DISSERTATION

OPTIMIZING RESILIENCE DECISION-SUPPORT FOR NATURAL GAS NETWORKS UNDER UNCERTAINTY

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ABSTRACT

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Community resilience in the aftermath of a hazard requires the functionality of complex, interdependent infrastructure systems become operational in a timely manner to support social and economic institutions. In the context of risk management and community resilience, critical decisions should be made not only in the aftermath of a disaster in order to immediately respond to the destructive event and properly repair the damage, but preventive decisions should to be made in order to mitigate the adverse impacts of hazards prior to their occurrence. This involves significant uncertainty about the basic notion of the hazard itself, and usually involves mitigation strategies such as strengthening components or preparing required resources for post-event repairs. In essence, instances of risk management problems that encourage a framework for coupled decisions before and after events include modeling how to allocate resources before the disruptive event so as to maximize the efficiency for their distribution to repair in the aftermath of the event, and how to determine which network components require preventive investments in order to enhance their performance in case of an event. In this dissertation, a methodology is presented for optimal decision making for resilience assessment, seismic risk mitigation, and recovery of natural gas networks, taking into account their interdependency with some of the other systems within the community. In this regard, the natural gas and electric power networks of a virtual community were modeled with enough detail such that it enables assessment of natural gas network supply at the community level. The effect of the industrial makeup of a community on its natural gas recovery following an earthquake, as well as the effect of replacing conventional steel pipes with ductile HDPE pipelines as an effective mitigation strategy against seismic hazard are investigated. In addition, a multi-objective optimization framework that integrates probabilistic seismic risk

assessment of coupled infrastructure systems and evolutionary algorithms is proposed in order to determine cost-optimal decisions before and after a seismic event, with the objective of making the natural gas network recover more rapidly, and thus the community more resilient. Including bi-directional interdependencies between the natural gas and electric power network, strategic decisions are pursued regarding which distribution pipelines in the gas network should be retrofitted under budget constraints, with the objectives to minimizing the number of people without natural gas in the residential sector and business losses due to the lack of natural gas in non-residential sectors. Monte Carlo Simulation (MCS) is used in order to propagate uncertainties and Probabilistic Seismic Hazard Assessment (PSHA) is adopted in order to capture uncertainties in the seismic hazard with an approach to preserve spatial correlation. A non-dominated sorting genetic algorithm (NSGA-II) approach is utilized to solve the multi-objective optimization problem under study. The results prove the potential of the developed methodology to provide risk-informed decision support, while being able to deal with large-scale, interdependent complex infrastructure considering probabilistic seismic hazard scenarios.

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DEDICATION

To my beloved parents for their unconditional love, support and sacrifices

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CHAPTER 1: INTRODUCTION

Community resilience in the aftermath of a disaster is determined based upon the functionality of complex, interdependent infrastructure systems – physical, social, and economic. These infrastructure systems – including transportation, telecommunication, electric power, water, and natural gas can be quite vulnerable to natural hazards and their disruption can disturb the social welfare and economic vitality of a community. As an example, Gordon et al. (1998) estimated that in the 1994 Northridge earthquake in Los Angeles, approximately one-quarter of business disruption losses were due to the failure of highway bridges. Therefore, in order for a community to be resilient, interdependent lifelines should remain functional, or return to functionality rapidly after a disruptive event. When lifeline network functionality is threatened by a natural hazard, community resilience which can be defined as "the ability to prepare for and adapt to changing conditions and withstand and recover rapidly from disruptions" (PPD-21, 2013) is called into action (Guidotti et al., 2016). The word resilience is rooted from the Latin word "resiliere" which means "to bounce back". The concept of resilience has evolved and has been used in different disciplines such as ecology, material science, psychology, economics, and engineering. The concept of resilience in the engineering domain is quite new in comparison to other domains (Hosseini et al., 2016). Several researchers have provided definitions for resilience in the engineering domain. Youn et al. (2011) defined engineering resilience as the sum of the passive survival rate (reliability) and proactive survival rate (restoration) of the system. Hollnagel et al. (2006) described engineering resilience as the intrinsic ability of a system to adjust its functionality in the presence of a disturbance and unpredicted changes. The American Society of Mechanical Engineers (ASME, 2009) defined resilience as the ability of a system to sustain external and internal disruptions without discontinuity of performing the system's function, or if the function is discontinued, to fully and rapidly recover the function.

In terms of community resilience, Koliou et al. (2018) reviewed the previous studies focusing on the effects of natural hazards on the built environment as well as social and economic systems within a community. They also discussed research needs in order to improve resilience assessment methodologies at the community level. They stated that one example of these gaps is including dependencies and interdependencies between the networks and components of a community in order to develop a methodology for community resilience assessment that properly correlates physical, social, and economic systems. Rosowsky (2019) explored the definitions of resilience in the context of civil engineering systems subjected to natural hazards. He considered a range of issues one should consider in articulating resiliency requirements for infrastructures systems, such as prioritization, triage, sequencing, and the ability to make emergency supplemental investments. He also discussed many of these dimensions and how associated decisions have political, social and economic dimensions.

