DISASTER RISK MANAGEMENT OF INTERDEPENDENT INFRASTRUCTURE SYSTEMS FOR COMMUNITY RESILIENCE PLANNING

BY

XIAN HE

DISSERTATION

Submitted in partial fulfillment of the requirements
for the degree of Doctor of Philosophy in Civil Engineering
in the Graduate College of the
University of Illinois at Urbana-Champaign, 2019

Urbana, Illinois

Doctoral Committee:

Assistant Professor Eun Jeong Cha, Chair
Professor Paolo Gardoni
Professor Yanfeng Ouyang
Assistant Professor Hadi Meidani

ABSTRACT

This research focuses on developing methodologies to model the damage and recovery of interdependent infrastructure systems under disruptive events for community resilience planning. The overall research can be broadly divided into two parts: developing a model to simulate the post-disaster performance of interdependent infrastructure systems and developing decision frameworks to support pre-disaster risk mitigation and post-disaster recovery planning of the interdependent infrastructure systems towards higher resilience.

The Dynamic Integrated Network (DIN) model is proposed in this study to simulate the performance of interdependent infrastructure systems over time following disruptive events. It can consider three different levels of interdependent relationships between different infrastructure systems: system-to-system level, system-to-facility level and facility-to-facility level. The uncertainties in some of the modeling parameters are modeled. The DIN model first assesses the inoperability of the network nodes and links over time to simulate the damage and recovery of the interdependent infrastructure facilities, and then assesses the recovery and resilience of the individual infrastructure systems and the integrated network utilizing some network performance metrics. The recovery simulation result from the proposed model is compared to two conventional models, one with no interdependency considered, and the other one with only system-level interdependencies considered. The comparison results suggest that ignoring the interdependencies between facilities in different infrastructure systems would lead to poorly informed decision making. The DIN model is validated through simulating the recovery of the interdependent power, water and cellular systems of Galveston City, Texas after Hurricane Ike (2008).

Implementing strategic pre-disaster risk mitigation plan to improve the resilience of the interdependent infrastructure systems is essential for enhancing the social security and economic prosperity of a community. Majority of the existing infrastructure risk mitigation studies or

projects focus on a single infrastructure system, which may not be the most efficient and effective way to mitigate the loss and enhance the overall community disaster resilience. This research proposes a risk-informed decision framework which could support the pre-disaster risk mitigation planning of several interdependent infrastructure systems. The characteristics of the Interdependent Infrastructure Risk Mitigation (IIRM) decision problem, such as objective, decision makers, constraints, etc., are clearly identified. A four-stage decision framework to solve the IIRM problem is also presented. The application of the proposed IIRM decision framework is illustrated using a case study on pre-disaster risk mitigation planning for the interdependent critical infrastructure systems in Jamaica. The outcome of the IIRM problem is useful for the decision makers to allocate limited risk mitigation budget or resources to the most critical infrastructure facilities in different systems to achieve greater community disaster resilience.

Optimizing the post-disaster recovery of damaged infrastructure systems is essential to alleviate the adverse impacts of natural disasters to communities and enhance their disaster resilience. As a result of infrastructure interdependencies, the complete functional restoration of a facility in one infrastructure system relies on not only the physical recovery of itself, but also the recovery of the facilities in other systems that it depends on. This study introduces the Interdependent Infrastructure Recovery Planning (IIRP) problem, which aims at optimizing the assignment and scheduling of the repair teams for an infrastructure system with considering the repair plan of the other infrastructure systems during the post-disaster recovery phase. Key characteristics of the IIRP problem are identified and a game theory-based IIRP decision framework is presented. Two recovery time-based performance metrics are introduced and applied to evaluate the efficiency and effectiveness of the post-disaster recovery plan. The IIRP decision framework is illustrated using the interdependent power and water systems of the Centerville virtual community subjected to seismic hazard.

ACKNOWLEDGEMENTS

I would like to express my deepest gratitude to my advisor, Dr. Eun Jeong Cha, for her elaborate guidance, enduring encouragement and persistent help throughout my M.S. and Ph.D. study. She is both my advisor and my role model as a professional female civil engineer. Apart from her critical thinking, attention to details and dedication to excellence, she also shows me how to balance life and work, and how to overcome all the obstacles along the way with a positive attitude. Working under her guidance has shaped me in many ways and her positive influence will no doubt pass beyond my graduate study and serve me well for many years to come. It's my fortune to be one of her students.

My sincere appreciation goes to my dissertation committee members: Dr. Paolo Gardoni, Dr. Yanfeng Ouyang and Dr. Hadi Meidani, who teach me several classes relevant to this research, and provide me with insightful advice and valuable guidance on several aspects of this research.

This research is supported by the National Institute of Standard and Technology (NIST) through Center for Risk-Based Community Resilience Planning [NIST Financial Assistance Award Number: 70NANB15H044], which is gratefully acknowledged. Some essential data used in this research is kindly made available by Frederico Ferreira Fonse Pedroso, Diana Cubas, Sideney Schreiner and Xijie Lv from the World Bank, which is also gratefully acknowledged.

I greatly appreciate my fellow colleagues and friends in the department, especially Sami Pant, Vamshi Krishna Gudipati, Chi-Ying Lin, Somashekar Viswanath and Yuguang Fu, who are always willing to help and give their best suggestions. Their accompany and friendship have made my graduate school life at UIUC enjoyable and memorable.

Special thanks go to my parents, Ling Chen and Yong He, for their unconditional love and support, which make possible for all the above mentioned wonderful things happen in my life.

To my advisor, who inspires my love of network.

To my family and friends, who give me a network of love.

TABLE OF CONTENTS

CHAPTER 1 INTRODUCTION 1

CHAPTER 2 LITERATURE REVIEW... 4

CHAPTER 3 INTERDEPENDENT INFRASTRUCTURE RECOVERY MODELING USING DYNAMIC INTEGRATED NETWORK MODEL.. 73

CHAPTER 4 INTERDEPENDENT INFRASTRUCTURE PRE-DISASTER RISK MITIGATION PLANNING 121

CHAPTER 5 INTERDEPENDENT INFRASTRUCTURE POST-DISASTER RECOVERY PLANNING 145

CHAPTER 6 CONCLUSIONS AND FUTURE WORK 165

REFERENCES 170

CHAPTER 1 INTRODUCTION

1.1. Motivation

The disaster resilience of communities or infrastructure systems is related to their ability to withstand the disruptive events and recover rapidly from the disruptions. Community resilience depends on the performance of its built environment, including buildings and infrastructure systems, and socioeconomic systems which are essential for the immediate response, short-term restoration and long-term recovery of a community following a disaster. Improving community resilience requires coordinated efforts of experts from multiple disciplines, including environmental science, engineering, sociology, information science, economics, etc. As a starting point, the research presented in this dissertation addresses the community resilience planning issue by focusing on the disaster risk management of the critical infrastructure systems in a community.

Nowadays, infrastructure systems rarely operate on their own. The normal operation of one facility in a system usually depends on the functioning of several other facilities, including those in other systems for product input and information sharing. Thus, when an infrastructure system is damaged and its service is disrupted, the disruption would soon propagate to other systems that depend on this damaged system and result in a widespread disruption of lifeline services. The need for considering infrastructure interdependencies in infrastructure disaster risk management for community resilience has been highlighted by the President's Commission on Critical Infrastructure Protection since 1997 (Foundations, 1997), and has been noted from the performance of the infrastructure systems under natural and manmade disasters in recent decades, such as 9/11 terrorist attack (2001), Hurricane Katrina (2005), Wenchuan earthquake and landslide (2008), Joplin tornado (2011), Superstorm Sandy (2012), Nepal earthquake (2015), Bangladesh monsoon flooding (2017), Indonesia earthquake and tsunami (2018) and so on.

Although the occurrence of natural or manmade hazards is unavoidable, their impact to the community's socioeconomic well-being could be reduced through implementing actions on improving the disaster resilience of its interdependent infrastructure systems. Three significant challenges of infrastructure disaster risk management are (1) developing mathematical models to better understand and quantify the post-disaster performance of interdependent infrastructure systems; (2) developing measurement metrics to provide yardsticks of the infrastructure performance; and (3) developing risk-informed decision frameworks to better guide the strategic pre-disaster risk mitigation and post-disaster recovery planning works. Good mathematical models, measurement metrics and decision frameworks should be the ones that are feasible, reasonable and applicable to various interdependent infrastructure systems under multiple hazards. Researches in this direction are useful for (1) the infrastructure investors to prioritize and better allocate their investment; (2) the infrastructure owners to optimize the infrastructure risk mitigation and recovery works; (3) the insurance, reinsurance and other relevant companies to better understand and manage the risks facing their businesses; (4) the policy-makers to update the codes, standards and regulations to better prepare their community for future disruptive events; and will eventually benefit the life quality of every individual person in a community.

1.2. Objective and Tasks

This research aims at developing models, metrics and decision frameworks for disaster risk management of interdependent infrastructure systems to support community resilience planning. The specific research tasks to accomplish the objective include:

(1) Review the current state of the research in disaster risk management of infrastructure systems for community resilience planning to identify progresses, challenges and gaps;

(2) Identify critical components (e.g.: facilities, lines) of some critical infrastructure systems in a community and their interdependencies;

(3) Develop a mathematical model to simulate the damage and recovery of

interdependent infrastructure systems under multi-hazards with considering the uncertainties;

(4) Introduce measurement metrics to evaluate the infrastructure performance;

(5) Develop risk-informed decision frameworks to support strategic pre-disaster risk mitigation and post-disaster recovery planning for interdependent infrastructure systems.

1.3. Organization of Dissertation

This dissertation describes the methodologies to complete the above research tasks, illustrated with examples or case studies. The remainder of this dissertation consists of five chapters, followed by a list of references. Chapter 2 reviews the state-of-art of current research and practice on infrastructure disaster risk management for community resilience planning. Chapter 3 introduces the Dynamic Integrated Network (DIN) model which simulates the damage and recovery of interdependent infrastructure systems under multi-hazards with considering the uncertainties. The modeling methodology, modeling parameter quantification, model comparison and model validation are presented in this chapter. In Chapter 4, a decision problem in the pre-disaster risk mitigation phase is defined. The corresponding decision framework and supporting measurement metrics used as decision criteria are also introduced. Similarly, in Chapter 5, the decision problem, decision framework and measurement metrics for the post-disaster recovery phase are presented. Finally, Chapter 6 summarizes the major contributions of this study and suggests recommendations for future research.

CHAPTER 2 LITERATURE REVIEW

This chapter describes the current state-of-the-art of the studies on disaster risk management for community resilience planning with an emphasis on infrastructure systems. Recent decades have witnessed a growing body of projects and studies on community disaster resilience planning. The efforts can be broadly grouped into five categories: (1) defining the concept of community resilience; (2) evaluating the community or infrastructure resilience quantitatively using mathematical models or qualitatively using conceptual frameworks; (3) modeling the post-disaster damage and recovery of infrastructure systems to support community resilience assessment; (4) developing infrastructure performance metrics to measure and evaluate the post-disaster performance of infrastructure systems; and (5) developing infrastructure risk management decision frameworks to better support the community resilience planning. In the following subsections, the community resilience initiatives in recent decades at various scales are presented first, followed by a review of the studies on the above five aspects.

2.1. Community Resilience Initiatives

Community resilience planning against natural and manmade disasters has gained traction around the world in recent decades. A wide variety of initiatives addressing the disaster preparedness, risk mitigation, emergency response, recovery and reconstruction of communities from disruptive events are taken by entities at different levels, including multinational development agencies, non-profit organizations, government agencies, foundations, corporations, research institutions, universities, and so on. Table 2-1 summarizes some representative community resilience initiatives in recent two decades with an emphasis on the efforts involving resilience planning for critical civil infrastructure systems. In reviewing these community resilience initiatives, the following aspects are considered:

(1) **Name**: the name of the initiative, such as the name of the program or project.

(2) **Organizer(s)**: the name of the organizer(s) who proposes and/or leads the initiative, such as the name of the multilateral development agency, government agency, foundation, research institution, corporation, university research group, etc..

(3) **Goal**: the aim of the initiative.

(4) **Scale**: the scale of the initiative, such as international, regional, national, local or organizational.

(5) **Dimensions**: different dimensions of community resilience that the initiative focuses on, such as buildings, cyber security, economics, emergency management, environment, finance, food and agriculture, governance, healthcare, infrastructure systems (e.g.: electric power, water and sanitation, natural gas and oil, transportation, telecommunication), logistics and supply chain, maritime security, military, natural resources, sociology, urban planning and so on.

(6) **Approaches**: the actions taken to reach the goal of the initiative, such as developing guideline documents or assessment tools, providing financial and/or technical assistance, organizing workshops and/or training programs for education purpose, conducting research, participating in the construction projects and so on.

(7) **Reference**: the reference of the initiative, such as the program website, link or reference of the related reports, documents or technical papers.

The community resilience initiatives in Table 2-1 are ordered first based on scale (from international to organizational) and then chronologically.

Table 2-1. Summary of the recent community resilience initiatives with an emphasis on infrastructure resilience initiatives.

No.	Name	Organizer(s)	Goal	Scale	Dimensions	Approaches	Reference
1	Building Resilience: Integrating Climate and Disaster Risk into Development	The World Bank Group	Building climate and disaster resilience to end extreme poverty and build shared prosperity for developing countries in the world	International	Buildings, economics, environment, finance, food and agriculture, governance, infrastructure systems, urban planning	Develop guideline documents, provide financial and technical assistance to developing countries in the world to build climate and disaster resilience	World Bank (2013)
2	Community-Based Disaster Risk Reduction (CBDRR) programmes	International Federation of Red Cross and Red Crescent Societies	Enabling healthy and safe communities, reduce vulnerabilities, strengthen resilience and foster a culture of peace around the world	International	Economics, emergency management, healthcare, governance, infrastructure systems, natural resources, sociology	Develop guideline documents, provide humanitarian assistance to improve humanitarian standards, work as partners in community development and in response to disasters, persuade decision-makers to act at all times in the interests of vulnerable people	International Federation of Red Cross and Red Crescent Societies (IFRC) (2014)

Table 2-1 (Cont.)

No.	Name	Organizer(s)	Goal	Scale	Dimensions	Approaches	Reference
3	United Nations International Strategy for Disaster Reduction Resilience Scorecard	United Nations	Providing a set of assessments that will allow local governments to monitor and review progress and challenges in the implementation of the Sendai Framework for Disaster Risk Reduction: 2015-2030, and assessing disaster resilience at both the preliminary level and detailed level	International	Buildings, economics, environment, finance, governance, healthcare, infrastructure systems, logistics and supply chain, natural resources, sociology, urban planning	Develop resilience assessment guideline documents and excel spreadsheets, educate the general public about resilient development	United Nations Office for Disaster Risk Reduction (2014)
4	The Global Resilience Institute & Global Resilience Research Network	The Northeastern University with the participation of 20 universities and research institutes from 14 countries around the world	Serving as both a channel and a catalyst for experts in industry, academia, and government to collaborate on solving the world's most pressing resilience challenges	International	Buildings, cybersecurity, governance, healthcare, infrastructure systems, sociology	Conduct multi- and interdisciplinary-research, develop new experiential education programs that will help prepare the next generation of leaders	Global Resilience Institute (2016)

Table 2-1 (Cont.)

No.	Name	Organizer(s)	Goal	Scale	Dimensions	Approaches	Reference
5	Rockefeller Foundation 100 Resilient Cities	The Rockefeller Foundation	Helping cities around the world become more resilient to the physical, social and economic challenges that are a growing part of the 21st century	International	Economics, environment, governance, healthcare, infrastructure systems, sociology	Provide funding, resources and technical assistances to support the membership cities around the world in developing and implementing resilience strategies for city services, programs and policies; hold workshops to educate the public about resilient planning and development	Rockefeller (2016)
6	Community-Based Disaster Risk Reduction Study	Arup	Improving the understanding of community resilience and influencing the building design and urban planning toward disaster resilient cities	International	Buildings, infrastructure systems, urban planning	Combine desk-based research and analysis with fieldwork	Arup (2018)
7	Resilience team in Stantec	Stantec Inc.	Improving community resilience across the globe	International	Buildings, infrastructure systems, urban planning	Provide professional engineering consulting service in disaster response and recovery, resilience assessment, mitigation, and design unites improvements	Stantec (2018)

Table 2-1 (Cont.)

No.	Name	Organizer(s)	Goal	Scale	Dimensions	Approaches	Reference
8	Regional Disaster Resilience and Homeland Security Program	The Center for Regional Disaster Resilience in The Pacific NorthWest Economic Region	Improving the Pacific Northwest's ability to withstand and recover and to protect its critical infrastructures from all-hazards disasters	Regional (northwest states of Alaska, Washington, Idaho, Montana, Oregon and Canadian provinces and territories of Alberta, British Columbia, Saskatchewan, Yukon & Northwest Territories)	Cybersecurity, finance, governance, infrastructure systems, maritime security, supply chain	Conduct research, develop advanced technologies and tools, propose action plans	Pacific Northwest Economic Region (2011)
9	Climate Change at the IDB: Building Resilience and Reducing Emissions	Inter-American Development Bank	Integrating climate change mitigation into development work to build resilience, reduce poverty and inequality in Latin America and the Caribbean countries	Regional (Latin America and Caribbean)	Environment, infrastructure systems	Conduct policy and strategy studies, provide financial and technical support to developing countries in Latin America and Caribbean	Gonzalez Diez et al. (2014)

Table 2-1 (Cont.)

No.	Name	Organizer(s)	Goal	Scale	Dimensions	Approaches	Reference
10	Economic Resilience Initiative	European Investment Bank	Rapidly mobilizing additional financing in support of the capacity of economies in the Southern Neighborhood and Western Balkans regions to boost economic resilience, absorb and respond to crises and shocks, such as the Syrian refugee crisis, while maintaining strong growth	Regional (Europe)	Economics, infrastructure systems	Invest in vital infrastructure, develop the private sector and stimulate growth and job creation, contribute to addressing root causes of migration	European Investment Bank (2016)
11	State and Societal Resilience	European Union	Strengthen the resilience of states and societies, further enhancing common actions on building resilience on the ground	Regional (Europe Union countries)	Economics, food and agriculture, healthcare, infrastructure systems	Provide humanitarian intervention, create jobs, invest in critical infrastructure systems, educate the public	European Union (2016)
12	Resilience Development	Asian Development Bank	Helping vulnerable communities and sectors in Asia to cope with climate variability and strengthen their resilience to the long-term and uncertain impacts of climate change	Regional (Asia)	Food and agriculture, healthcare, infrastructure systems	Conduct policy and strategy studies, provide financial and technical assistance to developing counties in Asia to build resilience to current and future climate variability	Asian Development Bank (2018)

Table 2-1 (Cont.)

No.	Name	Organizer(s)	Goal	Scale	Dimensions	Approaches	Reference
13	Sustainable solutions for risk reduction and risk management	The Asian Disaster Preparedness Center	Building the resilience of people and institutions to disasters and climate change impacts in Asia and the Pacific	Regional (Asia and the Pacific, member countries include: Bangladesh, Cambodia, China, India, Nepal, Pakistan, the Philippines, Sri Lanka, and Thailand)	Buildings, emergency management, governance, healthcare, infrastructure systems, sociology, urban planning	Develop and implement cross-sectoral programs and projects, conduct analysis and research, publish guidance documents, design and deliver training courses, workshops and national training centers	Asian Disaster Preparedness Center (2018)
14	Building Sustainable Cities	Asian Infrastructure Investment Bank	Investing in sustainable infrastructure and other productive sectors in Asia to improve social and economic outcomes	Regional (Asia)	Infrastructure systems	Conduct policy and strategy studies, provide financial and technical assistance to Asian countries to build resilient infrastructure systems	Asian Infrastructure Investment Bank (2018)
15	Increase Environmental Resilience	The Asia Foundation	Improving community resilience under disasters and climate change across a dynamic and developing Asia	Regional (Asia)	Cybersecurity, economics, environment, governance, infrastructure systems, natural resources, sociology, urban planning	Develop guidance documents, provide direct program support, distribute educational materials to nurture new talent and rising young leaders	The Asia Foundation (2018)

Table 2-1 (Cont.)

No.	Name	Organizer(s)	Goal	Scale	Dimensions	Approaches	Reference
16	Rebuild, Share, Prepare, Advise Advocate	SBP national organization	Becoming a leader in disaster resilience and recovery, shrinking the time between disaster and recovery	National (U.S.A)	Buildings, infrastructure systems	Rebuild home quickly after disasters, share rebuilding innovations with other rebuilding organizations, prepare home and business owners prior to and following disaster with specific steps to mitigate risk and improve resilience, advise policy makers immediately after a disaster so they can deploy federal dollars sooner, advocate for the reform of disaster recovery strategies in the U.S. to improve the predictability and speed of recovery, provide free resilience training in ten communities per year	SBP (2006)
17	Coastal Storms Program	Mississippi-Alabama Sea Grant Consortium and National Oceanic and Atmospheric Administration	Developing a tool which could perform self-assessment of community resilience to coastal hazards, identifying weaknesses a community may want to address prior to the next hazard event and guiding community discussion	National (U.S.A)	Economics, infrastructure systems, sociology, urban planning	Developed a self-assessment tool (guiding document) called Coastal Resilience Index	Sempier et al. (2010)

Table 2-1 (Cont.)

No.	Name	Organizer(s)	Goal	Scale	Dimensions	Approaches	Reference
18	Community Resilience System and the Campus Resilience Enhancement System	The Community and Regional Resilience Institute	Helping develop and then share critical paths that any America community or region may take to strengthen its ability to prepare for, respond to, and rapidly recover from significant man-made or natural disasters with minimal downtime of basic community, government, and business services	National (U.S.A)	Economic, emergency management, infrastructure systems, sociology	Combine community engagement activities with practical research activities, develop the web-enabled Community Resilience System and the Campus Resilience Enhancement System, conduct monthly interactive workshops	Community and Regional Resilience Institute (2013)
19	Planning Resilient Infrastructure	American Planning Association	Creating great communities for all by advancing planning through leadership in education, research, advocacy, and ethical practice	National (U.S.A)	Infrastructure systems	Develop guide documents	American Planning Association (2014)
20	International Security Program: Disaster Preparedness, Response, Recovery, and Resilience	The Center for Strategic and International Studies	Providing strategic insights and policy solutions to help decision-makers chart a course toward a better world	National (U.S.A)	Emergency management, governance, infrastructure systems	Conduct research and analysis and develop policy initiatives	Kostro & Riba (2014)

Table 2-1 (Cont.)

No.	Name	Organizer(s)	Goal	Scale	Dimensions	Approaches	Reference
21	National Preparedness Goal and National Planning Framework	Federal Emergency Management Agency	Building a secure and resilient nation with the capabilities required across the whole community to prevent, protect against, mitigate, respond to, and recover from the threats and hazards that pose the greatest risks, including natural disasters, disease pandemics, chemical spills and other manmade hazards, terrorist attacks and cyber-attacks	National (U.S.A)	Buildings, cybersecurity, economics, emergency management, environment, governance, healthcare, infrastructure systems, logistics and supply chain, sociology	Define goals and develop guidance documents	Federal Emergency Management Agency (2015 a, b)

Table 2-1 (Cont.)

No.	Name	Organizer(s)	Goal	Scale	Dimensions	Approaches	Reference
22	Community Resilience Planning Guide for Buildings and Infrastructure Systems	National Institute of Science and Technology	Providing a methodology for communities to develop long-term plans by engaging stakeholders, establishing performance goals for buildings and infrastructure systems, and developing an implementation strategy, by providing a mechanism to prioritize and determine the efficiency of resilience actions	National (U.S.A)	Buildings, infrastructure systems	Develop guidance documents and collect data from communities implementing the guidance documents to inform future versions	NIST (2015a)
23	Community Resilience Economic Decision Guide for Buildings and Infrastructure Systems	National Institute of Science and Technology	Providing a standard economic methodology for evaluating investment decisions aimed to improve the ability of communities to adapt to, withstand, and quickly recover from disruptive events	National (U.S.A)	Buildings, economics, finance, infrastructure systems	Develop guidance documents and the software-based EDGe$ (Economic Decision Guide Software) Tool	NIST (2015b)

Table 2-1 (Cont.)

No.	Name	Organizer(s)	Goal	Scale	Dimensions	Approaches	Reference
24	Community Resilience Center of Excellence	National Institute of Science and Technology researchers and partners from 12 universities led by Colorado State University	Developing system-level models and associated databases to support community resilience decision-making	National (U.S.A)	Buildings, economics, healthcare, infrastructure systems, sociology	Develop an open-source computational model known as IN-CORE and associated database	Ellingwood et al. (2016)
25	Regional Resiliency Assessment Program	U.S. Department of Homeland Security	Generating greater understanding and action among public and private sector partners to improve the resilience of a region's critical infrastructure	National (U.S.A)	Infrastructure systems	Conduct targeted studies and modeling, collect and analyze data on the critical infrastructure within the designated area, publish reports, organize workshops	U.S. Department of Homeland Security (2016)
26	Building mathematical foundation for resilience in systems engineering	The Risk and Decision Science Team in the US Army Crops Engineer Research and Development Center	Improving decision-making and stakeholder engagement through application and development of risk and decision science techniques	National (U.S.A)	Cybersecurity, environment, infrastructure systems, military, supply chain	Conduct research, provide risk decision advisory services, develop software and other tools	The Risk and Decision Science Team (2018)
27	Infrastructure Security	U.S. Department of Homeland Security	Working with businesses, communities, and local governments across the United States to enhance the security and resilience of the nation's critical infrastructure and to prepare for and recover from any hazard	National (U.S.A)	Infrastructure systems	Provide tools, resources, training programs and strategic guidance to public and private partners and coordinates the effort to promote the security and resilience of critical infrastructures	U.S. Department of Homeland Security (2018)

Table 2-1 (Cont.)

No.	Name	Organizer(s)	Goal	Scale	Dimensions	Approaches	Reference
28	SPUR's Sustainability and Resilience Agenda	San Francisco Planning and Urban Research Association (a member supported nonprofit organization)	Reducing ecological footprint and making cities resilient	Local (San Francisco Bay Area, California State, U.S.A)	Food and agriculture, infrastructure systems	Promote good planning and good government in the San Francisco Bay Area through research, education and advocacy	SPUR-San Francisco Planning and Urban Research Association (2009)
29	The Oregon Resilience Plan	Oregon Seismic Safety Policy Advisory Commission	Positively influencing decisions and policies regarding pre-disaster mitigation of earthquake and tsunami hazards, increasing public understanding of earthquake hazard, risk, exposure, and vulnerability through education, and be responsive to the new studies and/or issues raised around earthquakes and tsunamis	Local (Oregon State, U.S.A)	Emergency management, infrastructure systems	Develop guidance document, support earthquake education, research and legislation	Oregon Seismic Safety Policy Advisory Commission (2013)
30	Disaster recovery and community resilience work	The Queensland Reconstruction Authority	Making Queensland the most disaster resilient state in Australia	Local (Queensland State， Australia)	Emergency management, governance, infrastructure systems	Provide financial and technical assistance to Queensland government, businesses and educate the wider community to support the policy-making, reconstruction, disaster risk mitigation works	Queensland Reconstruction Authority (2018)

Table 2-1 (Cont.)

No.	Name	Organizer(s)	Goal	Scale	Dimensions	Approaches	Reference
31	Community Resilience Program	Los Angeles County Community Disaster Resilience Project	Translating lessons learned by leaders in the field into a pragmatic website useful for community-focused organizations engaged in increasing resilience in communities	Local (Los Angeles County, California State, U.S.A)	Buildings, environment, infrastructure systems, sociology	Develop web-based community resilience planning tools and hold programs, workshops and community activities to advocate for community resilience initiatives	Resilience in Communities (2018)
32	The ECIP (Enhanced Critical Infrastructure Protection) Dashboard	Argonne National Laboratory	Developing resilience measurement indices to facilitate infrastructure risk management decision-making	Organizational	Infrastructure systems	Develop the web-based tool called ECIP Dashboard to assess infrastructure vulnerability, risk and resilience and support disaster risk management related decision-making	Petit et al. (2013)
33	Communities Advancing Resilience Toolkit	University of Oklahoma Health Sciences Center	Enhancing community resilience through assessment, group processes, planning, and action	Organizational	Economics, healthcare, sociology, infrastructure systems	Develop a survey instrument, the Communities Advancing Resilience Toolkit, to assess community resilience; educate the next generation of community resilience leaders	Pfefferbaum et al. (2013)
34	Community Resilience Research	The RAND Corporation	Developing solutions to public policy challenges to help make communities throughout the world safer and more secure, healthier and more prosperous	Organizational	Economics, emergency management, healthcare, infrastructure systems	Develop guidance documents, conduct research	RAND Corporation (2018)

Table 2-1 (Cont.)

No.	Name	Organizer(s)	Goal	Scale	Dimensions	Approaches	Reference
35	Stanford Urban Resilience Initiative	Stanford University	Exploring the frontier of Resilience Science & Engineering, an emerging field which applies engineering analyses to broader questions of social impact and human behavior in the context of natural disasters and extreme events	Organizational	Buildings, infrastructure systems, urban planning	Develop the latest tools and technologies to build resilient communities, educate the next generation of leaders working in the community resilience field	Stanford Urban Resilience Initiative (2018)

It can be learned from Table 2-1 that community disaster resilience planning has gained wide attention at various scales, from international, regional, national, local to organizational scales. The wide range of community resilience research and programs are motivated by the impacts of catastrophic events in recent decades, such as 9/11 terrorist attack (2001), Hurricane Katrina (2005), Wenchuan Earthquake (2008), Joplin Tornado (2011), Great East Japan Earthquake (2011), Superstorm Sandy (2012), Bangladesh monsoon flooding (2017), Indonesia earthquake and tsunami (2018) and so on. The above community resilience initiatives are led by different types of organizations/institutions, which have different decision-makers, source of funding and governance structure for implementation. Example types of the organizers include: multinational development banks, multilateral development agencies, non-profit organizations, government agencies, foundations, research institutions, corporations, university research groups and so on. The approaches taken by these organizations to address community resilience issues are summarized in Figure 2-1.

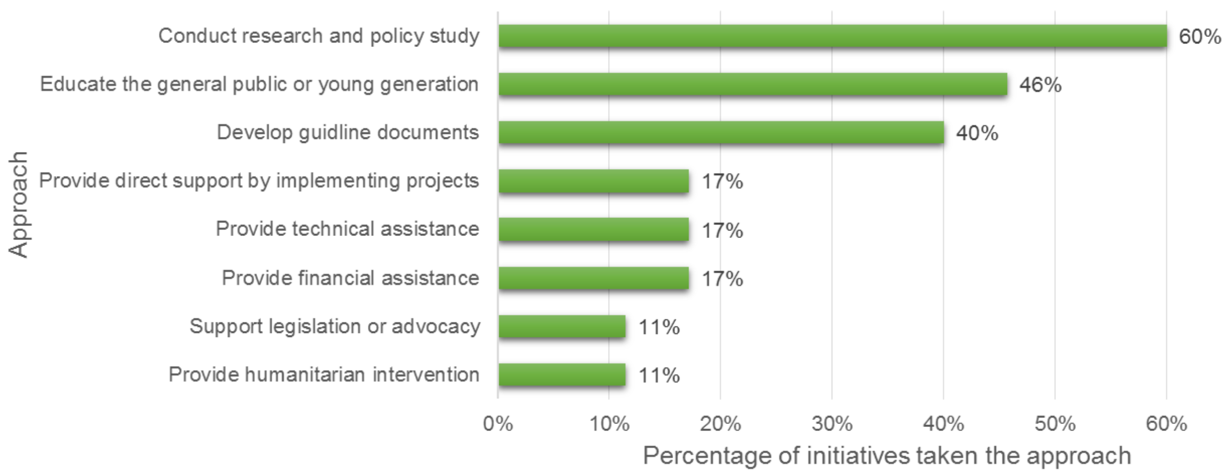


Figure 2-1. The approaches used to address community resilience by various organizations.

The statistics in Figure 2-1 indicate that most initiatives addressing the community disaster resilience planning are still in the research and development stage. Common approaches in this stage include: conducting disaster resilience research, developing methodologies and tools to assess community resilience, conducting strategy and policy studies to support the community resilience planning, and developing resilience assessment and implementation guideline documents. Only a small portion of the initiatives actually put plans into actions, such as providing financial, technical and/or humanitarian (e.g. material and logistic) interventions, implementing projects or programs to assist the pre-disaster risk mitigation (e.g. upgrading, retrofitting or frequent maintenance of existing buildings and infrastructure facilities) and post-disaster recovery (e.g. repairing or reconstructing damaged facilities) works. However, lots of efforts have been witnessed on educating the general public about resilient development and nurturing the next generation of community resilience leaders through workshops, training programs, advocacies, and so on. These educational programs can raise the public awareness of community disaster resilience related issues and lead to coordination efforts of people from all walks of life to work on disaster risk management and community resilience planning.

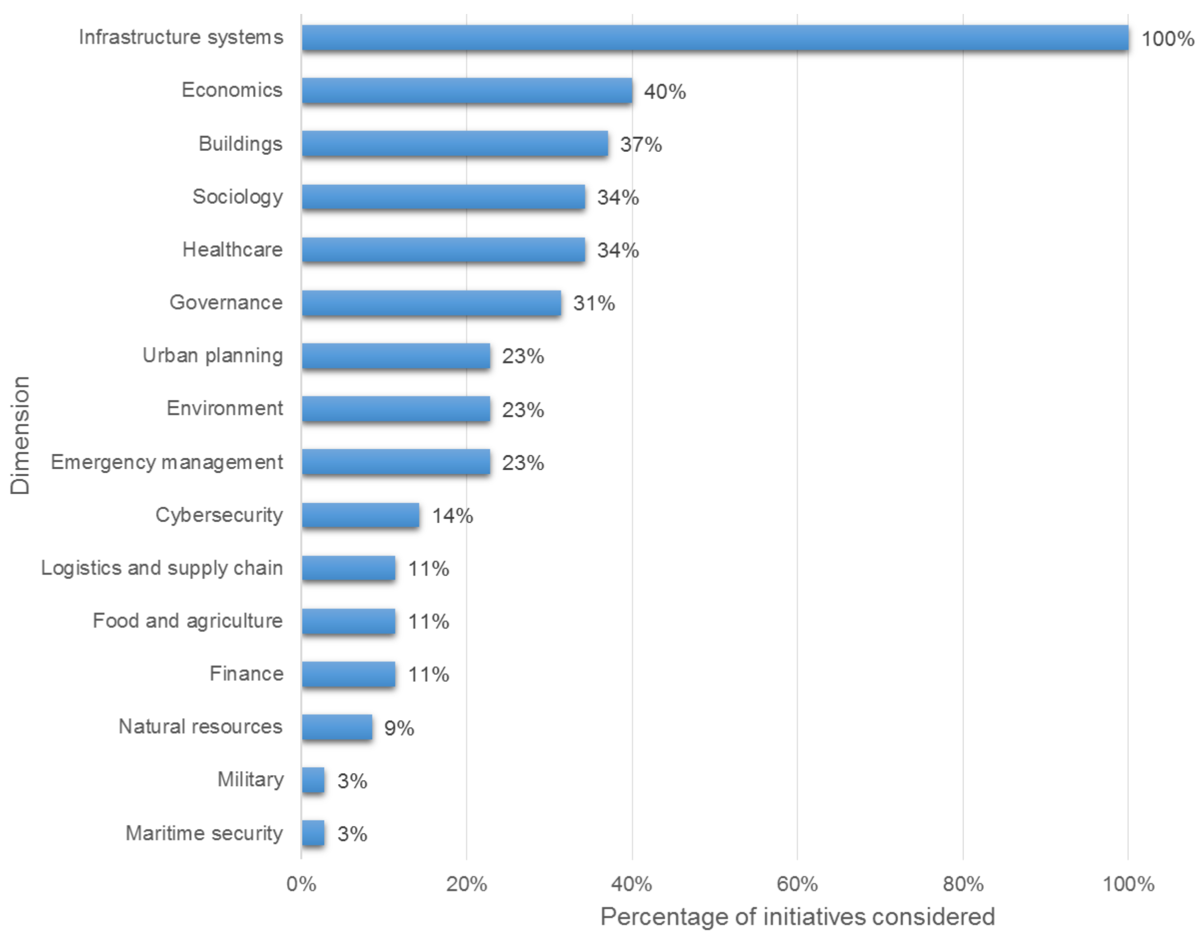


Figure 2-2. Different dimensions of community resilience considered by the initiatives.

Achieving community disaster resilience requires coordination efforts of experts from different fields since community resilience has various dimensions. Figure 2-2 shows the wide range of dimensions of community resilience that have been addressed by one or more initiatives listed in Table 2-1. Among all the 35 reviewed community resilience initiatives with an emphasis on infrastructure disaster resilience, 5 of them only focus on the critical civil infrastructure systems, without considering the interactions with any other systems. The rest of the initiatives all address community resilience with considering at least one more dimension(s) apart from the civil infrastructure systems. Many of the community resilience initiatives with an emphasis on infrastructure resilience also aim at improving the resilience of economic, social, healthcare, governance systems and the physical building environment to better achieve an overall community resilience. Some of the programs or studies also take the urban planning, environmental protection and emergency management into consideration. The coordination efforts of assessing and improving community resilience at multiple dimensions gradually become a trend in the most recent decade.

In summary, the catastrophic events in recent decades have motivated the community disaster resilience related studies and projects worldwide. The community disaster resilience planning has gained traction at various scales, from international, national, regional, local to organizational levels. Among all the community resilience initiatives with an emphasis on improving the resilience of critical civil infrastructure systems, more and more initiatives nowadays began to extend the efforts to a wider range of systems, such as social and economic systems, in order to better enhance the overall community resilience against natural and/or manmade hazards. However, the above review indicates that most of the community resilience projects or programs are only at a research and analysis stage. The proposed community disaster resilience plans, strategies or guidelines are not always implemented. Thus, it’s recommended that various levels of institutions, organizations, government agencies and local communities should further reinforce the corporation so that the proposed resilience plans, strategies and programs can be actually put into action.

2.2. Concept of Resilience

Clearly defining and understanding the concept of resilience is fundamental and essential to determine the direction and emphasis of each community resilience initiative, which is found to be common approach of the above-mentioned community resilience initiatives.

The term *resilience* is derived from the Latin word *resilio*, which means “to jump back” (Klein et al., 2003). There is an agreement in the literature that the concept of resilience originates from the field of ecology in 1970s (Holling, 1973; Klein et al., 2003; Zhou et al., 2010; Koliou et al., 2017). Over the years, the concept of resilience has wide application in a host of disciplines, ranging from psychology, ecology, education, environmental science, health-related science, sociology, economics to engineering and so on (Jeffcott, Ibrahim & Cameron, 2009; Cumming, 2011; Okvat & Zautra, 2011; Foster, O'brien & Korhonen, 2012; Biggs, Schlüter & Schoon, 2015; Sprecher et al., 2015; Mansfield et al., 2016; Gherhes, Vorley & Williams, 2018; Saja et al., 2018). Resilience is often viewed as consisting of three dimensions: the ability of an entity to resist or withstand the shock, the ability of the entity to recover from the shock, and its ability to adapt to future shocks. Here, the word “shock” can refer to any disruptive events, depending on the discipline that resilience is applied to. For example, parental mental illness can be the shock to a child when studying psychological resilience of the child (Foster, O'brien & Korhonen, 2012), while natural disasters such as hurricanes or earthquakes can be viewed as shocks to the infrastructure systems in a community when assessing the community infrastructure resilience (Ellingwood et al., 2016). Besides, there are disagreements in the literature as to the property of resilience, whether resilience is an ability, an outcome or a process.

A number of the resilience concept and corresponding property, type (application discipline) and dimensions, chronologically ordered, are listed in Table 2-2. Since this thesis mainly focuses on the community disaster resilience, or more specifically, the resilience to the natural or manmade hazards of the critical civil infrastructure systems in a community, the forgoing review of the community or infrastructure resilience concept are presented in disproportionate frequency. Definitions describing the resilience in other disciplines, such as ecology, psychology, sociology or material science, are representative of others in the literature.

Table 2-2. Summary of the concept of resilience with an emphasis on community disaster resilience.

No.	Type	Definition	Properties	Dimensions: Resist shocks	Dimensions: Recover from shocks	Dimensions: Adapt to future shocks	Reference
1	Ecological resilience	The ability of systems to absorb changes of state variables, driving variables, and parameters, and still persist.	Ability	√			Holling (1973)
2	Material resilience	The ability to store strain energy and deflect elastically under a load without breaking or being deformed.	Ability	√			Gordon (1978)
3	Community resilience	The capacity to absorb and recover from occurrence of a hazardous event.	Ability	√	√		Timmermann (1981)
4	General resilience	The capacity to cope with unanticipated dangers after they have become manifest and learn to bounce back to normal.	Ability	√	√		Wildavsky (1988)
5	Psychological resilience	The process of, capacity for, or outcome of successful adaptation despite challenging or threatening circumstances.	Process, ability, outcome	√	√	√	Masten, Best & Garmezy (1990)
6	Psychological and psychopathological resilience	The capacity for successful adaptation, positive functioning or competence, despite high-risk status, chronic stress, or following prolonged or severe trauma.	Ability	√	√	√	Egeland, Carlson, & Sroufe (1993)
7	Psychological and social resilience	The process through which mediating structures (e.g.: schools, church groups, family networks, and sporting organizations) and activity settings successfully adapt to adversity, stressful events, and oppressive systems.	Process	√	√	√	Sonn & Fisher (1998)
8	Community resilience	The ability of a community to withstand an extreme natural event without suffering devastating losses, damage, diminished productivity, or quality of life, and without a large amount of assistance from outside the community.	Ability	√			Mileti (1999)
9	Social resilience	The ability to withstand stresses and disturbances caused by social, political and economic changes.	Ability	√			Adger (2000)
10	Community resilience	The capability to bounce back and use physical and economic resources effectively to aid recovery following exposure to hazard events.	Ability	√	√		Paton (2000)

Table 2-2 (Cont.)

No.	Type	Definition	Properties	Dimensions			Reference
				Resist shocks	Recover from shocks	Adapt to future shocks	
11	Social and ecological resilience	The amount of disturbance a system can absorb and remain within a domain of attraction, the capacity for learning and adaptation and the degree to which the system is capable of self-organizing.	Ability	√	√	√	Carpenter et al. (2001)
12	Community resilience	The ability of social units (e.g. organizations, communities) to mitigate hazards, contain the effects of disasters when they occur, and carry out recovery activities in ways that minimized social disruptions and mitigate the effects of future hazards.	Ability	√	√	√	Bruneau et al. (2003)
13	Community resilience	The ability of individuals and communities to deal with a state of continuous, long term stress, which causes gaps between environment stimuli and their functional coping behavior; the ability to find unknown inner strengths and resources in order to cope effectively; the measure of adaptation and flexibility.	Ability	√	√	√	Ganor & Ben-Lavy (2003)
14	Community resilience	The ability of physical systems and human communities to survive and function under extreme stress.	Ability	√			Godschalk (2003)
15	Enterprise resilience	The ability and capacity of an enterprise or organization to withstand systemic discontinuities and adapt to new risk environment by effectively aligns is strategy, operations, management systems, governance structure and decision-support capabilities to the changing environment.	Ability	√	√	√	Starr, Newfrock & Delurey (2003)
16	Community resilience	The process of using material, physical, socio-political, socio-cultural, and psychological resources in a community to promote the safety of its residents, protect residents against injury and violence risks, and allow residents to recover after exposure to general adversity and injury risks.	Process	√	√		Ahmed et al. (2004)
17	Psychological resilience	An individual's ability to adapt to stress and adversity; a process that can be learned by anyone using positive emotions.	Process, ability	√	√	√	Tugade, Fredrickson & Feldman Barrett (2004)
18	Social and ecological resilience	The capacity of linked social-ecological systems to absorb recurrent disturbances, the capability of self-organization and building capacity for learning and adaptation	Ability	√	√	√	Adger et al. (2005)
19	General resilience	The capacity of a system to maintain its functions and structure in the face of internal and external change and to degrade gracefully when it must.	Ability	√			Allenby & Fink (2005)

Table 2-2 (Cont.)

No.	Type	Definition	Properties	Dimensions: Resist shocks	Dimensions: Recover from shocks	Dimensions: Adapt to future shocks	Reference
20	Infrastructure resilience	The capacity to prevent or protect against significant multi-hazard threats and incidents, including terrorist attacks, and to recover and reconstitute critical services with minimum devastation to public safety and health.	Ability	√	√		Infrastructure Security Partnership (2006)
21	Community resilience	The capacity or ability of a community to anticipate, prepare for, respond to, and recover quickly from impacts of disaster; it is not only the measure of how quickly the community can recover from the disaster impacts, but also the ability to learn, cope with or adapt to hazards.	Ability	√	√	√	Mayunga (2007)
22	Infrastructure resilience	The ability of a system to recover from adversity, either back to its original state or an adjusted state based on new requirements.	Ability	√	√	√	McCarthy (2007)
23	Community resilience	A process linking a set of adaptive capacities to a positive trajectory of functioning and adaptation after a disturbance.	Process	√	√	√	Norris et al. (2008)
24	Community resilience	The ability of a system to respond and recover from disasters and includes those inherent conditions that allow the system to absorb impacts and cope with an event, as well as post-event, adaptive processes that facilitate the ability of the system to re-organize, change, and learn in response to a threat.	Ability	√	√	√	Cutter et al. (2008)
25	Infrastructure resilience	The ability of a system to sustain external and internal disruptions without discontinuity of performing the system's function or, if the function is disconnected, to fully recover the function rapidly.	Ability	√	√		American Society of Mechanical Engineers (2009)
26	General resilience	The ability of a system to withstand a major disruption within acceptable degradation parameters and to recover within acceptable time and composite costs and risks	Ability	√	√		Haimes (2009)
27	Infrastructure resilience	The ability to anticipate, absorb, adapt to, and/or rapidly recover from a potentially disruptive event.	Ability	√	√	√	National Infrastructure Advisory Council (2009)
28	Social and ecological resilience	The capacity of a system to cope with shocks and undergo change while retaining essentially the same structure and function, and the ability to build and increase the capacity for learning and adaptation.	Ability	√	√	√	Walker et al. (2009)

Table 2-2 (Cont.)

No.	Type	Definition	Properties	Dimensions: Resist shocks	Dimensions: Recover from shocks	Dimensions: Adapt to future shocks	Reference
29	Infrastructure and economic resilience	The system's ability to reduce efficiently both the magnitude and duration of the deviation from targeted system performance levels.	Ability	√	√		Vugrin et al. (2010)
30	Economic resilience	The process of adapting to the changing competitive, technological and market pressures and opportunities that confronting local economy.	Process	√	√	√	Simmie & Martin (2010)
31	Logistics and supply chain resilience	The ability of a system to return to its original state or to a new more desirable one after experiencing a disturbance and avoiding occurrence of failure modes.	Ability	√	√	√	Cabral et al. (2011)
32	Infrastructure resilience	The intrinsic ability of a system to adjust its functionality in the presence of a disturbance and unpredicted changes. It is the sum of the passive survival rate (reliability) and the proactive survival rate (restoration) of a system.	Ability	√	√		Woods, Leveson & Hollnagel (2012)
33	Economic resilience	The policy-induced ability of an economy to recover from or adjust to the negative impacts of adverse exogenous shocks and to benefit from positive shocks.	Ability	√	√		Mancini (2012)
34	National and community resilience	The ability to prepare and plan for, absorb, recover from, or more successfully adapt to actual or potential adverse events.	Ability	√	√	√	National Research Council (2012)
35	Infrastructure resilience	The systems' ability to resist various possible hazards, absorb the initial damage from hazards, and recover to normal operation one or multiple times during a time period.	Ability	√	√		Ouyang & Dueñas-Osorio (2012)
36	Social resilience	The capacities to cope with the disruptions, to adapt to changing conditions, and transform to the new stable state.	Ability	√	√	√	Keck & Sakdapolrak (2013)
37	Infrastructure resilience	The ability of systems to prepare for and adapt to changing conditions, withstand and recover rapidly from disruptions.	Ability	√	√	√	Presidential Policy Directive (2013)
38	Community resilience	The capacity of a person, household or other aggregate unit to avoid poverty in the face of various stressors and in the wake of myriad shocks over time.	Ability	√	√		Barrett & Constas (2014)
39	Social and ecological resilience	The ability of social or ecological system to absorb disturbances while retaining the same basic structure and ways of functioning, the capacity of self-organization, and the capacity to adapt to stress and change.	Ability	√	√	√	International Panel of Climate Change (2014)

Table 2-2 (Cont.)

