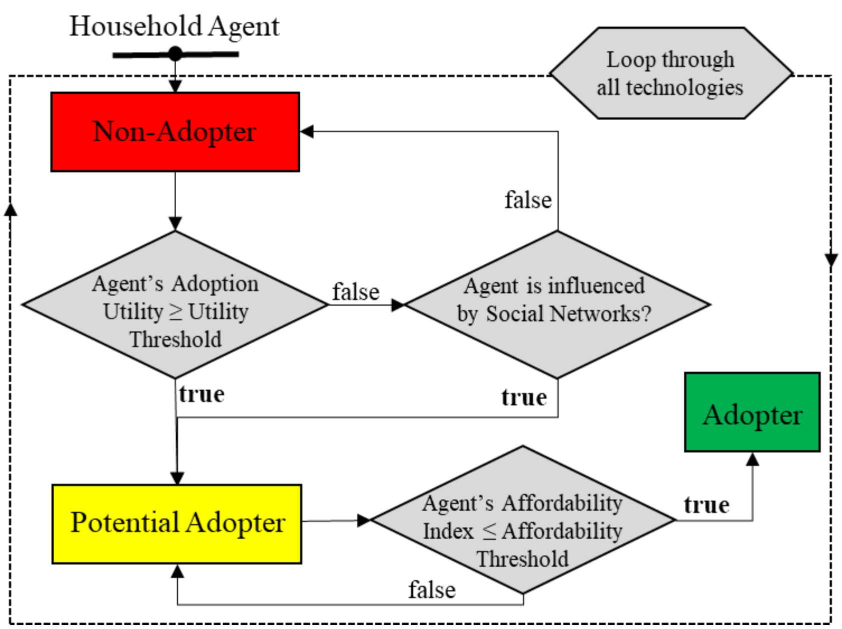

Figure 5-2. The Control-Flow Diagram for Agent Transitions Between Adoption States

Income growth and household size growth were the last attribute input parameters for the model. All of these inputs will generate a number of outputs, which demonstrate the basis of the type and timing of technology adoption by household agents. The simulation model outputs include the annual percentage distribution of all of the adoption states, the water demand reduction, and the different types of technology adopted over the predetermined time period of simulation which is twenty years.

5.4.4. Model Initialization and Implementation

In addition to developing a theoretically-driven ABM of household water conservation technology adoption, empirical data was used as values for initial conditions and model parameters to calibrate the ABM. To this end, data from the City of Miami Beach was used in the implementation of the ABM. The City of Miami Beach has more than ten thousand residential water consumers. To reduce the computational complexity of the model, a sample of 280 households that statistically represent the demographic distribution of the population was randomly selected and divided into three zip codes to be modeled. All 280 agents will start out as non-adopters; and, depending on different influences, will transition to potential adopter or adopter. The model then runs using Census data from these three zip codes, as well as individual household water use data provided by the Miami-Dade Utility. The census data includes information regarding median household income, education, average home ownership and average household size. Since some of the data provided by the Census are only average values, a triangular average distribution was used to assign each household a random value. A uniform distribution was also used to assign the household head age, garden size, and house size in square feet. Values of parameters such as head gender and house age were randomly assigned due to the unavailability of data. Moreover, data related to a household's source of water such as the number of showerheads, toilets, and faucets come from a custom distribution. While the model could have been made with hypothetical inputs not based on reality, utilizing real data helps to convey a better narrative about water technology adoption for future policy-making and regulation.

5.5. Model Verification and Validation

ABMs are often criticized for relying on informal and subjective validation or no validation at all (Berglund 2015). Validating ABMs developed for complex systems using historical data is difficult and infeasible because of the stochastic nature of human-behavior models (Mostafavi et al. 2015). (Schwarz and Ernst 2009) argued that socio-system models cannot be tested for their structure appropriateness in a meaningful way as the interconnections of social processes are vague in the sense that competing theories exist for most phenomena. ABMs are typically validated using internal verification of the features representing the model quality (Azar and Menassa 2014; Mostafavi et al. 2015). The verification of the ABM developed in this study was conducted through a gradual, systemic, and iterative process. The internal validity of the model was ensured through the use of grounded theories for modeling decision and behavioral processes of households. The theoretical and computational models were built rich in causal factors that can be examined to see what leads to particular outcomes. Each component of the model was checked for completeness, coherence, consistency, and correctness (4Cs) based on the performance of the model outputs. For instance, the model performance was verified by (i) taking the function of one component of the model and making sure it influences the outputs to the degree that is specified in the model; and (ii) running the simulation model with extreme values of each component and verifying the functionality of the model under that situation. Most errors that were discovered through verification had less to do with problems within the theories, and more regarding issues with coding correctly. Thus, most errors in the verification process were fixed relatively quickly and smoothly and then the aforementioned four features (4Cs) of the model were ensured. As there are no aggregated independent data available regarding the adoption of such water technologies in various lifestyles (Schwarz and Ernst 2009), the external validity of the ABM was conducted through the comparison of the model outcomes with the findings of other studies in the area of water conservation technology adoption. This technique has been also applied in a study by (Matsumoto 2008) for validating multi-agent models. As shown in Table 5-1, the results of the model reinforce what other studies have already noted. For example, the results of the model showed that the rate of adoption of water conservation technologies under various scenarios can lead to a 3–10% reduction in the overall water demand of the City of Miami Beach. This outcome is consistent with the findings of a study conducted by Lee et al. (2011a) that analyzed the impacts of the water conservation incentives on water demand in Miami-Dade County through surveys among the households. The study reports that about 6–14% water demand reduction was achieved during the implementation of two 4-year water conservation incentive programs in this area.

5.6. Scenario Setting

After the model was verified and validated, it was used for simulation experimentation and scenario setting. Each of the three water price strategies was analyzed based on the simulation model for different combinations of the model input parameters. The possible scenarios were established based on different combinations of the input parameters in the model, shown in Table 5-2. Through the combination of various values of the input parameters, 230 scenarios were generated in total. The combinations of these scenarios reflect changes in water pricing structure, rebate status, income growth, household size growth, utility threshold, affordability threshold, and social network structure. Accordingly, under each specific scenario, 100 runs of Monte-Carlo experiments were conducted to determine the mean value of the output parameters (i.e., the number of adoptions and the resulting water savings). In addition, in order to compare the scenarios equally across the analysis, a base scenario was created as the reference point for the comparison. also shows the values used for the parameters in the base scenario (see the last column).