Bruneau et al. (2003) defined a four-dimensional framework for community resilience, which is known as the resilience triangle model. The four dimensions they consider in their definition include: (i) Robustness, which is defined as the strength of a system to withstand any disruptive event in order to prevent losing its functionality, (ii) rapidity, which shows the speed or rate at which a system can return to its original state in order to meet an acceptable level of functionality, (iii) resourcefulness, which represents the ability to recognize and manage material (i.e., physical, technological, and information) and human resources in a case of emergency or disaster, in order to achieve predefined goals, and (iv) redundancy, which represents the extent of substitutable components or systems that can be used in the case of a disaster in order to minimize the likelihood and impact of disruptions.

Chang and Shinozuka (2004) proposed resilience measures that relate expected losses in future disasters to a community's seismic performance objectives. They used the four dimensions of community resilience previously proposed by Bruneau et al. (2003), which consists of technical, organizational, social, and economic dimensions. They demonstrated their proposed measurement framework by evaluating seismic resilience of the water delivery system in Memphis, Tennessee, comparing two retrofit strategies. They state that their resilience framework can be valuable for guiding mitigation and preparedness efforts. Miles and Chang (2003, 2004 and 2006) provided a conceptual model for disaster recovery in order to study community resilience. The basic notion of the model is based upon imperative relationships between a community's households, businesses, infrastructures, as well as its neighborhoods. They proposed five primary interrelated factors affecting recovery: (1) time, (2) space, (3) agents attributes, (4) interactions, and (5) policy. In this concept, spatial effects represent the importance of the topology of community components; meanwhile temporal effects illustrated the changes in the condition of a system during time. For example, households and businesses can be influenced by availability of water, power, natural gas, transportation, and local employment opportunities, which can have different conditions (i.e. performance/functionality) at different locations of the community during various timeframes. On the other hand, one example for the agent-attribute effects is the type of demand for businesses. The local transportation conditions and the recovery of households in neighborhoods are variables that can affect businesses with local demands, but they do not have a significant influence on businesses that export their products. Interaction effects represent the dependencies, cross-dependencies, and interdependencies across community components and networks. For example, the pumping stations in the water supply systems require electricity in order to be functional; or any disruption in the transportation system can delay repair of damaged components in, for example, the natural gas network. Households affect businesses in that not only do they provide employees for businesses but they are also consumers of their products. On the other hand, businesses affect households as they satisfy the households' demands. Finally, policy effects originate from the organizational decisions such as mitigation strategies and emergency planning before the event or restoration and resource prioritization in the aftermath of the disaster.

In terms of the infrastructure resilience, the National Infrastructure Advisory Council (PPD-21, 2013) defined the resilience of infrastructure systems as their ability to predict, absorb, adapt, and/or quickly recover from disruptive events such as natural disasters. It is noteworthy that infrastructure systems are considered a subdomain of both engineering and social domains as their lack of resilience can result in adverse impacts on well-being of communities (Hosseini et al., 2016). Moreover, infrastructure systems can have a significant influence on the economy of communities (Percoco, 2004). Since infrastructure functionality has a crucial role on social welfare and economic vitality of communities, a lot of research has recently focused on infrastructure systems' resilience. Shafieezadeh and Ivey Burden (2014) proposed a probabilistic framework for scenario-based resilience assessment of infrastructure systems. The developed method accounts for uncertainties in the process including the correlation of earthquake intensity measures, fragility assessment of structural components, estimation of repair requirements, the repair process, as well as the service demands. They applied the proposed methodology to a hypothetical seaport terminal and evaluated the system level performance of the seaport using various performance metrics. The results showed that medium to large seismic events may significantly disrupt the operation of seaports immediately after the event and that the recovery process may take months. They state that their proposed framework enables port stakeholders to systematically assess the most-likely performance of the system during expected future earthquake events. Guidotti et al. (2019) proposed probabilistic flow-based models for estimating the capacity and demand of critical infrastructure considering different levels of resolution. The model set in a probabilistic procedure that considered the impact of the disruptive event on the infrastructure. The procedure was capable of predicting the reduction or loss of functionality of the infrastructure in terms of their ability to provide essential goods or services. Physical infrastructure and social systems were integrated in the models in order to predict the change in demand on the infrastructure. The proposed methodology was applied to the modeling of the portable water network for the small coastal community of Seaside, Oregon considering a seismic event as scenario. The results showed that neglecting the interdependency between the physical infrastructure and social systems may result in estimates of higher demands on the physical systems, slower recovery time, as well as smaller impacts on society in terms of population dislocation.