No.	Type	Definition	Properties	Dimensions: Resist shocks	Dimensions: Recover from shocks	Dimensions: Adapt to future shocks	Reference
40	Infrastructure resilience	The ability of a system to adapt its behavior to maintain continuity of function (or operations) in the presence of disruptions.	Ability	√	√	√	Alderson, Brown & Carlyle (2015)
41	Food system resilience	The capacity over time of a food system and its units at multiple levels, to provide sufficient, appropriate and accessible food to all, in the face of various and even unforeseen disturbances.	Ability	√	√		Tendall et al. (2015)
42	Power system resilience	The system's ability to recognize, adapt to, and absorb disturbances in a timely manner.	Ability	√	√	√	Arghandeh et al. (2016)
43	Material resilience	The maximum elastic energy absorbed by a material when a load is applied.	Ability	√	√		Dessavre, Ramirez-Marquez & Barker (2016)
44	Power system resilience	The *operational resilience* refers to the characteristics that would secure operational strength for a power system, e.g., the ability to ensure the uninterrupted supply to customers or generation capacity availability in the face of a disaster. The *infrastructure resilience* refers to the physical strength of a power system for mitigating the portion of the system that is damaged, collapsed or in general becomes nonfunctional.	Ability	√	√		Panteli et al. (2017)
45	Infrastructure resilience	The ability to withstand and recover from deliberate attacks, accidents, or naturally occurring threats or incidents; the ability to prepare for and adapt to changing conditions.	Ability	√	√	√	Fujita et al. (2018)
46	Water system resilience	The ability to mitigate and recover from failure.	Ability	√	√		Huizar, Lansey & Arnold (2018)
47	Infrastructure resilience	The ability of a system to withstand stressors, adapt, and rapidly recover from disruptions.	Ability	√	√	√	Sharma, Tabandeh & Gardoni (2018)
48	Power system resilience	The ability to withstand and recover rapidly from deliberate attacks, accidents, or naturally occurring threats or incidents, adapt to changing conditions.	Ability	√	√	√	Shayeghi & Younesi (2019)

It can be learned from Table 2-2 that multiple definitions of resilience exist within the literature, with no broadly accepted single definition. This may be due to the fact that the resilience concept is shared by various disciplines, applied to a wide range of objects at different scales (e.g.: individual human beings, structural components, infrastructure systems, socio-ecological systems, socioeconomic systems, overall communities, etc.), and under different types of disruptive events (e.g.: mental disorder, stress, natural hazard, load, pollution, etc.). However, even though the definitions of resilience vary from case to case, some of them share common properties or dimensions.

There is a debating view in the literature as to the property of resilience, whether it's an ability, a process or an outcome. It's easy to be identified from Table 2-2 that the majority of researchers view resilience as an inherent ability or capacity of people, systems or communities to cope with the disruptions, while only one early literature defines psychological resilience as an outcome of successful adaptation of human beings to threatening circumstances (Masten, Best & Garmezy, 1990). Additionally, some researchers, especially in the psychology or community disaster resilience planning field, tend to view resilience as a process rather than an ability or an end. They understand resilience as a whole process of coping with, adapting to or learning from the changing conditions (Sonn & Fisher, 1998; Ahmed et al., 2004; Tugade, Fredrickson & Feldman Barrett, 2004; Norris et al., 2008; Simmie & Martin, 2010).

As for the dimensions of resilience, most of the reviewed literatures in Table 2-2 address resilience in multiple dimensions, including (1) the ability to absorb or resist external shocks; (2) the ability or speed to recover from impacts; and (3) the ability to adapt to future disruptions or the changing environment. A few conceptual definitions of resilience in early years only focus on the first dimension and view resilience as the ability to withstand the external shocks (Holling, 1973; Gordon, 1978; Mileti, 1999; Adger, 2000). This is a very narrow understanding of resilience, and nowadays, this dimension is usually described using the term vulnerability, reliability or robustness (Adger, 2006; Cutter et al., 2008; Reed, Kapur & Christie, 2009; Shirley, Boruff & Cutter, 2012; Sarkar et al., 2018). Apart from these few exceptions, all the other definitions of resilience focus on both the resistance to impact when it occurs (dimension (1)) and the rapid recovery from the impact over time (dimension (2)). The focus on the first two dimensions remains central to nearly all definitions of resilience regardless of the disciplines. The tripartite view of resilience (resisting impacts, rapid recovery, and adaptation to future disruptions) was first proposed in psychology field to describe psychological resilience (Masten, Best & Garmezy, 1990), and gradually became prevalent in the resilience definitions in all disciplines over the last decade. From this perspective, resilience is not simply the ability to absorb or resist external shocks and rapidly recover from the impacts to reach a pre-existing state, but also learn to adapt to future shocks and change to a new state that is more suitable or sustainable in the current environment.

In recent years, a tendency of addressing all three dimensions of resilience has been witnessed, especially in defining community or infrastructure disaster resilience. Many literatures considered the possibility of the infrastructure systems or communities to recover to a new equilibrium state in order to adapt to the post-disaster new normal condition or mitigate the future disaster impacts (Bruneau et al., 2003; Presidential Policy Directive, 2013; Fujita et al., 2018; Sharma, Tabandeh & Gardoni, 2018; Guidotti, Gardoni & Rosenheim, 2019). The post-disaster new normal may result from various policy or socioeconomic reasons, such as post-disaster demand or capacity change, removing old or building new infrastructure facilities, etc. A resilient community of infrastructure system is able to learn from the past disaster experience and reach to a better state of functioning. Rather than simply 'surviving' the disruptive events, a resilient community or infrastructure system may respond in creative ways and transform in an adaptive way to external shocks (Maguire & Cartwright, 2008). This transformation view of resilience is particularly useful for understanding how a community as a whole can respond positively to disruptions. It recognizes the powerful capacity of people from different walks of life in the community to learn from their experiences and to consciously incorporate this learning into their interactions with the broader social, economic and physical environment. This view of resilience is important since it acknowledges that people themselves can play a central role in mitigating the impact of disruptions and are able to shape their community towards a more disaster resilient one. Indeed, this broader perspective of resilience concept has inspired and guided worldwide efforts to promote community resilience to hazard events, as is shown in the community resilience initiatives summarized in section 2.1.

2.3. Resilience Assessment

The concept of resilience provides the basis of assessing resilience quantitatively. This section mainly focuses on the quantitative resilience assessment methods for civil infrastructure systems. Measuring the resilience of infrastructure systems is important to evaluate the performance of infrastructure systems under disasters and compare the effectiveness of different pre-disaster risk mitigation or post-disaster recovery plans, which can be found in nearly all the reviewed community resilience initiatives in section 2.1.

Lots of studies have attempted to quantify the resilience of civil infrastructure systems and many different methodologies have been proposed. Some representative resilience assessment methods are shown in Table 2-3. For each method listed in Table 2-3, the name of the resilience metric, the mathematical or conceptual definition of the metric, its methodological category, advantages, limitations and the reference of some representative works are clearly identified. The resilience assessment methods in Table 2-3 are broadly grouped into three categories: (1) subjective evaluation-based, (2) probability theory-based and (3) recovery curve-based. The subjective evaluation-based resilience assessment methods rely on expert judgements and estimations; the probability theory-based methods measure resilience probabilistically with considering the uncertainties, while the recovery curve-based methods calculate resilience from recovery curves of the infrastructure systems under disruptive events using some mathematical equations. A recovery curve of an infrastructure system represents the performance of the system at any time step over a certain duration following the occurrence of the disruptive event (Sharma, Tabandeh & Gardoni, 2018). The curve would experience a drop at the occurrence of the disruptive event and is typically a non-decreasing function of time following the disruptive event. An example recovery curve of an infrastructure system is shown in Figure 2-3. It's noted that the infrastructure system may recover to a post-disaster new normal state following the disaster. In the recovery curve shown in Figure 2-3, the horizontal axis shows the time, t, following the disruptive event, with t_0 = the time when the disruption occurs; t_1 = the time when the infrastructure system recovers; t_2 = the end point of the time period in consideration when calculating resilience using some methods in Table 2-3. The vertical axis in the recovery curve in Figure 2-3 represents the system performance indicator, $Q(t)$, which is a metric indicate the state or performance level of the infrastructure system over time. It will be discussed in more detail in section 2.5.

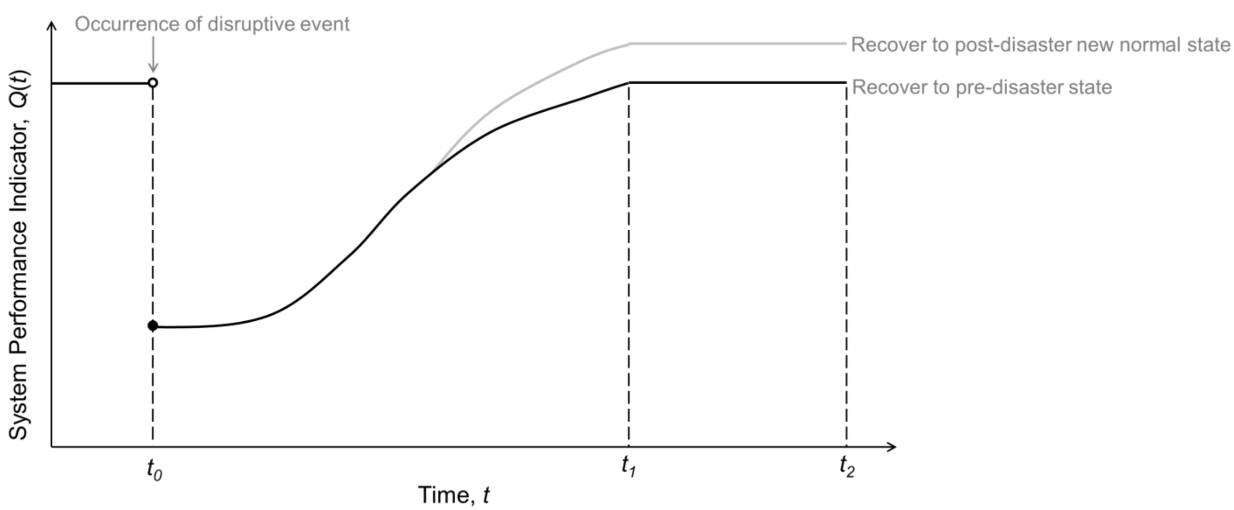


Figure 2-3. An example recovery curve of an infrastructure system following a disruptive event.

Table 2-3. Summary of the resilience assessment methods.

No.[1]	Metric	Definition	Advantages	Limitations	Reference
S-1	Community resilience indicators	29 community resilience indicators in six categories: ecological, social, economic, institutional, infrastructure and community competence are proposed. Each indicator is scored between 0 and 100. The score for each category is calculated using an unweighted average of each indicator, and the total score is calculated by taking the unweighted average of all categories.	• It can measure resilience comprehensively by considering multi-categories.	• The result is highly dependent upon expert estimation or self-evaluation, which is very subjective. • If the number of experts providing estimations to the surveys is not enough, then the result may not be reliable.	Cutter et al. (2008)
S-2	Resilience	The resilience is measured by the level of vulnerability and capability to recover from a disruptive event. A set of 152 questions divided into 6 sections of vulnerability assessment and 15 sections of recovery capability assessment are proposed. The importance of each factor is weighted by policymakers. The responses to the questions are combined using weighted sum approach to get the overall resilience.	• It can measure resilience comprehensively by considering multi-categories.	• The result is highly dependent upon expert estimation or self-evaluation, which is very subjective. • If the number of experts providing estimations to the surveys is not enough, then the result may not be reliable. • The weights provided by the policy makers are subjective.	Pettit (2008)

[1] The abbreviation before the number refers to the methodological category of each metric, where "S" stands for subjective evaluation-based, "P" stands for probability theory-based, "PS" stands for probability theory-based and subjective evaluation based, "R" stands for recovery curve-based metric.

Table 2-3 (Cont.)

No.	Metric	Definition	Advantages	Limitations	Reference
S-3	Resilience index	The resilience index is calculated as the weighted sum of the score of each component of resilience. The score is determined from expert estimation. The infrastructure resilience is composed of three levels. The components in the first level include: robustness, recovery and resourcefulness. Each of these level 1 categories can be further divided into subgroups (level 2), and each level 2 category can be further divided into level 3 subgroups.	• It can measure resilience comprehensively with using more levels, categories and subgroups.	• The result is highly dependent upon expert estimation, which is very subjective. • If the number of experts providing the estimation is small, then the result may not be very reliable.	Fisher & Norman (2010)
S-4	Coastal resilience index	The resilience index of low, medium or high is identified for different categories of a community (e.g. critical infrastructures and facilities, social systems, emergency plans, mitigation efforts, business plans, etc.) after completing a self-assessment evaluation.	• It can measure resilience comprehensively by considering multi-categories.	• The result is based on self-evaluation, which is very subjective and may be over- or under-rated. • If the number of experts providing estimations to the surveys is not enough, then the result may not be reliable.	Sempier et al. (2010)
S-5	Resilience	The resilience is categorized into six groups. The score for each indicator is collected from a survey and then the data are analyzed and combined into a single score using principal component analysis.	• It can measure resilience comprehensively by considering multi-categories.	• The result is highly dependent upon expert estimation, which is very subjective. • If the number of experts providing estimations to the surveys is not enough, then the result may not be reliable.	Shirali, Mohammadfam & Ebrahimipour (2013)

Table 2-3 (Cont.)

No.	Metric	Definition	Advantages	Limitations	Reference
P-1	Resilience between t_1 and t_2, $\mathrm{Re}(t_1,t_2)$	$\mathrm{Re}(t_1,t_2)=\dfrac{P_{FS}(t_1,t_2)}{P_F(t_1)}$ where $P_F(t_1)$ = the probability of failure at t_1; $P_{FS}(t_1,t_2)$ = a two-state transition probability, or the intersection probability that a system fails at t_1, and recovers at t_2.	• It's straightforward to understand.	• Determining the transition probability is a challenging task. It may require lots of input information. • It is associated only with recovery actions, while preparedness actions (vulnerability) are disregarded. • Quantifying resilience using a single metric may only provide partial information about actual resilience.	Li & Lence (2007)
PS-1	Resilience, $\Pr(A\,\vert\, i)$	Resilience is quantified as the probability of meeting both robustness and rapidity standards in event *i*. $\Pr(A\,\vert\, i)=\Pr(r_0 \le r^* \ \ and\ \ t_1 \le t^*)$ Where *A* = predefined performance standards; *i* = the hazard intensity; r_0 = vulnerability; r^* = robustness standard; t^* = rapidity standard.	• It's easy to interpret and straightforward to understand. • It considers the uncertainties in quantification of resilience.	• The performance standards are determined subjectively.	Chang & Shinozuka (2004)
PS-2	Resilience index, *Rix*	$Rix = P(R)=\lim\limits_{n\to\infty}\left(\dfrac{s}{n}\right)$ where *P*(*R*) = number of successful response; *s* = number of success; *n* = number of trails. Here, successful response means the recovery time and cost are both below the threshold value.	• It can consider both the recovery time and recovery cost. • It's easy to interpret.	• The acceptable recovery time and cost are determined subjectively.	Gay & Sinha (2012)

Table 2-3 (Cont.)

No.	Metric	Definition	Advantages	Limitations	Reference
R-1	Loss of resilience, R_L	$R_L = \int_{t_0}^{t_1} \left[1 - Q(t)\right] dt$	• It's easy to calculate and straightforward to understand. • It's generally applicable.	• It cannot distinguish the resilience associated with recovery curves having different trajectories but same area above the curves, such as the case in Figure 2-5 and Figure 2-6. • It assumes that the infrastructure system would recover back to its pre-disaster state, not considering post-disaster new normal. • Quantifying resilience using a single metric may only provide partial information about actual resilience.	Bruneau et al. (2003)
R-2	Resilience, R	$R = \frac{\int_{t_0}^{t_1} Q(t)\ dt}{t_1 - t_0}$	• It's easy to calculate and straightforward to understand.	• It cannot distinguish the resilience associated with recovery curves having different combinations of recovery times and recovery trajectories, such as the case in Figure 2-4 and Figure 2-5. • Quantifying resilience using a single metric may only provide partial information about actual resilience.	Bruneau & Reinhorn (2007); Cimellaro, Reinhorn & Bruneau (2010b); Ayyub (2014); Bonstrom & Corotis (2014); Shayeghi & Younesi (2019)

Table 2-3 (Cont.)

No.	Metric	Definition	Advantages	Limitations	Reference
R-3	Resilience, R	$R=\frac{\int_{t_0}^{t_2} Q(t)\ dt}{t_2-t_0}$	• It can distinguish the resilience associated with recovery curves having different recovery times, such as the case in Figure 2-4. • It's easy to calculate and straightforward to understand.	• It cannot distinguish the resilience associated with recovery curves having different trajectories but same area under the curves, such as the case in Figure 2-5. • It's needed to agree on a time period in consideration (the value of t_2) before calculation. • Quantifying resilience using a single metric may only provide partial information about actual resilience.	Reed, Kapur & Christie (2009); Cimellaro, Reinhorn & Bruneau (2010a); Decò, Bocchini & Frangopol (2013); He & Cha (2018b); Sun, Bocchini & Davison (2018)
R-4	Recovery-dependent resilience, RDR	$RDR=\frac{\int_{t_0}^{t_1}\left[1-Q(t)\right]\ dt+\alpha\times\int_{t_0}^{t_1} RE(t)\ dt}{t_1-t_0}$ where $RE(t)$ = recovery effort at time t; α = weighting factor to assign relative importance of systematic impact and total recovery effort.	• It considers the impact of resourcefulness during the recovery phase to the resilience.	• $RE(t)$ and α are hard to quantify. • It cannot distinguish the resilience associated with recovery curves having different combinations of recovery times and recovery trajectories, and same $RE(t)$ and α . • Quantifying resilience using a single metric may only provide partial information about actual resilience.	Vugrin, Warren & Ehlen (2011)

Table 2-3 (Cont.)

No.	Metric	Definition	Advantages	Limitations	Reference
R-5	Resilience, $R(X,T)$	$R(X,T)=\frac{1\cdot T^{*}-X\cdot T/2}{1\cdot T^{*}}$ where $X\in[0,1]$ = percentage of functionality lost after a disruption; $T\in[0,T^{*}]$ = time required for full recovery; T^{*} = a suitably long time interval over which lost functionality is determined.	• It can distinguish the resilience associated with recovery curves having different recovery times, such as the case in Figure 2-4. • It's easy to calculate and straightforward to understand.	• It uses the resilience triangle paradigm, which means that this method assumes that the disruptive event has an instantaneous impact and the recovery begin immediately and is a linear line. The instant drop of functionality, immediate start of recovery and linear recovery trajectory may not be realistic for some systems and events. • It cannot distinguish the resilience associated with recovery curves having different trajectories but same area above the curves, such as the case in Figure 2-5. • It's needed to agree on a time period in consideration (the value of T^{*}) before calculation. • It assumes that the system would recover back to its pre-disaster state. • Quantifying resilience using a single metric may only provide partial information about actual resilience.	Zobel (2011); Adams, Bekkem & Toledo-Durán (2012); Zobel & Khansa (2014); Sahebjamnia, Torabi & Mansouri (2015)

Table 2-3 (Cont.)

No.	Metric	Definition	Advantages	Limitations	Reference
R-6	Resilience at time *t*, $R(t)$	$R(t)=\frac{Recovery(t)}{Loss(t_d)}$ It describes the ratio of recovery at time *t* to the loss suffered by the system at some previous point in time t_d. If recovery is equal to the loss, then the system is fully resilient, and if there is no recovery, then no resilience is exhibited.	• It's easy to calculate and straightforward to understand.	• It is not considered as a system's property but rather as an effect of recovery actions, which means that if a system does not suffer any loss, there is no scope for a recovery and thus there is no scope to exhibit resilience. • It is associated only with recovery actions, while preparedness actions (vulnerability) are disregarded. • The parameters need to be further defined in order to formulate a consistent quantitative approach. • Quantifying resilience using a single metric may only provide partial information about actual resilience.	Henry & Ramirez-Marquez (2012); Zhang et al. (2018)
R-7	Annual Resilience, *AR*	$AR=E\left[\frac{\int_0^{t_2}Q(t)\ dt}{\int_0^{t_2}TP(t)\ dt}\right]$ where t_2 = 1 year; $TP(t)$ = target performance at time *t*.	• It can incorporate multiple inter-related hazards happened during one year, making the approach more applicable for real-world applications. • The target performance curve can be a constant line or a stochastic process.	• It needs more input data such as the annual occurrence frequency of different hazards. • It focuses only on the technical dimension of resilience and introduces the multiple hazards effects in a non-correlated manner. • Quantifying resilience using a single metric may only provide partial information about actual resilience.	Ouyang, Dueñas-Osorio & Min (2012)

Table 2-3 (Cont.)

No.	Metric	Definition	Advantages	Limitations	Reference
R-8	Dynamic resilience metric, ρ_i, for event *i*	$\rho_i = S_P \frac{F_r}{F_0}\frac{F_d}{F_0}$ where S_p = speed of recovery; F_0 = pre-disaster performance level; F_d = performance level immediately following the disruption; F_r = the performance level of the post-disaster new normal.	• It considers the possibility that the system may recover to a post-disaster new normal.	• This metric is not constrained on [0, 1], thereby making the extreme values difficult to comprehend. • It assumes that the speed of recovery follows exponential growth, which may not always be the case.	Francis & Bekera (2014)
R-9	(1) Resilience disparity, $\Delta(q_1, q_2)$ (2) Center of resilience, ρ_Q (3) Median of resilience, $\rho_{Q,0.5}$ (4) Mode of resilience, $\rho_{Q,\max}$ (5) Resilience quantile, $\rho_{Q,w}$ (6) Resilience bandwidth, χ_Q (7) Resilience skewness, ψ_Q	The mathematical definition of each metric can be found in the reference paper. The general idea is to view the recovery curve as the cumulative resilience function, which is similar to the cumulative distribution function in probability theory, and then use the comparable terms in probability theory to describe different characteristics of resilience.	• It can systematically describe the recovery curve and provide a whole picture of resilience. • It can distinguish any recovery curves, including the examples shown in Figure 2-4, Figure 2-5 and Figure 2-6.	• The calculation of these resilience metrics is a little bit complicated.	Sharma, Tabandeh & Gardoni (2018)

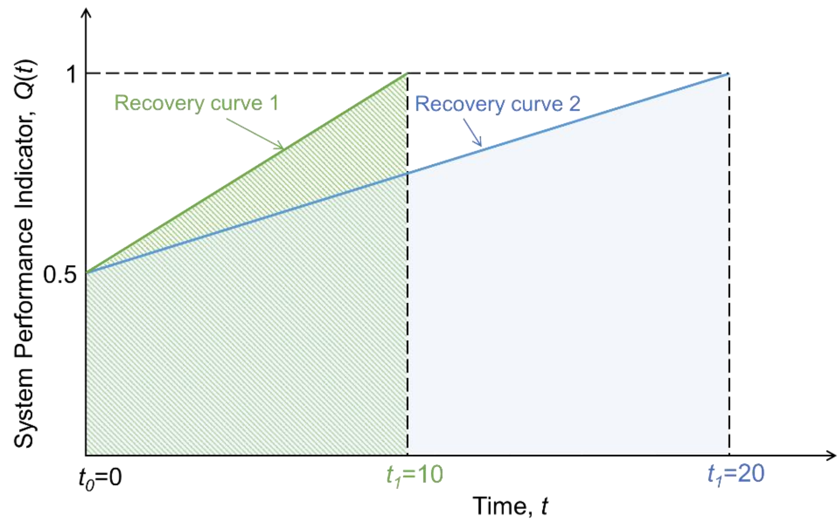


Figure 2-4. Two example recovery curves having the same normalized area under the curve, normalized by recovery time.

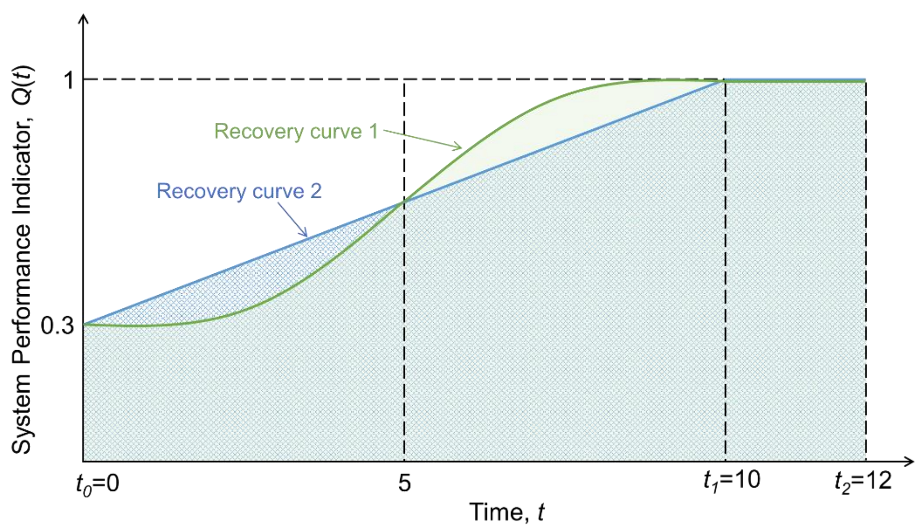


Figure 2-5. Two example recovery curves having the same area under the curve.

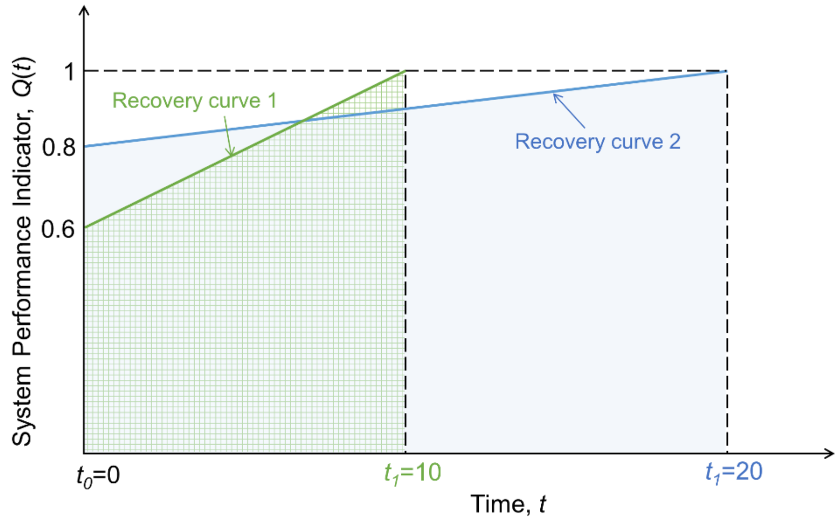


Figure 2-6. Two example recovery curves having the same area above the curve.

The forgoing review shows that several quantitative resilience assessment approaches exist, which can measure resilience either deterministically or probabilistically. The subjective evaluation-based methods usually start with assessing different characteristics (e.g. robustness, rapidity, redundancy) or different aspects of resilience (e.g. infrastructure resilience, social resilience, economic resilience) based on expert estimation or self-evaluation. The score for each category or indicator of resilience are then aggregated in some way (e.g. weighted or unweighted sum) to produce an index of resilience. The primary advantage of this type of approach is that the resilience can be assessed comprehensively by including more characteristics or aspects of resilience. However, the major limitation of this type of approach is that the assessment result is very subjective. Different experts may have very different perspectives about the infrastructure system's performance, or other indicators of community resilience. The result is especially unreliable if only few experts' opinions are collected.

The distinguishing feature of the probability theory-based approach is its acknowledgement of uncertainty in quantification of resilience. However, it can be noticed from Table 2-3 that most probability theory-based methods are used together with the subjective evaluation-based methods. This is due to the fact that most probability theory-based methods require the identification of some acceptable performance standards, such as the maximum acceptable loss or maximum acceptable recovery time, etc. These threshold values are usually determined based on expert judgements, which makes the quality of the evaluation results highly dependent upon the subjective expert judgements of the threshold values.

Among the three types of resilience assessment approaches, the recovery curve-based approach is least dependent upon subjective estimations and has the widest application. A recovery curve of infrastructure systems under a disruptive event provides a whole picture of the infrastructure performance under disasters to quantify resilience, since it could reflect the systems' vulnerability when disaster happens, the recovery time to the pre-disaster state or a post-disaster new normal state, and the performance of the infrastructure systems at each time step between the hazard occurrence and the fully recovery times. Although every single recovery curve-based resilience assessment method shown in Table 2-3 has its own pros and cons, this type of approach in general has been most widely accepted to measure resilience of infrastructure systems, either individually or as an integrated network. Implementing different pre-disaster risk mitigation or post-disaster recovery plans would change the trajectory of the recovery curve and the recovery curve-based resilience metric, thus making this type of approach suitable to compare different risk mitigation strategies or optimize different recovery plans. Since this research also uses the recovery curve-based resilience assessment method to develop framework to guide community infrastructure resilience planning, the following section would present a review of the state-of-research on infrastructure recovery modeling for resilience assessment.

2.4. Infrastructure Recovery Modeling for Resilience Assessment

Developing models to simulate the post-disaster damage and recovery of the infrastructure systems to better support disaster risk management decision making has become an important research topic of the community resilience initiatives reviewed in section 2.1. This section provides an overview of the existing infrastructure recovery models developed in recent decades, as are summarized in Table 2-4. For each methodology reviewed in Table 2-4, the methodological type, model highlights, its application, the resolution of the infrastructure interdependency considered in the model, and the reference of some representative works are clearly identified. The resolution of the modeled infrastructure interdependency is divided into four categories: (1) *not considered*: the model does not consider any interdependencies between different infrastructure systems or it's only suitable for modeling the recovery of one infrastructure system; (2) *system-to-system level*: only the interdependencies between one infrastructure system (as a whole) and another infrastructure system (as a whole) are considered; (3) *system-to-facility level*: the interdependencies between one infrastructure system (as a whole) and a facility from another infrastructure system are considered; (4) *facility-to-facility level*: the interdependencies between two infrastructure facilities between different infrastructure systems are considered. It is noted that no attempt is made to score or rank different methodologies. Rather, this review is intended to identify modeling strategies, features, and gaps in a manner that will support future research efforts. The reviewed methodologies in Table 2-4 are first grouped by methodological type, and then listed chronologically.

Table 2-4. Summary of the infrastructure recovery models for resilience assessment.

No.[2]	Model highlights	Application	Resolution of interdependency modeling[3]				Reference
			N/A	S-to-S	S-to-F	F-to-F	
A-1	The Sandia National Laboratory developed five versions of the agent-based models (Aspen, Aspen-EE, CommAspen, NABLE, cyber-Attack-Consequence Assessment Process) to simulate and analyze the performance of interdependent systems, where different systems are viewed as agents who follow simple rules of behavior to react to the changing environment.	Interdependent transportation, telecommunications, electric power, banking and finance, water, agriculture, emergency services, fossil fuels, and government systems		√			Basu, Pryor & Quint (1998); Barton et al. (2000); Barton et al. (2004); Brown, Beyeler & Barton (2004); Schoenwald, Barton, & Ehlen (2004); Ehlen & Scholand (2005); Eidson & Ehlen (2005); Phillips, Kelic & Warren (2008)
A-2	The Argonne National Laboratory developed three versions of agent-based simulation models (SMART II, SMART II++ and FAST) for utility companies to better plan and operate the system performance. The models use integrated set of agents and interconnections representing the infrastructure facilities and the connections between them.	Interdependent electric power and natural gas systems		√			North (2000, 2001a & b)

[2] The abbreviation before the number refers to the methodological type, where “A” refers to agent-based approach, “SD” refers to system dynamics-based approach; “IO” refers to input-output based method; “CGE” refers to computable general equilibrium-based method; “NT” refers to network topology-based method; “NF” refers to network flow-based method.

[3] “N/A” refers to no interdependency is considered; “S-to-S” refers to system-to-system level interdependency is considered; “S-to-F” refers to system-to-facility level interdependency is considered; “F-to-F” refers to facility-to-facility level interdependency is considered.

Table 2-4 (Cont.)

No.	Model highlights	Application	Resolution of interdependency modeling				Reference
			N/A	S-to-S	S-to-F	F-to-F	
A-3	The agent-based modeling technology is used to simulate the behavior of web system to the changing environment. The key characteristic of an agent is that it exists as an individual entity with location, capabilities, and memory. From the interaction among these agents "emerge" behaviors that are not predictable by the knowledge of a single agent.	Web system	√				Cardellini et al. (2006)
A-4	The Idaho National Engineering Laboratory developed the agent-based CIMS model to analyze the cascading failure associated with civil infrastructure interdependencies. It uses an agent-based approach to model infrastructure elements, the relations between elements, and individual component behavior.	Interdependent electric power grid and key assets, including schools, government facilities, hospitals, and water pumping stations				√	Dudenhoeffer, Permann & Boring (2006); Dudenhoeffer, Permann & Manic (2006); Dudenhoeffer et al. (2007)
A-5	A model is developed based on the socially rational multi-agent systems. The equilibrium of a fictitious play is considered to analyze the impacts of various levels of information available to the interconnected system operators on the outcomes of the decision-making process under physical or cyber-attack.	Power system	√				Bompard, Napoli & Xue (2009)
A-6	A framework is developed to model individual behavioral adaptation in the event of a no-notice crisis and its emergent effect on multiple infrastructures. The modeling environment provides policy makers and analysts a way to compare various response strategies and what if scenarios.	Interdependent social, transportation and cellular systems		√			Barrett et al. (2010)
A-7	An agent-based model is proposed which can integrate an environmental vulnerability indicator to better guide the decision-making process of the associated stakeholders. Such approach will aid urban planners to redevelop societies into a more resilient status.	Waste water treatment system	√				Eid & El-adaway (2016)

Table 2-4 (Cont.)

No.	Model highlights	Application	Resolution of interdependency modeling				Reference
			N/A	S-to-S	S-to-F	F-to-F	
SD-1	The Los Alamos, Sandia, and Argonne National Laboratories developed the CIPDISS which is intended for analysis of high-level behavior of metropolitan or regional infrastructure, taking into account the way disruptions in one sector may propagate to other infrastructure systems. Modeling is performed using a system dynamics methodology where an infrastructure system is broken down into simple items and processes (feedback loops, stocks, and flows), which interact to produce complex behaviors.	Interdependent transportation, health care, power, telecommunication and emergency service systems		√			Croope, S., & McNeil (2011); Steinberg, Santella, & Zoli (2011)
SD-2	EVA-INFRA-SD is developed with an objective of measuring system performance over time following a disaster scenario. It can identify the effects of the failure of one infrastructure component as they propagate through different systems.	Interdependent power, water and transportation systems			√	√	Tonmoy & El-Zein (2013)
IO-1	The Dynamic Inoperability Input-output Model (DIIM) is proposed to analyze how the system of interdependent sectors can be adversely affected as a result of initial perturbations to other sectors through willful attacks or natural disasters. The strength of interdependencies between different industry sectors is measured by the national and regional commodity-transaction data from the Bureau of Economic Analysis (BEA) and the Regional Input–Output Multiplier System (RIMS II).	Nearly 500 sectors of the U.S. economy		√			Haimes (2002); Crowther et al. (2004); Jiang & Haimes (2004); Haimes et al. (2005 a,b); Lian & Haimes (2006); Santos (2006); Crowther, Haimes & Taub (2007); Haimes (2008); Barker & Haimes (2009 a,b) Reed, Kapur & Christie (2009); Cagno et al. (2011); Zhang, Kong & Simonovic (2018a)

Table 2-4 (Cont.)

No.	Model highlights	Application	Resolution of interdependency modeling				Reference
			N/A	S-to-S	S-to-F	F-to-F	
CGE-1	The computable general equilibrium (CGE)-based approach is used to model the behavioral response of critical infrastructure systems to input shortages and changing market conditions. The proposed methodology advances the CGE analysis of major supply disruptions of critical inputs in four aspects.	Water distribution or power system	√				Rose & Liao (2005); Rose, Oladosu & Liao (2005)
CGE-2	The CGE-based multilayer infrastructure network (MIN) model is proposed which uses a market-based mechanism to address the disparate system characteristics. The MIN(S)CGE framework provides an elegant modeling platform to analyze multiple infrastructure systems and formulate their interdependencies.	Interdependent transportation and telecommunication systems; interdependent power and energy (e.g. fossil energy products such as oil, natural gas, and coal) systems		√			Peeta & Zhang (2009); Zhang & Peeta (2011 a, b)
NT-1	A model is proposed for the dynamic spreading of failures in networked systems. The model combines network nodes as active, bistable elements and delayed interactions along directed links. By means of simulations, the time-dependent spreading and cascade failures in different network topologies are explored. The model can be used to improve disaster preparedness and anticipative disaster response management.	A hypothetical network				√	Buzna, Peters & Helbing (2006)
NT-2	Several metrics are proposed to measure the network topology change following a disruption. The physical interdependency strength between two infrastructure facilities is quantified by the probability of failure of one facility given the failure of another facility.	Interdependent power and water systems				√	Dueña-Osorio, Craig & Goodno (2007)

Table 2-4 (Cont.)

No.	Model highlights	Application	Resolution of interdependency modeling				Reference
			N/A	S-to-S	S-to-F	F-to-F	
NT-3	A framework is developed to understand the robustness of interacting networks subject to cascading failure due to random removal of nodes. The result shows that a broader degree distribution increases the vulnerability of interdependent networks to random failure, which is opposite to how a single network behaves. Thus it highlights the need to consider interdependencies in designing robust networks.	Two hypothetical interdependent systems				√	Buldyrev et al. (2010)
NT-4	A framework for interdependent infrastructure systems vulnerability analysis is proposed which could be used to optimize interface network topology design to minimize cascading failure. Both long-term and focused vulnerability analyses are executed.	Interdependent power and water systems				√	Wang, Hong & Chen (2012)
NT-5	A five-phase probabilistic methodology is proposed which provides the ability to statistically characterize and model restoration for a given topology at a detailed enough level to be able to model dependency and potential interdependencies using mechanistic approaches.	Electric power system	√				Unnikrishnan & van de Lindt (2016)
NF-1	The interdependent layer network (ILN) model is proposed to model the performance of infrastructure systems with considering five types of dependencies. The model can be used to optimize service restoration by solving a set of linear programming mathematical equations.	Interdependent power and telecommunication systems				√	Wallace et al. (2001); Lee II, Mitchell & Wallace (2007)
NF-2	A six-step probabilistic approach is proposed to model infrastructure system resilience that considers its dependency on other systems and incorporates both physical damage and network functionality to estimate system recovery as a function of time.	One-way dependency of water system on power system				√	Guidotti et al. (2016)

Table 2-4 (Cont.)

No.	Model highlights	Application	Resolution of interdependency modeling				Reference
			N/A	S-to-S	S-to-F	F-to-F	
NF-3	A mathematical framework is developed to simulate the time variant performance of the electric power infrastructure system. The framework is capable of representing regional infrastructure by explicitly modeling their various capacities, demands, and corresponding supply measures.	Electric power system	√				Sharma & Gardoni (2018)
NF-4	A probabilistic network flow-based methodology is proposed to predict the reduction or loss of functionality of the infrastructure in terms of their ability to provide essential goods or services to satisfy the post-disaster demand.	Interdependent social system (human response such as evacuation or relocation) and water system			√		Guidotti, Gardoni & Rosenheim (2019)

The foregoing review shows that there exist several studies on the methodologies to model and simulate the performance of infrastructure systems under disruptive events to date. These existing methodologies can be classified into five broad types: agent-based approach, system dynamics-based approach, input-output-based approach, computable general equilibrium-based approach, network topology-based approach and network flow-based approach. The agent-based approach views civil infrastructure systems and the decision makers as autonomous agents which could interact with each other and its environment following a set of rules (Ouyang, 2014). An agent is a computational entity that receives information and acts on its environment in an autonomous way. Through the use of simulation techniques such as evolutionary learning techniques, linear and nonlinear programming, numerical simulation or Monte Carlo simulation, the interactive behavior of these agents can be examined as they make real-life decisions in an environment where agents communicate with each other and adapt their behaviors to changing conditions, all the while learning from their past experience (Pederson et al., 2006). The system dynamics-based approach models the interdependent complex adaptive systems using three core components: stocks (the accumulation of resources in a system), flows (the rates of change that alter those resources) and feedback loops (the information that determines the values of the flows) and analyzes their behavior over time based on nonlinear theory and feedback controls (Stapelberg, 2008; Hasan & Foliente, 2015). The input-output-based approach extends the principles of Leontief's Input-output (I-O) model in economics and makes it applicable to simulate the recovery of interdependent infrastructure systems following a disruptive event (Leontief & Leontief, 1986; Haimes et al., 2005 a, b). The computable general equilibrium-based approach can be viewed as an extension of the I-O model since it inherits the main features of the I-O models such as the consideration of interdependencies among economic sectors but overcomes some of its limitations including the linear assumption, lack of consumers' and producers' behavior responses to market and price constraints and so on (Rose, 2004; Rose & Liao, 2005). As is indicated by the name, the network topology-based approach models the civil infrastructure systems based on their topologies. The states of the nodes and links in the network can be either normal or damaged. The nodes can fail directly due to their vulnerability during hazards, or indirectly due to the disconnections from their dependent supply nodes (Patterson & Apostolakis, 2007; Adachi & Ellingwood, 2008). Some topology-based or functionality-based metrics can be used to measure the overall performance of the infrastructure network, which will be further discussed in section 2.5. Building upon the topology of the network, the network flow-based model takes into account the products, information or services delivered by the civil infrastructure system as network flows. Each node in the network can be either a supply, demand or transshipment node, while each link has a limited capacity with the commodities flow on the links.

The infrastructure interdependencies can be modeled at different resolutions. Some of the reviewed methodologies in Table 2-4 are developed for a specific infrastructure system, or focus on individual systems, which make them hard to be generalized into modeling the damage and recovery of other infrastructure systems, or the integrated interdependent infrastructure network. For those methodologies that can incorporate interdependencies between different infrastructure systems, many of them consider only the system-to-system level interdependencies, especially for the agent-based, system dynamics-based or input-output-based models. One of the advantages of incorporating the system-to-system level interdependency in modeling the post-disaster recovery and resilience of the infrastructure network is that it's simple and easy to be modeled. Besides, the data needed to assess the system-to-system level interdependencies, such as the performance data of various infrastructure systems under historical disasters, is relatively easier to be obtained. The disadvantage of only considering the system-to-system level interdependencies is that it simplifies the recovery process of the infrastructure system by ignoring the different damage levels and recovery times of the facilities within each system after a disaster. The modeling result may not be very helpful in guiding the strategic risk mitigation planning of a community in terms of identifying the most critical facilities in a system which needed to be repaired or upgraded in order to achieve higher resiliency. To overcome the limitation of only considering the system-to-system level interdependencies among different infrastructure systems and get a more refined modeling result, the facility-to-facility level interdependency/dependency are considered in some recovery models, especially in those network topology or network flow-based models. The refined modeling result could be more useful for supporting decisions for disaster risk management. However, not all systems can be modeled, or need to be modeled at the facility level given the nature and complexity of the system, and different modeling resolutions are needed for individual systems. In these situations, the system-to-facility level interdependencies/dependencies come into play. Based on the nature of system, some systems could be modeled using a network, while others, such as the social system, the manufacturing system and so on, could not. For those systems that could be represented by a network, different types of network topology exist. A system can be modeled as a network consisting of only isolated nodes (e.g. trees, lighthouses), or only links (e.g. roads, natural gas pipelines), or a more common network with nodes connected by the links (e.g. power system, water system). Considering the interaction of the systems with different natures when assessing the community resilience can help to understand the community resilience in a more comprehensive way. Besides, if a large number of systems needed to be considered when assessing the community resilience, modeling every system in the facility level may not be feasible due to long computation time. In this case, modeling some relatively unimportant (independent) systems at system level while modeling the most important (dependent) systems at facility level could lead to shorter computation time while still achieving the satisfied level of detail and accuracy of the modeling result. The summary in Table 2-4 reveals that only few methodologies are capable to consider system-to-facility level interdependencies. It would be more flexible and applicable if a recovery model could incorporate three different levels of the infrastructure interdependency, which is the direction of the proposed research.

2.5. Post-disaster Infrastructure Performance Metrics

As is indicated in the previous sections, the infrastructure recovery curve depicts the performance of the infrastructure system(s) over time following a disruptive event. Various post-disaster infrastructure performance metrics have been developed in recent decades through different community resilience initiatives or other related research efforts, which can be broadly grouped into three types based on the applicable phase. The first type focuses on assessing the hazard-resistant performance of infrastructure system at the time of hazard occurrence. Example metrics of this type include: reliability, probability of failure, vulnerability, robustness, flexibility, survivability and so on (Nicholson, 2003; Grubesic & Murray, 2006; Sun, Turnquist & Nozick, 2006; Abdel-Rahim et al., 2007; Murray, Matisziw & Grubesic, 2007; Berle, Asbjørnslett & Rice, 2011; Chen & Kasikitwiwat, 2011; Luping & Dalin, 2012; Snelder, van Zuylen & Immers, 2012; Chen, Kasikitwiwat & Yang, 2013; Faturechi & Miller-Hooks, 2014). The second type measures the performance of the infrastructure system at any point in time after a disruptive event and examples of metrics of this type includes connectivity, efficiency, accessibility, relative order of the largest cluster, flow capacity, travel time/distance, water pressure, etc. (Günneç & Salman, 2011; Guidotti et al., 2016; Zhang, Wang & Nicholson, 2017; He & Cha, 2018a). The third type of the metrics measure the performance of the infrastructure system over the entire recovery curve and can be used to evaluate the efficiency or effectiveness of the infrastructure recovery. Some of the metrics in this type, such as recovery time or rapidity, are often used to measure the efficiency of the recovery process (or how fast the recovery is), while other metrics of this type, such as skewness, are oftentimes used to quantify the effectiveness of the recovery (where the shape of the recovery trajectory is taken into consideration) (Bruneau et al., 2003; Reed, Kapur & Christie, 2009; Sharma, Tabandeh & Gardoni, 2018). A list of post-disaster infrastructure performance metrics, including the definitions, applicable system(s), applicable phase and the reference of some representative works, is shown in Table 2-5 alphabetically.

Table 2-5. Summary of the post-disaster infrastructure performance metrics.

No.	Metric	Definition	Applicable system	Applicable phase			Reference
				Only at hazard occurrence	Every time step during recovery phase	Overall recovery phase	
1	Accessibility	$A=\sum_i w_i \cdot a_i = \sum_i w_i \cdot \sum_{j \neq i} \frac{P_j}{t_{ij}^{\beta}}$ where A = accessibility of a road network; a_i = the accessibility of a road intersection point i; w_i = weight attached to the accessibility of road intersection point i; P_j = population attached to point j; t_{ij} = travel time between point i and j; β = a calibration parameter related to traffic count.	Transportation system		√		Chang & Nojima (2001); Antunes, Seco & Pinto (2003); Taylor (2012); Moya-Gómez (2018)
2	Average path length	$l=\frac{1}{N(N-1)}\sum_{i \neq j} d_{ij}$ where l = average path length of a graph; d_{ij} = the distance between node i and j; N = the total number of nodes in a graph. The average path length is a measure of how the network is scattered.	All		√		Holmgren (2006); Costa et al. (2007)
3	Average vertex degree	$\langle k \rangle = \frac{1}{N}\sum_{i=1}^{N} k_i$ where $\langle k \rangle$ = average vertex degree; k_i = vertex degree of node i; N = the total number of nodes in a graph. The vertex degree of a node is the number of edges connecting to the node.	All		√		Holmgren (2006); Costa et al. (2007)

Table 2-5 (Cont.)

No.	Metric	Definition	Applicable system	Applicable phase			Reference
				Only at hazard occurrence	Every time step during recovery phase	Overall recovery phase	
4	Characteristic path length	$L = \frac{1}{\frac{1}{2}n(n+1)} \sum_{i \geq j} d_{ij}$ where L = characteristic path length of the network; n = the number of nodes in the network; d_{ij} = the shortest path length between nodes i and j.	All		√		Dueñas-Osorio et al. (2007)
5	Clustering coefficient	$C = \frac{1}{n} \sum_{i} \frac{\lvert E[\Gamma_i] \rvert}{\frac{1}{2} d_i \cdot (d_i - 1)}$ where C =clustering coefficient; $\lvert E[\Gamma_i] \rvert$ = the number of edges in the neighborhood of node i; d_i = vertex degree of node i.	All		√		Holmgren (2006); Costa et al. (2007); Dueñas-Osorio et al. (2007)
6	Connectivity loss / Connectivity	$C_L = 1 - \left\langle \frac{N_g^i}{N_g} \right\rangle_i$ where C_L = connectivity loss; N_g = total number of source nodes (e.g. power generators from the power system); N_g^i = the number of source nodes that are connected to node i. The averaging is done over every node i.	All		√		Albert, Albert & Nakarado (2004); Clark & Watling (2005); Guikema & Gardoni (2009); Peeta et al. (2010); Bocchini & Frangopol (2011); Kurtz, Song & Gardoni (2015); He & Cha (2018a & b, 2019a)

Table 2-5 (Cont.)