Table 5-1. The External Validation of the Model Findings

Aspect of Technology Adoption	Findings of the Model	Examples of Other Studies with Similar Findings
Impact of conservation technology adoption on water demand reduction of the service area	Adoption of water conservation technology under various scenarios potentially could lead to a 3%–10% reduction in the overall demand of the City of Miami Beach.	About a 6%–14% reduction in water demand has been observed during the implementation of the water conservation incentives program for the residential consumers in Miami-Dade (Lee et al. 2011a)
Effect of water price strategy	Fixed charge strategy of water pricing, which provides cheaper water for households, led to a greater number of adoptions in the model.	"Pricing structure plays a significant role in influencing price responsiveness" (Espey et al. 1997). The higher the price of water, the less technology one would adopt; conversely, the lower the price of water, the more technology one would install (Olmstead and Stavins 2009).
Effect of rebate and incentives	Rebate allocation in low-income communities could increase the adoption of the expensive water conservation technologies.	Providing incentives such as rebates for retrofitting households with water-efficient technologies have shown mixed results in terms of reducing water use, especially when compared to price-based approaches (Lee and Tansel 2013)
Effect of social networks	Social interactions speeded up the diffusion of water conservation technology. Although the structure of a network was not important in the adoption of technology, it affected the time required for the adoption rate to reach an equilibrium.	"Social network type is not significant in determining mean energy use change, but is when considering the time required the network to reach equilibrium" (Anderson et al. 2014).
Effect of household income level	Income growth mostly influences a household's willingness to adopt water conservation technology.	"We have previously found financial variables to be important supplements to attitude measures in technology adoption modeling" (Lynne et al. 1995).

Table 5-2. The Variation of the Input Parameter Values for the Scenario Setting

Model Input Parameter	Possible Values	Value in Base Scenario
Water pricing structure	Fixed price; fixed charge; block prices	Fixed price
Rebate status	Rebate; no rebate	No rebate
Income growth (%)	−5; −4; −3; −2; −1; 0; 1; 2; 3; 4; 5	0
Household size growth (%)	−5; −4; −3; −2; −1; 0; 1; 2; 3; 4; 5	0
Utility threshold	10,000; 20,000; 30,000; 40,000; 50,000	30,000
Affordability threshold (%)	1, 1.5, 2, 2.5, 3	1.5
Social network structure	Random (N = 1); distance−based (R = 100); ring lattice (N = 1); scale−free (M = 1); small−world (N = 1, P = 0.1)	Random (N = 1)

5.7. Results and Discussion

Using the developed agent−based model, the scenario analyses of the simulated data were conducted in order to specify the effects of different factors on the water conservation technology adoption of households. Due to the stochastic nature of the simulation model, the 100 experiments related to each scenario led to varying outcomes, from which the mean value of percent adopter, number of adopted technologies, and overall demand reduction were abstracted and recorded. The results and corresponding discussions were formulated using three different forms of analysis as explained below.

5.7.1. Socioeconomic Scenario Analysis

Trend analysis across the various generated scenarios of income growth, water pricing strategy, rebate program, and utility threshold showed how much water households saved, how many households adopted, and which technologies were adopted under each scenario. Of these scenarios, certain trends regarding overall demand reduction—due to adoption of the technologies—were discerned and documented in Figure 7. The amount of residential water demand reduction due to the adoption of conservation technology was calculated based on the number and type of technologies adopted over the simulation period (i.e., 20 years). This study did not consider the behavioral aspects related to water conservation. The calculated residential water saving potential is only based on the adoption of conservation technologies. If the water conservation behaviors of the users are considered, the potential for residential water saving could be even more significant. Among the three water price strategies, the fixed charge strategy led to a more overall demand reduction. As shown in Figure 5-3, allocating rebates could increase its enhancement by 24% (4 m^3/day). The strategy of fixed charge with rebate resulted in a total of 8−12 m^3/day water savings more than the strategy of fixed price without rebate in various income growth rates. This amount means about 46%−72% increase in the overall residential water demand reduction amount. In Figure 5-3, for all water price strategies and rebate status, as the income increased, there was an exponential increase in overall water demand reduction after adoption of new and efficient technologies.

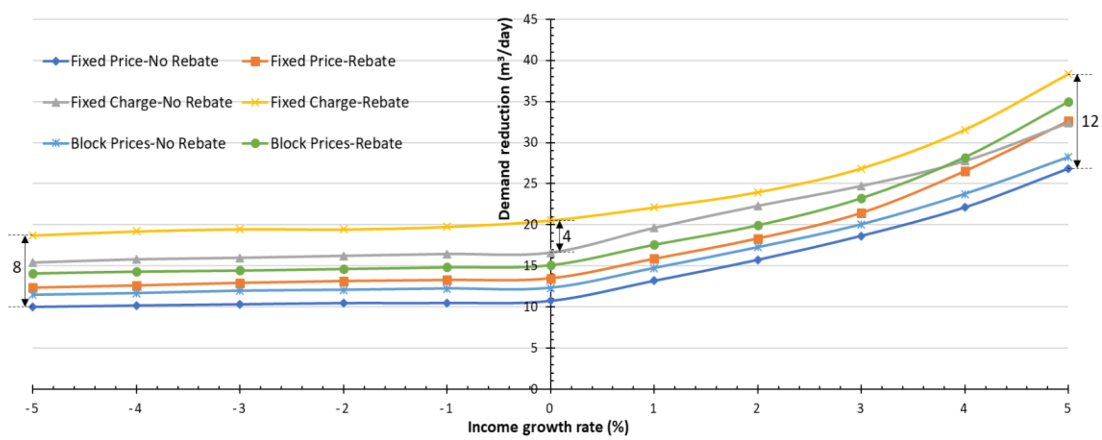

Figure 5-3. The Modeling Trends in the Overall Daily Water Demand Reduction

Although increased income led to more water savings derived by the adoption of conservation technologies, it might also lead to higher per capita water usage because higher-income households were shown to consume more water than lower-income households (Willis et al. 2013). Hence, the relationship between water usage, the adoption of water conservation technologies, and income is complex. Therefore, the number of technologies adopted were also accounted for in this study, and brought about interesting insights.

Figure 5-4a shows an exponential trend in the total adoption number of expensive technologies (i.e., toilet, washing machine, and dishwasher) under various water pricing structures and rebate programs. It was discovered that with rebate allocation, the total number of expensive technology adoptions increased by almost 50% regardless of water price strategy or income growth. In Figure 5-4b, the adoption of inexpensive technologies (i.e., kitchen and bathroom faucet and showerhead) does not increase significantly (less than 10%) under any water price scheme when a rebate is included for affluent households (i.e., positive income growth rates); however, it is significant among the households with negative income growth rates. In other words, the results showed that the effectiveness of rebate programs is dependent on two factors (i) the type of technology (i.e., expensive or inexpensive), for which the rebate is allocated; and (ii) the affluence of the community, in which the rebate program is implemented. Additionally, it can be observed that under the strategy of fixed charge with rebate allocation, the maximum number of inexpensive technologies were adopted, approximately independent of income growth rate. What can be noted, however, is that across all of the other water price and rebate strategies, income growth will lead to the higher adoption of both expensive and inexpensive technologies.