Furthermore, interdependencies play a substantial role in the performance of infrastructure, and thus the resilience of communities. During normal situations, these interdependencies can be beneficial and help networks operate near their optimized design capacity (Applied Technology Council, 2016; Guidotti et al., 2016; Nan and Sansavini, 2015; Ouyang et al., 2015). In the case of a disaster, however, interdependencies can have a substantial contribution to cascading effects and taking them into account can substantially alter the recovery process. Therefore, it is crucial to study the resilience of lifeline systems within a community including their interdependencies. An emerging body of research on functionality assessment and restoration modeling of interdependent infrastructure is ongoing. Dueñas-Osorio et al. (2007) presented the topological characterization of two interdependent small-sized real networks and investigated the effect of the degree of coupling between networks with a tunable parameter that drove networks from independence to complete interdependence. The results showed that detrimental responses are larger when interdependencies are included in the analyses. Zhang et al. (2016) examined the vulnerability of an interdependent power-water network system by taking into account the effect of cascading failures as well as the resulting load redistribution through the power network. They introduced a critical tolerance threshold in order to control the cascading failures in the power system and its propagation into the water network. Guidotti et al. (2016) modeled the direct effects of seismic events on response and functionality of a potable water distribution network and simulated the cascading effects of the damage to the electric power network on the potable water distribution network. The results quantified the loss of functionality and the delay in the recovery process due to dependency of the potable water network on the electric power network and emphasized the importance of considering dependencies between different networks in modeling the resilience of critical infrastructure. Dong and Frangopol (2017) studied an interdependent healthcare-bridge network subjected to seismic hazard considering the effects of extra travel and waiting time along with the structural damage to the hospitals and bridges. Argyroudis et al. (2015) examined the influence of interdependencies on performance of road networks for case of a seismic hazard. The interdependencies were modeled both through the network components in addition to other external networks. It was shown that interdependencies can substantially affect the performance of a road network, specifically at the urban level where building collapse has a significant impact on network functionality. Masoomi and van de Lindt (2018) modeled a water network, electric power network, school buildings, residential buildings, and businesses along with their relative spatial distribution and system interdependencies and investigated the restoration of a community in the aftermath of a tornado.

Resilience studies of natural gas distribution networks have been primarily focused on the performance evaluation and vulnerability assessment of natural gas pipelines in the case of seismic hazards (see e.g. Choo et al., 2007; Jeon and O'Rourke, 2005; Lanzano et al., 2014; Lanzano et al., 2013; O'Rourke et al., 2014; Omidvar and Kivi, 2016; Xie et al., 2013; Psyrras and Sextos, 2018; Tsinidis et al., 2019; Badida et al., 2019). A number of researchers have also focused on studying qualitative and quantitative methodologies for risk assessment of natural gas distribution networks (see e.g. Esposito et al., 2015; Han and Weng, 2011; Liu et al., 2018; Markowski and Mannan, 2009; Cimellaro et al. 2014; Praks et al., 2017; Urlainis et al., 2015; Yuhua and Datao, 2005; Zulfikar et al., 2016). Some researchers have also studied the interconnected natural gas network and electric power network systems. Ouyang and Wang (2015) developed a resilience assessment framework for interdependent systems with the focus on modeling and resilience contribution analysis of multi-systems' joint restoration processes. As an illustrative example, the methodology was used for evaluating the resilience of the interdependent power and gas systems in Houston, Texas under hurricane hazards, using five different types of joint restoration strategies. The results revealed that under limited restoration resources, a gas-aimed restoration strategy is the best for the gas system recovery. Chiang and Zavala (2016) developed a detailed optimal control model that captured spatiotemporal interactions between natural gas and electric transmission networks. They used the model to study flexibility and economic opportunities provided by coordination and applied the methodology to a large-scale case study in the Illinois system to show the coordination can enable the delivery of significantly larger amounts of natural gas to the power grid. Liu et al. (2017) proposed a framework that combined dynamic modeling and resilience analysis of interconnected critical infrastructure. Thy performed a resilience analysis on two interconnected critical infrastructures, a gas network and an electric power system, using numerical calculation of the resilience conditions in terms of design, operation, and control parameters values for certain failure scenarios. They state the results can be valuable to inform the decision making process of critical infrastructures operators and other stakeholders. Portante et al. (2017) proposes a framework for interdependency modeling in order to evaluate cascading failures within critical infrastructure systems. The framework permitted the integration and automation of the assessment process, including threat and hazard identification and data acquisition, as well as estimation and projection of the impact zones. The model was also capable of simulating the initial effects on infrastructure assets resulting from an initiating disruptive event and evaluation of propagating effects within each infrastructure system. Two state-level case studies were used in order to illustrate the approach in simulating the propagation of disruptions between the natural gas and electric power systems.

It should be noted, however, most of the natural gas network research has been dedicated to region-wide performance of natural gas networks and the system performance at the community level is seldom studied. Moreover, the bi-directional interdependency between natural gas and electric power network systems has been rarely studied. Modeling the natural gas network at the community level and considering interdependencies in resilience assessment of natural gas networks is important for risk-informed decision making is needed. Furthermore, decision making relating to preparedness and recovery has a crucial impact on maintaining safety, social wellbeing, and economic vitality of a community in the aftermath of a disaster. Thus, an optimal decision-making framework that quantifies the effect of different mitigation and recovery strategies needs to be developed in order to enhance the resilience of the communities after disasters.