No.	Metric	Definition	Applicable system	Applicable phase			Reference
				Only at hazard occurrence	Every time step during recovery phase	Overall recovery phase	
7	Efficiency	$E = \frac{1}{N(N-1)} \sum_{i \neq j} \frac{1}{d_{ij}}$ where E = average path length of a graph; d_{ij} = the distance between node i and j; N = the total number of nodes in a graph.	All		√		Costa et al. (2007); Dueña-Osorio, Craig & Goodno (2007); Nagurney & Qiang (2007); He & Cha (2018a & b, 2019a)
8	Flow capacity	Depends on system, could be traffic for road network, power flow for power system, water flow for water system, etc.	All		√		Lee et al. (2011); Guidotti et al. (2016)
9	Percentage of demand meet	The percentage of customers with infrastructure service.	All		√		Kameda (2000); Guidotti et al. (2016); He & Cha (2019c)
10	Power	The power flow in MW.	Power system		√		Fang et al. (2018)
11	Probability of failure	The probability of damage or loss of function.	All	√			Reed, Kapur & Christie (2009); Luna, Balakrishnan & Dagli (2011)
12	Rapidity	The rate of recovery.	All			√	Bruneau et al. (2003); Reed, Kapur & Christie (2009)
13	Recovery time	The time from infrastructure damage to full recovery.	All			√	Bruneau et al. (2003); Reed, Kapur & Christie (2009)

Table 2-5 (Cont.)

No.	Metric	Definition	Applicable system	Applicable phase: Only at hazard occurrence	Applicable phase: Every time step during recovery phase	Applicable phase: Overall recovery phase	Reference
14	Redundancy ratio	$R = \frac{1}{n}\sum_{v}\frac{1}{\left(\lvert S\rvert-1\right)^2}\sum_{j\in V\left[\Gamma^2(v)\right];\, j\neq v} I(v,j)$ where *R* = redundancy ratio; *n* = the number of nodes in the network; $\Gamma^2(v)$ = the neighbors of the neighbors of node *v*; $I(v,j)$ = the number of node-independent paths from *v* to *j*.	All		√		Dueñas-Osorio et al. (2007)
15	Relative order of the largest cluster	The number of nodes in the largest cluster (of connected nodes) divided by the total number of nodes in the network.	All		√		Holmgren (2006)
16	Reliability	The ability of the system to maintain normal operation before or under disruptions.	All	√			Hosseini, Barker & Ramirez-Marquez (2016); Soltani-Sobh et al. (2016); Panteli et al. (2017)
17	Robustness	The ability to withstand the hazard when it occurs. Can be calculated as the complement of vulnerability.	All	√			Bruneau et al. (2003); Reed, Kapur & Christie (2009)
18	Skewness	$s = \frac{\int_{t_0}^{t_1} R(t)\cdot(t-t_0)\, dt}{\int_{t_0}^{t_1} R(t)\, dt}$ where *s* = the skewness of the recovery trajectory; t_0 and t_1 = the end points of the time period in consideration; $R(t)$ = the recovery trajectory.	All			√	Zhang, Wang & Nicholson (2017); Sharma, Tabandeh & Gardoni (2018)

Table 2-5 (Cont.)

No.	Metric	Definition	Applicable system	Applicable phase			Reference
				Only at hazard occurrence	Every time step during recovery phase	Overall recovery phase	
19	Survivability	$Survivability = f(\mathrm{S}, \mathrm{E}, \mathrm{D}, \mathrm{V}, \mathrm{T}, \mathrm{P})$ where S is the set of acceptable service specifications, E describes the ways in which the system can degrade based on external challenges, D are the practical values of E, V is the relative ordering of service values $\mathrm{S} \times \mathrm{D}$, $\mathrm{T} \subseteq \mathrm{S} \times \mathrm{S} \times \mathrm{D}$ is the set of valid transitions between service states S given a challenge D, and P are the service probabilities that some $s \in$ S must meet dependability requirements. Survivability is the capability of a system to fulfill its mission, in a timely manner, in the presence of threats such as attacks or large-scale natural disasters.	All	√			Heegaard & Trivedi (2009); Sterbenz et al. (2010)
20	Travel time/distance	The driving or walking time/distance between two points in the road network, or the average of all driving or walking time/distance between any pair of points in the road network.	Transportation system		√		Asakura & Kashiwadani (1995); Chen, Kasikitwiwat & Yang (2007); Zhang & Wang (2017)
21	Vulnerability	$V = \frac{\tilde{P} - P_0}{P_0}$ where V = vulnerability; $\tilde{P}$ = post-disaster performance; P_0 = pre-disaster performance. It's defined as the drop in performance after the disaster.	All	√			Costa et al. (2007); Reed, Kapur & Christie (2009); MacKenzie & Barker (2012)
22	Water pressure / water quality	The pressure of the water flow in the network. Percentage of local demand nodes without issuance of a boil water notice (an indicator of water quality)	Water system		√		Guidotti et al. (2016)

Table 2-5 (Cont.)

No.	Metric	Definition	Applicable system	Applicable phase			Reference
				Only at hazard occurrence	Every time step during recovery phase	Overall recovery phase	
23	Weighted independent path	$IPW = \frac{1}{n}\sum_{i=1}^{n}\frac{1}{n-1}\sum_{j=1}^{n-1}K_{ij}$ where IPW = the average number of the independent pathways in a road network; n = the number of nodes in the network; K_{ij} = the number of independent pathways between node i and j. This metric could be weighted by reliability of each road, the emergency facilities or traffic.	Transportation system		√		Zhang et al. (2017, 2018)

The review in Table 2-5 shows that numerous post-disaster performance metrics for infrastructure systems were proposed in recent years. Although every metric has its own merits, most of the existing performance metrics for the infrastructure systems has one or several of the following limitations. The first type of the post-disaster infrastructure performance metrics, such as reliability, vulnerability and robustness, are suitable to measure the performance of infrastructure system only at the time of hazard occurrence and fail to take the whole recovery phase into consideration. This type of metric is of limited use when quantifying the performance of the infrastructure systems over time following a disruptive event. The second type of the metrics, such as connectivity, efficiency and accessibility, are used to measure the performance of the infrastructure system at one point in time during the recovery phase. Although they are suitable for measuring the change of infrastructure performance over time, they cannot reflect the overall performance of the infrastructure systems during the entire recovery phase. Thus, they are of limited use when trying to compare different recovery curves under different network topologies or recovery strategies. The third type of the metrics, such as skewness and recovery time, can measure the overall performance of the entire interdependent infrastructure network over the whole post-disaster recovery phase; however, they may also have some limitations under some circumstances. Besides, most of the metrics emphasize on measuring the functionality of infrastructure systems and fail to take the service disruptions to the end-users into consideration. In summary, it’s recommended to use several different metrics to measure the infrastructure performance from different perspectives and provide a more complete picture of the infrastructure performance under disasters to better guide the pre-disaster risk mitigation and post-disaster recovery planning.

2.6. Infrastructure Risk Management Decision-making for Community Resilience Planning

The previous sections present a number of existing studies on defining and quantifying infrastructure recovery or resilience. However, their usefulness is limited unless they can guide the planning for community resilience. As is highlighted before, resilience can be generally understood as the ability or the process of an entity to withstand a disruption, to recover from it rapidly either to the pre-disaster state or to a post-disaster new normal. All these components of resilience are the result of strategic pre-disaster risk mitigation planning and post-disaster resource allocation and recovery optimization efforts. The pre-disaster and post-disaster are two distinct phases of community resilience planning since they have different objectives, constraints, decision makers and so on. The existing literatures on infrastructure disaster risk management decision-making for community resilience planning are summarized in Table 2-6. For each reviewed work, its applicable phase and infrastructure system(s), whether the interdependency between different infrastructure systems is considered, the brief summary of the general approaches used and some references are clearly identified. The literatures in Table 2-6 are first categorized based on the applicable phase, then ordered chronologically.

Table 2-6. Summary of the infrastructure disaster risk management decision framework for community resilience planning.

No.	Applicable phase	Applicable system(s)	Interdependency considered?	Approaches	Reference
1	Pre-disaster	Gas and power systems	Yes	A mathematical model and solution procedure are proposed to optimize investments in interconnected infrastructures to achieve improvements in "time to recover" subject to a budget constraint.	Nozick et al. (2004); Xu et al. (2007)
2	Pre-disaster	A general infrastructure network	N/A	An evolutionary algorithm is proposed to optimize the topology of large-scale infrastructure network for higher resilience against cascading failures.	Ash & Newth (2007)
3	Pre-disaster	Bridge network	No	A numerical model is proposed to find the optimal bridge retrofit program that aims to maximize the postdisaster network evacuation capacity.	Chang et al. (2012)
4	Pre-disaster	Any infrastructure system that has a network topology	No	A mixed integer non-linear program is proposed to quantify the operational resilience of a critical infrastructure system. The proposed program aims to find out the best defense strategy in case of attacks.	Alderson, Brown & Carlyle (2014)
5	Pre-disaster	Transportation system (railroad network)	No	A mathematical optimization model and iterative heuristic algorithm solution approach are proposed to identify critical railroad infrastructure components to maximize rail network resilience.	Khaled et al. (2015)
6	Pre-disaster	Transportation system (bridge network)	No	A decision model is proposed to assist bridge authorities in determining a preferred maintenance prioritization schedule for a degraded bridge network in a community that optimizes the performance of transportation systems within budgetary constraints at a regional scale. The problem is solved using network analysis methods, structural reliability principles and meta-heuristic optimization algorithms.	Zhang & Wang (2017)
7	Pre-disaster	Power and gas systems	Yes	A game-theoretic attacker-defender and defender-attacker-defender modeling techniques are applied to assessing the resilience of interdependent critical infrastructure systems under worst-case disruptions and advising policymakers on making pre-disruption decisions for improving the resilience of interdependent infrastructures.	Fang & Zio (2019)

Table 2-6 (Cont.)

No.	Applicable phase	Applicable system(s)	Interdependency considered?	Approaches	Reference
8	Post-disaster	Telecommunication system	No	A multi-objective optimization approach for network restoration during disaster recovery is proposed. The proposed model permits tradeoffs between two objectives, minimization of system cost and maximization of system flow, to be evaluated.	Matisziw, Murray & Grubesic (2010)
9	Post-disaster	Transportation system (road network)	No	An innovative framework that integrates two newly developed models for resource utilization and multi-objective optimization are proposed to optimize the recovery efforts. The developed models provide new and unique capabilities, including (1) allocating limited reconstruction resources to competing recovery projects, (2) estimating the reconstruction duration and cost associated with implementing specific recovery plans, and (3) generating optimal trade-offs between minimizing the reconstruction duration and cost.	Orabi et al. (2010)
10	Post-disaster	Transportation system (road network); can be applied to several interdependent infrastructure systems	Yes	A rule-based decision framework is proposed to provide strategies to maximize resilience. A multi-objective optimization algorithm is used to improve the performance of interdependent networks of multiple systems.	Reed, Zabinsky & Boyle (2011)
11	Post-disaster	Transportation system (road network)	No	A two-stage stochastic model is proposed which could optimize the post-disaster recovery scheduling of the transportation systems to maximize its resilience.	Chen & Miller-Hooks (2012); Miller-Hooks, Zhang & Faturechi (2012)
12	Post-disaster	Transportation system (airport pavement network)	No	A mathematical model is proposed to address the problem of assessing and maximizing the resilience of an airport's runway and taxiway network under multiple potential damage-meteorological scenarios. The problem is formulated as a stochastic integer program that seeks an optimal allocation of limited resources to response capabilities and preparedness actions.	Faturechi, Levenberg & Miller-Hooks (2014)
13	Post-disaster	Transportation system (public metro system)	No	A two-stage stochastic programming model is developed to optimize the resilience of a metropolitan public transportation network. The model could generate alternative paths under disruptive conditions.	Jin et al. (2014)
14	Post-disaster	Transportation system (road network)	No	A multi-objective optimization model is proposed to optimize road recovery sequences and modes.	Vugrin, Turnquist & Brown (2014)

Table 2-6 (Cont.)

No.	Applicable phase	Applicable system(s)	Interdependency considered?	Approaches	Reference
15	Post-disaster	Power and water systems	Yes	Two component importance measures based on an interdependent networks resilience optimization model are proposed to prioritize the restoration process of the disrupted components in each infrastructure network such that the resilience of the interdependent infrastructure networks is maximized	Almoghathawi, Barker & Ramirez-Marquez (2017)
16	Post-disaster	Power system	No	An optimization model for the post-disaster restoration planning of infrastructure systems, taking into account the possibility of combining the construction of new components and the repair of failed ones, is proposed. The problem is formulated as mixed-integer binary linear program, and an efficient Benders decomposition algorithm is devised to cope with the computational complexity of its solution.	Fang & Sansavini (2017)
17	Post-disaster	Power, water and gas systems	Yes	A reduced-order representation, dubbed a recovery operator, of a high-fidelity time-dependent recovery model of interdependent infrastructure systems is proposed. The proposed compact representation provides simple yet powerful information regarding systemic recovery dynamics and enables generating fast suboptimal recovery policies in time-critical applications.	González et al. (2017)
18	Post-disaster	Gas pipeline system	No	A multi-objective optimization model is proposed which aims at minimizing both the loss from disruption and recovery time. The trade-off between generation, transmission, recovery costs and lost demand is analyzed. The model provides insights for improving the resilience of gas pipelines after disruption; and serves as a tool for analyzing strategic recovery and potential cascading failure effects in gas network.	He & Nwafor (2017)

Table 2-6 (Cont.)

No.	Applicable phase	Applicable system(s)	Interdependency considered?	Approaches	Reference
19	Post-disaster	Power and water system	Yes	A best-case decentralized model is proposed to allow controllers to develop a full recovery plan to minimize recovery cost. Accounting for network controllers' urgency in repairing their system, an ad hoc sequential game-theoretic-based model is proposed where interdependent infrastructure network recovery is represented as a discrete time non-cooperative game between network controllers that is guaranteed to converge to equilibrium. The computation time is reduced by finding a solution by applying a best-response heuristic	Smith et al. (2017)
20	Post-disaster	Transportation system (road-bridge network)	No	A resilience-based framework is proposed which could optimize the scheduling of the post-disaster recovery actions of the road-bridge transportation network. The framework is illustrated by using genetic algorithm to solve the post-disaster restoration schedule optimization problem for a hypothetical bridge network subjected to scenario seismic event.	Zhang, Wang & Nicholson (2017)
21	Post-disaster	Power system	No	A sequential discrete optimization approach is proposed, as a decision-making framework at the community level for recovery management. The proposed mathematical approach leverages approximate dynamic programming along with heuristics for the determination of recovery actions given limited resources.	Nozhati et al. (2018a)
22	Post-disaster	Power and water systems	Yes	A Markov decision process-based optimization approach is proposed which incorporates different sources of uncertainties to compute the restoration policies. The computation of optimal scheduling schemes using this method employs the rollout algorithm, which provides an effective computational tool for optimization problems dealing with real-world large-scale interdependent infrastructure systems.	Nozhati et al. (2018b)
23	Post-disaster	Power and telecommunication systems	Yes	A minimum cost flow assignment optimization problem is proposed to minimize the cost and maximize the total amount of load served during the recovery intervention with considering the interdependency between power and its monitor systems.	Tootaghaj et al. (2018)

Table 2-6 (Cont.)

No.	Applicable phase	Applicable system(s)	Interdependency considered?	Approaches	Reference
24	Post-disaster	Power and water systems	Yes	An optimization model for determining an optimal joint restoration strategy at infrastructure component level by minimizing the economic loss from the infrastructure failures is proposed.	Zhang, Kong & Simonovic (2018b)
25	Post-disaster	Power, water, transportation, food, fuel, healthcare and education systems	Yes	A holistic mathematical model is proposed to evaluate the vulnerability of an urban infrastructure system against the threats of cascading failures.	Lu et al. (2018)
26	Post-disaster	Power and water systems	Yes	A resilience-driven multi-objective restoration model is developed using mixed-integer programming that aims to maximize the resilience of the system of interdependent infrastructure networks while minimizing the total cost associated with the restoration process. The restoration model considers the availability of limited time and resources and provides a prioritized list of components, nodes or links, to be restored along with assigning and scheduling them to the available work crews.	Almoghathawi, Barker & Albert (2019)
27	Pre-disaster & post-disaster	Transportation system	No	A systematic approach is proposed for risk modeling and disaster management of transportation systems in the context of earthquake engineering.	Chang (2010); Chang, Elnashai & Spencer, (2012)
28	Pre-disaster & post-disaster	Water system	No	Two stochastic resilience-based component importance measures are developed to highlight the critical waterway links that contribute to waterway network resilience. An optimization approach is proposed determines the order in which disrupted links should be recovered for improved resilience.	Baroud, Barker & Ramirez-Marquez (2014)
29	Pre-disaster & post-disaster	Power system	No	A tri-level decision-making model supporting critical infrastructure resilience optimization against intentional attacks is proposed. A novel decomposition algorithm is introduced to exactly identify the best pre-event defense strategy (protecting vulnerable components and building new lines), the worst-case attack scenario, and the optimal post-event repair sequence of damaged components.	Ouyang & Fang (2017)

Table 2-6 (Cont.)

No.	Applicable phase	Applicable system(s)	Interdependency considered?	Approaches	Reference
30	Pre-disaster & post-disaster	Transportation system (road network)	No	A three-stage decision framework is proposed to support resilience planning for roadway networks regarding pre-disaster mitigation (Stage I), post-disaster emergency response (Stage II) and long-term recovery (Stage III). A stage-wise decision process is then formulated as a stochastic multi-objective optimization problem, which includes a project ranking mechanism to identify pre-disaster network retrofit projects in Stage I, a prioritization approach for temporary repairs to facilitate immediate post-disaster emergency responses in Stage II, and a methodology for scheduling network-wide repairs during the long-term recovery of the roadway system in Stage III.	Zhang et al. (2017, 2018)

The review in Table 2-6 shows that recent decade has witnessed a growing body of studies on infrastructure disaster risk management decision-making, but the following gaps are identified for future work.

(1) The majority of the literatures reviewed focus on optimizing the post-disaster recovery scheduling given limited available resources, while only few researches aim at optimizing the pre-disaster risk mitigation prioritization or investment. Improving the pre-disaster risk mitigation and preparedness and enhancing the post-disaster emergency response and long-term recovery are equally important in improving the community resilience, thus more studies are needed to improve the pre-disaster risk mitigation and preparedness;

(2) Most of the reviewed decision-making models or frameworks tend to focus on a single type of the infrastructure system, especially the transportation or power system, while ignoring the interdependencies between different infrastructure systems. However, improving the performance of one single infrastructure system under disasters may not be the most efficient and effective way to reduce the loss and enhance the overall community resilience. In a modern society, the infrastructure systems are usually interdependent upon each other. The proper operation of a facility in one infrastructure system not only depends on the operation of facilities in the same system, but also relies on the functioning of facilities in several other infrastructure systems for product input and information sharing. The service interruptions of the facilities in one infrastructure system could set off a cascading failure across the facilities in the interconnected systems after the disaster, which could pose both direct and indirect socioeconomic impacts. Furthermore, during the post-disaster recovery phase, the complete recovery of a facility in one infrastructure system depends not only on the physical restoration of itself, but also on the recovery of the facilities in other infrastructure systems that it depends on. Therefore, it is important to consider the interdependencies with other infrastructure systems when planning the pre-disaster risk mitigation or post-disaster recovery of any infrastructure system in order to achieve higher community resilience;

(3) To the author's knowledge, the majority of the studies available in the literature are still at the research and development stage. It's needed to develop user-friendly decision-making tools to better guide the decision-makers to prioritize pre-disaster risk mitigation and optimize post-disaster recovery planning actions;

(4) Most of the reviewed literatures do not consider the uncertainties when quantifying the recovery and resilience of the infrastructure systems, which are not suitable to support the risk-informed decision-making; and

(5) The existing decision models or frameworks have relatively weak integration of physical infrastructure systems with social and economic systems. The interactions between the physical, social and economic aspects should be further characterized and quantified to advance models and frameworks for more comprehensive community resilience planning.

2.7. Closure

This chapter provides a review of the current state-of-the-research on disaster risk management for community resilience planning with an emphasis on infrastructure systems. Some representative community resilience initiatives worldwide have been reviewed first. Then, the five most common directions of these community resilience research efforts have been reviewed, including: (1) defining the concept of resilience; (2) assessing resilience quantitatively; (3) modeling infrastructure recovery for resilience assessment; (4) measuring infrastructure performance under disruptive events, and (5) planning for infrastructure disaster risk management towards community resilience. This review has identified some of the research issues associated with each of the above five aspects. For example, despite a tendency of understanding the concept of resilience as the ability to withstand the shock, to recover from the shock rapidly and to adapt to post-shock new normal state, there are still lots of debates on how to best quantify resilience with incorporating the above three aspects. Besides, there exist many studies on post-disaster infrastructure performance modeling, but the interdependencies between facilities in different infrastructure systems has not been well incorporated yet in modeling the damage and recovery of the infrastructure systems. Thirdly, numerous metrics exist on measuring the infrastructure recovery performance, but most metrics have some limitations when applied to measure the performance of interdependent infrastructure systems under disasters. Last but not the least, in spite of extensive methodologies that have been developed to simulate the performance of interdependent infrastructure systems under different types of hazards, few studies have been done to extend the model in guiding the strategic pre-disaster risk mitigation and post-disaster recovery planning decision making for interdependent infrastructure systems.

This research addresses some of the above-mentioned research issues. First of all, the Dynamic Integrated Network (DIN) model is proposed which can simulate the damage and recovery of the infrastructure systems with considering different levels of interdependencies (e.g.: system-to-system, system-to-facility and facility-to-facility levels). Secondly, several infrastructure performance metrics (e.g.: the total service restoration time (TSRT), the skewness of the service restoration trajectory (SSRT), the total-facility-recovery-waiting-time (TFRWT) and the total-service-restoration-waiting-time (TSRWT)) are introduced to facilitate evaluating the efficiency and effectiveness of different pre-disaster risk mitigation or post-disaster recovery plans. Thirdly, two decision problems and the corresponding decision frameworks, applicable to either the pre-disaster or post-disaster phase, are proposed in this research to better guide the community resilience planning decision-making.

CHAPTER 3 INTERDEPENDENT INFRASTRUCTURE RECOVERY MODELING USING DYNAMIC INTEGRATED NETWORK MODEL

As shown in the literature review in the previous chapter, although there exist extensive studies on developing methodologies to model the post-disaster performance of infrastructure systems under disruptive events, the interdependencies among facilities in different infrastructure systems have not been very well incorporated into the damage and recovery modeling. In this research, the *interdependency* between two components is defined as the bidirectional relationship between two components through which the state of each component influences or is correlated to the state of the other. However, if the state of one component, N_i, influences or is correlated to the state of the other component, N_j, but not the other way around, then it's said that N_j is *dependent* upon N_i. The component can either be an infrastructure system, or an infrastructure facility in this study. Based on this classification of the network components, the interdependency/dependency relationship between two network components can be categorized into three levels: system-to-system, system-to-facility and facility-to-facility.

This chapter introduces the Dynamic Integrated Network (DIN) model, which can simulate the damage and recovery of the infrastructure systems after disruptive events with considering different levels of the interdependency/dependency relationships to better support community resilience planning decision-making. The methodologies of modeling the initial damage and recovery of the infrastructure facilities, systems and the integrated network with considering the uncertainties are introduced first. Then, the importance of considering the infrastructure interdependencies at a higher resolution is discussed by comparing the recovery modeling result from the DIN model with those from two other conventional models. Finally, the DIN model is validated to show that the proposed DIN model can produce comparable recovery estimations with physical reality.

3.1. Model Development

3.1.1. Overview of the Dynamic Integrated Network Model

The DIN model simulates the damage and recovery of the interdependent infrastructure systems after disruptive events to guide strategic pre-disaster risk mitigation and post-disaster recovery planning. The DIN model can be applied to simulate the performance of any infrastructure systems under any hazard or multi-hazards. There are four features of the DIN model, which can be summarized as dynamic, probabilistic, integrated and interdependent.

Firstly, the DIN model is dynamic since it can simulate the damage and recovery of the infrastructure facilities, systems and the integrated network over time following a disruptive event. Secondly, it is probabilistic since the uncertainties in the modeling variables can be considered probabilistically. Thirdly, the DIN model is integrated since it models the recovery of the critical facilities in different infrastructure systems and the end-users in a unified network, where the network nodes represent critical facilities and the network links represent the dependency relationships among them, as is illustrated in Figure 3-1. Fourthly, the DIN model can consider physical (e.g. product/material/service input and output), cyber (e.g. information sharing) and geospatial (e.g. co-location) interdependencies (Rinaldi, Peerenboom & Kelly, 2001), both at the system-to-facility level and the facility-to-facility level, which is of higher resolution compared with existing recovery models.

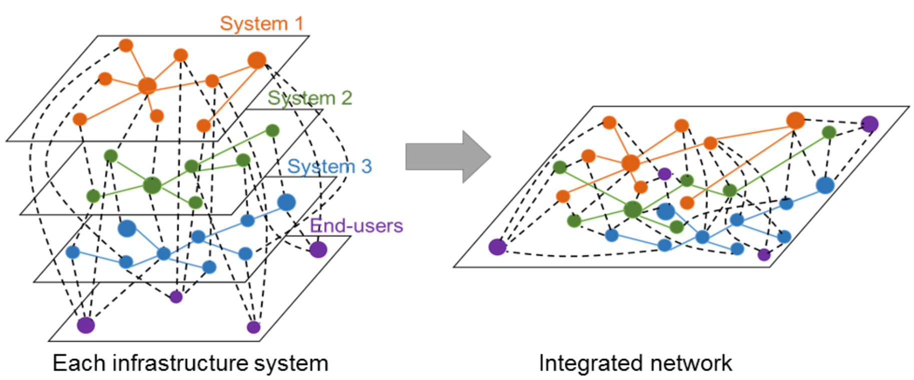


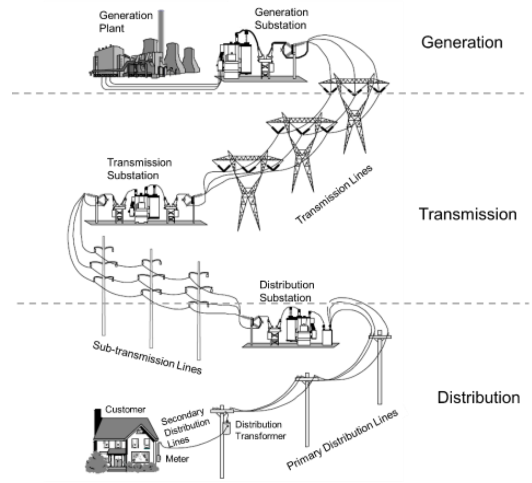
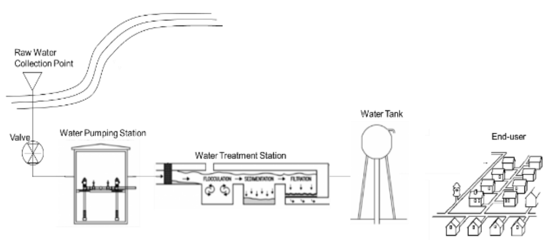
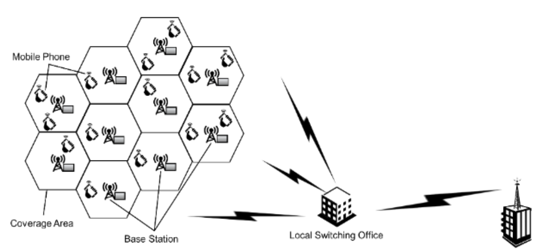
Figure 3-1. The integrated infrastructure network.

3.1.2. Interdependent Infrastructure Network

In the DIN model, different infrastructure systems are modeled as an integrated network where different infrastructure facilities are represented by different nodes. The nodes are connected by links through which products, information or services (PISs) flow. With using such a network model, the physical and cyber dependencies between individual facilities within and across different infrastructure systems can be explicitly considered, which is essential to investigate the failure and recovery of the individual facilities and systems. In the event of damage of a facility, the production of the damaged facility would decrease and hence affect the functionality of the facilities that rely on the damaged facility for any PIS. In this way, the damage of one facility would soon propagate to its neighbors and eventually affect the functionality of the whole network. Thus, the facility-to-facility level physical and cyber dependency relationships can be identified by considering the functionality failure modes of the facilities under disruptive events (e.g. cyber dependencies specifically refer to the dependency relationship between one facility with a telecommunication system facility).

To illustrate the methodology of identifying network nodes (critical facilities) and links (facility-to-facility level dependencies) based on failure modes of the infrastructure facilities under historical hazards, the interdependent electric power, water supply and cellular systems are used. The power, water and cellular systems are three of the most critical infrastructure systems in a community, since they are essential for the social security, public health and welfare, and the normal operation and/or recovery of most other infrastructure systems. The critical infrastructure facilities and their failure modes under past natural or manmade hazards of the interdependent power, water and cellular systems are summarized in Table 3-1.

Table 3-1. The critical facilities and failure modes of power, water and cellular systems.

System	Critical facilities	Failure modes	Example configuration	References
Electric power	• Power plants • Substations • Transmission towers • Distribution poles	• Physical damage of critical facilities • Failure of transmission and distribution lines • Failure of supporting infrastructure systems such as water system (for cooling) and SCADA system (for monitoring and control)	 	Davidson et al. (2003); O'rourke, Lembo & Nozick (2003); Liu et al. (2005); Brown (2008); Drabble (2011); Drabble (2012); Allan (2013); Short (2014); Unnikrishnan & van de Lindt (2016)
Water supply	• Raw water collection points • Pumping stations • Treatment plants • Storage tanks	• Physical damage of critical facilities • Broken water pipelines • Failure of supporting infrastructure systems such as the power system and SCADA system	 	Germanopoulos (1985); Mendenhall (1988); Drabble (2011); Grigg (2012)
Cellular	• Central offices • Switching offices • Cell sites	• Physical damage of critical facilities • Failure of supporting infrastructure systems such as power and/or water system(s)	 	Davidson et al. (2003); Banipal (2006); Comfort & Haase (2006); Poole (2006); Kwasinski (2011); Radio Regulations (2012)

The critical facilities and their failure modes summarized in Table 3-1 can be further used to identify the facility-to-facility level physical and cyber dependency relationships within and between the power, water and cellular systems, as is presented in Figure 3-2. This dependency relationship graph provides the basis for constructing the study regions used for illustrating the proposed DIN model in the following sections.

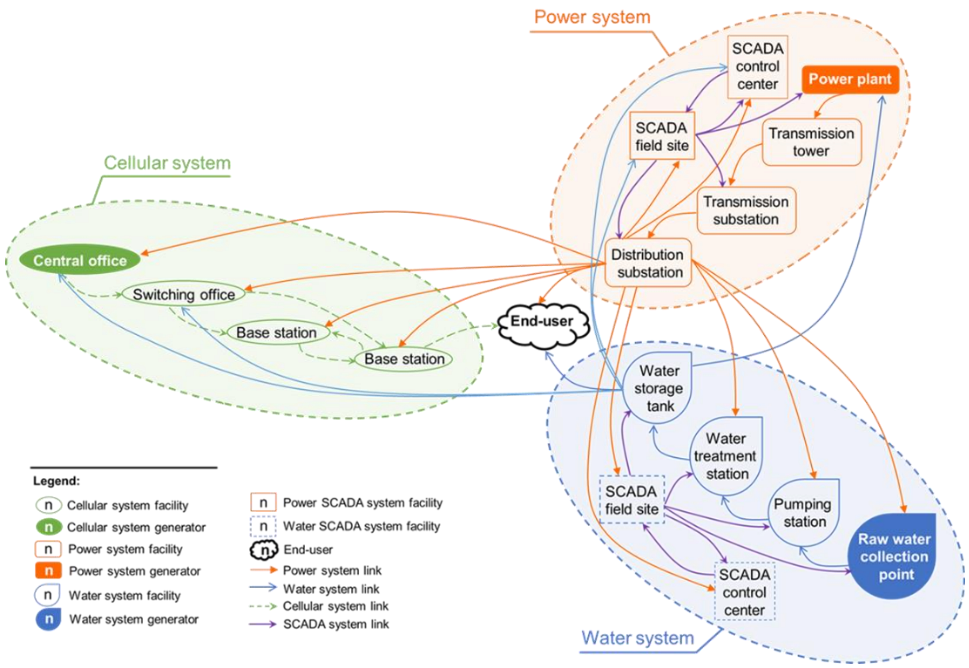


Figure 3-2. The facility-level dependencies within and across electric power, potable water and cellular systems.

The geospatial dependency relationship refers to the co-location of two facilities such that the damage of one facility would lead to the functional failure of another facility (Rinaldi, Peerenboom & Kelly, 2001). The information of co-location serves as additional input information used to determine the initial damage and the recovery of the corresponding network nodes and links. In other words, the initial damage of a node/link would be affected by the failure of its co-located nodes/links, and it may fully recover only after all of its co-located nodes/links recover. For example, if link *i* and link *j* are known to be in superposition, and link *i* is physically damaged under the disaster which can only be repaired till the T_i^{th} day after the disaster. Then, link j will also be viewed as damaged due to the geospatial dependency relationship and can only recover after $\max\{T_i, T_j\}$ days, where T_j is the time for link j to be physically recovered.

Although modeling the infrastructure dependency relationships at the facility-to-facility level can produce more refined modeling results compared to if only the system-to-system level interdependencies are considered, not all infrastructure systems can be, or need to be modeled at the facility level given the nature and complexity of the system, and different modeling resolutions are needed for individual systems. Thus, the system-to-facility level dependency/interdependency is introduced. The system-to-facility level dependency/ interdependency describes the relationship between a system and a facility in another system. Considering the system-to-facility level dependency/interdependency in modeling the post-disaster performance of interdependent civil infrastructure network can be especially useful in some situations, including: (1) when assessing the community resilience requires the modeling of several systems with different natures, and (2) when different systems are needed to be modeled at different resolutions to save the computation time. Based on the nature of system, some systems can be modeled as a network, while others, such as the social system or financial system, cannot. For those systems that can be represented by a network, different types of network topology exist. A system can be modeled as a network consisting of only isolated nodes (e.g. trees, lighthouses), or only links (e.g. roads, natural gas pipelines), or a more common network with nodes connected by the links (e.g. power system, water system). Considering the interaction of the systems with different natures when assessing the community resilience can help to understand the community resilience in a more comprehensive way. Besides, if a large number of systems needed to be considered when assessing the community resilience, modeling every system in the facility level may not be feasible due to long computation time. In this case, modeling some relatively unimportant systems at system level while modeling the most important systems at facility level can lead to shorter computation time while still achieving the satisfied level of detail and accuracy of the modeling result. In the proposed DIN model, the systems that do not have a network topology, or cannot be modeled using a common network with nodes connected by links are not explicitly modeled in the integrated network. Their effects to the damage and recovery of the other infrastructure systems are implicitly considered through some of the modeling parameters, which will be discussed in the following sections.

3.1.3. Modeling the Damage and Recovery of Network Nodes

The inoperability of a network node is defined as the inability of the corresponding facility to perform its intended functions. It reflects the degradation of a facility's capacity to deliver its intended PIS due to perturbations. It can be mathematically defined as the percentage of the node's output reduced from its ideal output triggered from disruptive events and/or demand change. Assessing the inoperability of the network nodes can help us quantify the initial impact of a disruptive event and the propagation and dissipation of that adverse impact on dependent infrastructure facilities. In this section, the methodology of assessing the inoperability of nodes over time is introduced first. Then, the determination of four important variables in the model, namely the dependency matrix, the recovery coefficient matrix, the recovery coefficient ratio matrix and the updated inoperability vector, is explained. It's noted that the operability of a node can be viewed as the complement of the inoperability of the node.

Currently, the proposed DIN model only considers the initial disruption in the operation of nodes resulting from the physical damage of corresponding facilities due to a catastrophic event. Thus, the initial inoperability of each node can be determined from the physical damage level. For simplicity, the initial inoperability is assumed to be proportional to the physical damage level determined from fragility curves. Damage of a facility occurs as a random event. The uncertainty in the initial damage of node can be captured by the fragility curves that describe the conditional probabilities of a facility to experience different damage states given an intensity of hazard. Many fragility curves for different types of buildings or infrastructure facilities are available in the existing literature which can be used to measure the initial inoperability of a facility. For example, a set of exceedance probability curves for five damage states (very minor, minor, moderate, severe and destruction damage) are available for different types of civil infrastructure facilities under different types of hazards (Hazus, 1999; HAZUS-MH, 2003; Scawthorn et al., 2006a, b; Vickery et al., 2006a, b; MRI, 2011). Using the set, cumulative distribution function (CDF) of damage states can be obtained for each given hazard intensity (e.g. hurricane wind speed, earthquake peak ground acceleration, flooding water depth). These CDFs are used to simulate the damage state of each node given a hazard scenario, which is used to estimate the inoperability. For simplicity, the initial inoperability of a node is assumed to be proportional to its damage level. The definition of damage states from ATC-13 (Applied Technology Council, 1985) can be used to assign a damage level to the damage states. The range of the damage level corresponding to very minor, minor, moderate, severe and destruction damage states are assumed to be 0 ~ 1%, 1 ~ 10%, 10 ~ 60%, 60 ~ 100% and 100%, respectively, in the following case studies in this research. The linear interpolation can be used to simulate a damage level between the boundaries. The method of obtaining the CDF of the damage level is illustrated in Figure 3-3.

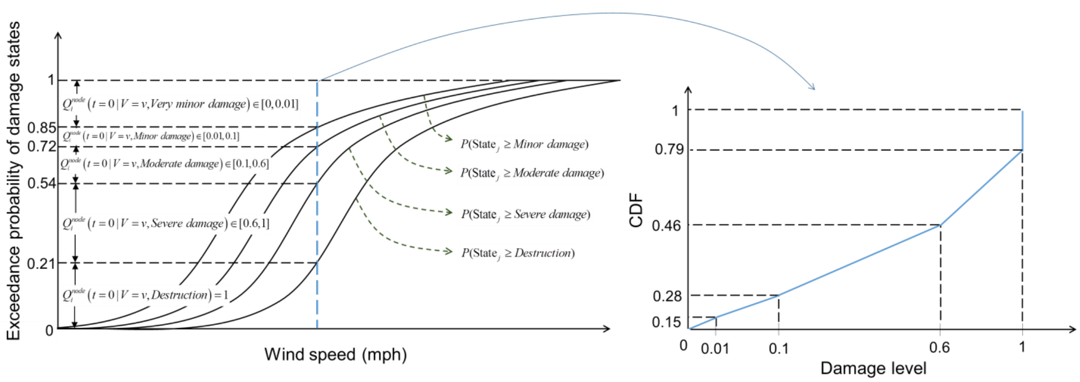


Figure 3-3. Cumulative distribution function of the damage level obtained from the curves of damage state exceedance probability.

In reality, several hazards often occur at the same time, such as hurricane and flooding, earthquake and tsunami, earthquake and landslide, etc. In such multi-hazard scenario, the initial inoperability of the nodes would be calculated separately under each hazard using the corresponding hazard intensities and fragility curves. Then, the overall initial inoperability of a node would be the maximum inoperability calculated from all types of the hazards.

The propagation of the inoperability of each node over time is modeled by considering the inoperability of the nodes that depend on this node, as well as the recovery rate of this node under the specific hazard. The DIN model builds upon the general framework of the Dynamic Inoperability Input-output Model (DIIM) to simulate the dynamic inoperability of each node. The DIIM was initially proposed by Haimes et al. (2005 a,b) to model how inoperability of an industry sector propagates and dissipates over time following a disruptive event. However, details of the DIIM framework cannot be used for simulating the functioning of the individual facilities of civil infrastructure systems because the DIIM is based on economic data and measures the performance of industries using monetary terms. The inoperability of each node at each given time in the proposed DIN model is calculated using Eq. (3-1):

$$\dot{\underline{q}}(t)=\underline{q}(t+1)-\underline{q}(t)=\underline{\underline{r}}\cdot\underline{\underline{B}}\left[\underline{\underline{A}}^{T}\cdot\underline{q}(t)-\underline{q}(t)\right] \tag{3-1}$$

where $\underline{q}(t)$ = the inoperability vector at time t; $\dot{\underline{q}}(t)$ = the time derivative of $\underline{q}(t)$ at time t; $\underline{\underline{B}}$ = the diagonal recovery coefficient matrix; $\underline{\underline{r}}$ = the diagonal recovery coefficient ratio matrix; $\underline{\underline{A}}$ = the dependency matrix. The methodologies to determine these variables are explained in the following sub-sections.

3.1.3.1. Dependency Matrix

The dependency relationships between the facilities are modeled using the dependency matrix in Eq. (3-1). In the DIN model, each element of the dependency matrix, A_{ij}, measures the importance of node *i* to the successful operation of node *j* among all the suppliers of node *j* during the post-disaster recovery phase. This dependency matrix differs from the interdependency matrix in the DIIM in the two aspects. First of all, the DIIM only considers the system-level interdependencies while the dependency matrix in this DIN model incorporates the facility-level dependencies within and across the systems. Secondly, the interdependency matrix in the DIIM uses monetary terms to determine the level of dependency between two industries. However, those monetary data in facility-level are not available nor represent the dependency between infrastructure facilities properly. In the DIN, the importance level of one facility in the successful operation of another facility among all its suppliers during the recovery phase is used to quantify the dependency between two facilities. Building upon the original DIIM, the dependency matrix, $\underline{\underline{A}}$, in this study is defined as the product of output matrix, $\underline{\underline{O}}$, and the input matrix, $\underline{\underline{I}}$. Each element, O_{ik}, in the output matrix represents the importance of the i^{th} node in producing the k^{th} PIS. Since each PIS is defined for each link and thus has only one supplier node, the importance value of the i^{th} node in producing that PIS is either 0 or 1. The value is 1 if the i^{th} node is its supplier, which means that if the i^{th} node is damaged, the production of the k^{th} PIS would be reduced by 100%. Thus, the entries in the output matrix, $\underline{\underline{O}}$, can only be 0 or 1. Each element, I_{kj}, in the input matrix in the proposed DIN model is defined as the relative importance of the k^{th} PIS in the successful operation of the j^{th} node among all the PISs that the j^{th} node would need during the recovery phase. In this research, it is assumed that all the PISs received by the j^{th} node have equal importance to the recovery of j^{th} node, since without either of them, j^{th} node cannot recover properly. By taking the product of the output matrix and input matrix, each entry, A_{ij}, in the dependency matrix reflects the importance of the i^{th} node in the successful operation of the j^{th} node during the recovery phase and is calculated by Eq. (3-2).

$$A_{ij} = \sum_{k} O_{ik} \cdot I_{kj} \tag{3-2}$$

3.1.3.2. Recovery Coefficient Matrix

In the DIN model, the recovery of the individual facilities is modeled by using the recovery coefficient matrix, $\underline{\underline{B}}$. It represents the recovery rate of civil infrastructure facilities given sufficient resources and repair crews during the recovery phase. There are multiple ways to compute the recovery rates for different types of the infrastructure facilities. It can be determined through expert estimation, or using simple linear regression analysis based on empirical data, as is described in MacKenzie & Barker (2012), or by using some other methodologies. If the simple linear regression analysis approach is used, the relationship for the linear regression analysis obtained from Eq. (3-1) can be solved for the inoperability of a single node *i* as:

$$q_i(t) = q_i(0) \cdot \mathrm{e}^{-r_{ii} \cdot B_{ii}(1-A_{ii})t} \tag{3-3}$$

The recovery coefficient ratio for a node *i*, r_{ii}, is 1 in this analysis given the sufficient resources and repair crews assumption in the definition of B_{ii}. Also, since in the DIN model, a node cannot produce a PIS which is directly consumed by itself (there are no link whose head and tail nodes are the same), the importance of a node *i* to the successful operation of itself, A_{ii} would always be 0. Thus, if the initial inoperability, $q_i(0)$, and the recovery time, T_i, to a desired inoperability level, $q_i(T_i)$, from a disruptive event are known for a node *i*, rearranging and taking the natural log of both sides of Eq. (3-3) yields the Eq. (3-4), which can be used for the simple linear regression analysis to predict the values of B_{ii}.

$$\ln\left[q_i(0)\right] = \ln\left[q_i(T_i)\right] + B_{ii} \cdot T_i \tag{3-4}$$

In this research, the mean, standard deviation and confidence interval of the recovery coefficients for critical facilities in electric power, water supply and cellular systems are computed from the regression analysis based on Eq. (3-4) for the use of the case studies in the following chapters. The data samples for the regression analysis are obtained from HAZUS®-MH2.2 (MRI, 2011) analysis and ATC-13 report (Applied Technology Council, 1985). For the data collection, the initial inoperability, $q_i(0)$, of different types of critical civil infrastructure facilities in power, water and cellular systems under seventy-three historical hurricanes from 1990 to 2008 were determined based on the HAZUS®-MH2.2 analysis result. The recovery times, T_i, for those types of facilities given different damage levels were determined based on the data provided in ATC-13 (Applied Technology Council, 1985). The ATC-13 contains the expert estimation of the recovery times for different types of facilities in power, water and cellular systems under different damage levels in earthquake hazards. It is assumed that the recovery times corresponding to different damage levels under the hurricane hazard is the same as those under earthquake hazard, just as the assumption made in HAZUS®-MH2.2 hurricane loss assessment model (MRI, 2011). Utilizing the data of the initial inoperability and recovery times identified as aforementioned, the regression analysis for all types of critical facilities in power, water and cellular systems were performed. The results are summarized in Table 3-2.

Table 3-2. The recovery coefficients for different types of facilities obtained from simple linear regression analysis.

Facility type	Power plants	Power transmission towers	Power substations	Water pumping stations	Water treatment plants	Water storage tanks	Cellular switching offices	Cell sites
Mean recovery coefficient	0.0032	0.0323	0.0087	0.0095	0.0057	0.0126	0.0056	0.0198
Standard deviation of the recovery coefficient	0.0004	0.0043	0.0012	0.0014	0.0007	0.0016	0.0007	0.0027
99.999% confidence interval	0.0011	0.0113	0.0029	0.0028	0.0020	0.0046	0.0021	0.0065
	0.0052	0.0534	0.0144	0.0162	0.0094	0.0206	0.0090	0.0331
R^2 of the regression analysis	0.4296	0.4479	0.4197	0.3918	0.4324	0.4415	0.4543	0.4149

It’s noted that the 99.999% confidence intervals are listed in Table 3-2 to show the variation in the estimation while covering more empirical data since the R^2 values are not high, and to guarantee that the lower bounds of the recovery coefficients are all above zero.

3.1.3.3. Recovery Coefficient Ratio Matrix

In reality, a damaged infrastructure facility may not always get sufficient repair resources or repair crews during the recovery phase. One reason is because the repair resources and/or repair crews may not reach the damaged facility site on time due to the damage or block of the road and bridge system (Chang, 2010; Chang, Elnashai & Spencer, 2012; Chang et al., 2012). The dependency of the facilities in the other infrastructure systems on the road and bridge system can be implicitly considered through the recovery coefficients, B_{ii}. If roads and/or bridges are damaged or blocked after the disaster, the recovery of the critical facilities in other systems would be slowed down. In the DIN model, a ratio, $r_i(t)$, would be multiplied to the recovery coefficient, B_{ii}, at each time step to reflect the impact of the damaged road and bridge system on facility *i* in the network.

Different methodologies can be used to estimate the recovery coefficient ratio. The following methodology is used to compute the recovery coefficient ratios for the damaged infrastructure facilities due to the damage of the road and bridge network in this research. If the repair crews and resources are assumed to come from any road segment end-points within *x* km of node *i*, and they drive following the shortest path, the recovery coefficient ratio for node *i* at time *t*, $r_i(t)$, can be calculated using Eq. (3-5) or Eq. (3-6):

$$r_i(t) = \frac{1}{n_i}\sum_{j=1}^{n_i}\frac{l_{ji}^o}{l_{ji}(t)} \tag{3-5}$$

$$r_i(t) = \frac{1}{n_i}\sum_{j=1}^{n_i}\frac{T_{ji}^o}{T_{ji}(t)} \tag{3-6}$$

where n_i = the number of road segment end-points within x km of node i; l_{ji}^o = the shortest path length from road point j to node i in an undamaged road and bridge network; $l_{ji}(t)$ = the shortest path length from road point j to node i in a post-disaster road and bridge network at time t; T_{ji}^o = the traveling time from road point j to node i in an undamaged road and bridge network; $T_{ji}(t)$ = the traveling time from road point j to node i in a post-disaster road and bridge network at time t. The value of the recovery coefficient ratio is inversely proportional to the traveling distance or time increase due to the damage or block of the road and bridge network.