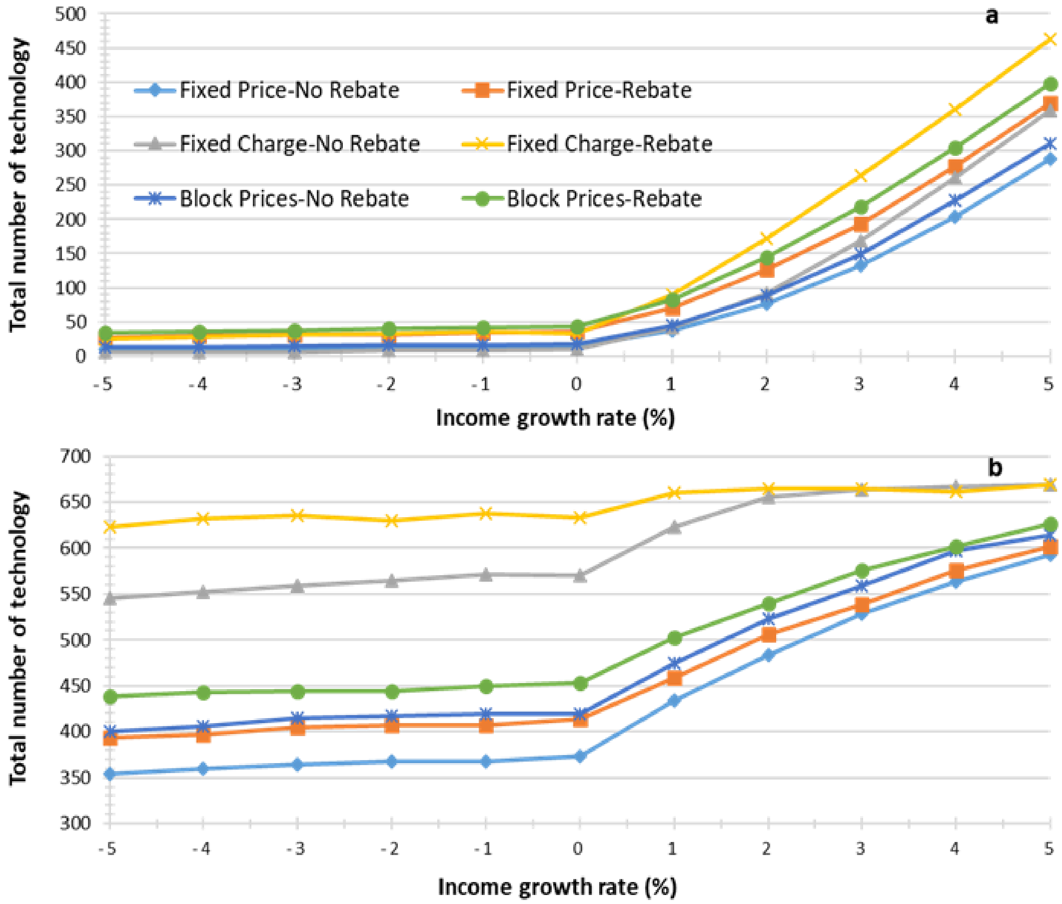

Figure 5-4. Modeling Trends on the Total Number of Adopted Technologies (a) Expensive Technology; (b) Inexpensive Technology

The analysis also considered the sensitivity of the results to the utility threshold values. The utility threshold had a negative linear correlation with the adoption rate. Figure 5-5 shows the mean frequency of adoption states (i.e., adopter, potential adopter, and non−adopter) under various utility threshold values in the base scenario. In this figure, as the threshold increased, the percent adopter decreased, regardless of water price strategy or rebate status. The greater the threshold, the greater the demographic and building characteristics have to be in order to adopt. In contrast, the lower the threshold, the lower importance is granted to these factors. For example, if it is anticipated that demographic and building characteristics will not be important in the adoption of water conservation technology for a specific community (i.e., lower utility threshold), the results show that there is even a potential of a 67% adoption under the base scenario.

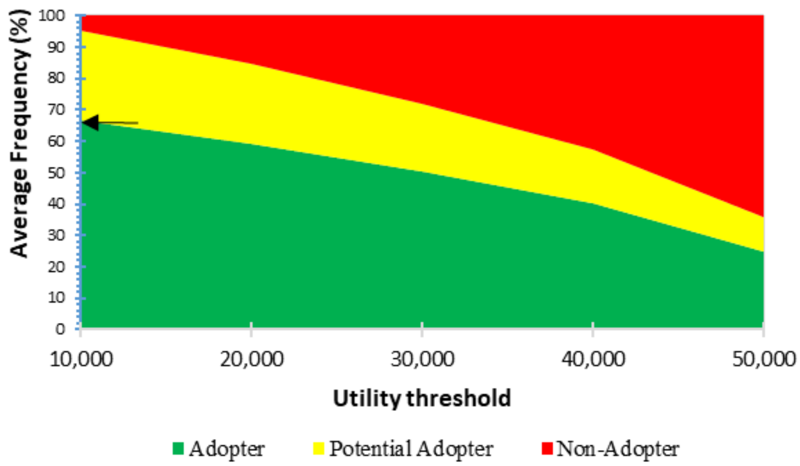

Figure 5-5. The Distribution of Adoption States Over Different Utility Threshold Values

5.7.2. Social Network Influence Examination

For all water pricing and rebate potential strategies, five structures of social networking were implemented and tested. Figure 5-6 demonstrates that among the social network structures, the highest percentage of households transitioned out from a non–adopter state through the scale–free network, followed by distance–based, then small–world networks. In the social networks with the random and ring lattice structures, the smallest household percentage was influenced into adopting water conservation technology. The results also showed that the effect of the social network structure on the adoption of water conservation technology is independent of water price strategy and rebate status. However, the adoption percentage fluctuates across the five social networks under each scenario of price strategy and rebate status.