OVERVIEW OF DISSERTATION

In this dissertation, a comprehensive approach is presented for optimal decision making for resilience assessment, seismic risk mitigation, and recovery of natural gas networks, taking into account their interdependency with other systems in the community. In this regard, the natural gas and electric power networks of a virtual community known as Centerville (Ellingwood et al., 2016) were modeled with enough detail such that it enables resilience assessment of natural gas network at the community level. Moreover, probabilistic seismic hazard assessment is considered in this dissertation, as it is crucial in capturing uncertainties in decision-making processes. A brief overview of the remaining chapters of this dissertation is summarized below:

Chapter 2 describes modeling natural gas networks and their components at the community level. It discusses fragility and restoration curves as well as repair rate equations that are developed based on available empirical data and expert judgment. In order to represent the performance of network components under seismic hazards, the fragility curves and repair rate equations are extracted from literature.

Chapter 3 discusses the interdependency approach for natural gas network and other systems. Modeling the interdependency between natural gas network and other systems as well as how disruption in one network can result in failures in the other are discussed. In order to consider the effect of cascading failures, a bi-directional dependence has been considered between the natural gas and electric power network in this dissertation.

Chapter 4 presents modeling of the earthquake hazard. Simulating spatial damage over the community when subjected to a seismic hazard is discussed to be employed further in the restoration analysis explained in the next chapter. In this dissertation, earthquake simulations are done using two different approaches: scenario-based and hazard-based. For scenario-based simulations, earthquake hazards are being generated using a well-known attenuation model for the considered scenarios. For hazard-based simulations, two earthquakes with return periods of 475 years and 2475 years are considered using probabilistic seismic hazard assessment, which is done based on the active faults existing around the community and the possible earthquakes they can generate. In both cases, the effects of liquefaction are also included.

Chapter 5 introduces a community restoration algorithm in order to model the recovery process of the affected natural gas network. The algorithm is capable of representing spatial and temporal depiction of the restoration process until the full restoration is achieved. The algorithm also captures dependencies and interdependencies across components and networks and includes the effect of cascading failures in the restoration analysis such that a component remains non-functional until all its supplier nodes are fully recovered and functional, even if the component itself is undamaged or has been already repaired. Mitigation strategies and optimized resource allocation processes are also discussed in this chapter in order to evaluate the effect of those strategies on pace of recovery in natural gas networks.

Chapter 6 represents the illustrative community model used in this dissertation. Indeed, to illustrate the methodology proposed, a virtual community known as Centerville is subjected to the considered earthquakes (both scenario- and hazard-based), in order to examine the restoration of communities in the aftermath of an earthquake. This chapter discusses the topology and structure of the natural gas as well as electric power networks and describes the bi-directional dependence considered across the networks. It should be noted that although only natural gas network and electric power network are considered in this dissertation, other critical infrastructure systems such as transportation, telecommunication, water, and emergency services can be modeled and integrated into the current model in future studies.

Chapter 7 introduces a platform for optimal decision making, resilience assessment, seismic risk mitigation, and recovery of natural gas networks, taking into account their interdependencies with other systems. An algorithm is developed in order to find the best locations for replacing the main steel distribution pipelines with earthquake-resistant HDPE pipelines under limited budgets. Focusing on residential and business sectors in the community as two main sectors affecting the social stability area, decisions can be made on what pipelines should be retrofitted in order to improve the speed of network recovery and achieve the preliminary goals of the community.

Finally, the overall summary and the conclusions, the anticipated contribution to the profession, as well as recommendations for future research studies are provided in Chapter 8 of this dissertation.

CHAPTER 2: COMPONENT MODELS FOR NATURAL GAS NETWORKS

Natural gas is a vital component and is a major source of the energy supply in worldwide. Natural gas has many applications, including in commercial applications, in residential sectors, in industry, and even in the transportation sector. According to the U.S. Energy Information Administration (EIA, 2017) energy form natural gas accounts for 29 percent of the total energy consumed in the United States, making it a key component of the nation's energy supply. Figure 2-1 shows the natural gas consumption by sector in the United States in 2017.