3.1.3.4. Updated Inoperability Vector

The inoperability, $q_i(t)$, of a node i may need to be updated after calculated from Eq. (3-1) due to the post-disaster demand change or delayed disruption of the operability of corresponding facility *i*.

3.1.3.4.1. Post-disaster Demand Change

According to the definition, the inoperability of a facility refers to the inability of the facility to perform its intended functions to satisfy its demand. Thus, the post-disaster demand change would also affect the inoperability of a facility. Taking the transportation system for example, the changes of people's travel behavior after disruptive events will affect the travel demand on the roads (Chen & Eguchi, 2003; Chang, 2010; Chang, Elnashai & Spencer, 2012; Chang et al., 2012; Nakanishi, Black & Matsuo, 2014; Kontou, Murray-Tuite & Wernstedt, 2017). Besides, severe disasters often cause lots of temporary and permanent social disruptions to the community, including large loss of life or property, major population loss, out-migration and even societal collapse. All of these will affect the demand of the civil infrastructure facilities after the disaster. Taking hurricane Katrina for example, the population of New Orleans in Louisiana became only 37% of its pre-disaster population four month after the hurricane in 2005 (Kates et al., 2006; Sastry, 2009; Groen & Polivka, 2010). The population of New Orleans was estimated to have reached about half of its previous size by mid-2006 (U.S. Census Bureau, 2006; Sastry, 2009). Even three years after the hurricane, the population of New Orleans was still only about 70% of its pre-disaster population (U.S. Census Bureau, 2007; Sastry, 2009). The declined population in New Orleans suggested that many lives were lost after the hurricane and many people who were forced to evacuate decided not to return (Sastry, 2009). This huge decline in the population after hurricane Katrina would have led to the decrease in the demand of power, water and/or other services in New Orleans.

A mathematical definition of the inoperability of a civil infrastructure facility *i* at time *t*, $q_i(t)$, without considering the demand change can be written in the form of Eq. (3-7):

$$q_i(t) = \frac{\tilde{x}_i(0) - x_i(t)}{\tilde{x}_i(0)}, t > 0 \tag{3-7}$$

where $\tilde{x}_i(0)$ = production of facility *i* under normal circumstances before the disaster; and $x_i(t)$ = reduced level of production caused by a disruption at time t (t > 0). If the demand of the civil infrastructure facility is decreased after a disaster, it means that the facility needs to produce a lower amount of PIS under this post-disaster new normal. Let's suppose that the post disaster demand (the new normal) of facility *i* is $\tilde{x}_i^*(0)$. Then, the inoperability of facility *i* at the initial step should be updated to Eq. (3-8):

$$q_i^*(0) = \frac{\tilde{x}_i^*(0) - \tilde{x}_i(0) \cdot \left[1 - q_i(0)\right]}{\tilde{x}_i^*(0)} = 1 - \frac{\tilde{x}_i(0)}{\tilde{x}_i^*(0)} \cdot \left[1 - q_i(0)\right] \tag{3-8}$$

where $q_i(0)$ = the inoperability of facility *i* based on its pre-disaster demand when the disaster happens; and $q_i^*(0)$ = the updated inoperability of facility *i* based on its targeted post-disaster demand when the disaster happens. The updated inoperability $q_i^*(0)$ is adjusted to 0 if $\tilde{x}_i(0)\cdot\left[1-q_i(0)\right]\geq\tilde{x}_i^*(0)$. This is to avoid the updated inoperability to be calculated negative. This case occurs when the decrease in the demand exceeds the decrease in the output of the facility. In other words, although the output of the facility decreased a little bit due to the hazard, the remaining output is still enough to satisfy the new demand after the disaster.

3.1.3.4.2. Delayed Disruption of Nodal Operability

The above discussion about the damage and recovery of network nodes is based on the assumption that all the damaged facilities would become inoperable immediately after the disaster strikes. However, this assumption may not be true under some special conditions. For example, some facilities, such as water pumping stations, telecommunication facilities or hospitals, usually have backup power system to guarantee that the facility can still remain functioning for a certain time after the disruptive event happens (Gruzs & Hall, 2000; Bruneau et al., 2003; Adachi & Ellingwood, 2008). In this case, the initial inoperability and the inoperability of the facility within the time that the backup power can hold should be changed to 0. More generally, the inoperability, $q_i(t)$, of a node *i* at time *t* would be updated to 0 after calculated from Eq. (3-1) within a certain time period if the disruption of the nodal operability would not happen until after this time period. It is noted here that the recovery status of the damaged facility is determined by the inoperability, of a node *i* at time *t* calculated using the originally (before updated) initial inoperability.

3.1.4. Modeling the Damage and Recovery of Network Links

Links in the civil infrastructure network provide passages to send PIS from one node to another. The damage of links in each system can affect the operation of that system and also other systems because of the interdependencies across the systems. It has been known that the damage of links can be extensive due to the distributed nature of the civil infrastructure system (U.S.

Congress, 1990; Dueñas-Osorio & Vemuru, 2009). Unlike the nodes, links have length and a link can experience multiple physical damages along its length. The number of damages along a link is usually modeled as a Poisson process (Adachi & Ellingwood, 2008; Guidotti et al., 2016). In the DIN model, a link is considered as damaged if failure occurs at any location of the link along its length. For example, the power distribution line shown in Figure 3-4 is modeled using a series system of sub-links segmented by the utility poles. The link would be considered as damaged if the failure of any utility pole along the length of the link occurs. Currently, the DIN model does not consider the secondary-effect of the damage of power distribution lines, which means that the over-loading of a power distribution line due to the re-routing of the power load from the already damaged power lines has not been incorporated yet in the model.

A link would not be physically recovered until all causes of failures are resolved and the PIS can flow on this link as is in the normal state. In the above power distribution line example, a damaged power distribution line would not be recovered until all utility poles along its length are recovered. There are several different methods to estimate the recovery time of a damaged link. For example, the ATC-13 has the maximum, minimum, mean and standard deviation of the recovery time of links corresponding to different damage levels in different critical infrastructure systems (e.g. power distribution lines, power transmission lines, water pipelines, telecommunication landlines) based on expert estimation (Applied Technology Council, 1985). The advantage of this methodology is that it's very straightforward to understand and easy to be used since no other additional input information is needed as long as the number of damages per unit length of a link is known. However, one limitation of this method is that the recovery time estimation is based on the damage level per unit length of a link. The recovery time of two links with the same damage level per unit length but having different lengths may vary a lot, especially when only limited number of repair crews is available. Another way to estimate the recovery time of a link is to view it as a function of the total number of damages along the link and the number of repair crews available (ALA, 2001; FEMA, 2003; Shi & O'Rourke, 2008;

Guidotti et al., 2016). This method does not have the limitation of the previously mentioned methodology, but it's difficult to be used since it requires a lot of additional input information, such as the number of the repair crews available, the repair rate for each repair crew, the repair sequence of the repair crews (e.g: whether different repair crews can work in parallel or in series, the time when the repair for each damaged link can begin, etc.), and so on. In order to focus more on the general framework of the DIN model, and due to the data availability issue, all the case studies in this research estimate the link recovery time following the first approach (the ATC-13 approach) for simplicity, except for the post-disaster recovery planning case study in section 5.3 that considers the effect of the number of repair crews available to the recovery time and schedule of the damaged network nodes and links.

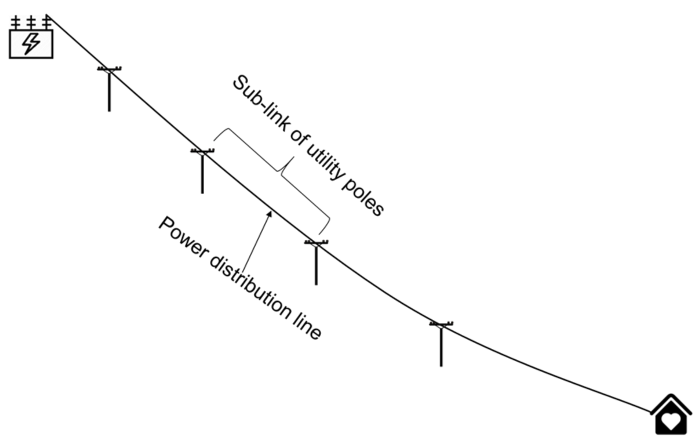


Figure 3-4. An example power distribution line modeled using a series system of sub-links.

3.1.5. Modeling the Damage and Recovery of the Integrated Network

The network topology will change over time due to the damage and recovery of network nodes and links, which can be used to measure the operability of each infrastructure system and the integrated network. The assumptions and methodologies for modeling the operability of each infrastructure system and the integrated network are introduced in this section.

3.1.5.1. Assumptions for Network Operability Modeling

The critical civil infrastructure network contains nodes of individual facilities and directional links representing the PIS flowing between the nodes. After a disruptive event, some nodes may be damaged, and the output of that nodes may decrease, which leads to a decrease of the input into the nodes relying on the service of the damaged nodes. Assume that each node has a threshold inoperability and each link has a threshold damage level below which the node or link is viewed as functioning to an accepted level. If the inoperability of a node or link is higher than this threshold, it implies that this facility or line must be shut down for repair. The threshold inoperability and threshold damage level for the nodes and links in each system may vary by facility and system and should be determined by the experts working in the relevant field through reviewing various failure scenarios for an accurate result. One example source of expert estimates for the threshold value is the ATC-13 (Applied Technology Council, 1985). In ATC-13, the heavy damage state with the inoperability 0.3 ~ 0.6 is regarded as *extensive damage requiring major repairs.* Based on this description, the threshold inoperability value can be assumed to be 0.3, which is the value used in the following case studies.

In the DIN model, the threshold values are used to identify the nonfunctioning nodes and links. The damaged links or the links going out of the nonfunctioning nodes from the network are removed while the other links and all the nodes would still be kept in the network. A link would be added back at the time when both the tail node and the link itself are recovered. A node would be recovered when its inoperability first becomes lower than the threshold inoperability. A physically damaged link would be recovered after its all failure mechanisms are resolved. A complete recovery of a network is defined as the state that the network becomes exactly the same as the pre-disturbance state. Figure 3-5 shows snapshots of a network, where damaged nodes are illustrated with no output links in initial damage state (Figure 3-5 (b)) and recovery phase (Figure 3-5 (c)). A complete recovery (Figure 3-5 (d)) is defined as the state that the network becomes exactly the same as the initial state (Figure 3-5 (a)), or when the network reaches its post-disaster new normal.

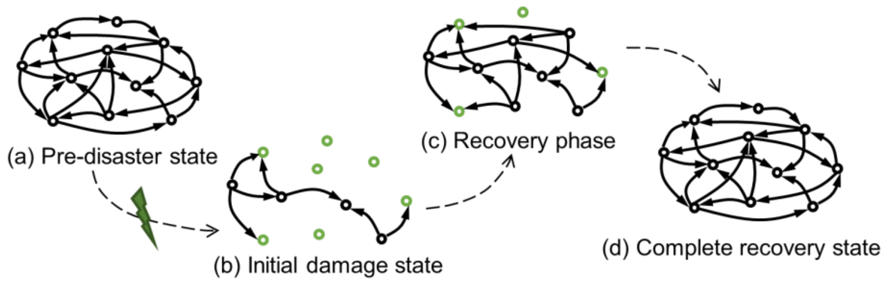


Figure 3-5. Recovery phases of an example network.

3.1.5.2. Assessing the operability of the integrated network

To measure the operability of the integrated network and thus to assess its resilience, some generic characteristic parameters of network can be used. Using a parameter, the operability of individual systems at each time *t* after a disruptive event is calculated first. Then, the values of the parameter can be normalized by dividing their values at each time by the values before a disruptive event. This non-dimensional metric is used to describe the operability, $Q_i(t)$, of the i^{th} infrastructure system at time *t*. Then, the operability of the whole network, $Q(t)$, can be calculated as a weighted sum of the operability values of all systems using Eq. (3-9).

$$Q(t) = \sum_{i=1}^{n} w_i \cdot Q_i(t) \tag{3-9}$$

where n is the number of infrastructure systems in the integrated network; w_i is the weight for the i^{th} system and the sum of w_i over all the systems is 1. The weight for each system can be determined based on the relative importance of each system to the whole network and the community.

3.1.5.3. Example Metrics of Network Operability

Major function of critical civil infrastructures is to provide PISs to end-users thus the connectivity between the nodes can be a good metric to evaluate the operability of the network. How efficiently the PISs flows across the whole network may also be a key measure of the network operability. Thus, one parameter measuring network connectivity (*connectivity*) and another parameter measuring the efficiency of the connection (*efficiency*) were selected for this study from literature reviews.

In the unperturbed state, an end-user can receive PISs from all the source nodes in infrastructure systems connected to it through other facilities. After a disruption, some facilities in between lose their functions and the number of sources nodes connected to a certain end-user decreases. A network parameter called *connectivity loss*, $\bar{C}_L$, can be used to measure the severity of such losses (Guo, Lawson & Planting, 2002). To measure the operability of a network, the *connectivity* of a network, C_L, determined as the complement of *connectivity loss*, can be used.

How efficiently the PIS flow across the whole network may also be a key measure of the network functionality. A network parameter, *efficiency*, *E*, is defined as the average of the reciprocals of the shortest path lengths between every two vertices in a graph (Dueñas-Osorio et al., 2007). The mathematical definitions of the parameters are summarized in Table 3-3.

Table 3-3. Definitions of the characteristic parameters measuring system operability.

$Q_i(t)$	Definition	
Connectivity	$C_L(t) = \frac{1}{n} \cdot \sum_{i=1}^{n} N_p^i(t)$	$N_p^i(t)$ = the number of paths from all source nodes to a certain end-user *i* at time *t*. *n*= the total number of end-users.
Efficiency	$E(t) = \frac{1}{N(N-1)} \sum_{i \neq j} \frac{1}{d_{ij}(t)}$	*N* = the number of nodes in a graph; $d_{ij}(t)$ = the shortest path length between node *i* and node *j* at time *t*.

3.1.6. Closure

This section introduced the DIN model which can simulate the damage and recovery of the infrastructure facilities, systems and the integrated network with considering the facility-to-facility level and system-to-facility level dependencies. The framework of the proposed DIN model is illustrated in Figure 3-6. In this model, the initial inoperability of each node is first determined from the physical damage level of the node that is calculated from probability of damage state curves. Similarly, the damage level of each link is calculated by considering the failure modes and the relevant probabilities. The inoperability of each node over time is then simulated using a mathematical equation modified from the DIIM which incorporates the dependency relationships between the facilities, different recovery rates for different types of the facilities, the recovery rate reductions due to the system-to-facility level dependencies and the post-disaster demand change of the facilities. At each step, a link would be removed from the network if the tail node of the link is damaged or the link itself is damaged. The damaged link is assumed to recover after the recovery time corresponding to the damage level of the link. The link would be added back to the network when its tail node is recovered and the link itself is recovered. By considering the varying network configuration of each system, the operability of each infrastructure system at each time step can be measured by some characteristic parameters from graph theory. The recovery of the integrated network over time is assessed by combining the operability of each infrastructure system using weighting scheme.

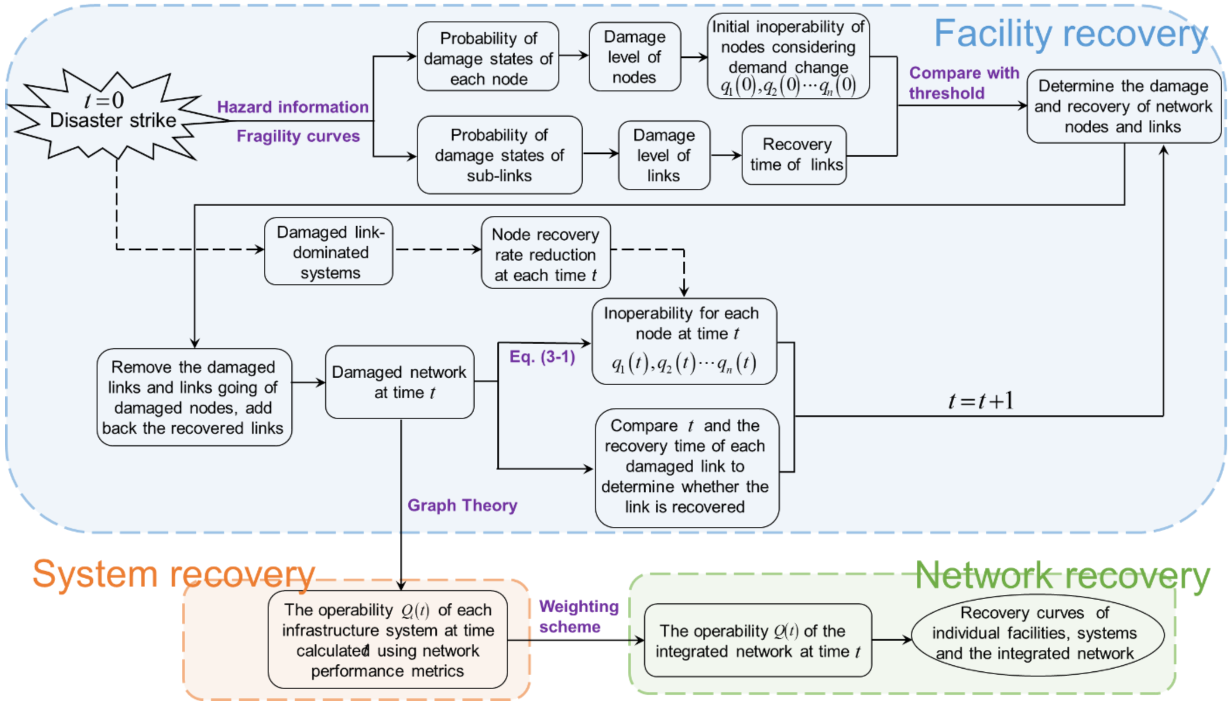


Figure 3-6. The framework of the DIN model.

The input information needed to run the DIN model includes: (1) the geospatial locations of the critical infrastructure facilities and their dependency relationships; (2) the hazard/multi-hazard intensities for each infrastructure facility; (3) the probability of damage state curves for each infrastructure facilities, including the implicitly modeled facilities; (4) the recovery rates for different types of infrastructure facilities and the recovery times for different types of infrastructure lines correspond to different damage levels; (5) the threshold operability levels to evaluate whether the infrastructure facilities or lines are functioning at a satisfied level, and (6) the post-disaster demand change of the facilities, if any. The output of the DIN model includes: (1) the operability of each infrastructure facility at both the temporal and spatial scales; (2) the recovery curves of each infrastructure facility, system and the integrated network with variations that capture the uncertainties; (3) the service restoration curves for the end-users, and (4) the recovery schedule of all damaged network nodes and links. Example plots for each type of the DIN model outputs are shown in Figure 3-7 ~ Figure 3-10.

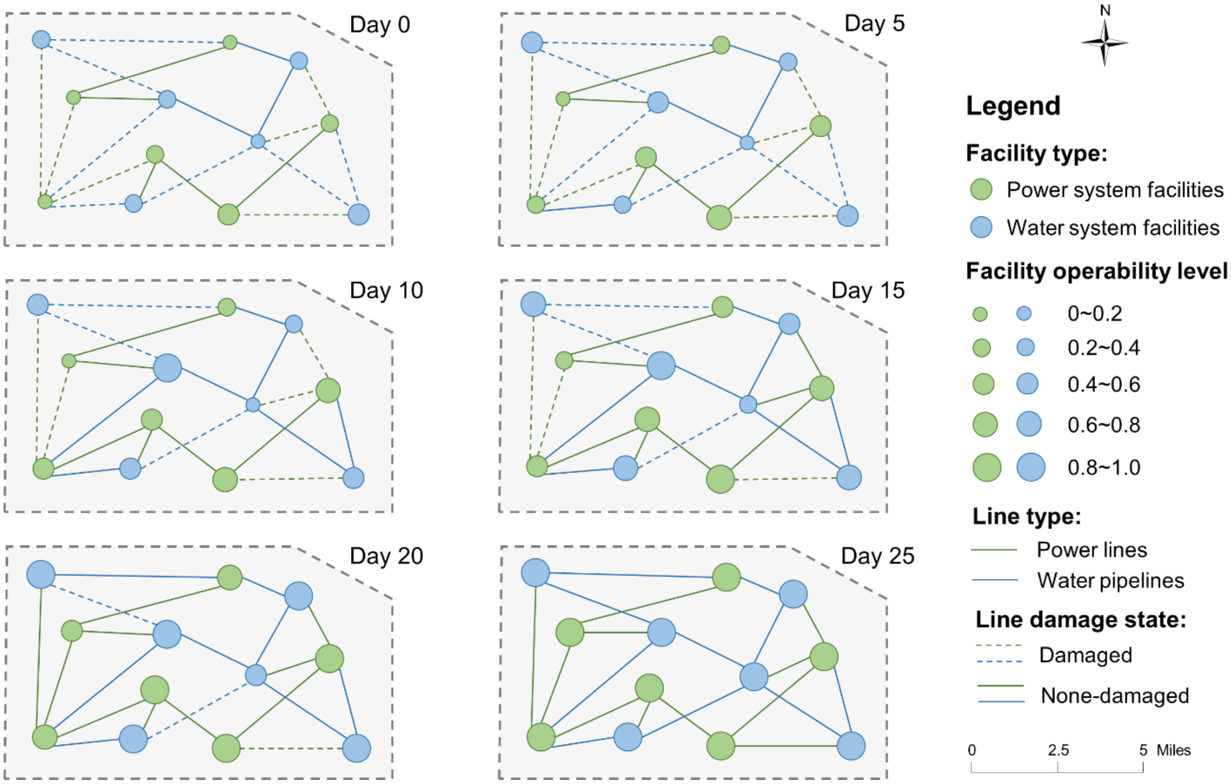


Figure 3-7. Example output of the DIN model (1): the operability of individual infrastructure facilities at both the temporal and spatial scales.

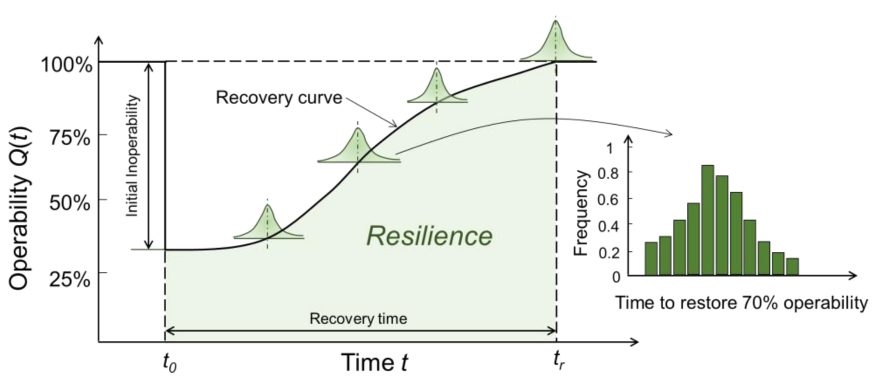


Figure 3-8. Example output of the DIN model (2): the recovery curves of individual infrastructure facilities, systems and the integrated network with variations.

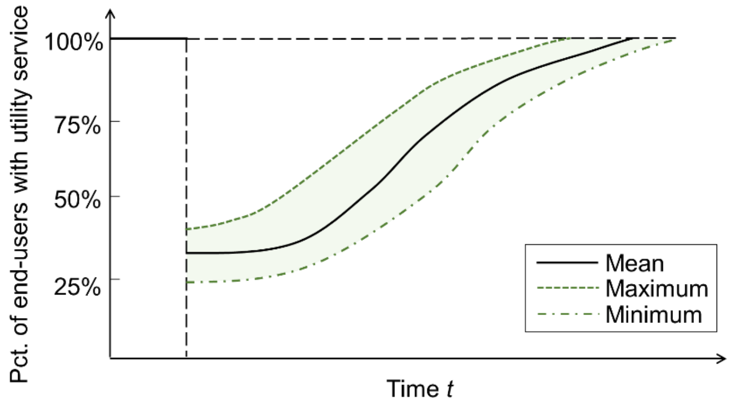


Figure 3-9. Example output of the DIN model (3): the service restoration curves for the end-users.

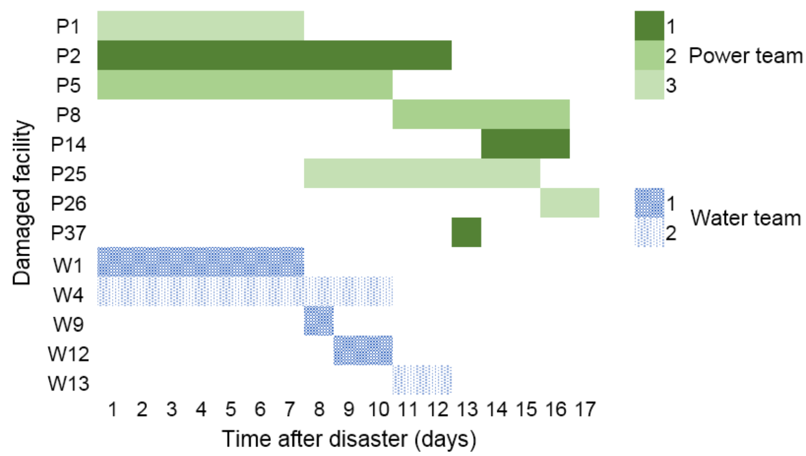


Figure 3-10. Example output of the DIN model (4): the recovery schedule of all damaged network nodes and links.

3.2. Model Comparison

To highlight the importance of considering interdependencies among infrastructure facilities in different systems, the DIN model is compared with two conventional recovery models, one without considering any inter-system interdependencies and the other one with considering only the system-to-system level interdependencies. For the comparison, a hypothetical study region consisting of interdependent power, water and cellular systems and a scenario hurricane hazard are developed, which are introduced first in the following sub-sections. Then, the DIN modeling result and its comparison with the results from two conventional recovery models are presented and discussed.

3.2.1. Hypothetical Study Region

A hypothetical study region located in the coastal area of Texas State, USA was built to illustrate the proposed DIN model. The area of the region is approximately 1,500 km^2, which is about the size of a big city such as Houston, TX. Electric power, water supply, and cellular systems are considered as the critical civil infrastructure systems in the region. The critical nodes and the dependency relationships between and within the three systems identified in Figure 3-2 are used to build the three infrastructure systems in this hypothetical region. The hypothetical study region is populated with six end-user groups, two power plants, two raw water collection points, two cellular central offices and several critical facilities between these generators of each system and the end-users. It includes total of 67 nodes and 174 links. The integrated network of the systems is shown in Figure 3-11. The numbers of each type of facilities are summarized in Table 3-4. The infrastructure systems are modeled in facility resolution and the end-users are modeled by group, which means that several residential, industrial or commercial buildings receiving the PISs from same suppliers are combined together and modeled as one end-user group node in the network. In the region, facilities of the same type are located as far away as possible. The length of a link is assumed to be proportional to the straight-line distance between the two end nodes of the link on Figure 3-11. Other systems not considered in this study are assumed to be 100% functional throughout the recovery.

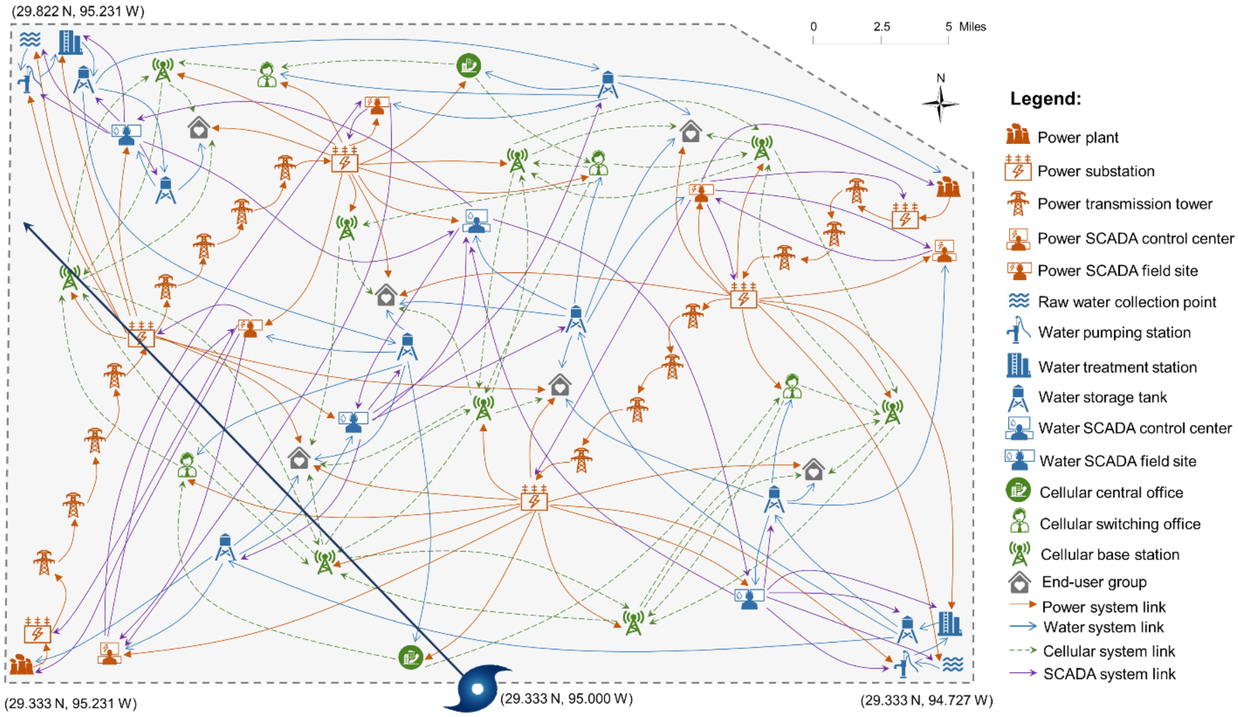


Figure 3-11. Critical nodes and links in the power, water and cellular systems of the hypothetical study region.

Table 3-4. The number of each type of the critical facilities in the hypothetical study region.

System	Facility type	Acronym	Number
Electric Power	Power plant	PP	2
	Substation	PS	6
	Transmission tower	PTT	15
	Power SCADA control center	PSCC	2
	Power SCADA field site	PSFS	3
Potable Water	Raw water collection point	WCP	2
	Pumping station	WPS	2
	Treatment station	WTS	2
	Storage tank	WST	8
	Water SCADA control center	WSCC	1
	Water SCADA field site	WSFS	3
Cellular	Cellular central office	CCO	2
	Cellular switching office	CSO	4
	Cell tower	CT	9
End-user	End-user group	EG	6
Total Number of Nodes			**67**
Total Number of Links			**174**

For the structural fragility curves and recovery times of the network links, estimates obtained from existing literatures are used (López et al., 2009; Ahmed, Arthur & Edwards, 2010; MRI, 2011; Shafieezadeh et al., 2014; Aslam, 2016). The structural type of each node is assumed to be one of industrial buildings, residential buildings, metal buildings, towers or substations and the corresponding fragility curves are obtained from the literatures (López et al., 2009; Ahmed, Arthur & Edwards, 2010; MRI, 2011; Shafieezadeh et al., 2014; Aslam, 2016). The recovery times of power transmission and distribution lines and water pipelines corresponding to different damage levels are found in ATC-13 (Applied Technology Council, 1985), which are listed in Table 3-5. The recovery times corresponding to other damage levels are calculated using interpolation. The central damage factor for power and SCADA lines are assumed to refer to the percentage of the line damaged by trees and/or structurally damaged utility poles. The recovery times for telephone trunks are used for SCADA landlines in this study, since the telephone line is a typical medium for SCADA system transmission (Daneels & Salter, 1999). Note that the recovery times found in ATC-13 were originally developed for earthquake hazard, which may not be same for hurricane hazard. These values are used in this study since no other study on recovery times for hurricane hazard has been found to date.

Table 3-5. The recovery times corresponding to different damage levels for power, water and SCADA system lines.

Power transmission lines		Power distribution lines		SCADA landlines		Water pipelines	
Central damage factor	Recovery time (days)	Central damage factor	Recovery time (days)	Central damage factor	Recovery time (days)	Breaks/km	Recovery time (days)
0	0	0	0	0	0	0	0
0.005	1	0.005	0.5	0.005	0.6	0.25	1.6
0.05	2.3	0.05	2.3	0.05	2	0.75	3.4
0.2	16.9	0.2	12.5	0.2	10.9	5.5	9.5
0.45	48.9	0.45	31.9	0.45	35.4	15	24.6
0.8	81.9	0.8	71	0.8	67.1	30	73.6
1	126.7	1	103.1	1	106.8	40	156.4

3.2.2. Scenario Hurricane Hazard

In this study, the study region in Figure 3-11 is considered to be hit by a Category 2 hurricane making landfall at (29.333 N, 95.000 W), which is at the bottom center of the region. The approach angle (the angle in degrees between the North direction and the hurricane track, taken clockwise positive from North (Georgiou, Davenport & Vickery, 1984)) is -44.64°, which is the mean approach angle for Texas landfall hurricanes calculated based on the historical hurricane track data from NOAA (US Department of Commerce, 2018). The wind field of the scenario hurricane is developed using the modified Georgiou's model which determines gradient wind speed at a location as a function of various parameters including central pressure difference, radius of maximum wind speed, landfall translation speed, angle from hurricane heading direction, distance from hurricane eye, and air density (Georgiou, Davenport & Vickery, 1984; Rosowsky, Sparks & Huang, 1999; Huang, Rosowsky & Sparks, 2001; Lee II, Mitchell & Wallace, 2007). The whole time history of the wind field is determined by utilizing a Markov chain and an exponential decay model for central pressure difference (Huang, Rosowsky & Sparks, 2001).

For the development of the scenario hurricane, the statistics of key parameters were obtained for the hurricanes that had made landfall on Texas coastal line based on the data collected from NOAA (US Department of Commerce, 2018), which are listed in Table 3-6. The scenario hurricane is developed by using the regional mean values of the radius of maximum wind speed, landfall translation speed, and decay rate. For the central pressure difference, the mean plus five times of standard deviation is used in order to simulate a Category 2 hurricane at landfall. The transition matrix in the Markov Chain used to simulate the decay of translation speed was also calculated based on the storm track data of the hurricanes landfalling at Texas from NOAA and is listed in Table 3-7 (US Department of Commerce, 2018). From the gradient wind speed generated by the Georgiou's model, the surface wind speed of hurricane is calculated using a conversion factor. The factor of 0.65 suggested by Lee and Rosowsky (2007) was used for this study. Considering the whole time history, the maximum surface wind speed was determined for the locations of all nodes, which was used to determine the initial damage level of the nodes. The maximum surface wind speed for each link was assumed to be the same for its tail node. The maximum wind speed experienced by each node or link ranges from 40.48 m/s to 45.30 m/s.

Table 3-6. The statistics of the key hurricane parameters for Texas landfalling hurricanes.

Parameter	Sample size	Mean	Standard deviation
Central pressure difference (mb)	52	47.37	18.69
Radius of maximum wind speed (km)	5	23.00	7.35
Landfall translation speed (m/s)	55	4.33	1.71
Decay rate	22	0.04	0.10

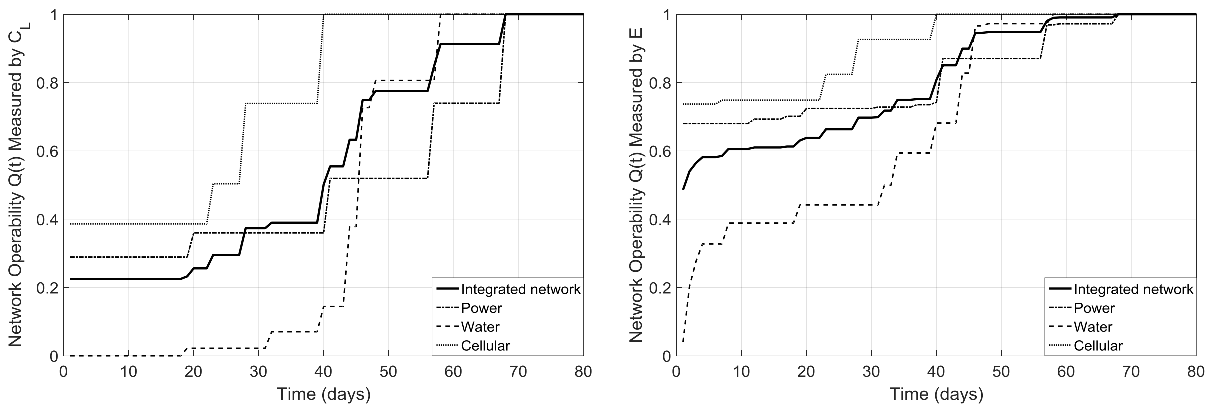
Table 3-7. Transition matrix for translation speed of Texas landfalling hurricanes.

	$V_T(t+1)/V_T(0)$						
$V_T(t)/V_T(0)^*$	0.8	1.0	1.2	1.4	1.6	1.8	2.0
0.8	0.75	0.21	0.00	0.02	0.00	0.00	0.02
1.0	0.20	0.40	0.24	0.11	0.04	0.00	0.00
1.2	0.06	0.18	0.39	0.24	0.00	0.06	0.06
1.4	0.08	0.00	0.25	0.33	0.17	0.13	0.04
1.6	0.11	0.00	0.00	0.33	0.11	0.22	0.22
1.8	0.00	0.00	0.20	0.00	0.40	0.00	0.40
2.0	0.00	0.00	0.00	0.10	0.00	0.10	0.80

3.2.3. Recovery Modeling Using Dynamic Integrated Network Model

Using the DIN, the initial damage and the recovery are determined for the integrated network of the power, water and cellular systems of the hypothetical study region subjected to the scenario hurricane hazard. The initial inoperability of a node is first determined by the expected physical damage level calculated from the corresponding fragility curves and is updated using Eq. (3-1) in each time step to simulate the whole recovery process. The time step used in this simulation is a day. The operability of the whole network is calculated with the weight of 1/3 for each system since the community would not function well without either one of them.

From the simulation, the initial inoperability of the nodes ranges between 0.0095 and 0.7050 which varies by the type and location of the node. It is observed that 16 out of 67 nodes and 67 out of 174 links in the study region are initially damaged by the scenario hurricane and the time for full recovery is 67 days. Furthermore, the times for the individual infrastructure systems and the integrated network to reach 30%, 60% and 90% operability levels are identified from the recovery curves shown in Figure 3-12. The 30%, 60%, 90% operability levels are the three milestones identified by the National Institute of Standards and Technology for community resilience planning (NIST, 2015). The times to reach the three milestones and full recovery for the individual systems and the integrated network are summarized in Table 3-8.



(a) (b)

Figure 3-12. The recovery of the civil infrastructure systems of the hypothetical study region measured by (a) *connectivity* and (b) *efficiency*.

Table 3-8. The time for each individual system and the integrated network to reach 30%, 60%, 90%, and 100% functionality levels using DIN model considering interdependency.

	Recovery time (days)							
Functionality level	*Connectivity*				*Efficiency*			
	Power	Water	Cellular	All	Power	Water	Cellular	All
30%	19	43	0	27	0	3	0	0
60%	56	45	27	43	0	39	0	7
90%	67	57	39	57	56	45	27	45
100%	67	57	39	67	67	67	39	67

The resilience of each infrastructure system and the integrated network can be calculated from the recovery curves in Figure 3-12. Resilience is a metric that measures the ability of a system to withstand an unusual perturbation and recover efficiently from the damage induced by such perturbation. For infrastructure systems, resilience is usually associated with the ability to deliver a certain service level even after the occurrence of an extreme event and recover to the desired level of operability as fast as possible. The time average of the area under the recovery curve is oftentimes used as a measure of resilience (Albert, R., Albert, I. & Nakarado, 2004; Reed, Kapur & Christie, 2009), as shown in Eq. (3-10). The range of this value is between 0 and 1 with the higher value suggesting the higher resilience.

$$R = \frac{\int_{t_1}^{t_2} Q(t)\ dt}{t_2 - t_1} \tag{3-10}$$

where R = the resilience of the network; $Q(t)$ = the operability of the network at time t ; t_1 and t_2 = the endpoint of the time interval under consideration (Bruneau et al., 2003; Reed, Kapur & Christie, 2009). Note that t_1 and t_2 may not be the starting and ending time of a recovery phase. For instance, if we are comparing the resilience of several infrastructure systems, with several recovery curves having different recovery times, the endpoint of the time inverval, t_2, would better to be a fixed value, e.g. the time when all the systems recover, for the comparison.

From Figure 3-12 and Table 3-8, it is found that the extent of damage, the recovery time, and the resilience vary by system. The cellular system has the highest resiliency among all the three systems since only 4 out of 15 cellular system nodes are damaged and they can fully recover after 39 days (resilience is 0.7610 and 0.9079 measured by C_L and E, respectively, when 80 days of reference period used. The reference period is same for all the following). The water system experiences the most severe damage with the damages of 10 out of 18 water system nodes and 51 out of 59 water system links. The full recovery time for the water system is 57 days (resilience is 0.4337 and 0.6931 measured by C_L and E, respectively). For the power system, only 2 nodes are damaged, but the recovery time is relatively long because 16 power system links are down (resilience is 0.5312 and 0.8243 measured by C_L and E, respectively). The operability of the integrated network is found to depend more on the recovery state of the highly damaged system as recovery progresses. In other words, the recovery process is dragged by the least resilient system especially close at the last stage. Thus, more repair crews and resources should be allocated for the recovery of the water and power systems during the post-disaster recovery phase and/or more resources should be allocated to improve the robustness of the water and power systems for pre-disaster risk management.

3.2.4. Comparison with a Model without Considering Inter-System Interdependency

In many existing studies, the performance or recovery of infrastructure systems has been investigated for individual systems (Hwang, Lin & Shinozuka, 1998; Albert, R., Albert, I. & Nakarado, 2004; Booker et al., 2010; Portante et al., 2011). Thus, the recovery estimation from the proposed DIN model which considers the interdependencies between different infrastructure systems is first compared with the estimation from a network model without a consideration of the inter-system interdependencies. For the comparison, a counterpart dependency model is built by eliminating the inter-system links from the model in Figure 3-2, which is shown in Figure 3-13. The corresponding hypothetical study region is developed by modifying the region in Figure 3-11 based on this counterpart dependency model, as is shown in Figure 3-14. The recovery curves with and without the consideration of the interdependencies between systems are shown in Figure 3-15 for each of the electric power, water supply and cellular systems, and their integrated network.

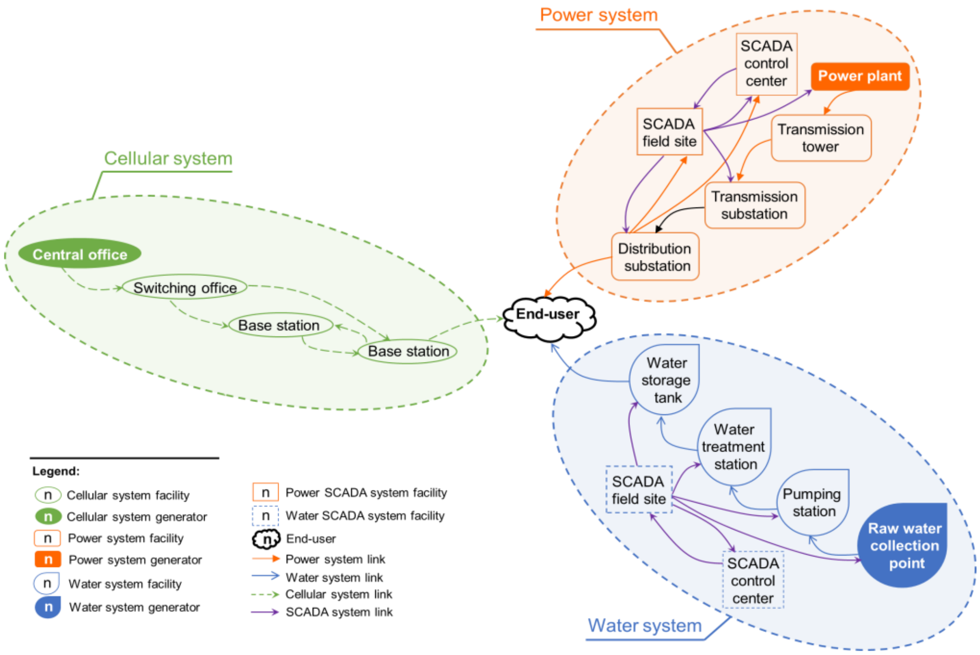


Figure 3-13. The facility-level dependencies within electric power, potable water and cellular systems.

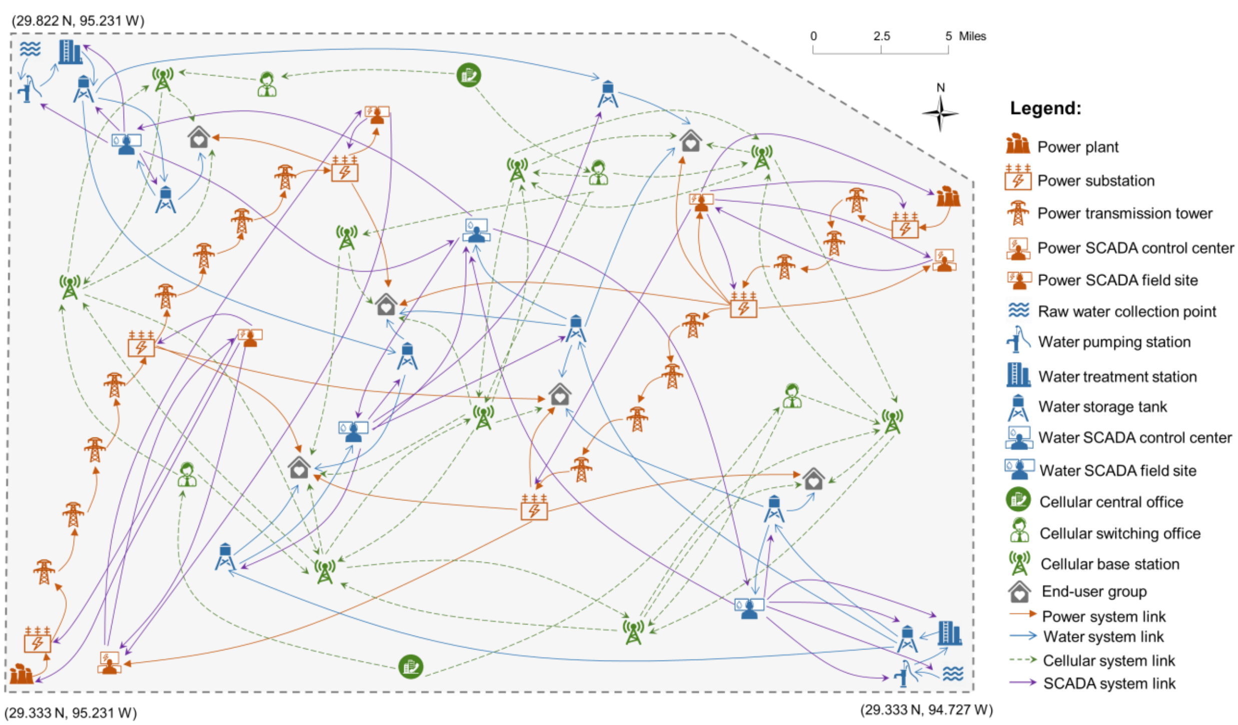


Figure 3-14. The hypothetical study region consisting of power, water and cellular systems without any interdependencies across systems.