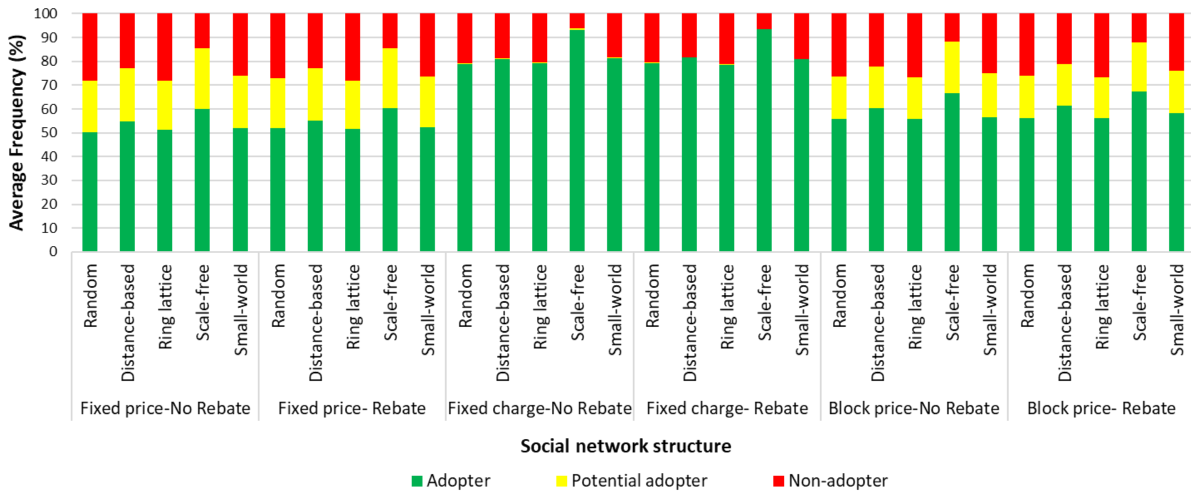

Figure 5-6. The Social Network Structure Influence on the Distribution of the Adoption States Over Different Scenarios

Another analysis conducted related to the effects of social network structures was about the rate (speed) of each structure in reaching the adoption equilibrium state. The adoption equilibrium means a steady or stable state where the adoption rate no longer changes (Anderson et al. 2014). From this point forward, there will be no significant increase or decrease in the adoption rate. The faster a social network structure reaches the adoption equilibrium, the earlier technology diffusion happens (Anderson et al. 2014) and consequently, more water is saved earlier. As shown in Figure 5-7, whenever a steady state was observed in these graphs, it was identified as the time at which the adoption rate reaches an equilibrium through the influence of social networks. As shown in Figure 5-7, among the social network structures, the distance−based network reached the equilibrium state most quickly followed by ring lattice then scale−free and small−world networks. The random network has not reached equilibrium over the twenty−year period. So the results indicate that if the peer effect is activated through a distance−based network structure, it can speed up the diffusion of water conservation technology more than other structures.

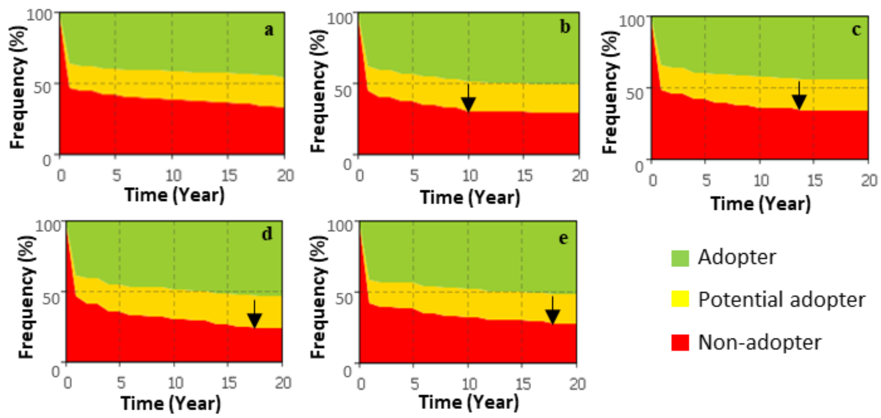

Figure 5-7. The Comparison of the Time to Reach the Equilibrium State Across the Social Network Structures of (a) Random; (b) Distance–based; (c) Ring lattice; (d) Scale–free; (e) Small–world

Under the base scenario, various numbers of connections per agents (N = 0–10) were tested for the random social network structure to evaluate the impact of the increasing connectivity level on the adoption rate of the agents' network. As shown in Figure 5-8, increasing the number of connections between the households improved their adoption rate significantly. However, it was identified that increasing the connectivity level of agents to more than 5 connections in the random network would have no additional impact on the adoption rate. This level of connectivity (i.e., N=5) in this network can be characterized as a tipping point, where the effect of connectivity level reaches a stable state.

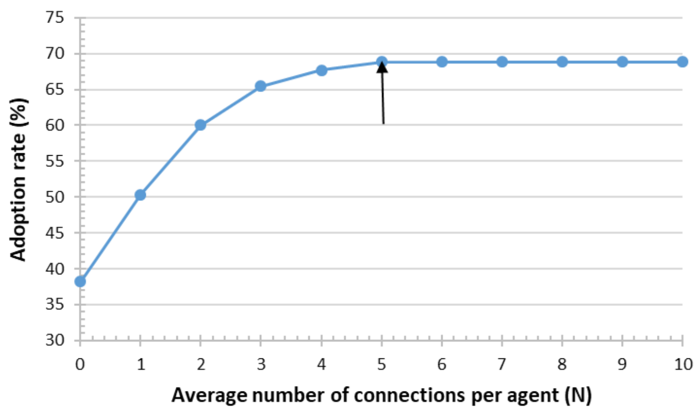

Figure 5-8. The Effect of the Connectivity Level in Social Networks on the Adoption Rate

The results of this study demonstrated that activating peer effect through social networks in a community can accelerate the diffusion of innovation regardless of the structure of social networks. Educating the public is one of the ways to achieve a greater rate of conservation diffusion (Corral-Verdugo et al. 2003). The idea of social marketing can be used to design effective information campaigns in order to encourage water consumers to adopt water conservation technology. Informational programs through various means of social media can increase the knowledge of residents about the benefits of adopting water conservation technologies. For instance, promoting water conservation technology adoption through mass media has the potential to reach a very large number of residential consumers (Weinreich 2006). Based on the results of the current study, future studies can further examine the effects of social media on users' choices of water conservation adoption.

5.7.3. Scenario Landscape Analysis

The results of the ABM simulation model should be processed to generate the scenario landscape and to identify pathways towards the desired outcomes. Classification and Regression Tree (CART) analysis was used to analyze the simulation data and explain the impact of different factors affecting the water conservation technology adoption. CART is a nonparametric technique for data mining that can select, from among a large number of variables, the most important variables in determining the desirable outcomes based on their interactions (Breiman et al. 1984). CART operates by recursively partitioning the data until the ending points, or terminal nodes, are achieved using preset criteria. It, therefore, begins by analyzing all explanatory variables and determining which binary division of a single explanatory variable best reduces the deviance in the response variable (final output) to produce accurate and homogenous subsets (Lawrence and Wrlght 2001). The CART analysis has two components: the predictor importance analysis and the regression tree. The predictor importance analysis distinguishes which variables lead the greatest significance for the response variable. The regression tree is a tree−structured representation in which a regression model is fitted to the data in each partition. The importance predictors of each parameter engender a tree diagram that illustrates all possible pathways (combination of different values of the variables) toward or against the final response variable (De'ath and Fabricius 2000).