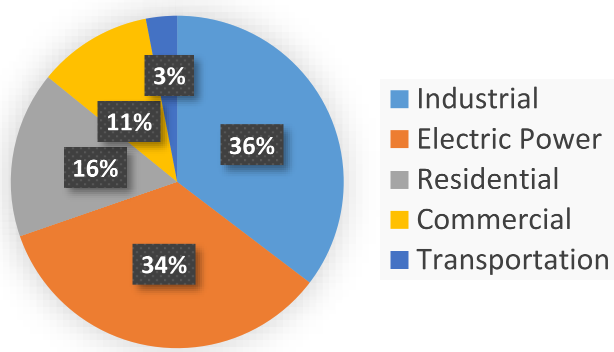

Figure 2-1: U.S. Natural Gas Consumption by Sector (source: EIA, 2017)

Like other lifelines, natural gas networks (NGN) are susceptible to physical damage during earthquakes. Indeed, seismic events have highlighted the vulnerability of NGNs and the consequences of NGNs' loss of functionality on community resilience (Esposito et al., 2013). Specifically, recent earthquakes have caused a lot of damage to NGNs. As an example, the 1971 San Fernando earthquake resulted in extensive damage to welded-steel transmission pipes. The 1923 Kanto Japan earthquake also caused over four thousand breaks to gas pipelines in the Tokyo region (Esposito et al., 2013). In addition to pipelines, damage to other aboveground facilities in NGNs have also been observed. Besides the lifeline disruption due to the physical damage, there are other possible consequences such as pollution of the waterways or onset of fires and explosion. The explosion subsequent to the 1971 San Fernando earthquake, which caused crater-like depressions in the streets, is a good example. Therefore, it is important to conduct accurate vulnerability assessment of NGN components in order to design communities that are more resilient.

Network Overview and Definitions of Components

A natural gas system consists of two main categories of components: 1) nodal elements (e.g. natural gas processing plants and city gate stations), and 2) link elements i.e. pipelines that connect the nodal components together. The main components of the NGN include the following:

1) Natural Gas Processing Plant (NGPP): These facilities serve as a critical component in natural gas networks and their disruption can significantly interrupt the whole network's functionality. The natural gas that is brought up from the underground to the wellhead contains hydrocarbons, carbon dioxide, hydrogen sulfide, and water together with many other impurities (Poe and Mokhatab, 2016). On the other hand, major transportation pipelines usually impose restrictions on the quality and make-up of the natural gas that is allowed into the pipelines. Therefore, the raw natural gas from wellhead must be processed in a safe way and with minimal environmental effect before it can be moved into the transmission pipelines. Although some of the required processing can be accomplished at or near the wellhead (field processing), the complete processing of natural gas is done at a processing plant that is usually located in a natural gas producing region. The objective of a NGPP is to separate natural gas, associated hydrocarbon liquids, acid gases, and water from a gas-producing well and condition these fluids for sale or disposal (Poe and Mokhatab, 2016). After the liquid components and impurities are removed from the natural

gas, the natural gas can be injected into transmission and distribution systems in order to be used as fuel by residential, commercial and industrial consumers (Kidnay et al., 2011). Figure 2-2 shows a typical NGPP. It should be noted that processing plants may be different sizes and can be significantly different in their feed and product.

Figure 2-2: Natural Gas Processing Plant (source: https://www.bicmagazine.com)

2) Compressor Stations (CS): Natural gas needs to be highly pressurized while travelling through the transmission network. In order to make sure that natural gas maintains its high pressure so it can be transported from transmission pipelines to distribution systems, there are compressor stations usually located every 60 to 160 km (40- to 100-miles) along the pipelines, which supply the gas with necessary amount of pressure to keep it flowing over long distances through the network (Folga, 2007). These stations compress the natural gas using either a turbine, motor, or an engine. In addition to compressing natural gas, some compressor stations contain some type of liquid separator and filters similar to the ones

used to dehydrate natural gas during its pressing in order to capture any liquids or undesirable particles from the natural gas in the pipeline (Folga, 2007). These facilities usually include one or more compressor units, auxiliary equipment for secondary functions such as power generation or cooling of discharge gas, as well as a Supervisory Control And Data Acquisition (SCADA) system (Pitilakis et al., 2014). A typical compressor station houses the gas turbine compressor package as well as the instrumentation controls and equipment required to monitor and operate the engines and compressors in a low-rise building that are can be made from steel or reinforced concrete. These stations are usually enclosed by a chain-link fence and most have some type of additional security equipment such as cameras and motion sensors (Folga, 2007). Figures 2-3 and 2-4 show photos of the exterior and interior of a NGN compressor station.

Figure 2-3: Exterior View of a Natural Gas Compressor Station (source: https://www.entecheng.com)

Figure 2-4: Interior View of a Natural Gas Compressor Station (source: http://go.jereh.com)

3) City Gate Stations (CG): These stations are the connection points between the high-pressure transmission and medium/low-pressure distribution networks in a natural gas system, and are sometimes called town border or tap stations (Folga, 2007). The main function of the city gate stations is to meter the natural gas and reduce its pressure in the transmission pipeline to the distribution system. Moreover, natural gas received at the city gate may not contain odorant (the compound that gives the natural gas its specific smell). Before the gas leaves the city gate station, odorant is added to the gas if it contains insufficient or no odorant (Folga, 2007). These stations are usually cased in one-story buildings which house regulators and mechanical equipment for gas pre-heating, gas odorizing, and control through a SCADA system (Pitilakis et al., 2014). Figure 2-5 shows a typical city gate station.