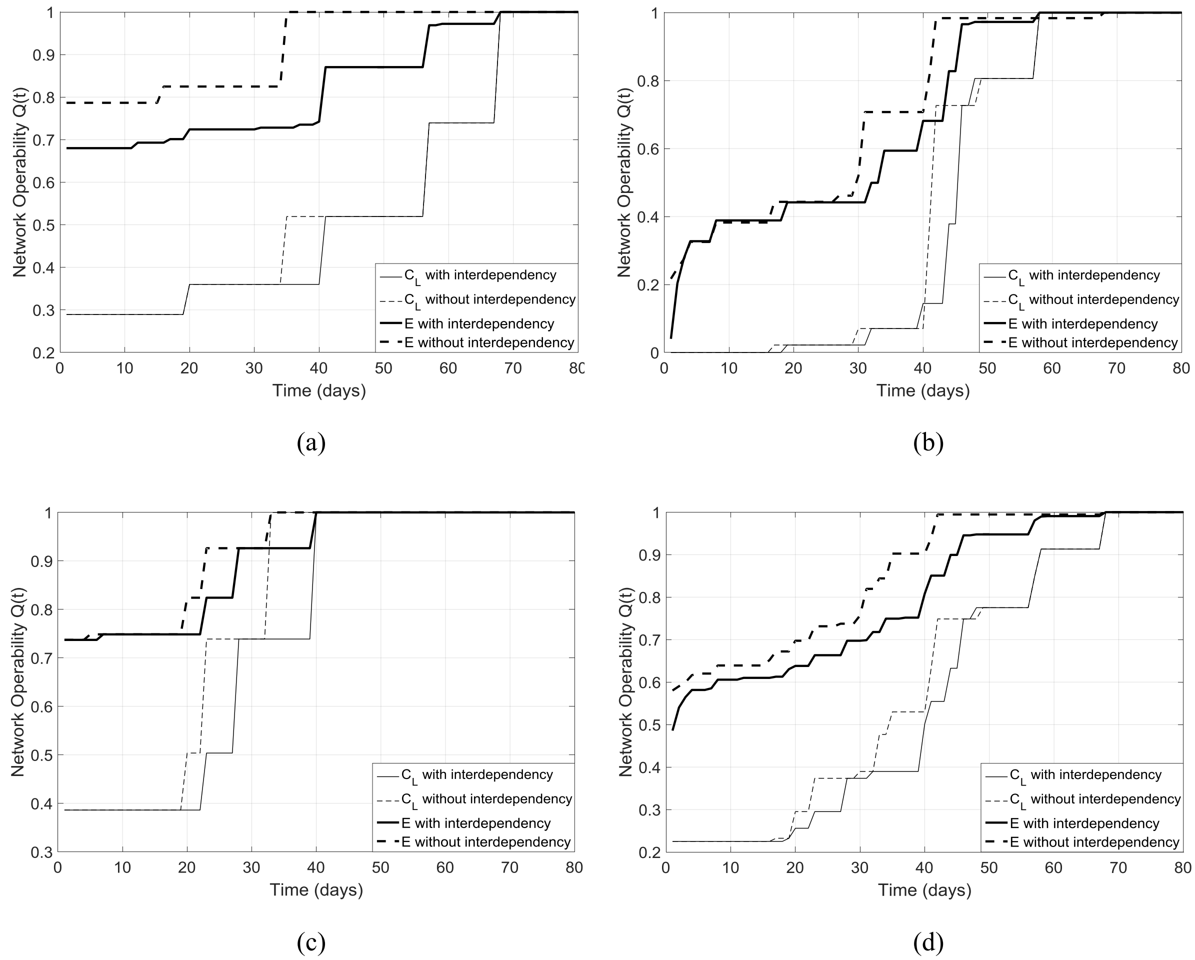


Figure 3-15. Comparison of the recovery curves of (a) electric power system, (b) water supply system, (c) cellular system and (d) the integrated network with and without considering interdependencies between systems.

From Figure 3-16, it is found that the recovery time for a given level of operability is estimated to be faster if inter-system interdependency is not considered. The recovery time estimated 7 days shorter (32 compared to 39 days) for cellular system. The recovery time for power and water system remains unchanged since the recovery times of the two systems are governed by the damage of the links, a power distribution line and a water pipeline. The recovery time for individual nodes also differs a lot between the two cases. The recovery times for the damaged nodes whose recovery time varies between the two cases are summarized in Table 3-9. It is found that considering the interdependency between the systems is especially important when assessing the water system recovery and resilience. This is due to water system depends the most on the other systems.

Table 3-9. The difference in node recovery times with and without considering inter-system interdependencies.

	Node recovery time (days)											
Node	33 -PSFS	34 - PSFS	35 - WCP	36 - WCP	49 - WSFS	50 - WSFS	51 - WSFS	52 - WSCC	54 - CCO	55 - CSO	57 - CSO	58 - CSO
With interdependency	16	40	31	18	45	43	33	31	6	22	39	27
Without interdependency	15	34	29	16	41	40	30	26	4	19	32	22
Percentage difference	-6.3%	-15.0%	-6.5%	-11.1%	-9.8%	-7.5%	-9.1%	-16.1%	-33.3%	-13.6%	-17.9%	-18.5%

The underestimation of the recovery time is also observed in the estimation of the times to reach the three recovery milestones if inter-system interdependencies are ignored. The time for individual infrastructure systems and the integrated network to reach the 30%, 60%, 90%, and 100% operability levels are listed in Table 3-10, which are comparable to the values in Table 3-8.

Table 3-10. The time for individual systems and the integrated network to reach 30%, 60%, 90%, and 100% functionality levels using conventional model without considering interdependency*.

	Recovery time (days)							
Functionality level	*Connectivity*				*Efficiency*			
	Power	Water	Cellular	All	Power	Water	Cellular	All
30%	19 (0%)	40 (-6.98%)	0 (0%)	22 (-18.52%)	0 (0%)	3 (0%)	0 (0%)	0 (0%)
60%	56 (0%)	41 (-8.89%)	22 (-18.52%)	40 (-6.98%)	0 (0%)	30 (-23.08%)	0 (0%)	3 (-57.14%)
90%	67 (0%)	57 (0%)	32 (-17.95%)	57 (0%)	34 (-39.29%)	41 (-8.89%)	22 (-18.52%)	34 (-24.44%)
100%	67 (0%)	57 (0%)	32 (-17.95%)	67 (0%)	34 (-49.25%)	67 (0%)	32 (-17.95%)	67 (0%)

* *Note*: The percentage difference values in the parentheses in this table are in comparison to the values in Table 3-8.

The underestimation of the recovery time would result in an overestimation of the resilience. The resilience for each of the system and the integrated network measured by C_L and E with and without considering the interdependency between systems are listed in Table 3-11. The water system has the largest difference between the resilience values from the two cases.

Table 3-11. Resilience for individual systems and the integrated network with and without considering interdependency.

	Resilience							
	Measured by C_L				Measured by E			
	Power	Water	Cellular	All	Power	Water	Cellular	All
With interdependency	0.5312	0.4337	0.7610	0.5753	0.8243	0.6931	0.9079	0.8084
Without interdependency	0.5432	0.4598	0.8030	0.6020	0.9184	0.7286	0.9239	0.8570
Percentage difference	2.25%	6.01%	5.51%	4.64%	11.41%	5.12%	1.76%	6.01%

The observed trend seems to be reasonable since without considering the inter-system interdependencies, a damaged node is assumed to be able to get everything it needs from other systems for its operation during the recovery process. If the interdependency between the systems is taken into account, however, insufficient supply of necessary PISs from other systems can slow down the recovery process of a damaged node. Thus, the recovery time for the whole network as well as the damaged nodes would be underestimated if the interdependency between systems is not properly considered. This underestimation on the recovery time and overestimation of the resilience may lead to an underestimation of potential losses and risks, which will lead to poorly-informed decisions for the recovery planning and risk mitigation.

3.2.5. Comparison with a Model with Considering System-to-System Level Interdependencies

To highlight the importance of modeling the infrastructure interdependencies at a higher resolution, the recovery estimation from the proposed DIN model which considers the dependencies at the facility-to-facility level is compared with the estimation from the conventional methodology that considers only the system-to-system level interdependencies (Jiang & Haimes, 2004; Haimes et al., 2005 a,b; Lian & Haimes, 2006; Crowther, Haimes & Taub, 2007; Barker & Haimes, 2009a,b; Reed, Kapur & Christie, 2009). The recovery curves for considering the system-to-system level interdependencies and for considering the facility-to-facility level dependencies were generated for the comparison.

Figure 3-16 shows the network of the hypothetical study region modified from Figure 3-11 by combining all the facilities in one system to be represented by one node. It was assumed that the distance from one system node to an end-user group in this modified network equals to the longest distance among all the distances from all source nodes in the system to the end-user group in the original network. The initial inoperability of a system node in Figure 3-16 was assumed to be the maximum initial inoperability of all the nodes in the original network. The recovery coefficient of this node was then used as the recovery coefficient of the corresponding system node in the modified network. The expected damage level and the recovery time for each link in the modified network were assumed to be the maximum expected damage level among all the links going from one system to another in the original network and the recovery time of the corresponding link.

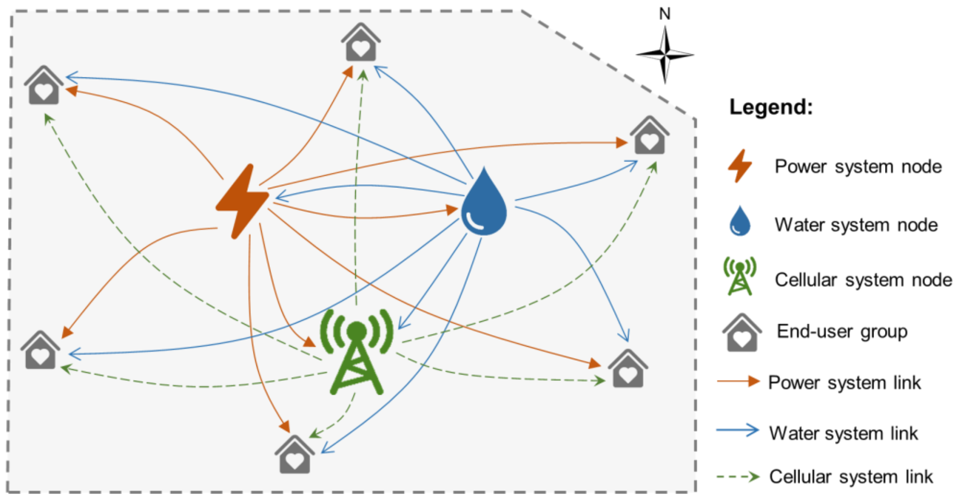
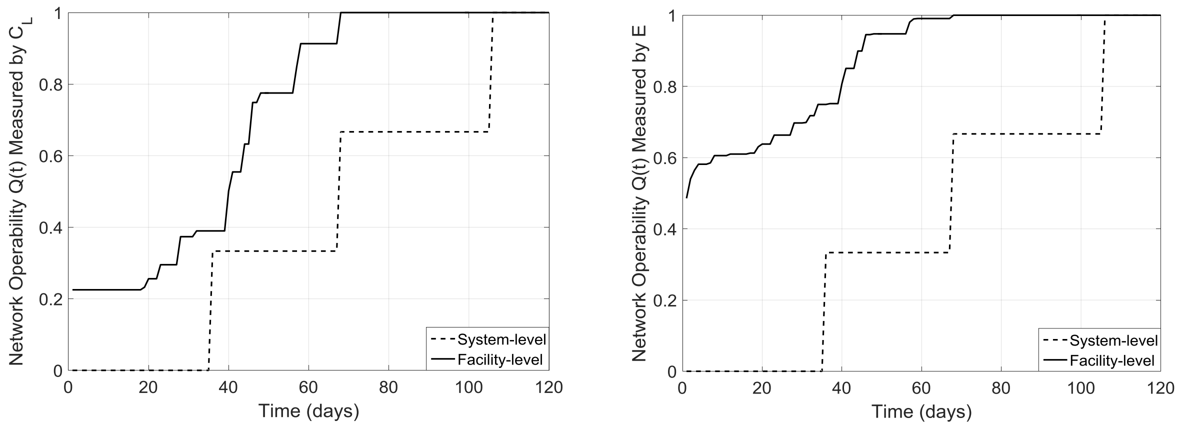


Figure 3-16. The hypothetical study region represented by a system-to-system level interdependency model.

The operability of the whole network measured by *connectivity* and *efficiency* of the model when only the system-to-system level interdependencies are considered is shown in Figure 3-17 together with the results from the DIN model. It is noted that the recovery time of the network is 38 days (56.72%) longer if system-to-system level interdependencies are considered rather than the facility-to-facility level dependencies. Besides, the operability of the network by considering the facility-to-facility level dependencies is always higher than by considering the system-to-system level interdependencies. The recovery of the network is described in a more refined way when the facility-to-facility level dependencies are considered. This is because by considering the dependencies at the facility level, each system can be partially damaged, the nodes in each system can recover at different times. However, if each system is viewed as one node, each system at a given time can only have the states of damaged or not damaged, which simplifies the modeling of the whole recovery process and overestimates the overall damage severity of each system. In conclusion, this comparative analysis suggests that the recovery times would be overestimated a lot if only system-to-system level interdependencies are considered. This overestimation may cause the waste of resources due to the over-preparation of the recovery tools and materials, unnecessary social disruptions due to the long-estimated recovery time and poorly-informed decision making for pre- and post-disaster risk management.



(a) (b)

Figure 3-17. The network operability measured by considering the system-to-system level interdependencies and facility-to-facility level dependencies: (a) measured by C_L, (b) measured by E.

3.2.6. Closure

The DIN model was compared with two conventional recovery models, one without considering any dependencies between the facilities in different infrastructure systems, the other one with considering only the system-to-system level interdependencies. The first comparison shows that if the inter-system interdependencies are ignored, the recovery time of the damaged nodes and the infrastructure systems would be underestimated, and the resilience would be overestimated, which would lead to an underestimation of the potential damages and losses. The second comparison indicates that if the system-to-system interdependencies are considered, instead of the facility-to-facility level dependencies, the recovery time of the damaged infrastructure systems would be overestimated, and the resilience be underestimated. Besides, the overall recovery trajectory would be modeled in a simplified way and overestimates the damage severity of each system, which would lead to waste of resources and unnecessary social disruptions. Both of these model comparisons show that if the facility-to-facility level dependencies within and across different infrastructure systems are not properly incorporated into the recovery modeling, the resulted damage severity, recovery time and resilience information would be misleading, which will in turn result in poorly informed decisions for pre-disaster risk mitigation and post-disaster recovery planning.

3.3. Model Validation

To validate the model with physical reality, the DIN model was applied to simulate the recovery of interdependent power, water and cellular systems in Galveston City, TX after Hurricane Ike, 2008.

3.3.1. Galveston Testbed

Galveston City a coastal island of Texas State with an area of 542 km^2. The critical facilities in electric power, water supply and cellular systems were identified using Google Earth. The GIS data of the road and bridge network in Galveston City was downloaded from US Census website (U.S. Census Bureau, 2016). Thirty-nine end-user groups were created based on Galveston city zoning division (City of Galveston, 2018), including 4 industrial areas, 16 residential areas and 19 commercial areas. The dependency relationships among electric power, potable water and end-user groups were determined based on the nearest facility assumption. All the end-user groups were assumed to receive the service from all the cellular towers since Galveston City is 46.67 km long and 7.40 km wide, which is within the coverage area of a typical cellular tower, 35.40 ~ 72.42 km (Bert Markgraf, 2018). The number of nodes in each type of the facilities in power, water, cellular systems is listed in Table 3-12. The dependency relationship between the nodes is shown in Figure 3-18. In total, there are 353 nodes and 578 links in the network.

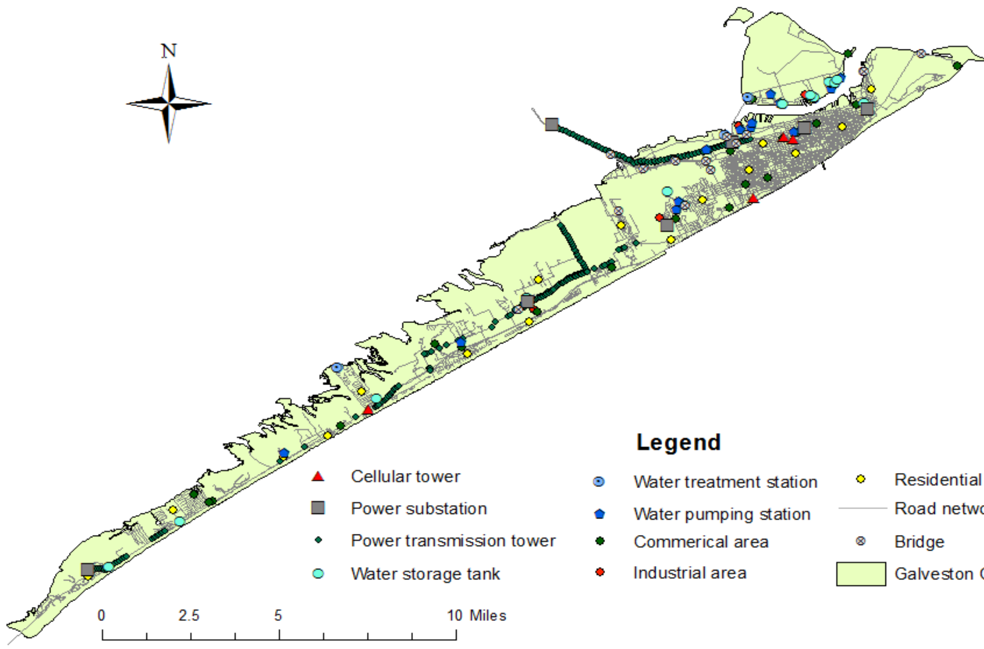


Figure 3-18. Critical facilities in power, water and cellular systems and the road network in Galveston City, TX.

Table 3-12. The number of each type of critical facilities modeled in the Galveston City infrastructure network.

System	Facility type	Number
Electric Power	Substation (PS)	7
	Transmission tower (PT)	268
Potable Water	Pumping station (WPS)	19
	Treatment station (WTS)	3
	Storage tank (WST)	13
Cellular	Cell tower (CT)	4
End-user Group	Industrial	4
	Residential	16
	Commercial	19
Total Number of Nodes		**353**
Total Number of Links		**578**

3.3.2. Hurricane Ike Hazard Information

The Hurricane Ike made landfall near Galveston City, TX as a Category 2 Hurricane in 2008. The maximum wind speeds and the maximum flood depth of Hurricane Ike at different infrastructure facility locations in Galveston were found in literature (Masoomi et al., 2011). The range of the hurricane wind speed in different locations of Galveston was between 120.84 m/s and 174.60 m/s. The range of the flood depth caused by storm surge and heavy rainfall was between 0.14 m to 4.71 m.

3.3.3. Recovery Modeling Using Dynamic Integrated Network Model

The post-disaster restoration of the interdependent power, water and cellular systems in Galveston City, TX after Hurricane Ike, 2008 was assessed by considering the uncertainties in the following variables: (1) the initial damage level of the network nodes, utility poles, and roads and bridges; (2) the restoration coefficients for network nodes; and (3) the restoration time of the network links, utility poles and the roads and bridges. The uncertainties considered in this study and their probability distribution parameters are summarized in Table 3-13. Here "restoration" refers to the short-term recovery, which refers to the process to restore all the services of the infrastructure systems to the end-users to satisfy the demand, even though some long-term recovery goals such as the network optimization, facility upgrade, and structural reconstruction have not been reached yet. For example, after 1995 Kobe Earthquake, the functional restoration time (the time used to restore all the service) was 7 days for electric power supply, 82 days for water supply and 85 days for natural gas supply. However, the seismic design code development for the lifeline systems, and the upgrade and reconstruction of some life system facilities continued over years following the earthquake (Kameda, 2000).

Table 3-13. The probabilistic models of the random variables in this analysis.

No.	Random variable	Probabilistic model
1	Initial damage level of damaged network nodes and implicitly modeled utility poles	Distribution determined from fragility curves
2	Initial damage level of damaged roads and bridges	Standard uniform distribution
3	Recovery coefficients of damaged network nodes	Normal distribution with mean and standard deviation (S.D.) listed in Table 3-2
4	Recovery times of damaged network links and implicitly modeled roads and bridges	Normal distribution with mean and S.D. listed in ATC-13 (Applied Technology Council, 1985)

The following assumptions were made for this analysis. First of all, it was reported that the State Highway 87, the Harborside Drive and the FM 3005 road were flooded and the Tiki Dr. Bridge is lightly damaged (The State of Texas, 2008; City of Galveston, 2009). Thus, the damage level of these damaged roads and bridges were assumed to follow standard uniform distribution since no data is available to determine the actual damage levels. The Pelican Island Bridge was reported to be destroyed (Stearns & Padgett, 2011) and thus was modeled with an initial damage level of 1. Although there may exist some other roads that are also damaged and/or blocked, this study didn't consider all these scenarios since no data about the location of these damaged roads are available. Secondly, the short-term restoration time for the damaged roads and bridges and network links were assumed to be one fourth of the long-term recovery time (Applied Technology Council, 1985), many existing literature suggest the period from the disaster impact to month 3 as short-term recovery, or rehabilitation, and month 3 on ward (usually around 12 months) often refers to long term recovery, or reconstruction (UNDRO, 1984; Schwab et al., 1998; U.S. Department of Homeland Security, 2011). Thirdly, in order to simulate the short-term restoration, the mean recovery coefficients in this analysis were increased to be four times of the long-term recovery coefficients, just as the short-term restoration coefficients used in (He & Cha, 2018a). The mean and standard deviation of the restoration coefficients for each facility type used in this analysis are shown in Table 3-14.

Table 3-14. The mean and standard deviation of the restoration coefficients for all critical facility types in Galveston City infrastructure network.

Facility type	PS	PT	WPS	WTS	WST	CT	End-user
Mean	0.0576	0.2136	0.0648	0.0376	0.0824	0.1324	0.1004
Standard deviation	0.0012	0.0043	0.0014	0.0007	0.0016	0.0027	0.0025

Apart from physical damage of the infrastructure systems, the Galveston City also experienced severe population drop after Hurricane Ike. The population was estimated to be 15,000 people below its pre-storm population of 58,000 (Colley & DeBlasio Sr, 2008). It is assumed in this analysis that the demand change for all critical civil infrastructure facilities in Galveston City is proportional to the population change, which means that the facilities only need to be restored to satisfy a post-disaster demand which is equal to 74.14% of their pre-disaster demand.

3.3.4. Model Validation Result

For validation purpose, the simulated power system restoration time was compared with the actual power system restoration time of Galveston City after Hurricane Ike, 2008. The Latin Hypercube simulation was run for 1,000 times until the mean (μ) and standard deviation (σ) of the power system restoration time converge. After running 1000 times, we have over 99% confidence that the true mean power system restoration time is within 1 day of the simulated mean power system restoration time. The variations of the restoration curves for the electric power system measured by *connectivity* and *efficiency* are shown in Figure 3-19. The uncertainties in the modeling parameters are found to result in significant variations in the estimated restoration times, which highlight the importance of considering the uncertainties in the restoration and recovery estimations. The information on the variations in the restoration time provides a whole picture of the risk, which can help the decision makers better make risk-informed decisions. The actual power system restoration time for Galveston City after Hurricane Ike was 23.17 days (Department of Energy, 2008), which is within the mean (29.94 days) minus/plus one standard deviation (7.76 days) of the simulated power system restoration time. It shows that the proposed DIN model can produce comparable result with the physical reality in general. The simulated mean power system restoration time is 29.94 days, which is longer than the actual power system restoration time. This overestimation could be a result from the non-accurate fragility curves used in this model. Besides, the restoration coefficients of the power system facilities may be larger than the values used in this study. The modeling results would be more accurate if more data about the fragility curves and the restoration coefficients become available in the future.

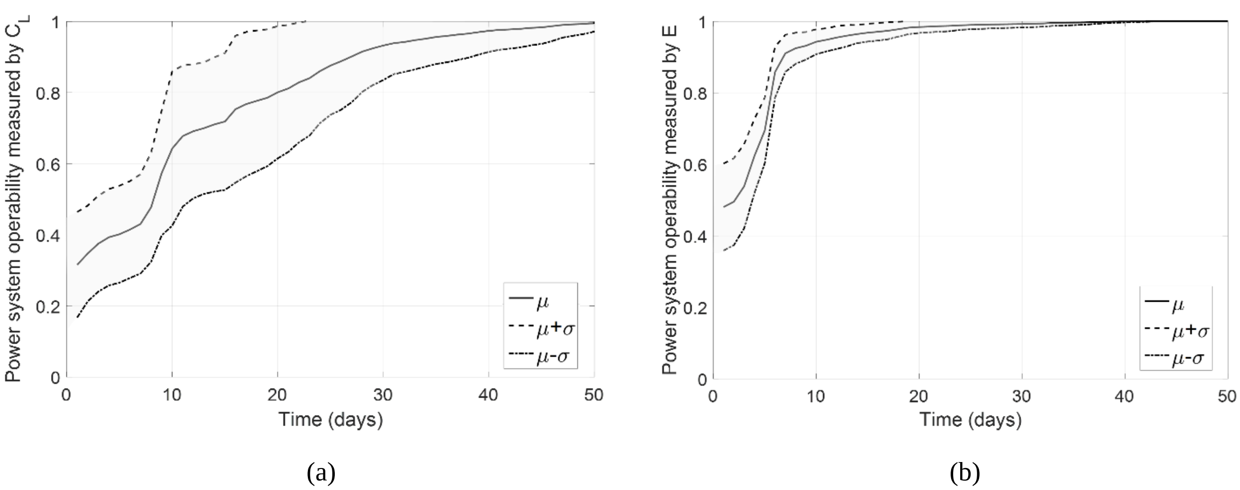


Figure 3-19. The variations of the power system restoration curves measured by (a) *connectivity* and (b) *efficiency*.

3.3.5. Closure

To validate the model with physical reality, the DIN model was applied to simulate the recovery of interdependent power, water and cellular systems in Galveston City, TX after Hurricane Ike (2008). In addition to facility-to-facility level dependencies in the power, water, and cellular systems, two types of system-to-facility level dependencies were incorporated in this analysis. First, the recovery rates of the damaged facilities in power, water and cellular systems were reduced because of the transportation system damage. Second, the post-disaster demand of the facilities was reduced in accordance with the post-Ike population drop of Galveston City. The uncertainties in some of the modeling variables were considered, such as the initial damage level and recovery coefficients of network nodes, the recovery time of the damaged network links and so on. The Monte Carlo Simulation with Latin Hypercube sampling was run for 1,000 times until the mean and standard deviation of the network recovery time converges. The actual power system recovery time for Galveston City after Hurricane Ike was 23.17 days, which is within the mean (29.94 days) minus/plus one standard deviation (7.76 days) of the simulated time. It shows that the proposed DIN model can produce comparable result with the physical reality.

CHAPTER 4 INTERDEPENDENT INFRASTRUCTURE PRE-DISASTER RISK MITIGATION PLANNING

The literature review in section 2.6 indicates that: (1) although there exists extensive studies on developing models to simulate the performance of infrastructure systems under disruptive events, only limited studies are available on developing decision frameworks to support the pre-disaster infrastructure risk mitigation planning; and (2) the few existing studies or projects on risk mitigation planning for infrastructure systems tend to focus on a single infrastructure system, without considering any interdependencies between the systems, which may not be the most efficient and effective way to reduce the loss and enhance the overall community resilience. To fill the gaps of extending infrastructure recovery models to support risk mitigation planning decision-making and considering infrastructure interdependencies in the decision-making process, this chapter introduces the Interdependent Infrastructure Risk Mitigation (IIRM) problem, which aims at developing optimal pre-disaster risk mitigation plans for the interdependent infrastructure systems under certain constraints. A four-stage decision framework to solve the IIRM problem is proposed. One innovation of this decision framework is that it includes the pre-decision processing stage, in which the facilities that deserve priority consideration for risk mitigation investment and intervention in the interdependent infrastructure systems are identified. This step is essential for making the infrastructure risk mitigation planning better targeted.

The remainder of this chapter is organized as follows: section 4.1 defines the IIRM problem and the four-stage decision framework. Section 4.2 illustrates the proposed IIRM decision framework using a case study on pre-disaster risk mitigation planning of the interdependent critical infrastructure systems in Jamaica. Finally, the contributions and significance of the IIRM decision framework are highlighted and summarized in section 4.3.

4.1. Interdependent Infrastructure Risk Mitigation Decision Problem

The IIRM decision problem is defined as the problem of developing an optimal pre-disaster risk mitigation plan for the interdependent infrastructure systems in a community to achieve greater community resilience under financial budget/fund and resources constrains. The main characteristics of the IIRM problem, including decision objective, applicable phase, decision makers and decision constraints are summarized in Table 4-1.

Table 4-1. Main characteristics of the IIRM decision problem.

Decision objective	Mitigation of the damage, social disruptions and economic losses when future hazard occurs through improving the resilience of interdependent civil infrastructure systems
Applicable phase	Pre-disaster risk mitigation phase
Decision makers	• Multi-national development banks (e.g. Asian Development Bank, Asian Infrastructure Investment Bank, European Development Bank, Inter-American Development Bank, World Bank, etc.) • Emergency management departments or agencies (e.g. Department of Homeland Security, Federal Emergency Management Agency (FEMA), Ministry of the Emergency Management of the People's Republic of China, etc.) • Disaster risk management related organizations (e.g. United Nations Office for Disaster Risk Reduction (UNISDR), etc.) • Utility companies (e.g. Memphis Light, Gas and Water Division, CenterPoint Energy, etc.) and other multi-infrastructure system owners
Decision constraints	Financial budget/fund, available resources, time

In the pre-disaster phase, the main objective of the infrastructure risk mitigation work is to make the existing infrastructure network more robust and/or redundant in order to reduce its vulnerability and minimize the service disruptions to the community when future hazard occurs. Some common practices during this phase include: (1) frequent maintenance of the existing facilities; (2) upgrading or retrofitting the existing facilities and (3) building new facilities. However, due to limited available budget/fund, resources and time, not all the facilities in the infrastructure network could be maintained, upgraded or rebuilt. Thus, identifying some critical facilities in all considered infrastructure systems that have the priority need for risk mitigation investment and intervention is especially important. The following subsections present a four-stage decision framework to solve the IIRM problem with considering the facility prioritization in the pre-decision processing step. This framework can be applied to any interdependent infrastructure systems under any type of hazard/multi-hazards. The flowchart of the IIRM decision framework is shown in Figure 4-1.

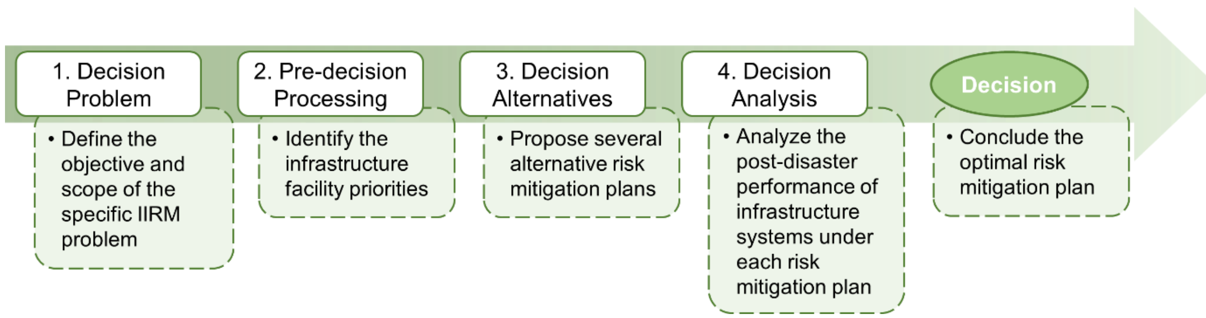


Figure 4-1. The flowchart of the IIRM decision framework.

4.1.1. Decision Problem

The first step of solving the IIRM problem is to define the objective and scope of the specific decision problem. Clearly identifying the decision objective, decision makers, constraints, study region and hazard types are important to facilitate the data collection and information gathering work. Any assumptions and other relevant information needed to define the specific IIRM decision problem (e.g. the current status of the infrastructure facilities, time since last maintenance, restrictions of new construction, etc.) should also be clarified in this step.

4.1.2. Pre-decision Processing: Priority Identification

Due to various constraints, the pre-disaster risk mitigation cannot be performed on all facilities in the infrastructure network. The more critical facilities in the network deserve priority consideration for the risk mitigation investment and interventions when only limited budget or resources are available. The task of the pre-decision processing stage is to prioritize the facilities in different interdependent infrastructure systems based on certain decision criteria. There are three steps to assess the priority of individual infrastructure facilities, which is shown in Figure 4-2.

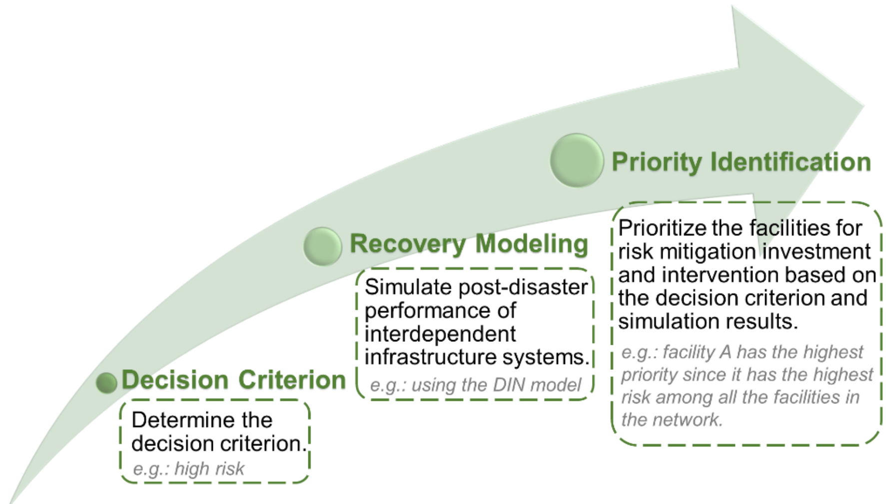


Figure 4-2. Priority assessment framework for infrastructure facilities in the pre-decision processing stage.

The decision criterion used to identify the criticality of the infrastructure facilities needs to be determined first. Some example decision criteria include: high vulnerability (low robustness), high risk, low redundancy, long recovery time, large number of customer served, etc. Next, the damage and recovery of the interdependent infrastructure systems subjected to disaster events are simulated with considering the dependency relationships among infrastructure facilities. Some existing methodologies to simulate the post-disaster performance of interdependent infrastructure systems can be used (Ouyang, 2014; He & Cha, 2019a). In the final step, the facilities that deserve priority consideration for risk mitigation investment and intervention are identified to assist developing alternative risk mitigation plans in the next stage.

4.1.3. Decision Alternatives

In this stage, several alternative risk mitigation plans are proposed. Although any facility could be included in the risk mitigation plan, priority is given to the critical facilities identified in the previous stage if only limited budget or resources are available. The plans can be formed by first listing all possible risk mitigation strategies for different types of infrastructure facilities and then allocating budget and resources to the suitable strategies for different critical facilities identified in the previous stage.

4.1.4. Decision Analysis

In the decision analysis stage, all the alternative risk mitigation plans proposed in the previous step are analyzed using decision analysis techniques. Some of the most widely used decision analysis tools and techniques include: cost-benefit analysis, decision matrix, Pareto analysis, PEST analysis, SWOT analysis, T-chart analysis, trade-off analysis and so on (Hall, Ashford & Söderbaum, 2008; Caramela, 2017). Post-disaster performance of the infrastructure systems is analyzed for all the alternative risk mitigation plans as part of the decision analysis. The decision analysis results are used to compare different risk mitigation plans in order to reach the final decision conclusion.

4.1.5. Decision

In this final stage, the optimal infrastructure risk mitigation plan(s) would be selected based on the decision analysis results. The optimal plan would be implemented on the infrastructure network and its effectiveness is recommended to be evaluated throughout the entire project period and updated if needed.

4.2. Case Study: Risk Mitigation Planning for Critical Infrastructure Systems in Jamaica

The proposed four-stage IIRM decision framework is illustrated using a case study on risk mitigation planning of the interdependent power, water and transportation systems in Jamaica subjected to hurricane hazards.

4.2.1. Decision Problem

In this case study, the IIRM problem aims at developing a strategic plan for critical infrastructure systems in Jamaica in order to reduce the service disruptions under future hurricane hazard. The key components of the problem are summarized in Table 4-2.

Table 4-2. The IIRM decision problem for Jamaica case study.

Decision objective	Reduction of service disruptions to critical end-user facilities by future hurricane hazard occurs
Constraints	Financial budget, resources and time
Study region	Jamaica
Infrastructure systems	Electric power, water supply and transportation (road) systems
Critical end-user facilities	Airports, hospitals and schools
Hazard type	Hurricane wind and rainfall-induced flooding hazards

Jamaica is chosen as the study region for the case study. Jamaica is the fourth-largest and fourth-most populous island country in the Caribbean Sea with an area of 10,990 km^2 and a population of 2.9 million (Niehoff, 2017; Potter, 2017; Wikipedia, 2018). The geographic location and unique topography make Jamaica one of the most exposed countries to natural hazards in the world, especially to hurricane hazards. The severity of the damage and loss of Jamaica caused by a hazard is also quite high due to its isolated location and socioeconomic structure. Past catastrophe events such as the 2007 Hurricane Dean witnessed huge civil infrastructure network damages which led to severe socioeconomic impact to Jamaica (Planning Institute of Jamaica, 2007). Some of the infrastructure facilities in Jamaica are located in high risk areas, not built to high standards, and poorly maintained, which exacerbate their vulnerability to natural disasters (Fay et al., 2017). Thus, strategic pre-disaster risk mitigation plans aiming at tackling these issues are needed to improve the resilience of the infrastructure systems and the overall socioeconomic well-being of Jamaica.

This study focuses on three of the most critical civil infrastructure systems in Jamaica: the electric power, water supply and transportation (road) systems. The hospitals, schools and airports in Jamaica are chosen to be the critical end-users of the infrastructure systems because of their functions for the medical care, sheltering and evacuation/rescue of people after a disaster, respectively. The dependency relationships among power, water and end-user facilities were determined based on the nearest facility assumption. Also, the post-disaster recovery of all the damaged power, water and end-user facilities are assumed to depend on the functionality of the road network. The number of each type of nodes (e.g. power plant, water pumping station, etc.) and links (e.g. power transmission line, road, etc.) modeled in the integrated network are listed in Table 4-3. The location of the network nodes and the road network are shown in Figure 4-3. In total, there are 1255 nodes and 2319 links modeled in the network for this case study.

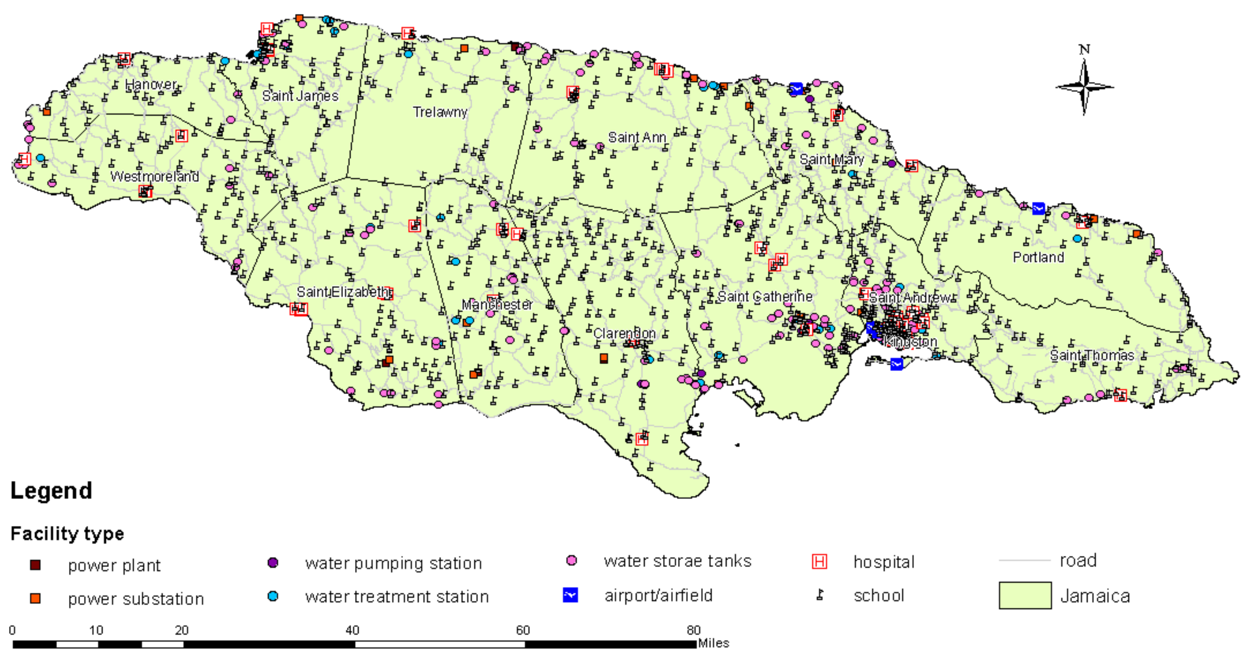


Figure 4-3. The locations of the critical facilities and the road network in Jamaica.

Table 4-3. The number of each type of nodes and links modeled in the integrated network.

System	Facility type	Number
Power	Power plant	10

	Power substation	25
	Power transmission line	26
	Power distribution line	1079
	Power transmission tower (implicitly modeled)	Every 320 m along transmission lines
	Power distribution poles (implicitly modeled)	Every 40 m along distribution lines
Water	Water pumping station	11
	Water treatment station	43
	Water storage tank	140
	Water pipeline	1214
Transportation	Road	836
End-user	Hospital	50
	Airport	5
	School	971
Total nodes		**1255**
Total links		**2319**

Eighteen scenario hurricanes affecting Jamaica with different landfall locations, heading directions and intensities were simulated using the modified Georgiou's model with modeling parameters determined from the historical hurricane track data from NOAA (Georgiou, Davenport & Vickery, 1984; Rosowsky, Sparks & Huang, 1999; Huang, Rosowsky & Sparks, 2001; Lee II, Mitchell & Wallace, 2007; US Department of Commerce, NOAA, 2018). The simulated hurricanes are shown in Figure 4-4. The wind field of the scenario hurricane is developed using the modified Georgiou's model which determines the gradient wind speed at each location as a function of various parameters including central pressure difference, radius of maximum wind speed, landfall translation speed, angle from hurricane heading direction, distance from hurricane eye, and air density (Georgiou, Davenport & Vickery, 1984; Rosowsky, Sparks & Huang, 1999; Huang, Rosowsky & Sparks, 2001; Lee II, Mitchell & Wallace, 2007). The statistics of the hurricane wind speed in Jamaica with three different mean recurrence interval (MRI) – 25, 50, and 100-yr MRI - were calculated from the probabilistic hurricane map of Jamaica, as are summarized in Table 4-4. These statistics were used to group the simulated 18 scenario hurricanes into the three intensity levels, with 6 hurricanes correspond to 25-yr MRI intensity, 6 hurricanes correspond to 50-yr MRI intensity and 6 hurricanes correspond to 100-yr MRI intensity.

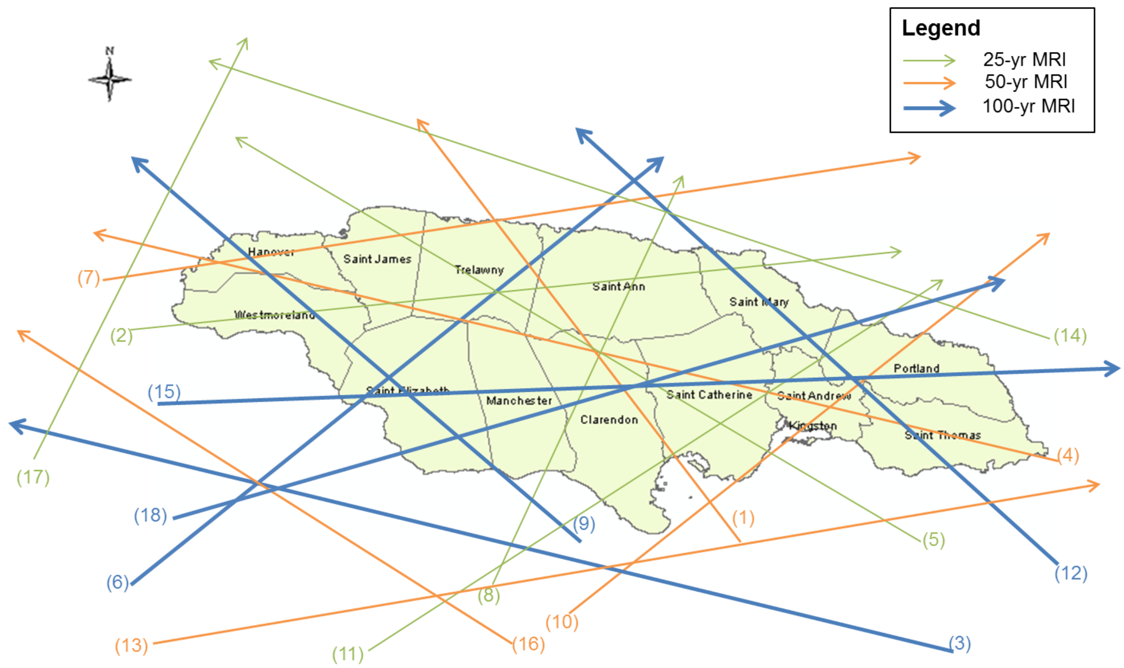


Figure 4-4. The landfall location, heading direction and intensity of 18 simulated scenario hurricanes.

Table 4-4. The statistics of the hurricane wind speed with 25, 50 or 100 year MRI in Jamaica (unit: mph).

MRI	Minimum	Maximum	Mean	Standard deviation	Mode
25 years	74.96301	126.0761	88.80642	11.8013	97
50 years	87.2297	147.3558	103.585	13.56736	114
100 years	97.59073	166.6462	116.7062	15.31542	125

After the wind speed for the location of each of nodes and links was determined for each scenario hurricane, the wind speed was then used to determine the rainfall rate and flooding water depth for the location, as is illustrated in Figure 4-5 (Tuleya, DeMaria & Kuligowski, 2007). The rainfall was assumed to continue from the time when the hurricane first hit the Jamaica Island to the time when the hurricane completely left Jamaica in this study.

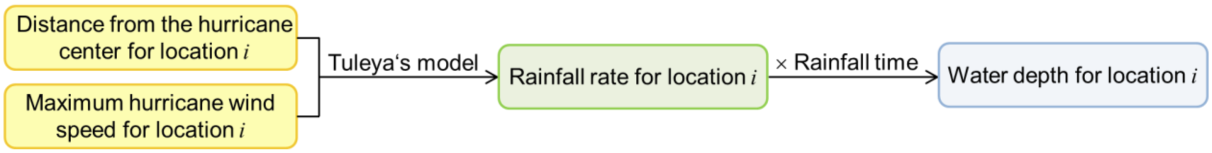


Figure 4-5. The methodology to simulate a rainfall-induced flooding hazard for scenario hurricane.

4.2.2. Pre-decision Processing: Priority Identification

The critical facilities in each of the power, water and transportation systems in Jamaica that have priority need for risk mitigation investment and interventions under hurricane hazards are identified using the framework presented in Figure 4-2, which is shown in the following sub-sections.

4.2.2.1. Decision Criterion

The decision criterion used for assessing the priority of the infrastructure facilities in this case study is *risk*, which means that the facilities with higher risk deserve priority consideration for risk mitigation investment or interventions. In this study, the term *risk* of an infrastructure facility is understood as the vulnerability of a facility (proportional to the probability of damage of a facility) and the consequence if this facility is damaged. If a facility is very likely to be damaged under a hazard but its damage would not cause severe socioeconomic consequences, then the facility is only viewed as vulnerable, but not risky under the hazard. However, if a facility is very likely to be damaged under a disaster and its damage would cause severe socioeconomic consequences, then the facility is said to be of high risk.

4.2.2.2. Recovery Modeling

The recovery modeling step is to simulate the post-disaster performance of the interdependent infrastructure systems. An ideal model to fulfill the purpose of this step is one that could (1) simulate the performance of several infrastructure systems over time under disruptive events as a whole; (2) consider the facility-to-facility level dependencies within and across different infrastructure systems; and (3) be able to account for the uncertainties in the simulation. The DIN model proposed in this research has the above-mentioned capabilities and is used for recovery modeling for this case study.

The modeling parameters in the DIN model such as the dependency matrix, recovery coefficients and threshold inoperability/damage level in Chapter 3 are adopted for the recovery modeling in this case study. The uncertainties in the variables considered in this case study and their probabilistic distributions are summarized in Table 4-5. The Monte Carlo simulation with Latin Hypercube sampling was used with 100 iterations for each of the 18 scenario hurricane hazards. The 100-iteration time is chosen since the mean and standard deviation of the network recovery time is found to converge within 100 iterations.

Table 4-5. The probabilistic models of the random variables in this analysis.