The predictor importance analysis of CART was conducted to highlight which parameters (mechanisms) fostered the greatest significance to the model outputs. The predictor importance analysis was conducted to determine which parameters (mechanisms) had the greatest effect on the model outputs. The results of this analysis are shown in Figure 5-9. The results show the importance of each independent parameter (e.g., income growth, water price structure, etc.) in determining different model outcomes: (a) Expensive Technology Adoption (ETA); (b) Inexpensive Technology Adoption; and (c) Overall Daily Water Demand Reduction (ODWDR). As shown in Figure 5-9 (panel c), the results demonstrated that income growth, affordability threshold, water price structure, and rebate program were the top four most important parameters (in descending order) affecting the total technology adoption (which results in ODWDR). The structure of social networks, utility threshold, and household size growth had less impact on water demand reduction. This order of importance is mostly consistent in the adoption of inexpensive technology. In the adoption of inexpensive technologies, water price was the most important parameter, followed by income growth and utility threshold (panel b). The adoption of inexpensive technologies was more dependent on socio−demographic and house characteristics (which is reflected in the utility threshold) than for expensive technologies. Nevertheless, income growth and affordability threshold, which are economic parameters, influenced the adoption of expensive technologies (panel a).

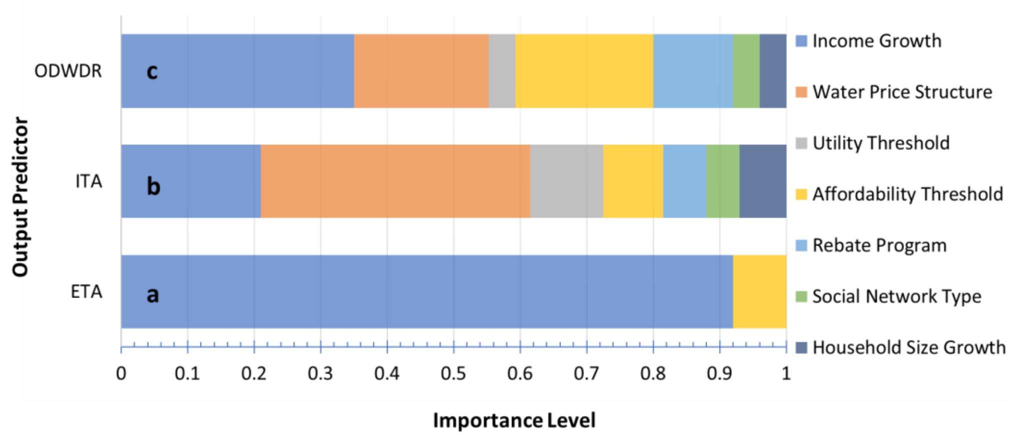

Figure 5-9. The Predictor Importance Analysis for the Model Outcomes

The simulated data were also utilized for meta−modeling using the regression tree of CART analysis. The scenario landscape was created based on the best fit of the CART model (Figure 5-10). In Figure 5-10, each path includes a set of branches representing the specific values of the most important parameters in determining the model outcome based on the predictor importance analysis. Each path leads to a terminal node (shown with bold border) representing the final outcome which is the overall daily water demand reduction (ODWDR). Basically, the scenario landscape of adoption patterns (Figure 14) demonstrates how the results (in terms of residential water demand reduction derived by conservation technology adoptions) would vary under different scenarios (combinations) of the underlying technology adoption mechanisms. As shown in the scenario landscape of adoption patterns (Figure 14), the residential water demand can be reduced potentially by as much as 5.8−18.3 m^3/day (see the red and green nodes) through the adoption of water conservation technology under different scenarios (which translates to about a 3%−10% reduction in the overall water demand of households in the service area).

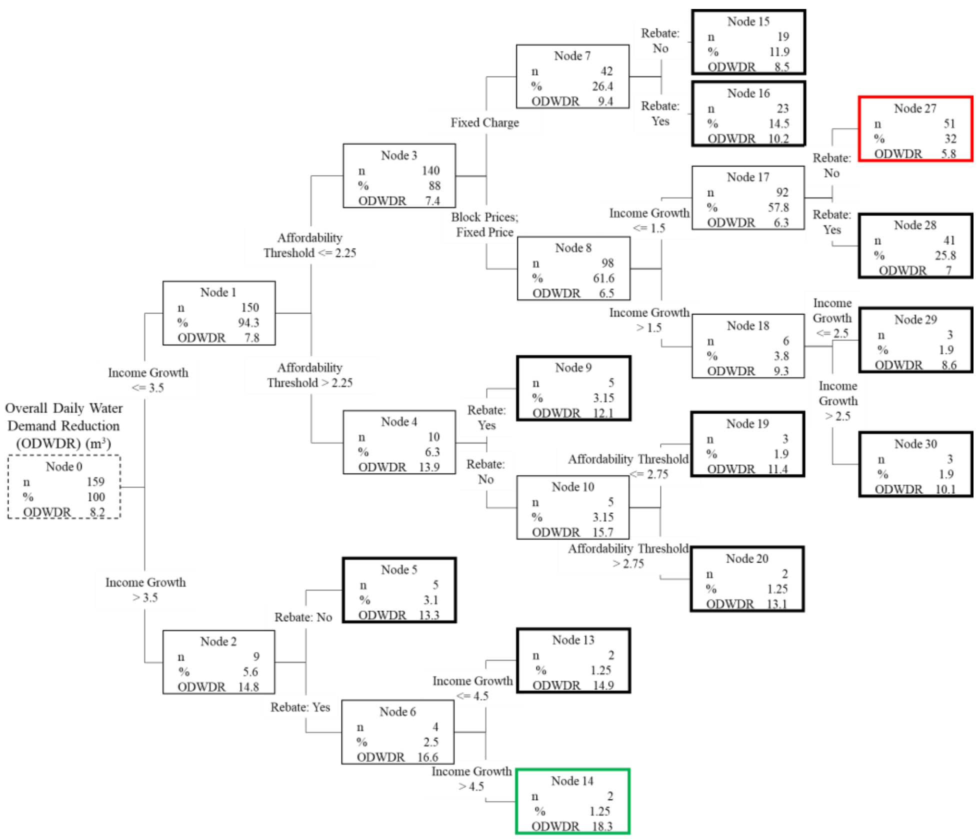

Figure 5-10. The Scenario Landscape of Adoption Patterns Using CART Analysis

5.8. Concluding Remarks

As water scarcity becomes more critical, demand−side management methods for conservation are increasingly necessary. The agent−based model and scenario analysis revealed concrete methods for encouraging household water conservation technology adoption. Firstly, income growth most influences potential adopter households' willingness to adopt, followed closely by water pricing strategy. With no regard to other factors, households adopted enough water conservation technologies to reduce the daily water demand by more than 7 m^3 (almost 8% of the city's daily residential water demand) under the fixed charge water pricing. This reduction was not met under the volume use charging strategies. While fixed charging strategies may lead people to pay less than their water use shows, it can make the adoption of water conservation technology affordable. This is especially true for households that are aware of water shortages, making them potential adopters.