Figure 2-5: Natural Gas City Gate Station (source: https://www.fiorentini.com)

4) District Regulating Stations (DR): These are local stations in the distribution networks that are used to control the pressure of the gas flowing through the distribution pipelines. They have a pressure reduction facility in order to set the gas pressure to the required level for end users. These stations are usually buried or housed in a metallic kiosk (Esposito et al., 2015). Figure 2-6 shows a district regulating station.

Figure 2-6: Natural Gas Processing Plant (source: https://www.tecnogas.es)

In general, natural gas pipelines can be divided into three main groups based on the level of pressure they operate at:

1) Supra-regional transmission pipelines: these pipelines operate at extremely high pressures and have large diameters (usually up to 120 cm (48 inches) in diameter). These pipelines can cover large areas.
2) Regional transmission/distribution pipelines: these pipelines also operate at higher pressure levels and are mainly used to connect the transmission networks to distribution systems.
3) Local distribution pipelines: these are smaller pipelines that usually operate in the medium- to low-pressure ranges through the distribution networks.

For pipelines, the material and connection types are determining factors in performance of the pipelines, since they govern the behavior and the potential failure modes of buried pipelines in an earthquake. Reports from the American Lifeline Alliance (ALA, 2001) and HAZUS-MH (FEMA, 2003) describe some of the most common types of materials and connections used in buried pipelines. It is noteworthy that, pipelines that are specifically designed for natural gas networks are usually made of relatively ductile materials such as steel (K Pitilakis et al., 2014). Another particular type of material is polyethylene (medium or high density, i.e. MDPE or HDPE), which is used in newer networks due to its high ductility.

Components Damage Models

In order to capture damage that occurs to natural gas network components, fragility curves can be used. A seismic fragility describes the performance of a component or a system subjected to earthquakes in probabilistic terms, and can be defined as a mathematical function that expresses the probability that a facility or a component exceeds some previously defined limit state, as a function of a certain intensity measure such as peak ground acceleration (Porter, 2015). Fragility models are used in order to estimate the risk of earthquake excitation acting on the components of different lifeline systems such as natural gas networks. The fragility of a structural component or system is usually expressed in the form of a lognormal cumulative distribution function (CDF) as shown in Equation (2-1):

$$F_r(x) = \Phi\left[\frac{\ln(x) - \lambda}{\xi}\right] \qquad (2-1)$$

where x = specified intensity measure (e.g. PGA or SA); $\Phi[*]$ = standard normal cumulative distribution function; λ = logarithmic median of the capacity; and ξ = logarithmic standard deviation of the capacity. Fragility functions are obtained either by structural modeling of the seismic performance of components and systems (known as analytical approach; e.g. Ellingwood, 2001; Singhal and Kiremidjian, 2002; Shinozuka et al., 2002; Noh et al., 2015), or using statistical analysis of failures observed during past earthquakes (known as the empirical approach; e.g. O'Rourke and So, 2000; Gardoni et al., 2002; Basoz et al., 2003; Straub and Der Kiureghian, 2008; Noh et al., 2015). In the analytical method, simulations include an analytical model of the structure subject to a set of ground motions having varying intensities. This process is known as incremental dynamic analysis (for more information on this see Vamvatsikos and Allin Cornell, 2002). Using the selected ground motion intensity in each simulation, the corresponding structural response/damage of the structure is recorded and used for fragility development. In the empirical method, the observed damage to the individual structure is recorded in addition to the intensity measure in case a ground motion instrument is present near that structure. However, as it is unlikely that there will be a strong ground motion instrument near the structure, usually the ground motion is estimated using ground motion prediction models or from a ground motion map such as the ShakeMaps produced by the USGS. It should be noted that, another class of fragility functions are known as expert opinion or judgment-based fragilities. An expert opinion fragility function is created by polling one or more experts in the field with the asset class in question, where the experts judge or predict failure probability as a function of environmental excitation (Porter, 2015). Examples of judgement-based fragilities can be found in Applied Technology Council (ATC, 1985).

For aboveground facilities (e.g. compressor stations and city gate stations), seismic fragility curves are usually based upon peak ground acceleration (PGA) and are often developed based upon available empirical data as well as expert judgment. These facilities may lose their functionality due to the failure of various components in these facilities, which include (K Pitilakis et al., 2014):

- Building: the collapse of the structure of the facility that covers the equipment may disrupt the functionality of the equipment;
- Electrical/Mechanical components: damage to these miscellaneous components can also result in non-functionality, especially if these components are unanchored;
- Electric power supply: lack of external power due to the electric power network disruption or the disconnection of the power lines and the facility building can also result in the facility become non-functional.