No.	Random variable	Probabilistic model
1	Initial damage level of the explicitly modeled network nodes except transmission towers and distribution poles	Distribution determined from fragility curves (López et al., 2009; MRI, 2011)
2	Initial damage level of the implicitly modeled power transmission towers and distribution poles	Distribution determined from fragility curves (Ahmed, Arthur & Edwards, 2010; Shafieezadeh et al., 2014; Aslam, 2016)
4	Recovery coefficients	Normal distribution with mean and standard deviation listed in Table 3-14
5	Explicitly modeled network link recovery times	Normal distribution with mean and standard deviation listed in ATC-13 (Applied Technology Council, 1985)
6	Implicitly modeled road recovery times	Normal distribution with mean and standard deviation listed in ATC-13 (Applied Technology Council, 1985)

4.2.2.3. Priority Identification

The infrastructure facilities in power, water and transportation systems are prioritized based on the decision criterion and the DIN modeling results. The road segments, and power and water facilities with different priority levels are identified in the following subsections.

4.2.2.3.1. Power and Water Systems

The facilities in the power and water systems that are both vulnerable and serve a large number of end-users are considered to be of high risk, thus deserve the priority consideration for risk mitigation investment and interventions. The vulnerability of the power and water facilities in the study was measured by the mean initial inoperability under all scenario hurricane hazards. The changes of the mean inoperability of the power or water system facilities over time under all simulated scenario hurricanes are shown in Figure 4-6 and Figure 4-7, respectively. The locations of the vulnerable power and water system facilities, including the ones that have long recovery times, are shown in Figure 4-8 and Figure 4-9, respectively.

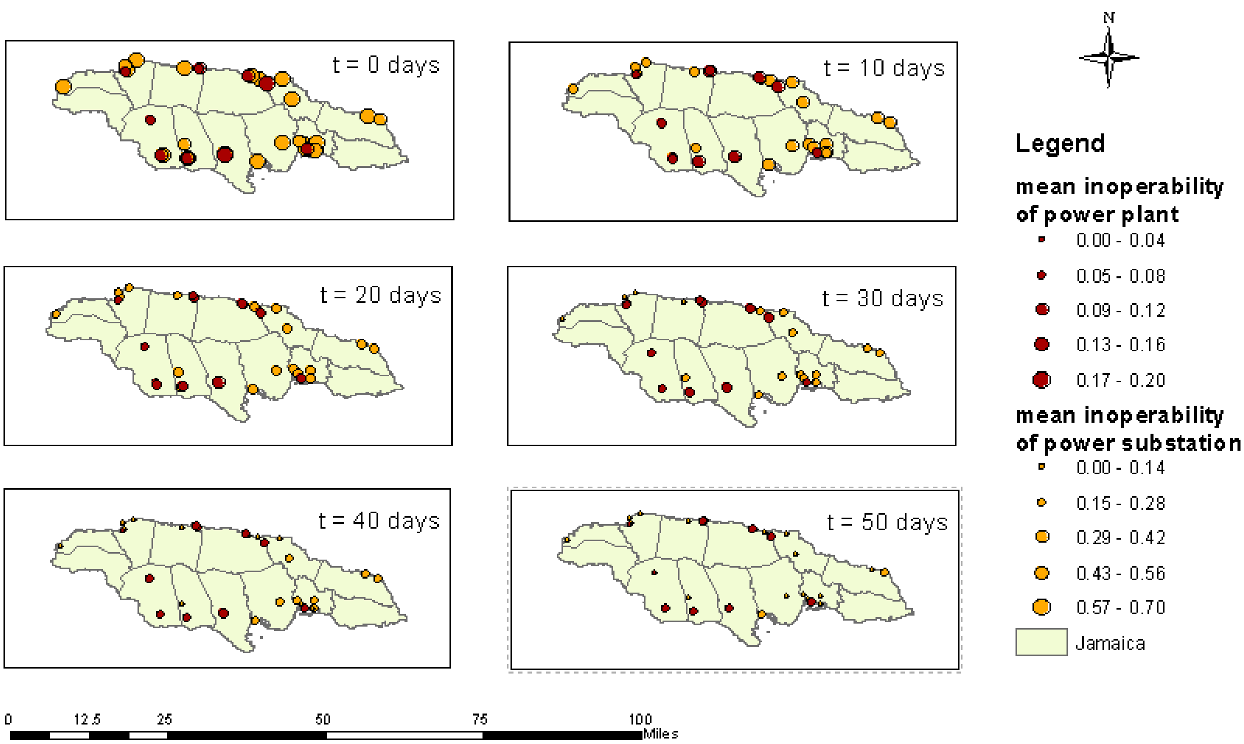


Figure 4-6. Mean inoperability change of the power system facilities in Jamaica under scenario hurricane hazards.

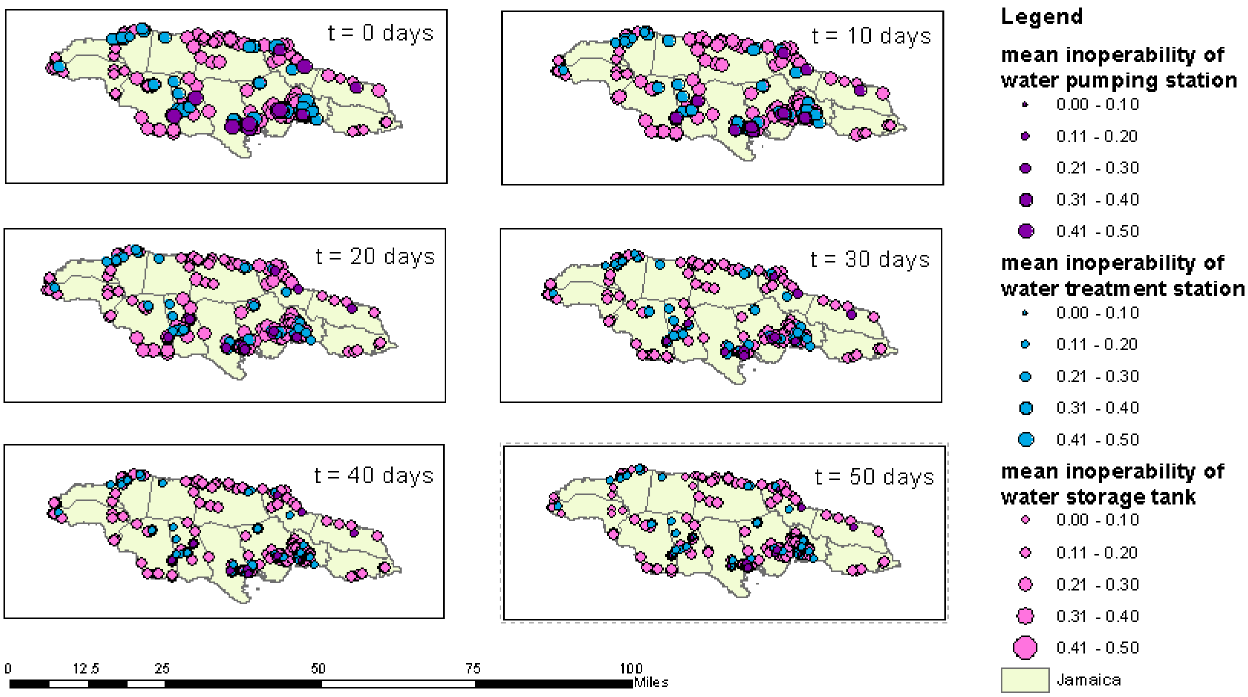
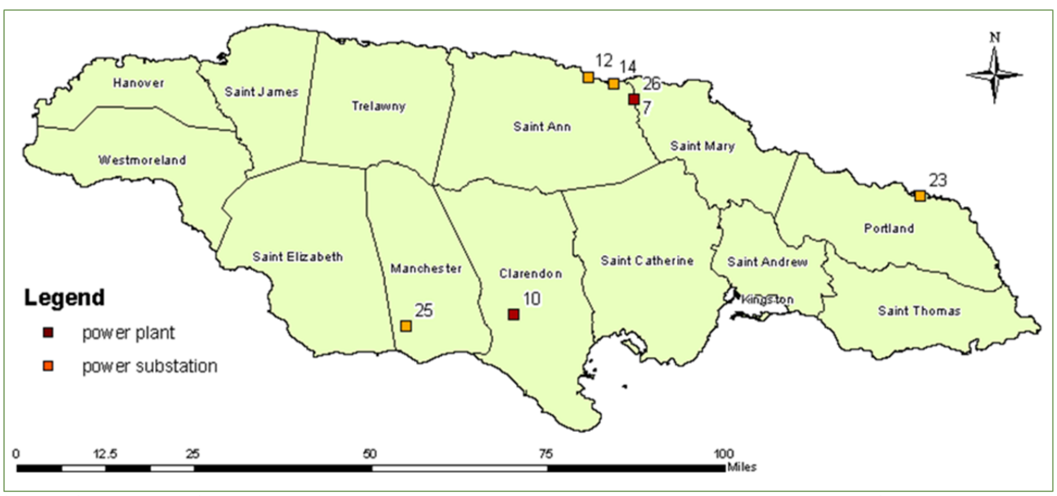


Figure 4-7. Mean inoperability change of the water system facilities in Jamaica under scenario hurricane hazards.

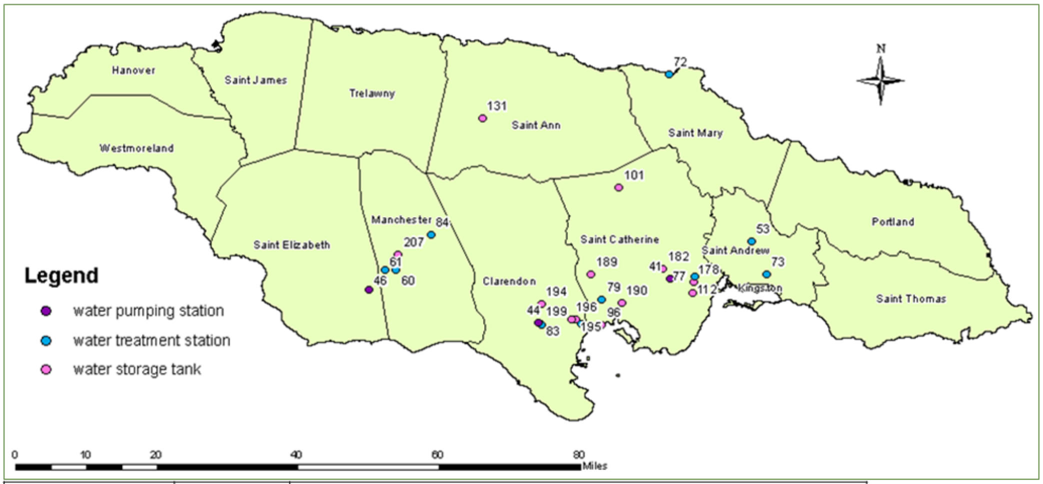


Node	Type	No. of facilities that would be affected					
		Water pumping station	Water treatment station	Hospital	Airport	School	**Total**
7	Power plant	3	3	4	2	151	**163**
10		1	2	1	0	89	**93**
12	Power substation	0	3	5	0	49	**57**
14		0	2	0	0	7	**9**
23		1	1	2	1	70	**75**
25		2	7	5	0	102	**116**
26		3	3	4	2	151	**163**

Priority level:

High
Median
Low

Figure 4-8. Vulnerable power system facilities in Jamaica under hurricane hazards.



Node	Type	No. of facilities that would be affected				
		Power plant	Hospital	Airport	School	Total
41	Water pumping station	0	3	0	23	**26**
44		0	1	0	27	**28**
46		2	11	0	232	**245**
53	Water treatment station	0	0	0	39	**39**
60		0	0	0	8	**8**
61		0	0	0	9	**9**
72		0	1	1	40	**42**
73		0	10	0	44	**54**
77		0	0	0	15	**15**
79		0	0	0	15	**15**
82		0	1	0	8	**9**
83		0	0	0	8	**8**
84		0	0	0	42	**42**
96	Water storage tank	0	0	0	2	**2**
101		0	1	0	25	**26**
112		0	0	0	7	**7**
131		0	0	0	11	**11**
178		0	0	0	6	**6**
182		0	0	0	7	**7**
189		0	0	0	12	**12**
190		0	0	0	3	**3**
194		0	1	0	19	**20**
195		0	0	0	2	**2**
196		0	0	0	3	**3**
199		0	0	0	8	**8**
207		0	0	0	8	**8**

Priority level:
High
Median
Low

Figure 4-9. Vulnerable water system facilities in Jamaica under hurricane hazards.

Taking water pumping station 46 in Figure 4-9 for example, it has the highest priority among all water system facilities since it is both highly likely to be damaged under the disaster and its damage would affect the normal operation of the largest number of end-users. Furthermore, the water pumping station provides service to two hydropower plants. Thus, if it is damaged, the power service to lots of end-users would also be affected. Therefore, this water pumping station have the highest priority need for risk mitigation investment and interventions among all water system facilities. Similar conclusion also applies to power plant 7 and power substation 25 and 26 in Figure 4-8.

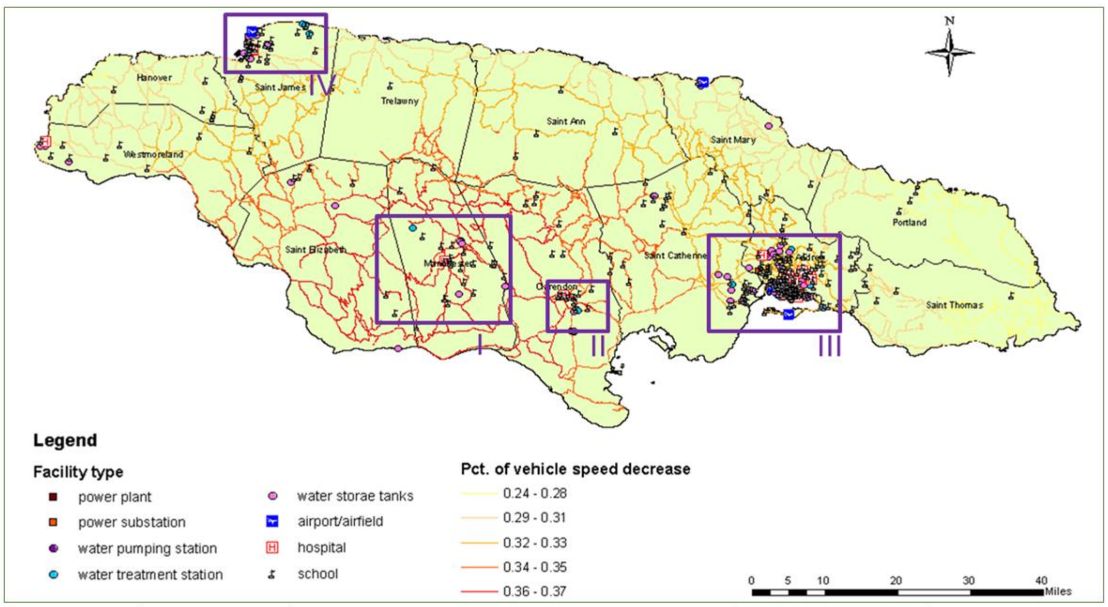
4.2.2.3.2. Transportation System

The road segments which are both vulnerable and causing severe socioeconomic consequences when damaged or blocked have high risk, thus deserve priority consideration for risk mitigation investment and interventions. The vulnerability of the roads in Jamaica was measured by the percentage of the vehicle speed decrease on the roads due to the hurricane rainfall-induced flooding. The speed of a vehicle traveled on a road with certain water inundation depth was calculated using the model proposed by Pregnolato et al. (2017). The mean percentage of vehicle speed decrease on the roads in Jamaica under all 18 simulated scenario hurricane hazards is shown in Figure 4-10 and Figure 4-11.

The socioeconomic consequence of the damaged road segments was measured by the decrease of the accessibility to some critical facilities. Accessibility to a critical facility at time *t* is inversely related to the average travel time increase from any road intersection points within a certain distance of the facility to that facility. Thus, the accessibility is determined using Eq. (4-1).

$$accessibility_i\left(t\right)=\frac{1}{n_i}\sum_{j=1}^{n_i}\frac{t_{ji}^0}{t_{ji}\left(t\right)} \tag{4-1}$$

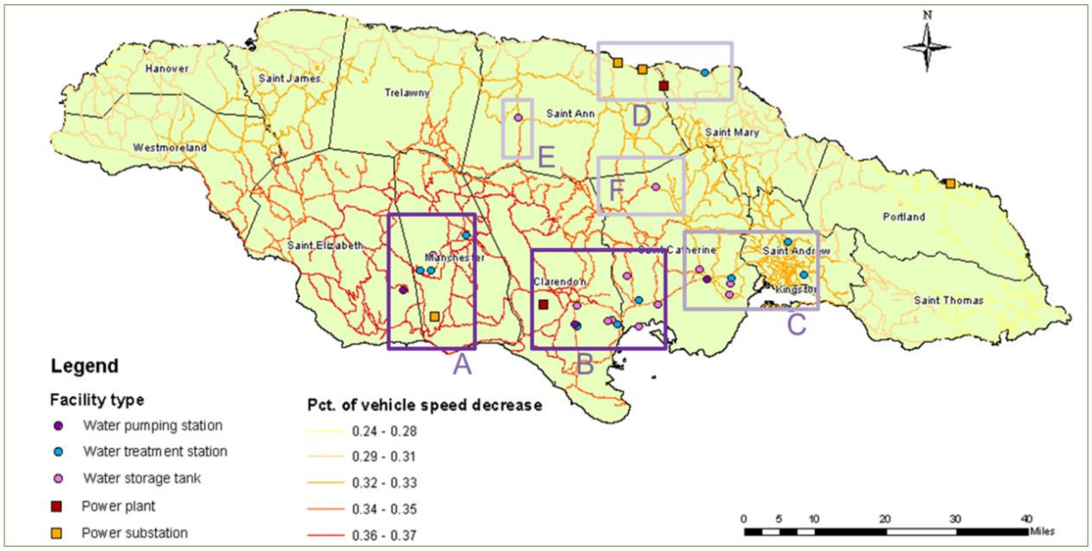
where $n_i =$ the number of road intersection points within a certain distance of node *i*; $t_{ji}\left(t\right)=$ the time to travel from road intersection point *j* to node *i* at time *t*; $t_{ji}^0 =$ the time to travel from road intersection point *j* to node *i* in an undamaged road network. In this study, the travel time from any road intersection points within 10 km of a facility to that facility is considered. The geographic locations of the infrastructure and end-user facilities whose accessibility would be most severely affected (top 30%) due to the road network damage under the hurricane rainfall-induced flooding hazard are shown in Figure 4-10. Similarly, the geographic locations of the vulnerable power and water facilities whose accessibility would be most severely affected (top 30%) due to the damaged or blocked road network under hurricane rainfall-induced flooding are shown in Figure 4-11. The regions in Jamaica which have both high vulnerable road segments and large number of critical facilities whose accessibility would be most severely affected due to the damage of the roads are identified in rectangular boxes in Figure 4-10 and Figure 4-11. The road segments in these regions have high risk, thus require priority need for risk mitigation intervention.



Region	Vulnerability	Length of roads (km)				No. of critical facilities
		Class A	Class B	Class C	Total	
I	High	57.31	63.02	296.16	416.49	37
II		0	52.05	107.14	159.19	20
III		231.23	203.82	397.17	832.22	230
IV	Low	0	0	105.33	105.33	52

Priority level:
High
Median
Low

Figure 4-10. High risk road segments with socioeconomic consequence measured by the number of critical infrastructure and end-users facilities been affected.



Region	Vulnerability	Length of roads (km)				No. of critical facilities	
		Class A	Class B	Class C	Total	Power	Water
A	High	41.51	33.81	240.77	316.09	1 (116)*	5 (295)
B		0	53.59	182.08	235.67	1 (93)	10 (15)
C		237.04	189.14	216.98	643.16	0	7 (134)
D		66.37	57.86	113.16	237.39	3 (229)	1(42)
E		0	0	91.52	91.52	0	1 (11)
F	Low	22.35	27.95	87.74	138.04	0	1 (26)

Priority level:
High
Median
Low

Note: The value in parenthesis shows the number of end-users (e.g. hospitals, schools and airports) whose service would be affected if the power or water system facilities are not recovered quickly due to the damage of the road network.

Figure 4-11. High risk road segments with socioeconomic consequence measured by the number of vulnerable power and water system facilities been affected.

Figure 4-10 and Figure 4-11 measure the socioeconomic consequence differently. Figure 4-10 focuses on the road segments whose damage would affect the accessibility to the critical facilities in other infrastructure systems and the end-users, while Figure 4-11 focuses on the road segments whose damage would affect the accessibility to the most vulnerable power and water system facilities. Roads in region III in Figure 4-10 have the highest priority need for risk mitigation interventions since these roads are very likely to be damaged under the disaster and their damage would affect the accessibility to the largest number of critical infrastructure and end-user facilities. The service restoration work of large number of potentially damaged critical water and power system facilities, the transmission of injured people to nearby hospitals and the evacuation/rescue of people to schools or airports would be affected if roads in this region are damaged or blocked. Roads in region A in Figure 4-11 require high priority consideration for risk mitigation investment and interventions since they have the highest vulnerability level and are connected to large number of vulnerable power and water system facilities whose failure would in turn disturb the service to the largest number of end-users. Even though the vulnerability of the roads in region D in Figure 4-11 are not as high as that for region B and C, these roads lead to several vulnerable power and water system facilities whose damage would disrupt the service to much more end-users compared to the roads in region B and C. Therefore, the roads in region D also have a high priority for investment and interventions.

4.2.3. Decision Alternatives

4.2.3.1. Risk Mitigation Strategies for Power, Water and Transportation Systems

Some suggested risk mitigation strategies for the power, water, transportation systems and critical end-user facilities are listed in Table 4-6. Although these strategies can be applied to any facilities in the corresponding system, the high-risk facilities identified in section 4.2.2.3 deserve priority consideration under limited budget or resources constraints. Besides, the budget is better to be distributed among facilities in different infrastructure systems if possible, rather than investing in one single infrastructure system. This is because the normal operation of a facility usually depends on the functioning of the facilities from other infrastructure systems. It's only when all the infrastructure systems serving the facility function properly after the disaster that the facility can regain its socioeconomic value.

Table 4-6. Suggested risk mitigation strategies for the critical infrastructure systems and end-user facilities.

System	Risk mitigation strategies
Power or water	• Having backup batteries, backup power generators and/or backup water tanks at the critical power and water facility sites; • Increasing the frequency of the maintenance for existing facilities; • Replacing and/or upgrading the aged components in existing facilities; • Raising the elevation of the critical components of the power and water system facilities.
Transportation (road)	• Improving the capacity of the drainage system along the road network to ensure that rain water could be more quickly drained away; • Building more greenbelts along the roads so that more rain water could be penetrated into the ground; • Increasing the frequency of maintenance of the road network such as cleaning the drainage and reinforcing the slopes; • Adding more lanes or building new roads to increase the redundancy of the road network; • Upgrading the roads such as raising the grade of the roads, switching from unpaved to paved roads or raising the elevation of the roads; • Implementing traffic rules to make sure the most important vehicles can go through while others take an alternative route during the post-disaster recovery phase.
End-user	• Having backup batteries, backup power generators and/or backup water tanks at the critical power and water facility sites; • Increasing the frequency of the maintenance for existing facilities; • Replacing and/or upgrading the aged components in existing facilities; • Raising the elevation of the critical components of the critical end-user facilities.

4.2.3.2. Alternative Risk Mitigation Plans

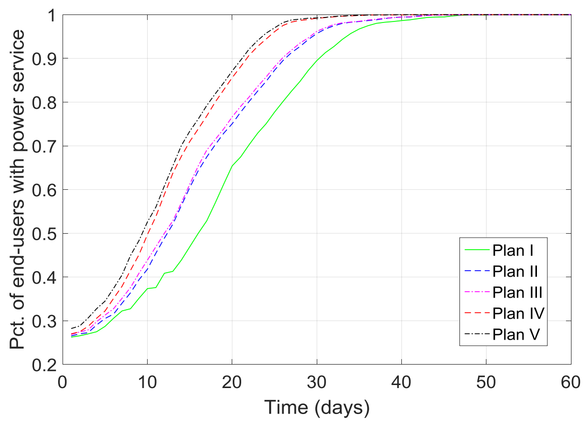
Alternative risk mitigation plans can be developed by combining suitable risk mitigation strategies in Table 4-6 to different set of critical facilities identified in section 4.2.2.3. In this study, five alternative risk mitigation plans (plan I~V) were proposed as an example. The infrastructure performance improvements achieved by each risk mitigation plan are assumed as shown in Table 4-7.

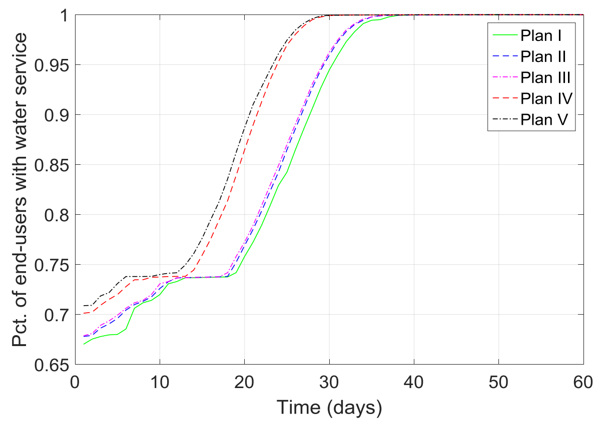
Table 4-7. Example of the risk mitigation plans I ~ V and the performance improvements.

Plan	Improvement of the infrastructure network performance achieved by implementing the plan
I	• The vehicle speed on the following road segments is increased by 30%: region A, B, C and D in Figure 4-11.
II	• The vulnerability of the following high-risk power and water system facilities is decreased by 20%: node 7, 25, 26 in Figure 4-8, and node 46 in Figure 4-9. • The vehicle speed on the following road segments is increased by 20%: region A and D in Figure 4-11.
III	• The vulnerability of the following high-risk power and water system facilities is decreased by 40%: node 7, 25, 26 in Figure 4-8, and node 46 in Figure 4-9. • The vehicle speed on the following road segments is increased by 40%: region A and D in Figure 4-11.
IV	• The vulnerability of the following high-risk power and water system facilities is decreased by 20%: node 7, 10, 12, 23, 25, 26 in Figure 4-8, and node 41, 44, 46, 53, 72, 73, 82, 84, 101, 194 in Figure 4-9. • The vehicle speed on the following road segments is increased by 20%: region A, B, C and D in Figure 4-11.
V	• The vulnerability of the following high-risk power and water system facilities is decreased by 40%: node 7, 10, 12, 23, 25, 26 in Figure 4-8, and node 41, 44, 46, 53, 72, 73, 82, 84, 101, 194 in Figure 4-9. • The vehicle speed on the following road segments is increased by 40%: region A, B, C and D in Figure 4-11.

4.2.4. Decision Analysis

In this study, the cost-benefit analysis was used to compare different risk mitigation plans. The total cost roughly increases from alternative plan I to V, but the exact value was not calculated due to data availability issue. The service restoration over time for all critical end-user facilities (including hospitals, schools and airports) in Jamaica under each scenario hurricane hazard for each risk mitigation plan was simulated using the DIN model. The mean power and water service restoration curves under all simulated scenario hurricane hazards for each risk mitigation plan are shown in Figure 4-12.





(a) (b)

Figure 4-12. Mean (a) power and (b) water service restoration curves for all end-users under all simulated scenario hurricane hazards for each risk mitigation plan.

Two resilience-based infrastructure network performance metrics are used to compare the efficiency and effectiveness of implementing different risk mitigation plans. The efficiency of the infrastructure service restoration is measured by the total service restoration time (TSRT), after which the service to all end-users is restored. The effectiveness of the infrastructure service restoration is measured by the skewness of the service restoration trajectory (SSRT), defined as the centroid of the area below the service restoration curve given the time period in consideration. The lower the TSRT or SSRT, the more efficient or effective the risk mitigation plan is. The power and water system service restoration evaluated by TSRT and SSRT under each risk mitigation plan are summarized in Table 4-8. The time period of 60 days was used to calculate SSRT in this study.

Table 4-8. The TSRT and SSRT of the power and water systems under each risk mitigation plan.

Plan	Power system		Water system	
	TSRT (days)	SSRT (days)	TSRT (days)	SSRT (days)
I	57	36.30	54	32.89
II	53	35.47	53	32.80
III	53	35.35	53	32.78
IV	45	34.72	45	32.45
V	43	34.50	43	32.37

4.2.5. Decision

The optimal pre-disaster risk mitigation plan is determined based on the decision analysis results. Figure 4-12 and Table 4-8 shows that the efficiency and effectiveness of the utility service restoration improve from plan I to plan V as the investment increases. It can be learned by comparing the plans I and II that allocating the risk mitigation budget and resources on several infrastructure systems (as in plan II) could yield better result compared to investing in a single infrastructure system (as in plan I). To select the optimal risk mitigation plan, the decision makers need to carefully weigh the costs and benefits of each plan. For example, if plan V cost far more than plan IV, the decision makers need to decide whether the 2 days' decrease of the utility service restoration time deserves this large amount of extra budget. If not, then plan IV could be the optimal risk mitigation plan in this case.

4.3. Closure

Strategic pre-disaster risk mitigation planning on interdependent infrastructure systems under limited budget and resources is essential to enhance the community resilience. This chapter proposes a decision framework on infrastructure risk mitigation planning with considering facility prioritization. The framework is illustrated with a case study on pre-disaster risk mitigation planning of interdependent power, water and transportation systems in Jamaica under hurricane hazard. This case study presents an ideal pre-disaster risk mitigation decision process where a decision maker is interested in improving the total resilience of multiple civil infrastructure systems. In the real world, theoretical optimal risk mitigation plan may not always be adopted due to some special policy or other constraints. The major contributions of this chapter include: (i) it introduces the IIRM problem to guide the pre-disaster risk mitigation planning of the infrastructure systems with considering the interdependencies of the facilities in different infrastructure systems. The decision objective, applicable phase, decision makers and constraints are clearly identified; (ii) it proposes a four-stage decision framework to solve the IIRM problem. One important step of solving the IIRM problem is to identify the critical facilities in each infrastructure system which deserve priority consideration for investment and interventions under certain constraints. This step is important since it can make the proposed risk mitigation plan better targeted; and (iii) several risk mitigation strategies for the power, water, transportation systems and the critical end-user facilities under hurricane hazard are proposed in this paper. These strategies are of great referential importance to other infrastructure systems or critical facilities as well for the pre-disaster risk mitigation purpose. The proposed IIRM decision problem and corresponding decision framework can be useful for the decision makers for multi-infrastructure system risk management.

It should be noted that the proposed IIRM decision problem and framework mainly focus on infrastructure risk mitigation planning in pre-disaster phase and is not developed for post-disaster recovery planning. Pre-disaster and post-disaster are two distinct phases for the community risk management and resilience planning. During the pre-disaster risk mitigation phase, the risk management work mainly focuses on increasing the robustness of the civil infrastructure network to better prepare the community for future disruptive events. However, the occurrence of natural disasters is unavoidable and sometimes, the hazard intensities of the extreme events are unpredictable. No pre-disaster risk mitigation plan could fully eliminate all the damage and losses caused by potential catastrophe events. Therefore, strategic post-disaster recovery planning is also important to enhance the community resilience under disruptive events. The research in the next chapter is focused on developing risk-informed decision framework to guide the post-disaster recovery optimization in order to better support community resilience planning.

CHAPTER 5 INTERDEPENDENT INFRASTRUCTURE POST-DISASTER RECOVERY PLANNING

Due to the infrastructure interdependencies, the complete recovery of a facility in one infrastructure system depends not only on the physical restoration of itself, but also on the recovery of the facilities in other infrastructure systems that it depends on. Therefore, it is important to consider the interdependencies with other infrastructure systems when planning the post-disaster recovery of any damaged infrastructure facility or system in order to achieve more efficient and effective recovery.

The foregoing literature review on post-disaster infrastructure performance evaluation and recovery planning in section 2.5 and 2.6 reveals the following issues. First of all, in spite of numerous methodologies and models that have been developed to simulate the performance of interdependent infrastructure systems under different types of hazards, few studies have been done to extend the model in guiding the strategic post-disaster infrastructure recovery planning decision making. Secondly, the few existing decision frameworks or models aiming at optimizing the post-disaster infrastructure recovery scheduling mainly focus on only one type of the infrastructure system (the transportation system), while ignoring the interdependencies among different infrastructure systems during the post-disaster recovery phase. Thirdly, although the existing infrastructure performance metrics all have their own merits in quantifying the infrastructure system performance under disruptive events, most of the metrics emphasize on measuring the functionality of the infrastructure systems and fail to take the service disruptions to the end-users into consideration. Furthermore, some performance metrics (e.g. water pressure, travel time, road network accessibility) are designed to evaluate the functionality of one specific infrastructure systems, which makes it hard to quantify the performance of the integrated infrastructure network where several interdependent infrastructure systems are considered together.

To fill these gaps, this chapter introduces the Interdependent Infrastructure Recovery Planning (IIRP) problem and proposes a game theory-based decision support framework which could guide the infrastructure owners determining the optimal assignment and scheduling of the repair teams with considering the recovery plans of the other infrastructure systems that it depends on during the post-disaster recovery phase. Besides, two recovery time-based performance metrics, the total-facility-recovery-waiting-time (TFRWT) and the total-service-restoration-waiting-time (TSRWT) are proposed to evaluate the efficiency and effectiveness of the post-disaster recovery plan, which can be applied to different infrastructure systems. Finally, the IIRP problem and the proposed decision support framework is illustrated with an example of optimizing the recovery of interdependent power and water systems in Centerville, a virtual community, after a seismic hazard scenario.

5.1. The Interdependent Infrastructure Recovery Planning Problem

5.1.1. Introduction to the IIRP Problem

During the post-disaster recovery phase, the main objective of infrastructure owners, such as the utility companies, telecommunication companies, railroad companies and the local Department of Transportation, is to repair the damaged infrastructure systems and restore the service to the end-users as efficiently and/or effectively as possible. The decision of the infrastructure owners in this phase can be summarized as determining *how much* and in *which order* resources need to be allocated to repair each of damaged facilities, or *how many* repair teams need to be sent to the affected region, and *which team* should repair *which facility* at *what time*. The IIRP problem is proposed to guide infrastructure owners determining the optimal assignment and scheduling of their repair teams during the post-disaster recovery phase by taking the recovery of other infrastructure systems into consideration. Key characteristics of the IIRP problem, including decision objective, decision makers, applicable phase, decision constraints and example decision criteria are defined and summarized in Table 5-1.

Table 5-1. Summary of the IIRP problem.

Decision objective	Repair the damaged infrastructure network and restore the service to the end-users as efficiently and/or effectively as possible after the disaster
Decision makers	Infrastructure owners, such as utility companies, telecommunication companies, railroad companies, local Department of Transportation, etc.
Applicable phase	Post-disaster recovery phase
Decision constrains	Limited number of repair crews, available resources, policy requirements for system performance (e.g.: acceptable performance level)
Example decision criteria	Infrastructure network recovery time, service restoration time, resilience, skewness, total facility recovery waiting time, total service restoration waiting time, cost, etc.

The decision framework for the proposed IIRP problem is comparable to game theory. Game theory is a science of strategies, or the optimal decision-makings of independent rational decision makers in an interactive situation. It focuses on multiple decision makers, or players, who decide independently, but contingent upon the strategy implemented by the other players (Myerson, 2013; Herrmann, 2015). The results in game theory describe what players should do if they want the optimal guaranteed payoff (Herrmann, 2015). In the IIRP problem, there are also multiple decision makers from different but interdependent infrastructure systems, one infrastructure owner's decision on the recovery strategy would be influenced by the strategies implemented on the other infrastructure systems that his/her system depends on. The outcome of the IIRP problem describes how the individual infrastructure owners could best plan their post-disaster recovery works. The decision-making process to solve the IIRP problem using a game theory-based approach is introduced in the following subsections.

5.1.2. Decision Support Framework for the IIRP Problem

Before solving the IIRP problem, the decision problem needs to be clearly defined through identifying the decision context in terms of the four key characteristics of the problem (decision objective, decision makers, decision criteria and decision constraints of a specific infrastructure recovery planning problem). Some other relevant information, such as the study region, hazard type, infrastructure damage scenario, etc. should also be identified.

A game theory-based decision framework to solve the IIRP problem is illustrated in Figure 5-1, with two decision makers from two interdependent infrastructure systems. Note that this decision framework could be easily expanded by adding more decision makers from more infrastructure systems. Decision process for each system starts with an initial estimation of total number of repair teams assigned. The optimal repair sequence to repair all the damaged facilities in one infrastructure system given the initial estimation of total number of repair teams is determined according to performance metric α (step ① in Figure 5-1). Different optimization techniques can be adopted, including genetic algorithms, enumeration, integer programming, combinatorial optimization and so on. Then, this optimal repair sequence is examined in order to determine whether its recovery could be further improved, with considering the recovery of the other infrastructure systems that this infrastructure system depends on. Taking the interdependent water and power systems for example, if the damaged water system facilities could be physically repaired in 10 days but the power system serving the water facilities could not be repaired until the 20th day, then there is no need to add more repair teams for the water system to further speed up its recovery process. If the recovery of the infrastructure system can be further improved (e.g. the power service can be restored before the water facilities been physically repaired), the current recovery performance of the infrastructure system measured by α has not reached to the acceptable performance level, and there are more repair teams available, then another repair team is added to further improve the recovery performance of the system. This recovery optimization process for each infrastructure system terminates when its recovery could not be improved further, or when its recovery performance has reached to the acceptable level, or when no more repair teams are available. The final number of repair teams and the corresponding optimal repair sequence forms the optimal post-disaster recovery plan for the infrastructure system. This decision framework is especially useful when the recovery plans of other infrastructure systems are available. This could happen when several infrastructure systems are controlled by one company and the information between different departments managing different infrastructure systems within the company can be easily exchanged.

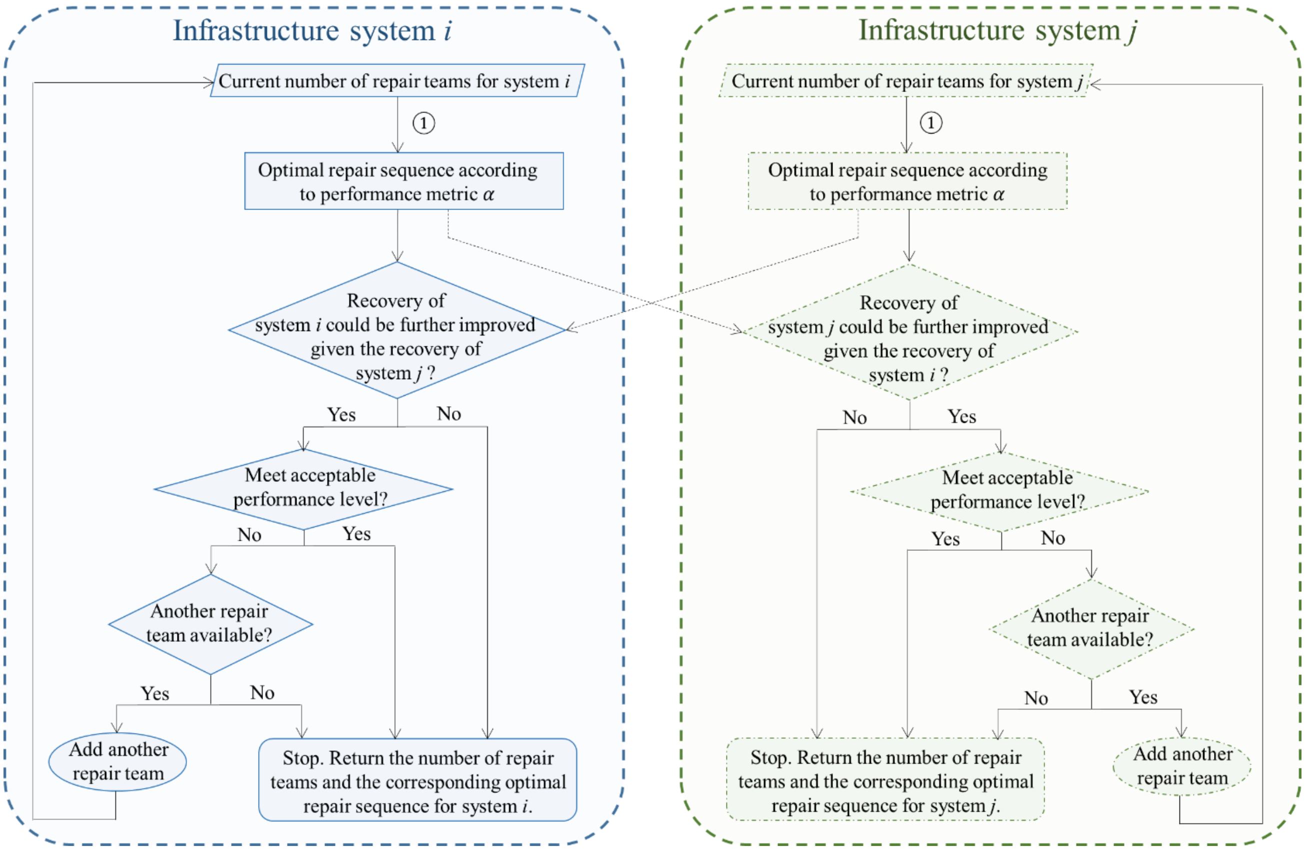


Figure 5-1. The game theory-based decision support framework of the IIRP problem with two decision makers.

5.2. Recovery Time-based Performance Metrics for Infrastructure Systems

As noted in section 2.5, numerous performance metrics for infrastructure systems were proposed in recent decades. However, most of the existing performance metrics for the infrastructure systems has one or several of the following issues. First, some metrics, such as reliability, vulnerability and robustness, are only suitable to measure the performance of infrastructure system at one specific point in time, at the time of hazard occurrence. Second, some other metrics, such as connectivity, efficiency and accessibility, are used to measure the performance of the infrastructure system at one point in time during the recovery phase. Third, many of the metrics are designed for evaluating the functionality of one specific type of infrastructure system, such as water pressure for water system, traffic flow capacity and travel time or distance for transportation system, which makes them unsuitable for assessing performance of integrated network of several interdependent systems. Fourth, most of the metrics emphasize on measuring the functionality of infrastructure systems and fail to take the service disruptions to the end-users into consideration.

This study introduces two recovery time-based performance metrics, the total-facility-recovery-waiting-time (TFRWT) and the total-service-restoration-waiting-time (TSRWT), both of which focus on the entire recovery phase of the infrastructure system as a whole and are applicable to any infrastructure systems. As indicated by the name, the TFRWT is defined as the total waiting time for all the damaged facilities in a system or in the integrated network to be completely repaired, and represents the efficiency of the recovery plan (how fast the damaged facilities could be repaired). On the other hand, the TSRWT is defined as the total waiting time for all the end-users in the network to fully get the infrastructure service back, and represents the effectiveness of the recovery plan (how fast the end-users could get all the service back). The two metrics can be expressed as:

$$\mathrm{TFRWT}(G) = \sum_{i=1}^{n} T_i^f \tag{5-1}$$

$$\mathrm{TSRWT}(G) = \sum_{j=1}^{m} T_j^e \tag{5-2}$$

where G is the integrated infrastructure network or single infrastructure system; T_i^f is the waiting time for damaged facility i in network G to be completely repaired; T_j^e is the waiting time for end-user j in network G until its service is fully restored; n and m represent the total number of damaged facilities and total number of end-users in network G, respectively.

These performance metrics measure the overall performance of the entire infrastructure network over the whole post-disaster recovery phase, which makes them suitable to be used for comparing the effects of different multi-infrastructure system recovery plans. Besides, they are not specific to an infrastructure system and can be applied to any infrastructure systems, either separately or as an integrated network. They are also straightforward and easy to be computed.

It is noted here that the proposed performance metrics can be further used to calculate other infrastructure network performance metrics, such as resilience. The resilience of an infrastructure network can be understood as the ability of the network to reduce the chance of a shock, to absorb a shock if it occurs and to recover quickly after a shock (Bruneau et al., 2003; Reed, Kapur & Christie, 2009; Sharma, Tabandeh & Gardoni, 2018). The value of resilience oftentimes is calculated from the recovery curve of the infrastructure network which depicts the performance of the network over time measured by a parameter. The resilience of an infrastructure network is oftentimes computed as the area under the recovery curve normalized by the time period in consideration (Reed, Kapur & Christie, 2009; He & Cha, 2018b). If the parameter used to plot the recovery curve is *the number of facilities functioning in the network* or *the number of end-users with infrastructure service*, and the time period in consideration is the recovery time, then the network resilience, $R(G)$, can be calculated from the $\mathrm{TFRWT}(G)$ or $\mathrm{TSRWT}(G)$, respectively, as:

$$R(G) = \frac{N \cdot T - \mathrm{TFRWT}(G)}{T} \, or \, \frac{M \cdot T - \mathrm{TSRWT}(G)}{T} \tag{5-3}$$

where N is the total number of facilities in network G; M is the total number of end-users in network G; T is the network recovery time/service restoration time. An example relationship between the network resilience and the proposed recovery time-based infrastructure performance metric TFRWT is depicted in Figure 5-2.

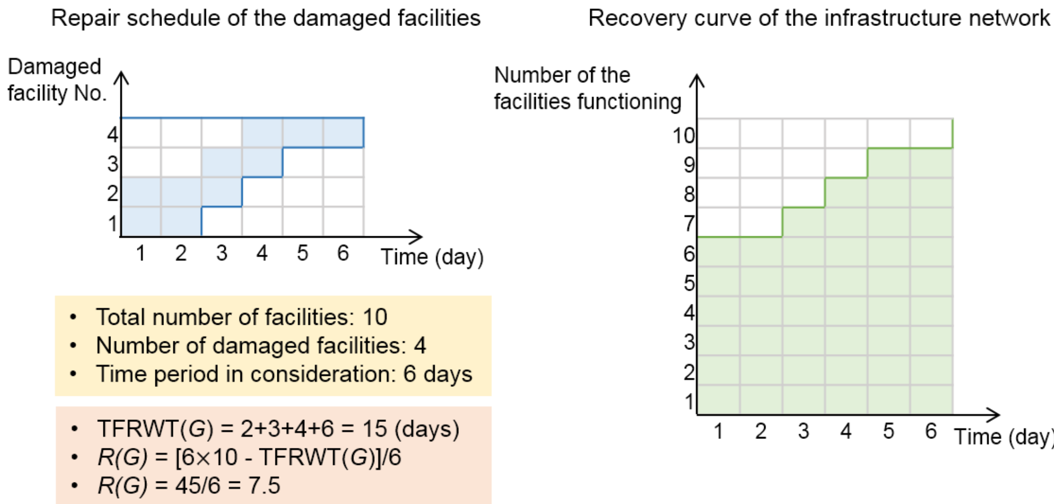


Figure 5-2. An example relationship between the network resilience and TFRWT.

5.3. Case Study: Post-disaster Recovery Planning for Centerville Power and Water Systems

The proposed decision support framework for IIRP problem is illustrated with a case study on post-disaster recovery planning of the interdependent power and water systems in Centerville Virtual Community subject to seismic hazard. The $\mathrm{TFRWT}(G)$ and $\mathrm{TSRWT}(G)$ are used as performance metrics for this decision-making.

5.3.1. Centerville IIRP Problem Definition

Centerville is a hypothetical community developed as a testbed for the NIST-Funded Center of Excellence for Community Resilience Planning to facilitate the research teams of performing various analyses and testing the methodologies (Ellingwood et al., 2016). Centerville is designed as a typical middle-class city, situated in a Midwestern State in the US with a size of approximately 8 km by 13 km and a population of about 50,000 (Ellingwood et al., 2016). Electric power and water supply systems are two of the most critical infrastructure systems in Centerville, since they are essential for the public health, welfare and proper functioning of most other civil infrastructure systems. A schematic of integrated network of Centerville's building zones, power and water systems is shown in Figure 5-3. The power system consists of 1 power plant, 1 transmission substation, 1 main grid substation, 2 distribution substations, 3 sub-distribution substations, 4 transmission towers and 20 distribution poles, connected by transmission and distribution lines. The water system has 2 reservoirs, 3 pumping stations, 2 treatment stations, 2 storage tanks connected by water pipelines. Only the large-diameter pipelines are explicitly represented in Figure 5-3, while the small diameter distribution lines are included in the demand nodes. Loss of electric power for the water reservoirs/wells, pumping stations or treatment stations would disrupt the water supply and lead to cascading infrastructure failures that may affect public safety and socioeconomic functioning of the community. The 12 building zones (classified into residential, commercial and industrial zones) in Centerville are modeled as one node in the network to reduce the size of the network. These 12 building zone nodes and 5 other critical facility nodes (including 1 school, 1 government building, 2 fire stations and 1 hospital) serve as the demand nodes of the power and water systems. The Centerville Department of Public Works is responsible for designing, construction, operating and maintaining the city's power and water infrastructures (Ellingwood et al., 2016). Thus, they serve as a decision maker of this IIRP problem.