Based on assessing different community profiles from the CART analysis, volumetric water charging strategies are best implemented in more affluent communities where income growth is more likely. Conversely, a fixed charge regime would be best suited for less affluent communities, where income growth is less common. Rebate allocation programs increased the adoption rate—especially for expensive technologies, which had an increase of 50%. The findings suggest that municipalities and water agencies can use rebate allocation programs either with volumetric water pricing strategies or across less affluent communities. This pathway leads to a desired amount of water demand reduction. The adoption of inexpensive technology—i.e., kitchen and bathroom faucet, showerhead—did not increase at all when a rebate was included, and this was especially so in households with high income growth rates. In fact, the adoption of inexpensive technologies is significantly dependent on socio−demographic and household characteristics than for expensive ones. This indicates that targeting households to adopt inexpensive technology needs to involve outreach programs more than rebate policy.

Another important finding was related to the effects of social networks. The adoption percentage fluctuated across all five social networking schemes under each scenario of water price and rebate status. However, the distance−based network, among all network types, reached equilibrium in a shorter period. This means that the peer effect through neighboring social connections can speed up technology adoption potential more so than other social networks.

In terms of water pricing, for households who are already potential adopters, implementing a fixed charge strategy makes the adoption of water conservation technology more affordable. Offering rebates for technologies along with volumetric water pricing will lead communities to adopt enough technology to reach the desired water demand reduction levels. More broadly, if agencies' goals are to increase the rate of technology adoption, they must consider which pricing and rebate policies will be the most successful in their particular community. The planning and governance of water price has a greater importance on household adoption of water conservation technology than any other demographic, household, or social networking factors. The results of this study are important to consider in improving demand−side conservation management strategies. It should be noted that the modeling approach was utilized in this study to explore possible patterns of water conservation technology adoption and examine the underlying mechanisms rather than making predictions. While the research fostered a unique way to evaluate water conservation technology patterns, there are past studies (see Table 1) that, despite using a variety of different methods, found similar findings to the model. This, in turn, served as a point of external validation to the model’s results. These results provide a clear course of action for the future development of household water conservation technology adoption programs and provide further evidence that demand–side management strategies will help foster a solution to urban water conservation problems.

5.9. Limitations and Future Studies

While the findings of this study will help municipalities and water agencies to strategically encourage the household adoption of water conservation technology, they do pose some limitations. Unfortunately, not every demographic characteristic of an individual can have could be accounted for, such as religious identity, race, sexual orientation, or even number of children in the household. That is not to say that all of these demographics would have had an impact on the utility value and household’s adoption state, but it could have fostered more inclusive results. These characteristics were not considered due to a lack of information from the Census or water research. In the future, these identities will hopefully become more prominent in mainstream Census and demographic research, allowing for their inclusion in these models. Another important note about this model is that the only dynamic parameters considered were house age and social network influence (peer effect). The other input parameters in the model (such as threshold values) are static, which inhibits the ability of capturing feedback mechanisms. Through a feedback mechanism, households can reflect upon their decisions and change accordingly (Azar and Al Ansari 2017). For example, the water pricing stays the same over the simulation period (20 years) and does not change based on the rate of adoption. While it is possible for government officials to change water pricing regime after a certain amount of time based on the adoption rate (as a feedback mechanism), this model did not account for them. In the model presented in this study, no feedback mechanism was incorporated as the inclusion of feedback mechanisms in the diffusion of innovations requires new methods of parametrization, calibration, and validation (van Oel et al. 2010). Hence, it is of great importance to consider the feedback mechanisms in water conservation technology adoption of households in future studies. Future studies can also evaluate additional mechanisms and phenomena affecting the water conservation technology adoption. For example, the impact of implementing water outage policies in a community on the conservation technology adoption behavior of households can be added to the model developed in this study. Despite these limitations, this study presented valuable findings towards better understanding the underlying mechanism of water conservation technology adoption for residential consumers.

6. CONCLUSIONS

6.1. Summary

This research was conducted with the overarching objective of assessment of long-term resilience in urban water infrastructure systems. This research conceptualized the urban water infrastructure system as a complex system composed of interconnected components including physical infrastructures, human actors (e.g., decision makers and users), and external stressors. Water utility agencies and infrastructure managers face significant challenges to enhance the long-term resilience of their urban water infrastructure systems to the impacts of external stressors due to the existence of deep uncertainty, funding constraints, lack of knowledge, etc. To enable informed resilience planning and adaptation decisions, the present study utilized a simulation approach for theory development and exploratory analysis of long-term resilience in water infrastructure systems.

To accomplish the objectives of this research, various interrelated studies pertaining to different dimensions of the urban water infrastructure system resilience were implemented as explained in Chapters 2-5 and summarized as following:

First, the long-term resilience performance of water distribution systems in the presence of external stressors such as aging infrastructure, population changes, and funding fluctuations was studied. This study characterized the water distribution system as a complex system and offered a multi-agent simulation model to quantify its components, dynamic processes, and external stressors acting on the water distribution system. Accordingly, the model was used to depict performance regimes of the system under various scenarios, which enabled the detection of regime shifts to evaluate the long-term resilience.

Second, an investigation into the competitiveness of dual distribution systems at a municipal scale was formed to examine whether these systems could improve the resilience of water distribution infrastructure systems. This study developed a dynamic, time-dependent simulation model that captured the long-term dynamic behavior of both dual and singular distribution systems. Accordingly, the dual and singular systems were compared based upon their performance measures (e.g., condition, leakage, breakage, energy loss, service reliability) as well as their life-cycle costs over a 50-year analysis period.

Third, in light of the deep uncertainties and high complexities surrounding the impacts of climate change on coastal communities, the emergence of long-term resilience in hazards-humans-infrastructure nexus was investigated. This study created a multi-agent simulation model using grounded decision theories and empirical data. The model integrates adaptation decision-making processes of utility agencies with the performance of water supply infrastructure under the impacts of saltwater intrusion. Then, the simulation model was used to uncover the effectiveness of the adaptation planning approach in the enhancement of long-term resilience.

Last but not least, a demand-side water management strategy, the utilization of water-saving technology, was explored for improving the resilience of coastal water system. This study developed a theoretically and empirically driven agent-based simulation model that captures the underlying mechanisms and phenomena influencing the technology adoption decision of households. The simulation model was used to generate various scenario experiments to determine the simultaneous effect of socio-demographics, social networks, and water policies (e.g., water pricing and rebates) on technology adoption rates of various profiles of communities.