Various sources in the literature represent fragility curves for the aboveground components (ALA, 2001; Berahman and Behnamfar, 2007; FEMA, 2003; O'Rourke and So, 2000; Iervolino et al., 2004). Note that if the damage to the facility is addressed by simply considering the seismic vulnerability of the building that shelters the equipment, then the corresponding fragility curves of that building can be used in order to represent the vulnerability of the whole facility. However, if the aim is to include the mechanical and electrical component behavior in the vulnerability assessment procedure, then overall fragility curves which represent the system fragility should be utilized in order to capture the vulnerability of the facility. The overall fragility curves are usually generated using a fault-tree analysis considering redundancies and subcomponent behavior (FEMA, 2003). In such case, Boolean logic is implicitly used within the procedure of defining each particular damage state. For example, a minor damage to a compressor station - which can result in short-time malfunction of the facility, may be represented by either the loss of electrical power or a slight damage to the building that shelters the equipment.

Like many other underground components, buried pipelines are very sensitive to permanent ground deformation (resulting from different types of ground failure, i.e. lateral spreading, liquefaction and landslide) in addition to transient ground deformation (resulting from seismic wave propagation). There is abundant literature on fragility relationships for buried pipelines. The fragilities for these components may be represented based on different intensity measures such as PGA (Chen et al., 2002; Hamada, 1991; Isoyama et al., 2000), PGV (Maison et al., 1995; Maruyama and Yamazaki, 2010; O'Rourke and Ayala, 1993; O'Rourke and Jeon, 1999; O'Rourke et al., 2012; Pineda-Porras and Ordaz-Schroeder, 2004), PGD (Eidinger and Avila, 1999; O'Rourke et al., 2012; ALA, 2001). Some researchers have also represented the fragility for buried pipelines in terms MMI (macroseismic intensity) or PGS (peak ground strain) (Chen et al., 2002; O'Rourke and Deyoe, 2004; O'Rourke and Jeon, 1999). Nonetheless, representing fragility curves for buried pipelines as equations based on peak ground displacement (PGD) and peak ground velocity (PGV) are the most common (ALA, 2001; FEMA, 2003). These equations are referred to as *RR* equations. In essence, these semi-empirical equations represent the number of repairs per unit length of the pipeline. The equations are usually developed according to the number of repairs recorded by field crews (e.g. ALA, 2001; O'Rourke and Ayala, 1993) and do not clearly demonstrate all possible failure modes for buried pipelines subjected to ground deformations. The probability of having n repairs in a pipe segment with length L can be evaluated using a Poisson probability distribution as in Equation (2-2):

$$P(N = n) = \frac{[(RR)(L)]^n}{n!} e^{-(RR)(L)} \qquad (2-2)$$

However, it should be noted that the main source of damage to buried pipelines is usually the permanent ground deformation, as proved by previous earthquakes (K Pitilakis et al., 2014). During the 1971 San Fernando earthquake, the steel pipelines withstood significant ground shaking, but suffered severe damage due to abrupt vertical and lateral dislocation as a result of lateral spreading (EERI, 1986; O'Rourke, 1988). In the 1906 San Francisco earthquake, lateral spreading accounted for only around 5% of the built-up area affected by the earthquake; meanwhile, approximately 50% of the damage occurred to the pipelines within one block of these zones, which shows the high impact of ground failure on pipeline damage (O'Rourke and Liu, 1999). In the 1964 Niigata earthquake, liquefaction resulted in substantial damage to pipelines, where the average failure ratio for one of the pipeline systems was as high as 0.97 per km with all kinds of failure types such as pipe body breaks, weld breaks, and joint separation (K Pitilakis et al., 2014).

The pipelines used in natural gas network are usually continuous pipelines like welded-steel pipes. These pipelines typically fail due to compressive strain that induces buckling of the pipe body, or warping and wrinkling of the pipe wall (ALA, 2001; K Pitilakis et al., 2014). Moreover, pipeline damage in the natural gas network are categorized as either leakages or breaks, with different *RR* equations. If ground failure is the primary reason for damage to the pipeline, it is reasonable to assume that the proportions of leaks and breaks are 0.2 and 0.8, respectively; in the meantime, if the major cause of damage is ground shaking, leaks and breaks proportions will be 0.8 and 0.2, respectively. Moreover, for each network component, HAZUS-MH also provides restoration curves that provide the conditional probability of restoration for a certain initial damage at a given time after failure, which is also adopted in this dissertation.

CHAPTER 3: APPROACHES FOR MODELLING INTERDEPENDENCE

As previously mentioned, interdependencies can have a substantial contribution in cascading failures in the case of a disaster, and it is crucial to study the resilience of lifeline systems within a community including their interdependencies. A number of studies have utilized different approaches in order to model interdependency within the community. Rinaldi et al. (2001) defined four main classes of interdependencies between infrastructures, including physical, cyber, geographic, and logical. In this context, a physical interdependency arises from a physical linkage between the networks and two infrastructure systems are considered physically interdependent if the state of functionality in one network is dependent on the material output(s) of the other. For cyber interdependency, an infrastructure has a cyber interdependency if its functionality is dependent on the information transmitted from another infrastructure. A geographic interdependence occurs when elements of multiple infrastructures are in close spatial proximity such that a local environmental event can result in change of functionality status for all of the infrastructures. Finally, two infrastructures are logically interdependent if the state of each network depends on the state of the other system via a mechanism that is not classified as physical, cyber, or geographic. As an example, human decisions and interventions play an important role in logical interdependencies.