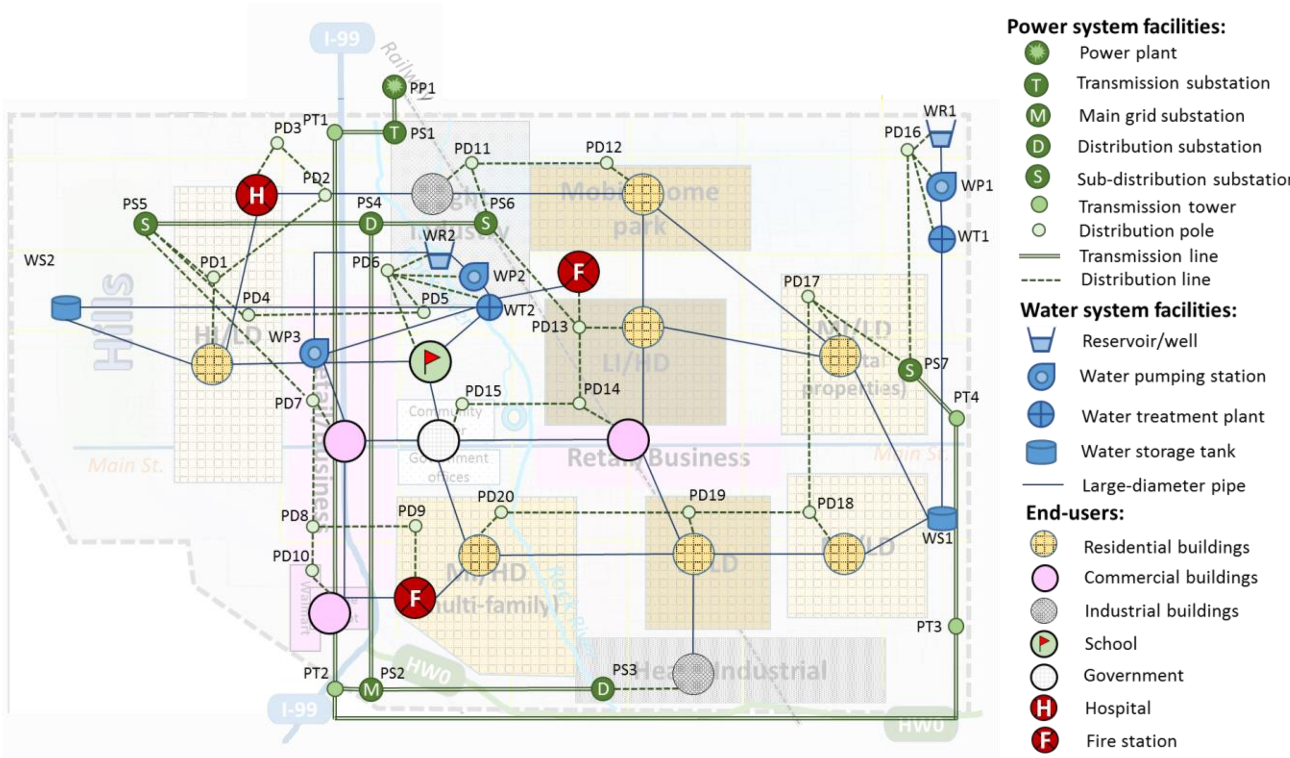


Figure 5-3. The integrated network model for Centerville's power and water systems and end-user groups.

The infrastructure systems and end-user facilities in Centerville are subjected to an earthquake with a magnitude of 6.5 and epicenter located approximately 25 km southwest of the city. The PGA, PGV and PGD at different locations in Centerville were obtained from the ground motion prediction equations by Fernandez and Rix (2006). The statistics of the ground motion intensities at different infrastructure facility or end-user facility locations in Centerville is summarized in Table 5-2.

Table 5-2. The statistics of the PGA, PGV and PGD in Centerville under the scenario earthquake hazard.

	PGA (g)	PGV (cm/s)	PGD (cm)
Mean	0.2742	17.0057	4.3116
Standard deviation	0.0149	1.5033	0.4261
Maximum	0.3019	19.8892	5.1379
Minimum	0.2451	14.1369	3.5058

The power and water systems in Centerville suffers severe damages after the earthquake. The expected physical damage level of the infrastructure facilities was estimated using the probability of damage state curves in HAZUS-MH and the damage level definitions for damage states in ATC-13 (Applied Technology Council, 1985; FEMA, 2003). According to ATC-13, a facility with damage level greater than 0.1 represents the facility suffering significant damage that warranting repair. Based on this ATC's damage level definition, all the power plants, power substations, water reservoirs/wells and water pumping stations in Centerville are determined to suffer the damage levels that warranting repair. The vulnerability of the power transmission and distribution lines under earthquake hazard is found to be negligible under the scenario earthquake, and consequently does not need repair (Shinozuka et al., 2007; Eidinger & Kempner, 2012). The water pipeline damage under earthquake hazard is categorized as either leaks or breaks, the number of which follows Poisson distribution with the mean value setting to be the repair rate multiplying by pipe length (Adachi & Ellingwood, 2008; Guidotti et al., 2016). In this case study, the expected number of damage for each water pipeline was calculated with the HAZUS-MH repair rate model (FEMA, 2003) and none of the pipelines suffers any leak or break, consequently does not require any repair work. In summary, there are 8 out of 32 power system facilities and 5 out of 9 water system facilities in Centerville suffer different levels of damages and need repair after the earthquake hazard. The structural types, and initial damage states and damage levels for all types of infrastructure facilities in Centerville are summarized in Table 5-3.

Table 5-3. Summary of structural types, and initial damage states and damage levels for all types of infrastructure facilities in Centerville.

Node No.	Facility type	Structural type*	Damage state**	Expected damage level	Require repair
PP1	Power plant	EPP3	Moderate	0.2665	Yes
PS1	Power substation	ESS5	Heavy	0.5291	Yes
PS2	Power substation	ESS3	Heavy	0.3975	Yes
PS3	Power substation	ESS1	Moderate	0.2444	Yes
PS4	Power substation	ESS1	Moderate	0.2478	Yes
PS5	Power substation	ESS1	Moderate	0.2657	Yes
PS6	Power substation	ESS1	Moderate	0.2323	Yes
PS7	Power substation	ESS1	Moderate	0.2030	Yes
WR1	Water reservoir / well	PWE1	Moderate	0.1446	Yes
WR2	Water reservoir / well	PWE1	Moderate	0.1754	Yes
WP1	Water pumping station	PPP3	Moderate	0.1408	Yes
WP2	Water pumping station	PPP3	Moderate	0.1850	Yes
WP3	Water pumping station	PPP3	Moderate	0.1706	Yes
WT1	Water treatment station	PWT3	Light	0.0406	No
WT2	Water treatment station	PWT3	Light	0.0240	No
WS1	Water storage tank	PST5	Light	0.0595	No
WS2	Water storage tank	PST5	Light	0.0789	No

* *The structural type classification is the same as in HAZUS-MH* (FEMA, 2003).

** *The damage state classification is the same as in ATC-13* (Applied Technology Council, 1985).

The Centerville Department of Public Works (CDPW) is in charge of the post-earthquake recovery works of Centerville's power and water infrastructures. The overall objective of the CDPW is to repair the damaged infrastructure network and restore the utility service to all the end-users as fast as possible, since both the CDPW and the end-users in Centerville will suffer service interruption cost accumulated as days go by (Sullivan, Vardell & Johnson, 1997). Detailed decision contexts for this case study are as follows. It is assumed that there are 2 power infrastructure repair teams and 1 water infrastructure repair team in Centerville that are immediately available after the earthquake event. Also, three more repair teams for each of the power and water systems are located in the city adjacent to Centerville community, which could reach the damaged facility sites in Centerville to support the post-disaster recovery a day after, if needed. Asking the repair teams in the adjacent city to aid the post-disaster recovery for Centerville infrastructure systems requires extra cost and negotiation of the CDPW. However, the CDPW has the policy of restoring the utility service within 2 weeks (14 days) after a disruption event. Thus, each of the heads of the power sector and the water sector makes a decision on recovery plan, which could minimize the service disruption time while using as less outside repair teams as possible while meeting the policy requirement. Since both of the power and water sectors are in the CDPW, it is assumed that repair plans of each utility system are shared with the other sector. A summary of the decision makers, decision objective, tasks, constraints and decision criteria of the IIRP problem for Centerville infrastructure recovery planning case study is shown in Table 5-4.

Table 5-4. A summary of the IIRP problem for Centerville infrastructure recovery planning case study.

Decision makers	(i) Power sector head for the power system and (ii) water sector head for the water system, both within the CDPW.
Objective for each decision maker	Repair the damaged infrastructure system and restore the utility service to all the end-users as fast as possible.
Tasks for each decision maker	(i) Determine the number of repair teams sent to the damaged facility site; (ii) Determine the assignment and scheduling of the repair teams to repair all the damaged infrastructure facilities.
Constraints for each decision maker	(i) Limited number of repair teams: 2 local + 3 outside repair teams available for power system, and 1 local + 3 outside repair teams available for water system. (ii) Service restoration time for all the end-users should be within 2 weeks (14 days).
Decision criteria	TFRWT or TSRWT, cost

The IIRP problem defined as in Table 5-4 is solved using the proposed decision support framework shown in Figure 5-1. In this analysis, the post-disaster recovery of the interdependent power and water systems in Centerville is simulated for different repair sequences to determine the optimal repair sequence given a certain number of repair teams (step 1 in Figure 5-1). A desired model to accomplish this task is one that could simulate the performance of the infrastructure network at both the facility and system levels, and considering the dependency relationships between the infrastructure facilities within and across systems. The DIN model proposed in this research has the above-mentioned properties and is chosen to model the post-disaster recovery of the Centerville infrastructure network for this case study.

5.3.2. Infrastructure Recovery Planning Results

As the first step, all possible repair sequences to repair 8 damaged power facilities or 5 damaged water facilities in Centerville given 2 local power system repair teams and 1 local water system repair team are first enumerated using permutation, then the optimal repair sequence is determined based on one of the performance metrics, TFRWT and TSRWT. Using TSRWT as the performance metric, the optimal repair sequence under this constraint yield the service restoration time of 25 days. Since the 25 days service restoration time for all end-users exceeds the acceptable performance level (14 days), and it is the recovery of damaged power system facilities that drags the recovery process down, one more power system repair team was added to accelerate the post-disaster recovery. This process is repeated until the TSRWP could not be improved further, or the service restoration time reaches to 14 days, or no more repair teams are available. The intermediate optimal repair sequences obtained for the constraints of the number of recovery team varying through the optimization process are shown in Figure 5-4.

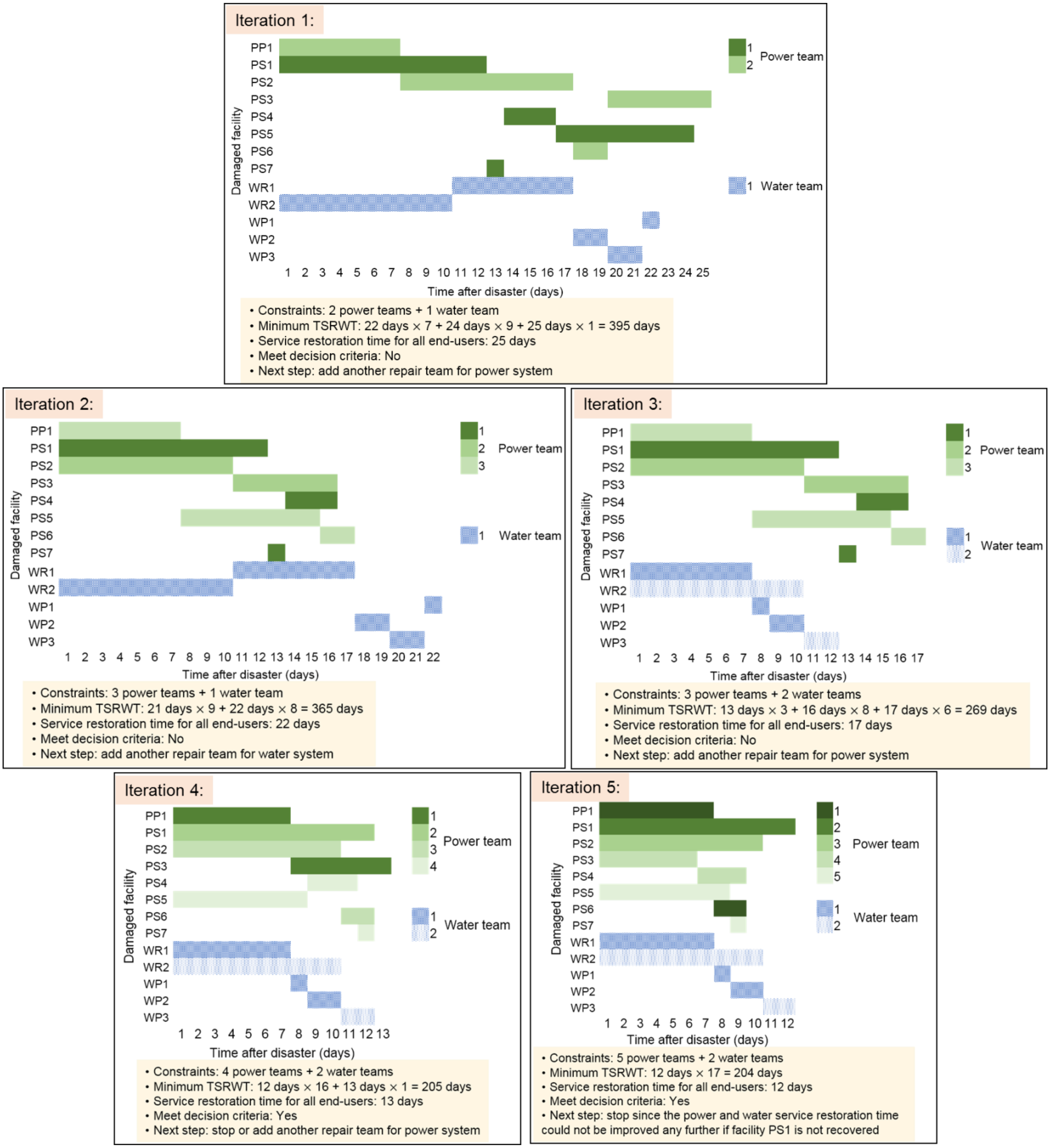


Figure 5-4. The optimization process of the repair sequences for Centerville utility systems.

It can be learned from Figure 5-4 that if only 2 local power repair teams and 1 local water repair team are used (iteration 1), the service restoration time for all end-users is 25 days, with TSRWT equals to 395 days for all 17 end-user groups under the optimal repair sequence. If one more power repair team is added (iteration 2), the service restoration time could be reduced to 22 days, with TSRWT equals to 365 days under the optimal repair sequence. In this scenario, the recovery of the water system drags the utility service restoration time down, so one more water repair team is added (iteration 3). It could reduce the utility service restoration time for all end-users to 17 days with 96 days of decrease in TSRWT (i.e. 365 days – 269 days = 96 days), which is a significant improvement. However, the service restoration time still does not meet the policy requirement of less than 14 days, and it's attributed to the slow recovery of the power system, so one more power system repair team is added (iteration 4). Under this scenario, the service restoration time finally drops to 13 days and the TSRWT reduced to 205 days. Although the service restoration time in this scenario already meet the policy requirement, the recovery of the infrastructure network could still be improved if one more power repair team is added (iteration 5). Adding this 5th power repair team could reduce the service restoration time by 1 day to 12 days and reduce the TSRWT from 205 days to 204 days.

It's noted here that the optimal repair sequence under the 5 power repair teams and 2 water repair teams scenario (iteration 5) is indeed the "global optimal" solution for this case study IIRP problem, since the service restoration time for power or water system could not be reduced any further. The only power transmission substation (PS1) directly connected to the only power plant (PP1) in Centerville suffers most severe damage and takes the longest time to recover. Even though the other power or water system facilities could be physically repaired within the 12th day, they have to wait until the recovery of PS1 to restore their services. This special situation also highlights the importance of considering the interdependencies between different infrastructure systems when making the post-disaster recovery plan. If the decision maker of the water system is not informed of the recovery plan of the power system on which it depends, the decision maker would likely choose to add another water repair team to reduce the water facility recovery time from 12 days to 10 days. However, if the decision maker of the water system is aware that the power service cannot be restored until the 12^{th} day, this extra water repair team will not be needed since no improvement of the water service restoration time (i.e. benefits) can be achieved by hiring another repair team (i.e. costs).

Although the iteration 5 indeed provide the global optimum, it is noted that the reduction in TSRWT from iteration 4 is only 1 day, which means only one end-user group (i.e. the industrial building zone on the South of Centerville) will benefit from this improvement and the benefit is only 1 day. In this case, cost can be adopted as an additional decision criterion to help deciding whether the 5^{th} power repair team added in iteration 5 is needed. Then, the head of the power sector weighs the costs and benefits before making the decision. In this study, we assume that the benefits of restoring the power service one day earlier to that end-user group outweighs its cost of hiring another repair team, thus the optimal repair sequence under the 5 power repair teams and 2 water repair teams scenario is adopted as the optimal post-disaster recovery plan for the utility network in Centerville.

Another insight that could be learned from this case study is that different optimal repair sequences would be obtained if different performance metrics and corresponding decision criteria are used. Figure 5-5 shows two optimal repair sequences for Centerville utility systems using 5 power repair teams and 2 water repair teams measured by TSRWT or TFRWT. If the decision makers from the infrastructure systems care most about the service restoration time for the end-users, the TSRWT or service restoration time for all end-users would be used as the performance metric. The repair sequence that could yield the lowest TSRWT or minimum service restoration time for all end-users is the one that is optimum, just like the repair sequence shown on the left side of Figure 5-5. Under this decision criterion, the facilities that serve larger percentage of the end-users would be repaired first, such as PP1, PS1, PS2, WR1 and WR2 in this study, even though some of these facilities take a much longer time to be repaired. On the other hand, if the number of damaged facilities repaired within a certain period of time is used to measure the efficiency of the post-disaster recovery, then the decision makers from the infrastructure systems would choose TFRWT as the performance metric and the repair sequence which yields the minimum TFRWT under the same constraints is the global optimal solution, just like the one shown on the right hand side of Figure 5-5. In this scenario, the facilities that take the shortest time to recover would be repaired first, such as PS6, PS7, WP1, WP2 and WP3 in this study. In this case, the TFRWT could be reduced from 117 days to 83 days, but the TSRWT and service restoration time for all end-users both increases significantly (i.e. 51 days longer for TSRWT and 3 days longer for service restoration time of all end-users). This example highlights the importance of choosing proper performance metrics and decision criteria before planning the post-disaster recovery of damaged infrastructure systems.

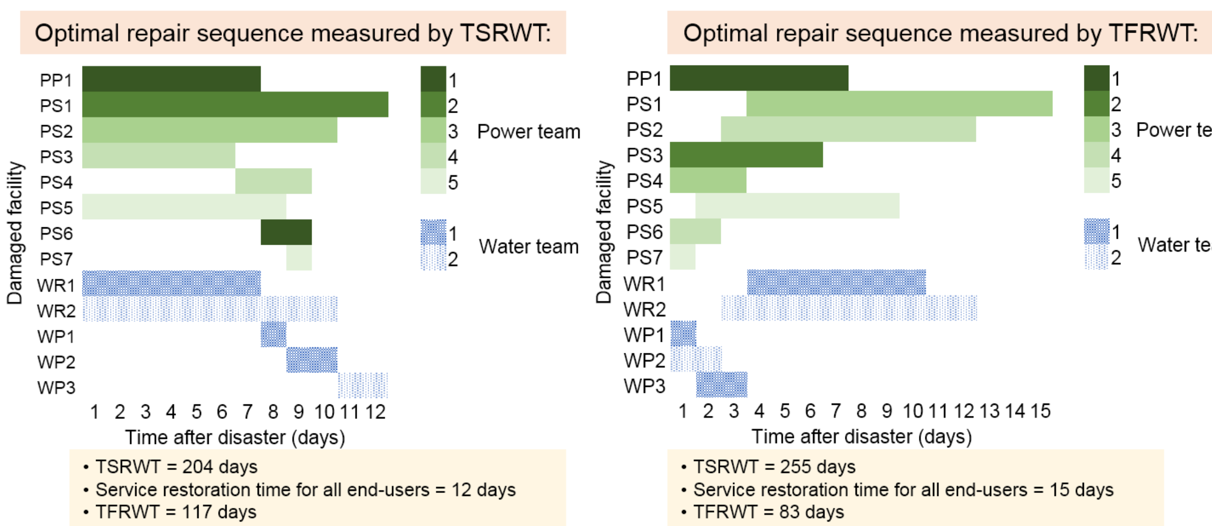


Figure 5-5. Optimal repair sequences for Centerville utility systems using 5 power repair teams and 2 water repair teams measured by TSRWT or TFRWT.

5.4. Closure

This chapter introduced the Interdependent Infrastructure Recovery Planning (IIRP) problem to guide the risk-informed decision-making for post-disaster recovery planning. Solving the IIRP problem can assist the decision makers of infrastructure systems in determining the optimal assignment and scheduling of their repair teams during the post-disaster recovery phase by considering the recovery plan of its dependent infrastructure systems. The objective, decision makers, applicable phase, tasks, constraints and decision criteria of the IIRP problem are clearly defined. A game theory-based decision framework to solve the IIRP problem is proposed, which can be applied to any interdependent infrastructure systems under any types of disruptive events. Two recovery time-based infrastructure performance metrics, the total-facility-recovery -waiting-time (TFRWT) and the total-service-restoration-waiting-time (TSRWT) were proposed to facilitate the comparison of different post-disaster recovery plans. The TFRWT could evaluate the efficiency of a recovery plan while TSRWT focuses on the effectiveness of the recovery plan. These two performance metrics measure the overall performance of individual infrastructure systems or the integrated infrastructure network over the entire post-disaster recovery phase, and are straightforward to understand and easy to compute.

The proposed IIRP decision support framework and the recovery time-based performance metrics were illustrated with a case study of planning the post-disaster recovery of the interdependent power and water systems in Centerville Virtual Community after a scenario earthquake hazard. The case study demonstrates that the presented IIRP decision support framework can provide detailed repair assignment and scheduling for each repair team and individual damaged infrastructure facilities, which can be directly used for the decision makers of the infrastructure systems to plan the post-disaster recovery. In addition, the results of the case study highlight the importance of considering the interdependencies between different infrastructure systems when planning the post-disaster recovery of individual systems. Besides, choosing the proper performance measurements and decision criteria before making the post-disaster recovery plans is crucial since different performance measures or decision criteria would lead to different results.

Although providing detailed post-disaster recovery planning assignments and scheduling results on each repair team and damaged infrastructure facility over the entire post-disaster recovery phase is helpful, the size of the problem could become extremely huge when many repair teams and damaged facilities are under consideration. Therefore, it's necessary to develop more efficient algorithms or use heuristic approaches to solve the IIRP problem with good enough (approximate) solutions under reasonable amount of time.

CHAPTER 6 CONCLUSIONS AND FUTURE WORK

6.1. Summary and Conclusions

Natural and manmade disasters cause huge damages and economic losses each year. Although the hazard occurrence is unavoidable, the damages and losses could be reduced by improving the resilience of infrastructure systems. Nowadays, the infrastructure systems are interdependent upon each other. The normal operation of a facility in one system usually depends on several other facilities in other systems for product input and information sharing. However, when disaster happens, the dependencies among infrastructure facilities would aggravate the initial damage caused by the disasters and lead to cascading failures. Therefore, it is important to consider the dependencies among infrastructure facilities in different systems when modeling the damage and recovery of infrastructure systems under disruptive events for community resilience planning. The literature review on disaster risk management of infrastructure systems reveals that: (1) although there exists extensive literatures on modeling the recovery and resilience of infrastructure systems under disruptive events, the interdependencies between facilities in different infrastructure systems are not very well incorporated in the models; (2) only few studies exists on developing decision frameworks to support communities' pre-disaster risk mitigation and post-disaster recovery planning for interdependent infrastructure systems. Therefore, the objective of this research is to develop a model which can simulate the damage and recovery of the interdependent infrastructure systems under disruptive events and proposed decision frameworks to better support the community's pre-disaster risk mitigation and post-disaster recovery planning.

The specific summary and conclusions from Chapter 3~5 are given below:

(1) *Model development:* the DIN model is proposed in this study to simulate the damage and recovery of the interdependent infrastructure systems after disruptive events. It has the following four features:

- *Dynamic*: the DIN can model the post-disaster performance of the infrastructure facilities, systems and the integrated network over time following a disruptive event.
- *Integrated*: the critical facilities in different infrastructure systems and the end-users are modeled in a unified network, where nodes represent infrastructure facilities and end-users while the links represent dependency relationships among them.
- *Probabilistic*: the uncertainties in some of the modeling parameters are captured by probabilistic models.
- *Interdependent*: the DIN model can incorporate physical, cyber and geospatial interdependencies at different levels, including: system-to-system level, system-to-facility level and facility-to-facility level.

(2) *Model comparison*: the DIN model is compared with two conventional infrastructure recovery models, one with no interdependency considered, and the other one with only system-level interdependencies considered. The comparative study suggests that the recovery time would be underestimated if no interdependency is considered, or be overestimated if only system-level interdependency is considered, both of which would lead to poorly informed decisions for community resilience planning.

(3) *Model validation*: the DIN model is validated through simulating the recovery of the interdependent power, water and cellular systems of Galveston City, Texas after Hurricane Ike (2008). The simulated power system recovery time is comparable to the actual time, which demonstrates that the proposed DIN model can produce comparable results to physical reality.

(4) *Model application to guide pre-disaster risk mitigation decision-making*: the IIRM decision problem is proposed with the objective of reducing the socioeconomic impact when future hazard occurs through improving the resilience of the

interdependent infrastructure network. The objective, decision makers, constraints and some common strategies are clearly identified. A four-stage decision framework to solve the IIRM problem is also presented. One novel contribution of this decision framework is that it considers the pre-decision processing step, which prioritizes the infrastructure facilities in different systems for risk mitigation investment and intervention.

(5) *Model application to guide post-disaster recovery planning decision-making*: the IIRP decision problem is proposed which aims at repairing the damaged infrastructure network and restore the service to the end-users as efficiently and/or effectively as possible after the disaster. The IIRP problem can be solved by optimizing the assignment and scheduling of the repair teams for an infrastructure system with considering the repair plan of the other infrastructure systems during the post-disaster recovery phase. Key characteristics of the IIRP problem, such as objective, decision makers, constraints and example decision criteria are clearly identified. A game theory-based IIRP decision framework is presented. Two recovery time-based performance metrics, the *total facility recovery waiting time* and *total service restoration waiting time* are introduced and applied to evaluate the efficiency and effectiveness of the post-disaster recovery plan.

It is noted that the proposed DIN model and two decision frameworks are general and can be applied to any infrastructure systems under any types of hazards.

6.2. Recommendations for Future Research

Disaster risk management of interdependent infrastructure systems for community resilience planning is a highly complex topic. The current understanding of the post-disaster infrastructure performance and the ways to improve community disaster resilience still remain limited. This section identified some future research directions in the course of the research conducted in this dissertation to advance current practices and knowledge:

(1) At this point, the damage and recovery models for physical infrastructure, building environment, social and economic systems are mostly developed independently. Some advanced methods are needed to integrate the post-disaster infrastructure performance with the building environment and associated social and economic systems to better support the community resilience planning. There is a need for studies to investigate the interdependencies between the physical, social and economic systems following a hazard event and to evaluate how they affect the community resilience as a whole.

(2) Due to security consideration, some of the location or post-disaster performance data for critical infrastructure systems are very hard to obtain, which makes it difficult to quantify some of the modeling parameters. The DIN model needs to be further calibrated and validated if more data become available in the future.

(3) Optimizing the post-disaster infrastructure recovery scheduling and assessment plan to facilitate emergency response is critical to help the affected communities to build back faster and better. However, the size of the problem could become extremely huge when many repair teams and damaged facilities are under consideration. This would lead to an extremely long time to solve the optimization problem, which is not realistic during the post-disaster emergency response phase. Therefore, it’s necessary to develop more efficient algorithms or use heuristic approaches to solve the post-disaster recovery planning problem with good enough (approximate) solutions under reasonable amount of time.

(4) Currently, most of the infrastructure recovery modeling and disaster risk management decision-making studies are still at the research and development phase. There is a need to develop risk-informed end-user tools to better guide the decision makers to understand the infrastructure performance, its interactions with the building

environment, social and economic systems, and explore different pre-disaster risk mitigation or post-disaster recovery strategies to better support community resilience investment and planning.

REFERENCES

Abdel-Rahim, A., Oman, P., Johnson, B., Benke, M., Butapati, S., and Kalidindi, R. (2007). "Modeling urban surface transportation network dependability and security." *Final Rep. No. KLK238-N07-02*, National Institute for Advanced Transportation Technology (NIATT), Univ. of Idaho, Moscow, ID.

Adachi, T., & Ellingwood, B. R. (2008). Serviceability of earthquake-damaged water systems: Effects of electrical power availability and power backup systems on system vulnerability. *Reliability engineering & system safety*, *93*(1), 78-88.

Adams, T. M., Bekkem, K. R., & Toledo-Durán, E. J. (2012). Freight resilience measures. *Journal of Transportation Engineering*, *138*(11), 1403-1409.

Adger, W. N. (2000). Social and ecological resilience: are they related?. *Progress in human geography*, *24*(3), 347-364.

Adger, W. N., Hughes, T. P., Folke, C., Carpenter, S. R., & Rockström, J. (2005). Social-ecological resilience to coastal disasters. *Science*, *309*(5737), 1036-1039.

Adger, W. N. (2006). Vulnerability. *Global environmental change*, *16*(3), 268-281.

Ahmed, A., Arthur, C., & Edwards, M. (2010). Collapse and pull–down analysis of high voltage electricity transmission towers subjected to cyclonic wind. In IOP Conference Series: Materials Science and Engineering (Vol. 10, No. 1, p. 012004). IOP Publishing. *9th World Congress on Computational Mechanics and 4th Asian Pacific Congress on Computational Mechanics*, 19–23 July, 2010, Sydney, Australia.

Ahmed, R., Seedat, M., Van Niekerk, A., & Bulbulia, S. (2004). Discerning community resilience in disadvantaged communities in the context of violence and injury prevention. *South African Journal of Psychology*, *34*(3), 386-408.

ALA. (2001). *Seismic fragility formulations for water Systems: Part 1 – guideline, American lifelines alliance, April, ASCE*. Retrieved from http://www.americanlifelinesalliance.org/. (Last access: 03/27/2019)

Albert, R., Albert, I., & Nakarado, G. L. (2004). Structural vulnerability of the North American power grid. *Physical review E*, 69(2), 025103.

Alderson, D. L., Brown, G. G., & Carlyle, W. M. (2014). Assessing and improving operational resilience of critical infrastructures and other systems. In *Bridging Data and Decisions* (pp. 180-215). Informs.

Alderson, D. L., Brown, G. G., & Carlyle, W. M. (2015). Operational models of infrastructure resilience. *Risk Analysis*, *35*(4), 562-586.

Allan, R. N. (2013). *Reliability evaluation of power systems*. Springer Science & Business Media.

Allenby, B., & Fink, J. (2005). Toward inherently secure and resilient societies. *Science*, *309*(5737), 1034-1036.

Almoghathawi, Y., Barker, K., & Ramirez-Marquez, J. E. (2017). Resilience-Based Measures for Importance Ranking of Interdependent Infrastructure Networks Components Across Uncertain Disruption Scenarios. In *Proceedings of the 12th International Conference on Structural Safety and Reliability*(pp. 6-10).

Almoghathawi, Y., Barker, K., & Albert, L. A. (2019). Resilience-driven restoration model for interdependent infrastructure networks. *Reliability Engineering & System Safety*, *185*, 12-23.

American Planning Association (June, 2014). *Planning for Post-Disaster Recovery Briefing Paper 3.* Retrieved from: https://www.planning.org/publications/document/9139461/. (Last access: 12/15/2018)

American Society of Mechanical Engineers (ASME) (2009). *All-hazards Risk and Resilience.* Innovative Technological Institute (ITI). Washington, D.C.: ASME ITI, LLC.

Applied Technology Council. (1985). Earthquake Damage Evaluation Data for California. *Applied Technology Council.*

Antunes, A., Seco, A., & Pinto, N. (2003). An accessibility–maximization approach to road network planning. *Computer‐Aided Civil and Infrastructure Engineering*, *18*(3), 224-240.

Arghandeh, R., Von Meier, A., Mehrmanesh, L., & Mili, L. (2016). On the definition of cyber-physical resilience in power systems. *Renewable and Sustainable Energy Reviews*, *58*, 1060-1069.

Arup (2011). *Arup's work has contributed to an improved understanding of community resilience.* Retrieved from: https://www.arup.com/projects/community-based-disaster-risk-reduction-study. (Last access: 12/15/2018)

Asakura, Y., & Kashiwadani, M. (1995). Traffic assignment in a road network with degraded links by natural disasters. *Journal of the Eastern Asia Society for Transportation Studies*, *1*(3), 1135-1152.

Ash, J., & Newth, D. (2007). Optimizing complex networks for resilience against cascading failure. *Physica A: Statistical Mechanics and its Applications*, *380*, 673-683.

Asian Development Bank (2018). *Resilience Development*. Retrieved from: https://www.adb.org/themes/climate-change-disaster-risk-management/issues/resilient-development. (Last access: 12/14/2018)

Asian Disaster Preparedness Center (2018). *Asian Disaster Preparedness Center website.* Retrieved from: https://www.adpc.net/igo/contents/adpcpage.asp?pid=2. (Last access: 12/15/2018)

Asian Infrastructure Investment Bank (August, 2018). *Study on Sustainable Cities*. AIIB Strategy, Policy and Budget Department. Retrieved from: https://www.aiib.org/en/policies-strategies/operational-policies/sustainable-cities/.content/_download/sustainable-cities-study.pdf. (Last access: 12/14/2018)

Aslam, H. S. H. (2016). Age-dependent reliability analysis and development of a fuzzy based condition rating tool for timber utility poles (Doctoral dissertation, University of British Columbia).

Ayyub, B. M. (2014). Systems resilience for multihazard environments: Definition, metrics, and valuation for decision making. *Risk Analysis*, *34*(2), 340-355.

Barker, K., & Haimes, Y. Y. (2009a). Assessing uncertainty in extreme events: Applications to risk-based decision making in interdependent infrastructure sectors. *Reliability Engineering & System Safety*, *94*(4), 819-829.

Barker, K., & Haimes, Y. Y. (2009b). Uncertainty analysis of interdependencies in dynamic infrastructure recovery: Applications in risk-based decision making. *Journal of Infrastructure Systems*, *15*(4), 394-405.

Baroud, H., Barker, K., & Ramirez-Marquez, J. E. (2014). Importance measures for inland waterway network resilience. *Transportation research part E: logistics and transportation review*, *62*, 55-67.

Barrett, C., Beckman, R., Channakeshava, K., Huang, F., Kumar, V. A., Marathe, A., ... & Pei, G. (2010, September). Cascading failures in multiple infrastructures: From transportation to communication network. In Critical infrastructure (CRIS), 2010 5th international conference on (pp. 1-8). IEEE.

Barrett, C. B., & Constas, M. A. (2014). Toward a theory of resilience for international development applications. *Proceedings of the National Academy of Sciences*, *111*(40), 14625-14630.

Barton, D. C., Eidson, E. D., Schoenwald, D. A., Stamber, K. L., & Reinert, R. K. (2000). Aspen-EE: an agent-based model of infrastructure interdependency. *SAND2000-2925. Albuquerque, NM: Sandia National Laboratories*.

Barton, D. C., Edison, E. D., Schoenwald, D. A., Cox, R. G., & Reinert, R. K. (2004). Simulating economic effects of disruptions in the telecommunications infrastructure. *Report no. SAND2004-0101. January*.

Basu, N., Pryor, R., & Quint, T. (1998). ASPEN: A microsimulation model of the economy. *Computational Economics*, *12*(3), 223-241.

Banipal, K. (2006). Strategic approach to disaster management: lessons learned from Hurricane Katrina. *Disaster Prevention and Management: An International Journal*, *15*(3), 484-494.

Berle, O., Asbjørnslett, B. E., & Rice, J. B. (2011). Formal vulnerability assessment of a maritime transportation system. *Reliability Engineering & System Safety*, 96(6), 696-705.

Bert Markgraf. (2018). How Far Can a Cell Tower be for a Cellphone to Pick up the Signal. Retrieved from: http://smallbusiness.chron.com/far-can-cell-tower-cellphone-pick-up-signal-32124.html. (Last access: 07/18/2018)

Biggs, R., Schlüter, M., & Schoon, M. L. (Eds.). (2015). Principles for building resilience: sustaining ecosystem services in social-ecological systems. Cambridge University Press.

Bocchini, P., & Frangopol, D. M. (2011). Connectivity-based optimal scheduling for maintenance of bridge networks. *Journal of Engineering Mechanics*, *139*(6), 760-769.

Bompard, E., Napoli, R., & Xue, F. (2009). Assessment of information impacts in power system security against malicious attacks in a general framework. *Reliability Engineering & System Safety*, *94*(6), 1087-1094.

Bonstrom, H., & Corotis, R. B. (2014). First-order reliability approach to quantify and improve building portfolio resilience. *Journal of Structural Engineering*, *142*(8), C4014001.

Booker, G., Torres, J., Guikema, S., Sprintson, A., & Brumbelow, K. (2010). Estimating cellular network performance during hurricanes. *Reliability Engineering & System Safety*, 95(4), 337-344.

Brown, R. E. (2008). *Electric power distribution reliability.* CRC press.

Brown, T., Beyeler, W., & Barton, D. (2004). Assessing infrastructure interdependencies: the challenge of risk analysis for complex adaptive systems. *International Journal of Critical Infrastructures*, *1*(1), 108-117.

Bruneau, M., Chang, S. E., Eguchi, R. T., Lee, G. C., O'Rourke, T. D., Reinhorn, A. M., ... & Von Winterfeldt, D. (2003). A framework to quantitatively assess and enhance the seismic resilience of communities. *Earthquake spectra*, 19(4), 733-752.

Bruneau, M., & Reinhorn, A. (2007). Exploring the concept of seismic resilience for acute care facilities. *Earthquake Spectra*, *23*(1), 41-62.

Buldyrev, S. V., Parshani, R., Paul, G., Stanley, H. E., & Havlin, S. (2010). Catastrophic cascade of failures in interdependent networks. *Nature*, *464*(7291), 1025.

Buzna, L., Peters, K., & Helbing, D. (2006). Modelling the dynamics of disaster spreading in networks. *Physica A: Statistical Mechanics and its Applications*, *363*(1), 132-140.

Cabral, I., Grilo, A., Leal, R. P., & Machado, V. C. (2011, June). Modelling lean, agile, resilient, and green supply chain management. In *Information Technology Interfaces (ITI), Proceedings of the ITI 2011 33rd International Conference on*(pp. 365-370). IEEE.

Cagno, E., De Ambroggi, M., Grande, O., & Trucco, P. (2011). Risk analysis of underground infrastructures in urban areas. *Reliability Engineering & System Safety*, *96*(1), 139-148.

Caramela, Sammi (July 4, 2017). Techniques and Tools to Help You Make Business Decisions. Business News Daily. https://www.businessnewsdaily.com/6162-decision-making.html. (Last access: 12/20/2018)

Cardellini, V., Casalicchio, E., Tucci, S., & dei Ministri, P. D. C. (2006). AGENT-BASED MODELING OF WEB SYSTEMS IN CRITICAL INFORMATION INFRASTRUCTURES. *Proceedings of complex network infrastructure protection. Rome*.

Carpenter, S., Walker, B., Anderies, J. M., & Abel, N. (2001). From metaphor to measurement: resilience of what to what?. *Ecosystems*, *4*(8), 765-781.

Chang, L. (2010). Transportation System Modeling and Applications in Earthquake Engineering. *MAE Center Report No. 10-03*. Retrieved from: https://www.ideals.illinois.edu/handle/2142/16625. (Last access: 03/27/2019)

Chang, L., Elnashai, A. S., & Spencer Jr, B. F. (2012). Post-earthquake modelling of transportation networks. *Structure and infrastructure Engineering*, *8*(10), 893-911.

Chang, L., Peng, F., Ouyang, Y., Elnashai, A. S., & Spencer Jr, B. F. (2012). Bridge seismic retrofit program planning to maximize postearthquake transportation network capacity. *Journal of Infrastructure Systems*, *18*(2), 75-88.

Chang, S. E., & Nojima, N. (2001). Measuring post-disaster transportation system performance: the 1995 Kobe earthquake in comparative perspective. *Transportation Research Part A: Policy and Practice*, *35*(6), 475-494.

Chang, S. E., & Shinozuka, M. (2004). Measuring improvements in the disaster resilience of communities. *Earthquake spectra*, *20*(3), 739-755.

Chen, A., and Kasikitwiwat, P. (2011). "Modeling capacity flexibility of transportation networks." *Transp. Res. Part A*, 45(2), 105–117.

Chen, A., Kasikitwiwat, P., and Yang, C. (2013). "Alternate capacity reliability measures for transportation networks." *J. Adv. Transp.*, 47(1), 79–104.

Chen, A., Kim, J., Zhou, Z., & Chootinan, P. (2007). Alpha reliable network design problem. *Transportation Research Record*, *2029*(1), 49-57.

Chen, L., & Miller-Hooks, E. (2012). Resilience: an indicator of recovery capability in intermodal freight transport. *Transportation Science*, *46*(1), 109-123.

Chen, Y., & Eguchi, R. T. (2003). Post-earthquake road unblocked reliability estimation based on an analysis of randomicity of traffic demands and road capacities. In Advancing Mitigation Technologies and Disaster Response for Lifeline Systems (pp. 916-925).

Cimellaro, G. P., Reinhorn, A. M., & Bruneau, M. (2010a). Framework for analytical quantification of disaster resilience. *Engineering structures*, *32*(11), 3639-3649.

Cimellaro, G. P., Reinhorn, A. M., & Bruneau, M. (2010b). Seismic resilience of a hospital system. *Structure and Infrastructure Engineering*, *6*(1-2), 127-144.

City of Galveston, Texas (April, 9, 2009). Long-term Community Recovery Plan. Retrieved from: http://www.galvestontx.gov/DocumentCenter/View/192. (Last access: 07/18/2018)

City of Galveston (2018). Galveston City Zoning Division. Retrieved from: http://gis.cityofgalveston.org/gisweb/Browse_Galveston/. (Last access: 07/18/2018)

Clark, S., & Watling, D. (2005). Modelling network travel time reliability under stochastic demand. *Transportation Research Part B: Methodological*, *39*(2), 119-140.

Colley, J., & DeBlasio Sr, S. M. (2008). Hurricane ike impact report. *Governors Office of Homeland Security, Tech. Rep.*

Comfort, L. K., & Haase, T. W. (2006). Communication, coherence, and collective action the impact of hurricane Katrina on communications infrastructure. *Public Works management & policy*, *10*(4), 328-343.

Community and Regional Resilience Institute (2013). *Community resilience system*. Community and Regional Resilience Institute (CARRI 2013) Community Resilience System. Retrieved from http://www.resilientus.org/recentwork/community-resilience-system, http://www.resilientus.org/wpcontent/uploads/2013/05/CRS-Final-Report.pdf. (Last access: 12/18/2018)

Costa, L. D. F., Rodrigues, F. A., Travieso, G., & Villas Boas, P. R. (2007). Characterization of complex networks: A survey of measurements. *Advances in physics*, *56*(1), 167-242.

Croope, S., & McNeil, S. (2011). Improving resilience of critical infrastructure systems postdisaster: recovery and mitigation. *Transportation Research Record: Journal of the Transportation Research Board*, (2234), 3-13.

Crowther, K. G., Dicdican, R. Y., Leung, M. F., Lian, C., Williams, G. M., Haimes, Y. Y., ... & Santos, J. R. (2004). *Assessing and managing risk of terrorism to Virginia's interdependent transportation systems* (No. FHWA/VTRC 05-CR6,).

Crowther, K. G., Haimes, Y. Y., & Taub, G. (2007). Systemic Valuation of Strategic Preparedness Through Application of the Inoperability Input‐Output Model with Lessons Learned from Hurricane Katrina. *Risk Analysis*, *27*(5), 1345-1364.

Cumming, G. S. (2011). Spatial resilience: integrating landscape ecology, resilience, and sustainability. *Landscape ecology*, *26*(7), 899-909.

Cutter, S. L., Barnes, L., Berry, M., Burton, C., Evans, E., Tate, E., & Webb, J. (2008). A place-based model for understanding community resilience to natural disasters. *Global environmental change*, *18*(4), 598-606.

Daneels, A., & Salter, W. (1999, October). What is SCADA. In International Conference on Accelerator and Large Experimental Physics Control Systems (pp. 339-343).

Davidson, R. A., Liu, H., Sarpong, I. K., Sparks, P., & Rosowsky, D. V. (2003). Electric power distribution system performance in Carolina hurricanes. *Natural Hazards Review*, *4*(1), 36-45.

Decò, A., Bocchini, P., & Frangopol, D. M. (2013). A probabilistic approach for the prediction of seismic resilience of bridges. *Earthquake Engineering & Structural Dynamics*, *42*(10), 1469-1487.

Department of Energy. (2008). Hurricane Ike Situation Reports. Retrieved from: https://www.oe.netl.doe.gov/named_event.aspx?ID=20. (Last access: 07/18/2018)

Dessavre, D. G., Ramirez-Marquez, J. E., & Barker, K. (2016). Multidimensional approach to complex system resilience analysis. *Reliability Engineering & System Safety*, *149*, 34-43.

Drabble, B. (2011, May). Dependency based collaboration: Ontology based information management. In *Collaboration Technologies and Systems (CTS), 2011 International Conference* on (pp. 579-586). IEEE.

Drabble, B. (2012, May). Information propagation through a dependency network model. In *Collaboration Technologies and Systems (CTS), 2012 International Conference* on (pp. 266-272). IEEE.

Dudenhoeffer, D. D., Permann, M. R., & Boring, R. L. (2006, February). Decision consequence in complex environments: Visualizing decision impact. In *Proceeding of Sharing Solutions for Emergencies and Hazardous Environments. American Nuclear Society Joint Topical Meeting: 9th Emergency Preparedness and Response/11th Robotics and Remote Systems for Hazardous Environments* (pp. 211-218).

Dudenhoeffer, D. D., Permann, M. R., & Manic, M. (2006, December). CIMS: A framework for infrastructure interdependency modeling and analysis. In *Proceedings of the 38th conference on Winter simulation* (pp. 478-485). Winter Simulation Conference.

Dudenhoeffer, D. D., Permann, M. R., Woolsey, S., Timpany, R., Miller, C., McDermott, A., & Manic, M. (2007, July). Interdependency modeling and emergency response. In *Proceedings of the 2007 summer computer simulation conference* (pp. 1230-1237). Society for Computer Simulation International.

Dueñas-Osorio, L., Craig, J. I., Goodno, B. J., & Bostrom, A. (2007). Interdependent response of networked systems. *Journal of Infrastructure Systems*, 13(3), 185-194.

Dueña-Osorio, L., Craig, J. I., & Goodno, B. J. (2007). Seismic response of critical interdependent networks. *Earthquake engineering & structural dynamics*, *36*(2), 285-306.

Dueñas-Osorio, L., & Vemuru, S. M. (2009). Cascading failures in complex infrastructure systems. *Structural safety*, 31(2), 157-167.

Egeland, B., Carlson, E., & Sroufe, L. A. (1993). Resilience as process. *Development and psychopathology*, *5*(4), 517-528.

Ehlen, M. A., & Scholand, A. J. (2005, July). Modeling interdependencies between power and economic sectors using the N-ABLE agent based model. In *Proceedings of the IEEE power engineering society general meeting* (pp. 2842-2846).

Eid, M. S., & El-adaway, I. H. (2016). Sustainable disaster recovery: Multiagent-based model for integrating environmental vulnerability into decision-making processes of the associated stakeholders. *Journal of Urban Planning and Development*, *143*(1), 04016022.

Eidinger, J. M., & Kempner, Jr, L. (2012). Risk assessment of transmission system under earthquake loading. In *Electrical Transmission and Substation Structures 2012: Solutions to Building the Grid of Tomorrow* (pp. 183-192).

Eidson, E. D., & Ehlen, M. A. (2005). NISAC agent-based laboratory for economics (N-ABLE™): Overview of Agent and Simulation Architectures. *Sandia National Laboratories Technical Report SAND2005-0263*.