Accordingly, this research identified four sets of important theoretical constructs related to long-term resilience of water infrastructure systems from simulation results. The results showed that (i) internal dynamics (e.g., renewal strategies) related to stressors-humans-infrastructure interactions shape the performance regime of water distribution infrastructure and changes in internal dynamics and/or external stressors could lead to regime shifts (ii) over the course of five decades, the dual infrastructure was ultimately more cost-effective than the singular infrastructure, although initial capital outlays were substantially greater in the former relative to the latter; (iii) although the state of nature (i.e., sea-level rise severity) dominantly drives the resilience of coastal water supply infrastructure systems, its influence could fully be mitigated through an adaptive planning approach given the sufficiency of capital funding; and (iv) water pricing structure and household income growth were the leading determinants of technology adoption-induced water demand reduction.

6.2. Contributions

This research advanced the science of resilience in urban water infrastructure systems by developing novel simulation models that adequately captured and quantified dynamics of different components (i.e., physical infrastructures, human actors, and external stressors) encompassing water infrastructure systems. Using these simulation models, certain theoretical constructs and insights were built that can be used by decision-makers and policy-makers to improve the resilience performance of their water infrastructure systems under the uncertain impacts of various external stressors. The overall contributions of this research are threefold, explained as follows.

6.2.1. Theoretical Contributions

The theory of infrastructure resilience is an emerging topic which is still expanding in the literature. In particular, the comprehensive understanding of infrastructure resilience in urban water systems is rather limited. This research made multiple theoretical contributions to the body of knowledge. First, this research enabled building complex system-based theories for a more advanced understanding of water infrastructure resilience. Indeed, this research proposed a complex-system based framework inspired from ecological and economic sciences for the assessment of a new paradigm of resilience in urban water infrastructure systems, called "long-term resilience."

Second, based on the conceptualization of water infrastructure resilience using a complex system-based framework, this research addressed an important and yet unexplored aspect of resilience assessment in water infrastructure systems, which is consideration of emergent properties such as internal dynamics, performance regimes, and tipping point behaviors. Similar to other complex systems, capturing the emergent properties in complex water infrastructure systems is critical for gaining a better understanding of the integrative behaviors and resilience performance of infrastructure systems. For instance, identification of performance regime shifts is pivotal for resilience assessment because due to significant physical and institutional inertia in infrastructure systems, undesirable performance regime shifts are very difficult to reverse. However, there is currently little to no research pertaining to emergent properties in water infrastructure systems. The complex system-based conceptualization and findings pertaining to resilience-related emergent properties in this research highlighted the significance of considering emergent properties in assessment of long-term resilience of water infrastructure systems.

Third, this research also contributed to the theory of infrastructure resilience by proposing resilience planning in stressors-humans-infrastructure nexus. In fact, this research incorporated capacities of human actors (i.e., social and organizational systems) in improvement of infrastructure resilience. Despite an abundance of studies on resilience assessment of infrastructure systems, most of previous studies lack the consideration of the dynamic behaviors and interactions of institutional decision-makers and/or infrastructure users with the physical infrastructures. However, this research enabled understanding the coupled effects of adaptive behaviors of decision makers and climate change stressors (as an external stressor) on the long-term resilience of water infrastructure systems.

6.2.2. Methodological Contributions

Another main scholarly contribution of this research is its adoption of a simulation methodology for theory development and exploratory assessment in water infrastructure resilience research. Simulation has been mainly used in infrastructure resilience research for creating predictive and optimization tools for planning analysis and decision-making. Given the unique characteristics of water infrastructure systems, in which there are inherent limitations for creating new theories due to the constraints related to conducting empirical experiments, the use of simulation approaches could lead to significant new theories in various areas. This research highlighted the potential and provided cases for the implementation of simulation-based approaches in infrastructure resilience research.

This research created multiple novel simulation models that adequately captured and quantified dynamics of different components (i.e., physical infrastructures, human actors, and external stressors) encompassing water infrastructure systems. This research developed: (i) a multi-agent simulation model of a water distribution system that integrates utility agencies' renewal decision-making processes with the physical degradation of infrastructure networks so as to examine performance regimes, and hence resilience, of the system in the presence of various scenarios of external stressors (e.g., population change, funding fluctuations); (ii) a dynamic time-dependent simulation model that captures long-term performance measures of dual and singular water distribution systems, such as network condition, leakage, breakage, energy loss, and level of service, as well as their network-level life-cycle costs; (iii) a multi-agent simulation model that brings together the stochastic modeling of sea-level rise-induced hazards (i.e., saltwater intrusion), decision-theoretic modeling of utility agencies' adaptive decision-making processes, and empirically-driven modeling of water infrastructure performance so as to capture the coupled impacts of adaptation planning and coastal hazards on the long-term resilience of water supply infrastructure systems; and (iv) an agent-based simulation model that incorporates different mechanisms (e.g., socio-demographics, social networks, water policies) involved in the decision-making process for water conservation technology adoption of households using theoretical constructions such as Innovation Diffusion, Peer Effect, and Affordability.

6.2.3. Practical Contributions

In each and every of the four studies conducted in this research, a real case study data from a real urban area (city or county) in the United States was utilized to confirm that the created simulation models marked a useful contribution to the field. Therefore, the models and theoretical constructs developed in this research could substantially enhance the ability and awareness of municipalities, water utilities, city planners, government agencies, and non-profit groups in implementing water infrastructure policies and investments. In particular, decision makers and practitioners could use the findings of this research to: (i) assess the resilience of water infrastructure systems with greater accuracy and thus, formulate policies (e.g., renewal strategy) that enhance the sustainability and resilience of their infrastructure systems; (ii) understand the long-term infrastructure transformation, performance measures, and life-cycle costs associated with the dual systems, obtain a clear course of action for the future development of urban water distribution infrastructure systems, and enhance their institutional capacity for implementing more sustainable and resilient alternative water strategies; (iii) make more informed decisions for adaptive design, operation, and management of coastal water supply infrastructure systems, and identify adaptation strategies and decision factors that improve the long-term resilience performance of their infrastructure system under the impacts of saltwater intrusion; and (iv) shed light on the relative likelihood of water conservation technology adoption by households, obtain further evidence that demand-side management strategies will help foster a solution to urban water conservation problems, and thus implement strategic interventions to encourage the household adoption of water conservation technology and raise the rate of technology-driven water saving.

Although this research was conducted in the context of urban water infrastructure systems, the theoretical constructs created in this research might also be adopted in enhancing the resilience of infrastructure systems in other sectors (e.g., roadways, wastewater, power) that face significant uncertainty and complexity.