Ellingwood, B. R., Cutler, H., Gardoni, P., Peacock, W. G., van de Lindt, J. W., & Wang, N. (2016). The centerville virtual community: A fully integrated decision model of interacting physical and social infrastructure systems. *Sustainable and Resilient Infrastructure*, *1*(3-4), 95-107.

European Investment Bank (2016). *Economic Resilience Initiative.* Retrieved from: http://www.eib.org/en/projects/initiatives/resilience-initiative/index.htm. (Last access: 12/14/2018)

European Union (June, 2016). *Shared Vision, Common Action: A Stronger Europe: A Global Strategy for the European Union's Foreign and Security Policy.* Retrieved from: https://europa.eu/globalstrategy/sites/globalstrategy/files/pages/files/eugs_review_web_7.pdf. (Last access: 12/14/2018)

Fang, J., Su, C., Chen, Z., Sun, H., & Lund, P. (2018). Power system structural vulnerability assessment based on an improved maximum flow approach. *IEEE Transactions on Smart Grid*, *9*(2), 777-785.

Fang, Y., & Sansavini, G. (2017). Emergence of antifragility by optimum postdisruption restoration planning of infrastructure networks. *Journal of Infrastructure Systems*, *23*(4), 04017024.

Fang, Y., & Zio, E. (2019). Game-Theoretic Decision Making for the Resilience of Interdependent Infrastructures Exposed to Disruptions. In *Critical Infrastructure Security and Resilience* (pp. 97-114). Springer, Cham.

Faturechi, R., Levenberg, E., & Miller-Hooks, E. (2014). Evaluating and optimizing resilience of airport pavement networks. *Computers & Operations Research*, *43*, 335-348.

Faturechi, R., & Miller-Hooks, E. (2014). Measuring the performance of transportation infrastructure systems in disasters: A comprehensive review. *Journal of infrastructure systems*, 21(1), 04014025.

Fay, Marianne; Andres, Luis Alberto; Fox, Charles James Edward; Narloch, Ulf Gerrit; Straub, Stephane; Slawson, Michael Alan (2017). *Rethinking infrastructure in Latin America and the Caribbean: spending better to achieve more (English)*. Washington, D.C.: World Bank Group. Retrieved from: http://documents.worldbank.org/curated/en/676711491563967405/Rethinking-infrastructure-in-Latin-America-and-the-Caribbean-spending-better-to-achieve-more. (Last access: 08/13/2018)

FEMA, H. (2003). Multi-hazard loss estimation methodology, earthquake model. *Washington, DC, USA: Federal Emergency Management Agency*.

Federal Emergency Management Agency. (2015a, February 6). *National preparedness goal*. Washington, DC: Author. Retrieved from https://www.fema.gov/nationalpreparedness-goal. (Last access: 12/12/2018)

Federal Emergency Management Agency. (2015b). *National planning frameworks*, National Prevention Framework. Washington, DC: Author. Retrieved from https://www.fema.gov/national-planning-frameworks. (Last access: 12/12/2018)

Fernández, J. A., & Rix, G. J. (2006, April). Soil attenuation relationships and seismic hazard analyses in the upper Mississippi embayment. In *Proceedings of the 8th US National Conference on Earthquake Engineering, San Francisco, California* (pp. 18-22).

Fisher, R., & Norman, M. (2010). Developing measurement indices to enhance protection and resilience of critical infrastructure and key resources. *Journal of business continuity & emergency planning*, *4*(3), 191-206.

Foster, K., O'brien, L., & Korhonen, T. (2012). Developing resilient children and families when parents have mental illness: A family-focused approach. *International Journal of Mental Health Nursing*, *21*(1), 3-11.

Foundations, C. (1997). Protecting America's Infrastructures, The Report of the President's Commission on Critical Infrastructure Protection, October 1997. *National Defense University, Washington DC.*

Francis, R., & Bekera, B. (2014). A metric and frameworks for resilience analysis of engineered and infrastructure systems. *Reliability Engineering & System Safety*, *121*, 90-103.

Fujita, H., Gaeta, A., Loia, V., & Orciuoli, F. (2018). Resilience analysis of critical infrastructures: a cognitive approach based on granular computing. *IEEE Transactions on Cybernetics*.

Ganor, M., & Ben-Lavy, Y. U. L. I. (2003). Community resilience: Lessons derived from Gilo under fire. *Journal of Jewish Communal Service*, *79*(2/3), 105-108.

Gay, L. F., & Sinha, S. K. (2012). Novel resilience assessment methodology for water distribution systems. In *Pipelines 2012: Innovations in Design, Construction, Operations, and Maintenance, Doing More with Less* (pp. 61-69).

Georgiou, P. N., Davenport, A. G., & Vickery, B. J. (1984). Design wind speeds in regions dominated by tropical cyclones. In *Wind Engineering 1983, Part 3A* (pp. 139-152).

Germanopoulos, G. (1985). A technical note on the inclusion of pressure dependent demand and leakage terms in water supply network models. *Civil Engineering Systems*, 2(3), 171-179.

Gherhes, C., Vorley, T., & Williams, N. (2018). Entrepreneurship and local economic resilience: the impact of institutional hysteresis in peripheral places. *Small Business Economics*, *51*(3), 577-590.

Global Resilience Institute (2016). The Global Resilience Institute at Northeastern University. Retrieved from: https://globalresilience.northeastern.edu/about/overview/. (Last access: 12/13/2018)

Godschalk, D. R. (2003). Urban hazard mitigation: creating resilient cities. *Natural hazards review*, *4*(3), 136-143.

González, A. D., Chapman, A., Dueñas‐Osorio, L., Mesbahi, M., & D'Souza, R. M. (2017). Efficient infrastructure restoration strategies using the recovery operator. *Computer‐Aided Civil and Infrastructure Engineering*, *32*(12), 991-1006.

Gonzalez Diez, Verónica M.; Verner, Dorte; Corrales, Maria Elena; Puerta, Juan Manuel; Mendieta Umaña, Maria Paula; Morales, Carlos; Suarez, David; Linares, Ana María; Scholl, Lynn; Quintanilla, Oscar; Celse L'Hoste, Margareth; Alvarez Prado, Lourdes; Molina, Adriana; Marto, Ricardo; Christensen, Jens Hesselbjerg; Ashwill, Maximillian; Diewald, Christoph; Schneider, Robert; Lisansky, Judith; Uquillas, Jorge; Redwood, John. (November 2014). *Climate Change at the IDB: Building Resilience and Reducing Emissions*. Inter-American Development Bank. Retrieved from: https://webimages.iadb.org/publications/english/document/Climate-Change-at-the-IDB-Building-Resilience-and-Reducing-Emissions.pdf. (Last access: 12/14/2018)

Gordon, J. (1978). *Structures*. Harmondsworth, UK: Penguin Books.

Grigg, N. S. (2012). *Water, wastewater, and stormwater infrastructure management*. CRC Press.

Groen, J. A., & Polivka, A. E. (2010). Going home after Hurricane Katrina: Determinants of return migration and changes in affected areas. Demography, 47(4), 821-844.

Grubesic, T., and Murray, A. (2006). "Vital nodes, interconnected infrastructures, and the geographies of network survivability." *Ann. Assoc. Am. Geogr.*, 96(1), 64–83.

Gruzs, T. M., & Hall, J. (2000). AC, DC or hybrid power solutions for today's telecommunications facilities. In *Telecommunications Energy Conference, 2000. INTELEC. Twenty-second International* (pp. 361-368). IEEE.

Guidotti, R., Chmielewski, H., Unnikrishnan, V., Gardoni, P., McAllister, T., & van de Lindt, J. (2016). Modeling the resilience of critical infrastructure: The role of network dependencies. *Sustainable and resilient infrastructure*, *1*(3-4), 153-168.

Guidotti, R., Gardoni, P., & Rosenheim, N. (2019). Integration of physical infrastructure and social systems in communities' reliability and resilience analysis. *Reliability Engineering & System Safety*.

Guikema, S., & Gardoni, P. (2009). Reliability estimation for networks of reinforced concrete bridges. *Journal of Infrastructure Systems*, *15*(2), 61-69.

Günneç, D., & Salman, F. S. (2011). Assessing the reliability and the expected performance of a network under disaster risk. *OR spectrum*, *33*(3), 499-523.

Guo, J., Lawson, A. M., & Planting, M. A. (2002). From make-use to symmetric IO tables: an assessment of alternative technology assumptions. WP2002-03, *Bureau of Economic Analysis*, US Department of Commerce, USA.

Haimes, Y. Y. (2002). Roadmap for modeling risks of terrorism to the homeland. *Journal of Infrastructure Systems*, 8(2), 35-41.

Haimes, Y. Y., Horowitz, B. M., Lambert, J. H., Santos, J. R., Lian, C., & Crowther, K. G. (2005a). Inoperability input-output model for interdependent infrastructure sectors. I: Theory and methodology. *Journal of Infrastructure Systems*, *11*(2), 67-79.

Haimes, Y. Y., Horowitz, B. M., Lambert, J. H., Santos, J., Crowther, K., & Lian, C. (2005b). Inoperability input-output model for interdependent infrastructure sectors. II: Case studies. *Journal of Infrastructure Systems*, *11*(2), 80-92.

Haimes, Y. Y. (2009). On the definition of resilience in systems. *Risk Analysis: An International Journal*, *29*(4), 498-501.

Hall, R. P., Ashford, N. A., & Söderbaum, P. (2008). Trade-off analysis (with a revised Rawlsian decision-making philosophy) as an alternative to cost-benefit analysis in socio-technical decisions. *Towards the def. of a measurable environmentally sustainable transport*, 79.

Hasan, S., & Foliente, G. (2015). Modeling infrastructure system interdependencies and socioeconomic impacts of failure in extreme events: emerging R&D challenges. *Natural Hazards*, *78*(3), 2143-2168.

Hazus, M. H. (1999). Earthquake loss estimation methodology—technical and user manuals. *Federal Emergency Management Agency, Washington*.

He, F., & Nwafor, J. (2017, April). Gas pipeline recovery from disruption using multi-objective optimization. In *Technologies for Homeland Security (HST), 2017 IEEE International Symposium on* (pp. 1-6). IEEE.

HAZUS-MH, F. E. M. A. (2003). Flood Model: Technical Manual. *Federal Emergency Management Agency*.

He, X., & Cha, E. J. (2018a). Modeling the damage and recovery of interdependent critical infrastructure systems from natural hazards. *Reliability Engineering & System Safety*.

He, X., & Cha, E. J. (2018b). Modeling the damage and recovery of interdependent civil infrastructure network using Dynamic Integrated Network model. *Sustainable and Resilient Infrastructure*, 1-16.

He, X., & Cha, E. J. (2019a). Probabilistic Infrastructure Recovery Modeling with Considering Different Levels of Interdependency. *Natural Hazards Review.* (*Submitted; NHENG-918*)

He, X., & Cha, E. J. (2019b). Risk-informed Decision Framework for Interdependent Infrastructure Risk Mitigation Planning. *Risk Analysis.* (*Submitted; RA-00596-2018*)

He, X., & Cha, E. J. (2019c). Game Theory-Based Decision Support Framework for Interdependent Infrastructure Recovery Planning. *Journal of Infrastructure Systems.* (*Submitted; ISENG-1528*)

Heegaard, P. E., & Trivedi, K. S. (2009). Network survivability modeling. *Computer Networks*, *53*(8), 1215-1234.

Henry, D., & Ramirez-Marquez, J. E. (2012). Generic metrics and quantitative approaches for system resilience as a function of time. *Reliability Engineering & System Safety*, *99*, 114-122.

Herrmann, J. W. (2015). Engineering decision making and risk management. John Wiley & Sons.

Holling, C. S. (1973). Resilience and stability of ecological systems. *Annual review of ecology and systematics*, 4(1), 1-23.

Holmgren, Å. J. (2006). Using graph models to analyze the vulnerability of electric power networks. *Risk analysis*, *26*(4), 955-969.

Hosseini, S., Barker, K., & Ramirez-Marquez, J. E. (2016). A review of definitions and measures of system resilience. *Reliability Engineering & System Safety*, *145*, 47-61.

Woods, D. D., Leveson, N., & Hollnagel, E. (Eds.). (2012). *Resilience engineering: concepts and precepts*. Ashgate Publishing, Ltd..

Huang, Z., Rosowsky, D. V., & Sparks, P. R. (2001). Long-term hurricane risk assessment and expected damage to residential structures. *Reliability engineering & system safety*, 74(3), 239-249.

Huizar, L. H., Lansey, K. E., & Arnold, R. G. (2018). Sustainability, robustness, and resilience metrics for water and other infrastructure systems. *Sustainable and Resilient Infrastructure*, *3*(1), 16-35.

Hwang, H. H., Lin, H., & Shinozuka, M. (1998). Seismic performance assessment of water delivery systems. *Journal of Infrastructure Systems*, 4(3), 118-125.

Infrastructure Security Partnership (Organization). (2006). *Regional disaster resilience: A guide for developing an action plan*. DIANE Publishing Inc..

International Federation of Red Cross and Red Crescent Societies (2014). *IFRC Framework for Community Resilience.* Retrieved from: https://media.ifrc.org/ifrc/wp-content/uploads/sites/5/2018/03/IFRC-Framework-for-Community-Resilience-EN-LR.pdf. (Last access: 12/14/2018)

International Panel of Climate Change (IPCC). (2014). *Climate change 2014: Synthesis report. Contribution of working groups I, II and III to the fifth assessment report of the intergovernmental panel on climate change.* Geneva: Author. Retrieved from: https://www.ipcc.ch/report/ar5/syr/. (Last access: 1/6/2019)

Jeffcott, S. A., Ibrahim, J. E., & Cameron, P. A. (2009). Resilience in healthcare and clinical handover. *BMJ Quality & Safety*, *18*(4), 256-260.

Jiang, P., & Haimes, Y. Y. (2004). Risk management for Leontief‐based interdependent systems. *Risk Analysis*, *24*(5), 1215-1229.

Jin, J. G., Tang, L. C., Sun, L., & Lee, D. H. (2014). Enhancing metro network resilience via localized integration with bus services. *Transportation Research Part E: Logistics and Transportation Review*, *63*, 17-30.

Kameda, H. (2000). Engineering management of lifeline systems under earthquake risk. *Bulletin of the New Zealand Society for Earthquake Engineering*, *33*(3), 248-264.

Kates, R. W., Colten, C. E., Laska, S., & Leatherman, S. P. (2006). Reconstruction of New Orleans after Hurricane Katrina: a research perspective. *Proceedings of the national Academy of Sciences*, 103(40), 14653-14660.

Keck, M., & Sakdapolrak, P. (2013). What is social resilience? Lessons learned and ways forward. *Erdkunde*, 5-19.

Khaled, A. A., Jin, M., Clarke, D. B., & Hoque, M. A. (2015). Train design and routing optimization for evaluating criticality of freight railroad infrastructures. *Transportation Research Part B: Methodological*, *71*, 71-84.

Klein, R. J., Nicholls, R. J., & Thomalla, F. (2003). Resilience to natural hazards: How useful is this concept?. *Global Environmental Change Part B: Environmental Hazards*, *5*(1), 35-45.

Kontou, E., Murray-Tuite, P., & Wernstedt, K. (2017). Duration of commute travel changes in the aftermath of Hurricane Sandy using accelerated failure time modeling. *Transportation Research Part A: Policy and Practice*, *100*, 170-181.

Koliou, M., van de Lindt, J. W., McAllister, T. P., Ellingwood, B. R., Dillard, M., & Cutler, H. (2017). State of the research in community resilience: progress and challenges. *Sustainable and Resilient Infrastructure*, 1-21.

Kostro, Stephanie Sanok; Riba, Garrett (November, 2014). *Achieving Disaster Resilience in U.S. Communities*. Center for Strategic and International Studies. Retrieved from: https://csis-prod.s3.amazonaws.com/s3fs-public/legacy_files/files/publication/141016_Kostro_DisasterResilience_Web.pdf. (Last access: 12/15/2018)

Kurtz, N., Song, J., & Gardoni, P. (2015). Seismic reliability analysis of deteriorating representative US West Coast bridge transportation networks. *Journal of Structural Engineering*, *142*(8), C4015010.

Kwasinski, A. (2011, October). Effects of notable natural disasters from 2005 to 2011 on telecommunications infrastructure: Lessons from on-site damage assessments. In *Telecommunications Energy Conference (INTELEC), 2011 IEEE 33rd International* (pp. 1-9). IEEE.

Lee, K. H., & Rosowsky, D. V. (2007). Synthetic hurricane wind speed records: development of a database for hazard analyses and risk studies. Natural Hazards Review, 8(2), 23-34.

Lee, Y. J., Song, J., Gardoni, P., & Lim, H. W. (2011). Post-hazard flow capacity of bridge transportation network considering structural deterioration of bridges. *Structure and Infrastructure Engineering*, *7*(7-8), 509-521.

Lee II, E. E., Mitchell, J. E., & Wallace, W. A. (2007). Restoration of services in interdependent infrastructure systems: A network flows approach. *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews),* 37(6), 1303-1317.

Leontief, W. W., & Leontief, W. (1986). *Input-output economics*. Oxford University Press on Demand.

Li, Y., & Lence, B. J. (2007). Estimating resilience for water resources systems. *Water Resources Research*, *43*(7).

Lian, C., & Haimes, Y. Y. (2006). Managing the risk of terrorism to interdependent infrastructure systems through the dynamic inoperability input–output model. *Systems Engineering*, 9(3), 241-258.Liu, H., Davidson, R. A., Rosowsky, D. V., & Stedinger, J. R. (2005). Negative binomial regression of electric power outages in hurricanes. *Journal of infrastructure systems*, 11(4), 258-267.

López, A. L., Rocha, L. E. P., Escobedo, D. L., & Sesma, J. S. (2009). Reliability and vulnerability analysis of electrical substations and transmission towers for definition of wind and seismic damage maps for Mexico. *In Proceedings of the 11th Americas Conference on Wind Engineering*, San Juan, Puerto Rico.

Lu, L., Wang, X., Ouyang, Y., Roningen, J., Myers, N., & Calfas, G. (2018). Vulnerability of interdependent urban infrastructure networks: Equilibrium after failure propagation and cascading impacts. *Computer‐Aided Civil and Infrastructure Engineering*, *33*(4), 300-315.

Luna, R., Balakrishnan, N., & Dagli, C. H. (2011). Postearthquake recovery of a water distribution system: discrete event simulation using colored petri nets. *Journal of Infrastructure Systems*, 17(1), 25-34.

Luping, Y., and Dalin, Q. (2012). “Vulnerability analysis of road networks.” *J. Transp. Syst. Inform. Technol.*, 12(1), 105–110.

McCarthy, J. A. (2007). Introduction: from protection to resilience: injecting'Moxie'into the infrastructure security continuum. *Critical Thinking: Moving from Infrastructure Protection to Infrastructure Resilience*, 2-3.

MacKenzie, C. A., & Barker, K. (2012). Empirical data and regression analysis for estimation of infrastructure resilience with application to electric power outages. *Journal of Infrastructure Systems*, 19(1), 25-35.

Maguire, B., & Cartwright, S. (2008). *Assessing a community's capacity to manage change: a resilience approach to social assessment*. Canberra: Bureau of Rural Sciences.

Mancini, A., Salvati, L., Sateriano, A., Mancino, G., & Ferrara, A. (2012). Conceptualizing and measuring the ‘economy’dimension in the evaluation of socio-ecological resilience: a brief commentary. *International Journal of Latest Trends in Finance and Economic Sciences*, *2*(3), 190-196.

Mansfield, C. F., Beltman, S., Broadley, T., & Weatherby-Fell, N. (2016). Building resilience in teacher education: An evidenced informed framework. *Teaching and Teacher Education*, *54*, 77-87.

Masoomi, H., van de Lindt, J. W., Ameri, M. R., Do, T. Q., & Webb, B. M. (2018). Combined Wind-Wave-Surge Hurricane-Induced Damage Prediction for Buildings. *Journal of Structural Engineering*, *145*(1), 04018227.

Matisziw, T. C., Murray, A. T., & Grubesic, T. H. (2010). Strategic network restoration. *Networks and Spatial Economics*, *10*(3), 345-361.

Masten, A. S., Best, K. M., & Garmezy, N. (1990). Resilience and development: Contributions from the study of children who overcome adversity. *Development and psychopathology*, *2*(4), 425-444.

Mayunga, J. S. (2007). Understanding and applying the concept of community disaster resilience: a capital-based approach. *Summer academy for social vulnerability and resilience building*, *1*, 16.

Mendenhall, W. (1988). *Risk Management of Water Supply and Sanitation Systems*. Macmillan Pub Co.

Mileti, D. (1999). Disasters by design: A reassessment of natural hazards in the United States. Joseph Henry Press.

Miller-Hooks, E., Zhang, X., & Faturechi, R. (2012). Measuring and maximizing resilience of freight transportation networks. *Computers & Operations Research*, *39*(7), 1633-1643.

Moya-Gómez, B., Salas-Olmedo, M. H., García-Palomares, J. C., & Gutiérrez, J. (2018). Dynamic accessibility using big data: the role of the changing conditions of network congestion and destination attractiveness. *Networks and Spatial Economics*, *18*(2), 273-290.

Myerson, R. B. (2013). *Game theory*. Harvard university press.

MRl, H. M. (2011). Multi-Hazard Loss Estimation Methodology: Hurricane Model. *Department of Homeland Security, FEMA*, Washington, DC.

Murray, A., Matisziw, T., and Grubesic, T. (2007). "Critical network infrastructure analysis: Interdiction and system flow." *J. Geogr. Syst.*, 9(2), 103–117.

Nagurney, A., & Qiang, Q. (2007). A network efficiency measure for congested networks. *EPL (Europhysics Letters)*, *79*(3), 38005.

Nakanishi, H., Black, J., & Matsuo, K. (2014). Disaster resilience in transportation: Japan earthquake and tsunami 2011. *International Journal of Disaster Resilience in the Built Environment*, *5*(4), 341-361.

National Infrastructure Advisory Council (US). (2009). *Critical infrastructure resilience: Final report and recommendations*. National Infrastructure Advisory Council.

Nicholson, A. (2003). Transport network reliability measurement and analysis. Transportes, 11(2).

Niehoff, A. H. (2017). *Caribbean transformations*. Routledge.

NIST. (2015a, October). *Community resilience planning guide for buildings and infrastructure systems, volumes I and II.* Gaithersburg, MD: NIST Special Publication 1190. Retrieved from: https://doi.org/10.6028/NIST.SP.1190v1. doi: 10.6028/NIST.SP.1197.

NIST. (2015b, October). *Community resilience economic decision guide for buildings and infrastructure systems*. Gaithersburg, MD: NIST Special Publication 1197. doi: 10.6028/NIST.SP.1197.

Norris, F. H., Stevens, S. P., Pfefferbaum, B., Wyche, K. F., & Pfefferbaum, R. L. (2008). Community resilience as a metaphor, theory, set of capacities, and strategy for disaster readiness. *American journal of community psychology*, *41*(1-2), 127-150.

North, M. J. N. (2000). *SMART II: the spot market agent research tool version 2.0* (No. ANL/DIS/CP-103634). Argonne National Lab., IL (US).

North, M. J. (2001a). Multi-agent social and organizational modeling of electric power and natural gas markets. *Computational & Mathematical Organization Theory*, *7*(4), 331-337.

North, M. J. (2001b). Toward strength and stability: Agent-based modeling of infrastructure markets. *Social Science Computer Review*, *19*(3), 307-323.

Nozhati, S., Sarkale, Y., Ellingwood, B., Chong, E. K., & Mahmoud, H. (2018). Near-optimal planning using approximate dynamic programming to enhance post-hazard community resilience management. *arXiv preprint arXiv:1803.01451*.

Nozhati, S., Sarkale, Y., Chong, E. K., & Ellingwood, B. R. (2018). Optimal Stochastic Dynamic Scheduling for Managing Community Recovery from Natural Hazards. *arXiv preprint arXiv:1812.10194*.

Nozick, L. K., Turnquist, M. A., Jones, D. A., Davis, J. R., & Lawton, C. R. (2004, January). Assessing the performance of interdependent infrastructures and optimizing investments. In *37th Annual Hawaii International Conference on System Sciences, 2004. Proceedings of the* (pp. 7-pp). IEEE.

NRC (National Research Council). (2012). Disaster resilience: A national imperative, *National Academies Press*, Washington, DC.

Okvat, H. A., & Zautra, A. J. (2011). Community gardening: A parsimonious path to individual, community, and environmental resilience. *American journal of community psychology*, *47*(3-4), 374-387.

Orabi, W., Senouci, A. B., El-Rayes, K., & Al-Derham, H. (2010). Optimizing resource utilization during the recovery of civil infrastructure systems. *Journal of management in engineering*, *26*(4), 237-246.

Oregon Seismic Safety Policy Advisory Commission. (February, 2013). *The Oregon resilience plan: Reducing risk and improving recovery for the next Cascadia earthquake and tsunami*. Salem, OR. Retrieved from http://www.oregon.gov/OMD/OEM/osspac/docs/Oregon_Resilience_Plan_Final.pdf. (Last access: 12/14/2018)

O'rourke, T. D., Lembo, A. J., & Nozick, L. K. (2003). Lessons learned from the World Trade Center disaster about critical utility systems. *Beyond September 11th: an account of post-disaster research. Natural hazards research & applications information center, public entity risk institute, and institute for civil infrastructure systems. University of Colorado, Boulder, CO,* 275.

Ouyang, M., & Dueñas-Osorio, L. (2012). Time-dependent resilience assessment and improvement of urban infrastructure systems. *Chaos: An Interdisciplinary Journal of Nonlinear Science*, *22*(3), 033122.

Ouyang, M., Dueñas-Osorio, L., & Min, X. (2012). A three-stage resilience analysis framework for urban infrastructure systems. *Structural safety*, *36*, 23-31.

Ouyang, M. (2014). Review on modeling and simulation of interdependent critical infrastructure systems. *Reliability engineering & System safety*, 121, 43-60.

Ouyang, M., & Fang, Y. (2017). A mathematical framework to optimize critical infrastructure resilience against intentional attacks. *Computer‐Aided Civil and Infrastructure Engineering*, *32*(11), 909-929.

Pacific Northwest Economic Region. (2011). The Center of Regional Disaster Resilience. Retrieved from http://www.regionalresilience.org/. (Last access: 12/13/2018)

Panteli, M., Mancarella, P., Trakas, D. N., Kyriakides, E., & Hatziargyriou, N. D. (2017). Metrics and quantification of operational and infrastructure resilience in power systems. *IEEE Transactions on Power Systems*, *32*(6), 4732-4742.

Paton, D. (2000). Emergency Planning: Integrating community development, community resilience and hazard mitigation. Journal of the american society of Professional emergency Managers, 7, 109-118.

Patterson, S. A., & Apostolakis, G. E. (2007). Identification of critical locations across multiple infrastructures for terrorist actions. Reliability Engineering & System Safety, 92(9), 1183-1203.

Peeta, S., & Zhang, P. (2009). Modeling infrastructure interdependencies: theory and practice. Safety, Reliability and Risk of Structures, Infrastructures and Engineering System. CRC Press, Osaka.

Peeta, S., Salman, F. S., Gunnec, D., & Viswanath, K. (2010). Pre-disaster investment decisions for strengthening a highway network. *Computers & Operations Research*, *37*(10), 1708-1719.

Pederson, P., Dudenhoeffer, D., Hartley, S., & Permann, M. (2006). Critical infrastructure interdependency modeling: a survey of US and international research. *Idaho National Laboratory*, *25*, 27.

Petit, F. D. P., Bassett, G. W., Black, R., Buehring, W. A., Collins, M. J., Dickinson, D. C., ... & Phillips, J. A. (2013). Resilience measurement index: An indicator of critical infrastructure resilience (No. ANL/DIS-13-01). *Argonne National Lab.(ANL)*, Argonne, IL (United States).

Pettit, T. J. (2008). *Supply chain resilience: development of a conceptual framework, an assessment tool and an implementation process* (Doctoral dissertation, The Ohio State University).

Pfefferbaum, R., Pfefferbaum, B., Van Horn, R. L., Klomp, R. W., Norris, F. H., & Reissman, D. B. (2013). The communities advancing resilience toolkit (CART): An intervention to build community resilience to disasters. *Journal of Public Health Management & Practice, 19*(3), 250–258.

Phillips, L. R., Kelic, A., & Warren, D. E. (2008). *Cyber and physical infrastructure interdependencies* (No. SAND2008-6192). Sandia National Laboratories.

Planning Institute of Jamaica (2007). *The socio-economic and environmental impact of Hurricane Dean on Jamaica*. Retrieved from: http://www.eldis.org/document/A71745. (Last access: 08/13/2018)

Poole, I. (2006). *Cellular communications explained: from basics to 3G*. Elsevier.

Portante, E. C., Craig, B. A., Malone, L. T., Kavicky, J., Folga, S. F., & Cedres, S. (2011, December). Epfast: a model for simulating uncontrolled islanding in large power systems. In *Proceedings of the Winter Simulation Conference* (pp. 1763-1774). Winter Simulation Conference.

Potter, R. B. (2017). *The urban Caribbean in an era of global change*. Routledge.

PPD (Presidential Policy Directive). (2013). "Critical infrastructure security and resilience." PPD-21. Retrieved from: https://obamawhitehouse.archives.gov/the-press-office/2013/02/12/presidential-policy-directive-critical-infrastructure-security-and-resil. (Last access: 1/1/2019)

Queensland Reconstruction Authority (2018). Queensland Government, Queensland Reconstruction Authority website. Retrieved from: https://www.qra.qld.gov.au/. (Last access: 12/14/2018)

Radio Regulations (2012). Volume 1: Articles International Telecommunications Union-Radiocommunication Sector Std.

RAND Corporation (2018). *Community Resilience.* Retrieved from: https://www.rand.org/topics/community-resilience.html. (Last access: 12/14/2018)

Reed, D. A., Kapur, K. C., & Christie, R. D. (2009). Methodology for assessing the resilience of networked infrastructure. *IEEE Systems Journal*, *3*(2), 174-180.

Reed, D. A., Zabinsky, Z. B., & Boyle, L. N. (2011). A framework for optimizing civil infrastructure resiliency. In *Structures Congress 2011* (pp. 2104-2112).

Resilience in Communities (2018). *Community Resilience Program.* Retrieved from: http://resilienceincommunities.com/about/. (Last access: 12/15/2018)

Rinaldi, S. M., Peerenboom, J. P., & Kelly, T. K. (2001). Identifying, understanding, and analyzing critical infrastructure interdependencies. *IEEE Control Systems*, *21*(6), 11-25.

Rockefeller. (2016). 100 Resilient Cities. Retrieved from: http://www.100resilientcities.org/. (Last access: 12/12/2018)

Rose, A. (2004). Economic principles, issues, and research priorities in hazard loss estimation. In *Modeling spatial and economic impacts of disasters* (pp. 13-36). Springer Berlin Heidelberg.

Rose, A., & Liao, S. Y. (2005). Modeling regional economic resilience to disasters: A computable general equilibrium analysis of water service disruptions. *Journal of Regional Science*, *45*(1), 75-112.

Rose, A., Oladosu, G., & Liao, S. Y. (2005, August). Regional economic impacts of terrorist attacks on the electric power system of Los Angeles: a computable general disequilibrium analysis. In *Second Annual Symposium of the DHS Center for Risk and Economic Analysis of Terrorism Events, University of Southern California, Los Angeles, CA*.

Rosowsky, D. V., Sparks, P. R., & Huang, Z. (1999). Wind field modeling and hurricane hazard analysis. Clemson University.

Sahebjamnia, N., Torabi, S. A., & Mansouri, S. A. (2015). Integrated business continuity and disaster recovery planning: Towards organizational resilience. *European Journal of Operational Research*, *242*(1), 261-273.

Saja, A. A., Teo, M., Goonetilleke, A., & Ziyath, A. M. (2018). An inclusive and adaptive framework for measuring social resilience to disasters. *International journal of disaster risk reduction*.

Santos, J. R. (2006). Inoperability input−output modeling of disruptions to interdependent economic systems. *Systems Engineering*, *9*(1), 20-34.

Sarkar, S., Kumar, S., Bhowmick, S., & Mukherjee, A. (2018). Centrality and Community Scoring Functions in Incomplete Networks: Their Sensitivity, Robustness, and Reliability. In *Machine Learning Techniques for Online Social Networks* (pp. 135-154). Springer, Cham.

Sastry, N. (2009). Tracing the effects of Hurricane Katrina on the population of New Orleans: The displaced New Orleans residents pilot study. *Sociological methods & research*, 38(1), 171-196.

SBP (2006). *SBP website.* Retrieved from: http://sbpusa.org/about-us. (Last access: 12/15/2018)

Scawthorn, C., Blais, N., Seligson, H., Tate, E., Mifflin, E., Thomas, W., ... & Jones, C. (2006a). HAZUS-MH flood loss estimation methodology. I: Overview and flood hazard characterization. *Natural Hazards Review*, *7*(2), 60-71.

Scawthorn, C., Flores, P., Blais, N., Seligson, H., Tate, E., Chang, S., ... & Lawrence, M. (2006). HAZUS-MH flood loss estimation methodology. II. Damage and loss assessment. *Natural Hazards Review*, *7*(2), 72-81.

Schwab, J., Topping, K. C., Eadie, C. C., Deyle, R. E., & Smith, R. A. (1998). *Planning for post-disaster recovery and reconstruction (pp. 483-484)*. Chicago, IL: American Planning Association.

Sempier, T. T., Swann, D. L, Emmer, R., Sempier, S. H, & Schneider, M. (November, 2010). "*Coastal community resilience index: A community self-assessment*. MAGSP-08-014. Retrieved from: http://www.gulfofmexicoalliance.org/projects/files/83Community_Resilience_Index.pdf. (Last access: 12/14/2018)

Shafieezadeh, A., Onyewuchi, U. P., Begovic, M. M., & DesRoches, R. (2014). Age-dependent fragility models of utility wood poles in power distribution networks against extreme wind hazards. *IEEE Transactions on Power Delivery*, *29*(1), 131-139.

Sharma, N., & Gardoni, P. (2018). Modeling the time-varying performance of electrical infrastructure during post disaster recovery using tensors. *Routledge Handbook of Sustainable and Resilient Infrastructure*, 263.

Sharma, N., Tabandeh, A., & Gardoni, P. (2018). Resilience analysis: A mathematical formulation to model resilience of engineering systems. *Sustainable and Resilient Infrastructure*, *3*(2), 49-67.

Shayeghi, H., & Younesi, A. (2019). Resilience Metrics Development for Power Systems. In *Power Systems Resilience* (pp. 101-116). Springer, Cham.

Shi, P. & O'Rourke, T. D. (2008). *Seismic response modeling of water supply systems. Mceer-08-0016, 352*. Retrieved from: https://mceer.buffalo.edu/publications/catalog/reports/Seismic-Response-Modeling-of-Water-Supply-Systems-MCEER-08-0016.html (Last access: 03/27/2019)

Shinozuka, M., Dong, X., Chen, T. C., & Jin, X. (2007). Seismic performance of electric transmission network under component failures. *Earthquake engineering & structural dynamics*, *36*(2), 227-244.

Shirali, G. A., Mohammadfam, I., & Ebrahimipour, V. (2013). A new method for quantitative assessment of resilience engineering by PCA and NT approach: A case study in a process industry. *Reliability Engineering & System Safety*, *119*, 88-94.

Shirley, W. L., Boruff, B. J., & Cutter, S. L. (2012). Social vulnerability to environmental hazards. In *Hazards Vulnerability and Environmental Justice* (pp. 143-160). Routledge.

Schoenwald, D. A., Barton, D. C., & Ehlen, M. A. (2004, June). An agent-based simulation laboratory for economics and infrastructure interdependency. In *American Control Conference, 2004. Proceedings of the 2004* (Vol. 2, pp. 1295-1300). IEEE.

Short, T. A. (2014). *Electric power distribution handbook*. CRC press.

Simmie, J., & Martin, R. (2010). The economic resilience of regions: towards an evolutionary approach. *Cambridge journal of regions, economy and society*, *3*(1), 27-43.

Smith, A. M., González, A. D., Dueñas - Osorio, L., & D'Souza, R. M. (2017). Interdependent Network Recovery Games. *Risk Analysis*.

Snelder, M., van Zuylen, H., and Immers, L. (2012). "A framework for robustness analysis of road networks for short term variations in supply." *Transp. Res. Part A*, 46(5), 828–842.

Soltani-Sobh, A., Heaslip, K., Scarlatos, P., & Kaisar, E. (2016). Reliability based pre-positioning of recovery centers for resilient transportation infrastructure. *International Journal of Disaster Risk Reduction*, *19*, 324-333.

Sonn, C. C., & Fisher, A. T. (1998). Sense of community: Community resilient responses to oppression and change. *Journal of community psychology*, *26*(5), 457-472.

Sprecher, B., Daigo, I., Murakami, S., Kleijn, R., Vos, M., & Kramer, G. J. (2015). Framework for resilience in material supply chains, with a case study from the 2010 rare earth crisis. *Environmental science & technology*, *49*(11), 6740-6750.

SPUR-San Francisco Planning and Urban Research Association. (2009). ―When is a Building Safe Enough?. In *San Francisco urban research association*, Issue 479, February 2009, 654 Mission Street, San Francisco, CA. Retrieved from: http://www.spur.org, http://www.spur.org/sites/default/files/publications_pdfs/SPUR_Seismic_Mitigation_Policies.pdf. (Last access: 12/14/2018)

Stanford Urban Resilience Initiative (2018). Stanford Urban Resilience Initiative Website. Retrieved from: http://urbanresilience.stanford.edu/. (Last access: 12/14/2018)

Stantec (2018). *Stantec Resilience Group Website*. Retrieved from: https://www.stantec.com/en/markets/urban-places/resilience. (Last access: 12/12/2018)

Stapelberg, R. F. (2008). Infrastructure systems interdependencies and risk informed decision making (RIDM): impact scenario analysis of infrastructure risks induced by natural, technological and intentional hazards. *Journal of systemics, Cybernetics and Informatics*, *6*(5), 21-27.

Starr, R., Newfrock, J., & Delurey, M. (2003). Enterprise resilience: managing risk in the networked economy. *Strategy and Business*, *30*, 70-79.

Stearns, M., & Padgett, J. E. (2011). Impact of 2008 Hurricane Ike on bridge infrastructure in the Houston/Galveston region. *Journal of Performance of Constructed Facilities*, 26(4), 441-452.

Steinberg, L., Santella, N., & Zoli, C. (2011). Baton Rouge post-Katrina: the role of critical infrastructure modeling in promoting resilience.

Sterbenz, J. P., Hutchison, D., Çetinkaya, E. K., Jabbar, A., Rohrer, J. P., Schöller, M., & Smith, P. (2010). Resilience and survivability in communication networks: Strategies, principles, and survey of disciplines. *Computer Networks*, *54*(8), 1245-1265.

Sullivan, M. J., Vardell, T., & Johnson, M. (1997). Power interruption costs to industrial and commercial consumers of electricity. *IEEE Transactions on industry applications*, *33*(6), 1448-1458.

Sun, Y., Turnquist, M., and Nozick, L. (2006). “Estimating freight transportation system capacity, flexibility, and degraded-condition performance.” *Transportation Research Record 1966*, Transportation Research Board, Washington, DC (1), 80–87.

Sun, W., Bocchini, P., & Davison, B. D. (2018). Resilience metrics and measurement methods for transportation infrastructure: the state of the art. *Sustainable and Resilient Infrastructure*, 1-32.

Taylor, M. A. (2012). Remoteness and accessibility in the vulnerability analysis of regional road networks. *Transportation research part A: policy and practice*, *46*(5), 761-771.

The Risk and Decision Science Team, US Army Crops (2018). *Risk and Decision Science.* Retrieved from: https://www.erdc.usace.army.mil/Media/Fact-Sheets/Fact-Sheet-Article-View/Article/920870/risk-and-decision-science/. (Last access: 12/18/2018)

The State of Texas, Division of Emergency Management. (December 8, 2008). Retrieved from: https://www.fema.gov/pdf/hazard/hurricane/2008/ike/impact_report.pdf. (Last access: 07/18/2018)

Tendall, D. M., Joerin, J., Kopainsky, B., Edwards, P., Shreck, A., Le, Q. B., ... & Six, J. (2015). Food system resilience: defining the concept. *Global Food Security*, *6*, 17-23.

Timmermann, P. (1981). Vulnerability, resilience and the collapse of society. *Environmental Monograph*, *1*, 1-42.

Tonmoy, F. N., & El-Zein, A. (2013, September). Vulnerability of infrastructure to sea level rise: a combined outranking and system-dynamics approach. In *Proceedings of the 22nd Conference on European Safety and Reliability (ESREL-2013), Amsterdam, The Netherlands* (Vol. 29).

Tootaghaj, D. Z., Bartolini, N., Khamfroush, H., He, T., Chaudhuri, N. R., & La Porta, T. (2018). Mitigation and Recovery from Cascading Failures in Interdependent Networks under Uncertainty. *IEEE Transactions on Control of Network Systems*.

Tugade, M. M., Fredrickson, B. L., & Feldman Barrett, L. (2004). Psychological resilience and positive emotional granularity: Examining the benefits of positive emotions on coping and health. *Journal of personality*, *72*(6), 1161-1190.

U.S. Census Bureau. (2006). Special Population Estimates for Impacted Counties in the Gulf Coast Area. Washington, DC. Retrieved from: http://www.census.gov/Press-Release/www/emergencies/impacted_gulf_estimates.html. (Last access:12/18/2018)

U.S. Census Bureau. (2007). Population Estimates. Washington, DC. Retrieved from: http://www.census.gov/popest/index.html. (Last access: 07/18/2018)

U.S. Census Bureau (2016). US Census TIGER Products. Road Network of Galveston County, TX. Retrieved from: https://www.census.gov/geo/maps-data/data/tiger.html. (Last access: 07/18/2018)

U.S. Congress, Office of Technology Assessment (1990). *Physical vulnerability of electric systems to natural disaster and sabotage*. Washington, DC: U.S. Government Printing Office.

U.S. Department of Commerce, National Oceanic and Atmospheric Administration (2018). NOAA Historical Hurricane Tracks dataset. Retrieved from: https://coast.noaa.gov/hurricanes/. (Last access: 07/18/2018)

U.S. Department of Homeland Security, National Disaster Recovery Framework, Washington, D.C. (September, 2011). Retrieved from: https://www.fema.gov/pdf/recoveryframework/ndrf.pdf. (Last access: 07/18/2018)

U.S. Department of Homeland Security (2016). *Regional Resiliency Assessment Program*. Retrieved from https://www.dhs.gov/regional-resiliencyassessment-program. (Last access: 12/12/2018)

U.S. Department of Homeland Security (2018). *Critical infrastructure security*. Retrieved from: https://www.dhs.gov/topic/critical-infrastructure-security. (Last access: 12/12/2018)

UNDRO. (1984). UNDRO Preparedness aspects. *Disaster Prevention and Mitigation, A Compendium of Current Knowledge*, 11.

United Nations Office for Disaster Risk Reduction. (2014, March 10). *Disaster Resilience Scorecard for Cities, Based on the — Ten Essentials ‖ defined by the United Nations International Strategy for Disaster Risk Reduction (UNISDR) for Making Cities Resilient*. Developed for The United Nations Office for Disaster Risk Reduction (UNISDR) by IBM and AECOM, Version 1.5. Retrieved from: https://www.unisdr.org/campaign/resilientcities/assets/documents/guidelines/UNISDR_Disaster%20resilience%20scorecard%20for%20cities_Detailed.pdf. (Last access:12/12/2018)

Unnikrishnan, V. U., & van de Lindt, J. W. (2016). Probabilistic framework for performance assessment of electrical power networks to tornadoes. *Sustainable and Resilient Infrastructure*, *1*(3-4), 137-152.

Vickery, P. J., Lin, J., Skerlj, P. F., Twisdale Jr, L. A., & Huang, K. (2006). HAZUS-MH hurricane model methodology. I: Hurricane hazard, terrain, and wind load modeling. *Natural Hazards Review*, *7*(2), 82-93.

Vickery, P. J., Skerlj, P. F., Lin, J., Twisdale Jr, L. A., Young, M. A., & Lavelle, F. M. (2006). HAZUS-MH hurricane model methodology. II: Damage and loss estimation. *Natural Hazards Review*, *7*(2), 94-103.

Vugrin, E. D., Warren, D. E., Ehlen, M. A., & Camphouse, R. C. (2010). A framework for assessing the resilience of infrastructure and economic systems. In *Sustainable and resilient critical infrastructure systems* (pp. 77-116). Springer, Berlin, Heidelberg.

Vugrin, E. D., Warren, D. E., & Ehlen, M. A. (2011). A resilience assessment framework for infrastructure and economic systems: Quantitative and qualitative resilience analysis of petrochemical supply chains to a hurricane. *Process Safety Progress*, *30*(3), 280-290.

Vugrin, E. D., Turnquist, M. A., & Brown, N. J. (2014). Optimal recovery sequencing for enhanced resilience and service restoration in transportation networks. *International Journal of Critical Infrastructures*, *10*(3-4), 218-246.

Walker, B. H., Abel, N., Anderies, J. M., & Ryan, P. (2009). Resilience, adaptability, and transformability in the Goulburn-Broken Catchment, Australia. *Ecology and society*, *14*(1).

Wallace, W. A., Mendonça, D., Lee, E., Mitchell, J., & Chow, J. (2001). Managing disruptions to critical interdependent infrastructures in the context of the 2001 World Trade Center attack. *Impacts of and Human Response to the September 11, 2001 Disasters: What Research Tells Us*.

Wang, S., Hong, L., & Chen, X. (2012). Vulnerability analysis of interdependent infrastructure systems: A methodological framework. *Physica A: Statistical Mechanics and its applications*, *391*(11), 3323-3335.

Wikipedia (2018). Jamaica. Retrieved from: https://en.wikipedia.org/wiki/Jamaica. (Last access: 08/13/2018)

Wildavsky, A. B. (1988). *Searching for safety* (Vol. 10). Transaction publishers.

World Bank. 2013. *Building Resilience: Integrating Climate and Disaster Risk into Development*. Washington, DC. © World Bank. https://openknowledge.worldbank.org/handle/10986/16639 License: CC BY 3.0 IGO.

Xu, N., Nozick, L. K., Turnquist, M. A., & Jones, D. A. (2007, January). Optimizing investment for recovery in interdependent infrastructure. In *System Sciences, 2007. HICSS 2007. 40th Annual Hawaii International Conference on*(pp. 112-112). IEEE.

Zhou, H., Wang, J., Wan, J., and Jia, H. (2010). “Resilience to natural hazards: a geographic perspective.” *Natural Hazards*, 53(1), 21–41.

Zobel, C. W. (2011). Representing perceived tradeoffs in defining disaster resilience. *Decision Support Systems*, *50*(2), 394-403.

Zobel, C. W., & Khansa, L. (2014). Characterizing multi-event disaster resilience. Computers & Operations Research, 42, 83-94.

Zhang, C., Kong, J. J., & Simonovic, S. P. (2018a). Restoration resource allocation model for enhancing resilience of interdependent infrastructure systems. *Safety Science*, *102*, 169-177.

Zhang, C., Kong, J., & Simonovic, S. P. (2018b). Modeling joint restoration strategies for interdependent infrastructure systems. *PloS one*, *13*(4), e0195727.

Zhang, X., Mahadevan, S., Sankararaman, S., & Goebel, K. (2018). Resilience-based network design under uncertainty. *Reliability Engineering & System Safety*, *169*, 364-379.

Zhang, P., & Peeta, S. (2011a). A generalized modeling framework to analyze interdependencies among infrastructure systems. *Transportation Research Part B: Methodological*, *45*(3), 553-579.

Zhang, P., & Peeta, S. (2011b). Dynamic analysis of interdependent infrastructure systems. In *Proceedings of the 90th annual meeting of the transportation research board, Washington, DC (CD-ROM)*.

Zhang, W., & Wang, N. (2017). Bridge network maintenance prioritization under budget constraint. *Structural safety*, 67, 96-104.

Zhang, W., Wang, N., & Nicholson, C. (2017). Resilience-based post-disaster recovery strategies for road-bridge networks. *Structure and Infrastructure Engineering*, *13*(11), 1404-1413.

Zhang, W., Wang, N., Nicholson, C. D., & Tehrani, M. H. (2017). Stage-wised Resilience Planning for Transportation Networks. In *12th International Conference on Structural Safety & Reliability-ICOSSAR*.

Zhang, W., Wang, N., Nicholsonc, C., & Tehrani, M. H. (2018). A Stage-wise Decision Framework for Transportation Network Resilience Planning. *arXiv preprint arXiv:1808.03850*.