6.3. Limitations

There are some limitations in this research, which should be addressed in future studies. First, there are some simplified assumptions in the conceptual frameworks of this research. For example, service reliability indicator (ratio of supply to demand) was assumed to be the only measure of resilience in this research. However, other important performance indicators including functionality, quality, and cost can be incorporated into consideration in future studies. Another example pertains to the agent-based model of households' water conservation technology adoption, which assumed that the water pricing stays the same over the simulation period (20 years) and does not change based on the rate of adoption. However, it is possible for government officials to change water pricing regime after a certain amount of time based on the adoption rate. This is recognized as feedback mechanisms in modeling, which is of great importance to be considered in agent-based modeling of technology adoption behaviors in future studies.

Second, this research created agent-based and multi-agent simulation models, which are often criticized for relying on informal and subjective validation or no validation at all (Berglund 2015). Validating this sort of simulation models developed for complex systems is difficult and infeasible because of the stochastic nature of human-behavior models and lack of sufficient historical data. Although the simulation models developed in this research were typically validated using internal verifications and face validations of the features representing the model quality, they could not be tested for their structure appropriateness in a meaningful way as the interconnections of social processes are vague in the sense that competing theories exist for most phenomena. Therefore, future studies should seek new methods and techniques for validating the simulation models.

Third, this research missed the consideration and capture of some components and dynamics existing in stressors-humans-infrastructure nexus. For instance, the influence of consumer actors within this nexus was modeled exogenously with a prescribed rate of population growth and water demand. However, the dynamics of infrastructure users' behaviors should be considered in holistic evaluation of the long-term resilience of infrastructure systems. Another example refers to the comparison of dual and singular systems which was primarily from pipeline infrastructure perspective. However, it is recognized that there might be some other dynamics, such as water reservoir infrastructure considerations (required for non-potable water storage), that could influence the decision of dual system implementation. The other example is lack of considering the impact of overexploitation of the freshwater aquifers on the movement of salinity interface. Therefore, additional dynamics can be captured and modeled using the proposed frameworks in future studies.

Fourth, this research utilized a new approach and methodology to investigate long-term resilience quantitatively in the context of urban water infrastructure systems. Theoretical constructs were built from observations in three case studies (i.e., city of Fort Collins, Miami-Dead county, and city of Miami beach). In future studies, more case studies across different regions need to be conducted to further test the proposed simulation frameworks and validate the theoretical constructs.

6.4. Recommendations for Future Work

In addition to considering and addressing the limitations and boundaries of this study, which were discussed above, there are some other avenues that can be undertaken as future research. The recommendations for future research fall under the area of policy assessment in water infrastructure. There are different classes of policy problems pertaining to water infrastructure system-of-systems in which the framework proposed in this research could be applied to facilitate a more comprehensive analysis of policies. At the national and global levels, future studies could create policy analysis models based on the proposed framework, or expand the developed simulation models, to examine the possible outcomes of policies related to different policy problems. The activities and interactions of different players in the water infrastructure system-of-systems could be abstracted and simulated to model the adaptive emergent behavior of the system. The following are examples of the classes of problems in which the application of the created framework or the expansion of the developed simulation models could be beneficial in understanding the dynamics of the systems and simulating the outcomes of the policies:

- *Analysis of the dynamics of water-energy-food nexus:* There are clear consequences for the public health, the economy and the environment when the water-energy-food nexus becomes unbalanced. The proposed framework could be used to model the intersection of these systems to understand how they rely upon each other to function and how they can have a significant impact on each other. Such models can be used to uncover how various national policies and management on topics such as fracking and food and energy subsidies affect water-energy-food nexus in both positive and negative ways.
- *Assessment of disaster resilience:* Disaster resilience is the ability of individuals, communities, and institutions to adapt to and recover from hazards, shocks or stressors without compromising long-term prospects for development. The proposed simulation framework could be used to model and examine the impacts of different levels of water infrastructure service losses caused by disasters (e.g., hurricanes) on the well-being of households residing in a community. The framework would enable capturing and integrating household characteristics (e.g., socio-demographics, social capital, resources, and previous disaster experience), physical infrastructure attributes, and extreme disruptive events. It would provide insights to create simulation models that

capture complex mechanisms underlying households' tolerance for water outages. Such models can be expanded based on the simulation models created in this study to provide water utility agencies with an analytical tool for prioritization of water infrastructure service restoration actions in order to effectively mitigate the societal impacts of service losses.

Overall, such policy analysis models would provide policy-makers and city-planners with tools to better understand the effects of policies in water infrastructure, explore scenarios which yield desired policy outcomes, and make policies that are robust across a range of uncertain parameters.

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APPENDIX

Table A1. The Coefficients and Values for Adoption Utility Function Variables

Variable	Value	Coefficient	Distribution Type
Education:			Real data
· High school or less	If Yes = 1, if No = 0	1.92	
· Some college	If Yes = 1, if No = 0	2.58	
· College graduate	If Yes = 1, if No = 0	2.91	
· Advanced degree	If Yes = 1, if No = 0	4.39	
Income			Real data
· Less than $40,000	If Yes = 1, if No = 0	0	
· $40,000–$75,000	If Yes = 1, if No = 0	1.07	
· Above $75,000	If Yes = 1, if No = 0	1.58	
Home ownership	Owner = 1, Renter = 0	1.84	Real data
Head gender	Female = 1, Male = 0	1.21	Random
Resident (head) age	Years	1.01	Histogram
House size	Square feet	1	Uniform (70; 56,000)
Garden size	Square feet	1	Uniform (0; 8000)
House age	Years	0.99	Random (1100)
Household size	Numbers	0.98	Real data

Table A2. The Attributes of Water Conservation Technologies in the Model

Technology	Price ($)	Potential Rebate ($)	Expected Water Savings (gal/day/capita)	Category
Bathroom faucet	15	15	0.57	Inexpensive
Kitchen faucet	15	15	2.8	Inexpensive
Showerhead	100	25	4.85	Inexpensive
Toilet	420	50	1.63	Expensive
Washing machine	670	150	6.91	Expensive
Dishwasher	500	50	0.35	Expensive

Table A3. The Attributes and Parameters of Social Network Structures

Network Structure	Attribute	Parameter	Parameter values
Random	Assigns each agent a random number of connections within the given average.	Average number of connections per agent (N)	N = 0−10
Distance−based	If the distance between two agents is less than the given maximum connection range (the maximum distance in meters between agents for there to be a connection), then both agents are connected.	Maximum connection ranges (R)	R = 0−500
Ring lattice	Agents are connected according to their closeness to each other while also forming a ring.	Average number of connections per agent (N)	N = 0−10
Small−world	Connections between agents are similar to the ring lattice, while also including some long-distance relationships. The neighbor link probability is the chance that two agents connected to the same neighbor may also connect to each other.	Average number of connections per agent (N); and Neighbor link probability (P)	N = 0−10 P = 0−1
Scale−free	Some agents have multiple connections (considered as hubs), while others have very few connections.	Number of hubs (M)	M = 1−10