Researchers have used the physical definition of interdependency in order to study the response of interconnected networks. Dueñas-Osorio et al. (2007b) investigated the effect of seismic disruptions on the performance of physically interdependent networks. Several degrees of interconnectedness were explored and interdependent network fragility curves were introduced in order to display the effect of different strengths of coupling. Based on the results, mitigation actions were proposed and propagation of their effects were studied. Robert and Morabito (2008) presented a set of tools in terms of consequence curves and flexible cartographic representations that enabled the management of physical interdependencies among critical infrastructures. Based on the resources exchanged through the interdependent networks, these tools allowed the visualization of the evolution of domino effects in time and space, giving the infrastructure managers the potential to set up convenient preventive and protective measures in order to avoid their propagation. Poljanšek et al. (2012) developed a probabilistic reliability model in order to generate network fragility curves of spatially distributed interconnected network systems subjected to natural hazards. The developed methodology was applied to the interconnected European gas and electricity transmission networks such that the gas-fired power plants formed the physical connections between the two networks. Modeling the physical interdependencies, the propagation of failures in gas networks were identified using fragility curves and the effect of gas network failures on electricity network were captured. Wang et al. (2012) also developed a framework for vulnerability analysis of interdependent infrastructure systems. Considering the physical interdependency between the networks, the methodology was applied to the power and water systems of a major city in China and the results were used for ranking critical components for protection purposes. Using the available restoration curves from the 2011 Tohoku Earthquake in Japan, Cimellaro et al. (2014) proposed a method for calculation of regional resilience considering different degrees of physical interdependency between the infrastructures. Kong and Simonovic (2019) developed a methodology for multiple hazard spatiotemporal resilience assessment of infrastructure systems considering the physical interdependencies. They applied the methodology on a simplified two-layer interdependent infrastructure network as a case study, showing the physical interdependence among infrastructures further magnifies the impact on resilience value.

On the other hand, some researchers have studied geographical, cyber, and logical interdependence between the infrastructure systems (e.g. Amin, 2010; Healy and Palepu, 2003; Johansson and Hassel, 2010; Ramachandran et al., 2015). Although the classification used by Rinaldi et al. (2001) provides a basic foundation for modeling infrastructure interdependencies, the clear way of modeling interdependencies between the infrastructures is not discussed in their study, and the authors emphasize the need for further research on developing explicit ways to model interdependencies.

Several researchers have developed different approaches that are potentially capable of explicitly modeling interdependencies between the infrastructures. Ouyang (2014) classified these explicit approaches into six categories: empirical approaches, agent-based approaches, system dynamics based approaches, economic theory based approaches, network-based approaches, and other approaches. These are briefly explained below.

EMPIRICAL APPROACHES

In empirical approaches, the critical infrastructure systems' interdependencies are analyzed according to historical accident or disaster data and expert experience. Empirical approaches provide the opportunity to identify significant and frequent failure patterns (e.g. Chou and Tseng, 2010; McDaniels et al., 2007), quantify interdependency strength metrics to inform decision makers (e.g. Zio and Sansavini, 2011), and perform empirically based risk analyses (e.g. Utne et al., 2011).

AGENT-BASED APPROACHES

In agent-based approaches, it is assumed that the complex behavior of interdependent infrastructures emerge from many individual and relatively simple interactions of autonomous agents (Kaegi et al., 2009). In this context, most critical infrastructures' components can be considered as agents, and each agent interacts with other agents and its environment based upon a set of rules that mimics the way a real counterpart of the same type would respond. Agent-based approaches have been widely used in order to model the interdependencies between infrastructures (e.g. Barton et al., 2004; Basu et al., 1998; North, 2001), and are capable of modeling behaviors of decision-makers, capturing all types of interdependencies, providing scenario-based what-if analysis, and can also be integrated with other modeling techniques in order to provide more comprehensive analysis (Ouyang, 2014).

SYSTEM DYNAMICS BASED APPROACHES

System dynamics-based approaches take a top-down method in order to analyze and model complex interdependent infrastructures. The key concepts that are used in these approaches are feedback, stock and flow. Feedback loops represent the connections between infrastructure components, including the direction of interdependencies. Stocks show different states of the system, and flow rates control the levels of these states over time. Using a causal-loop diagram that captures the causal influence among different variables, and a stock-and-flow diagram that describes the flow of information through the system, system dynamic approaches are capable of modeling the interdependencies between critical infrastructures (Brown et al., 2004; Stapelberg, 2008).

ECONOMIC THEORY BASED APPROACHES

Economic theory-based approaches generally work based on interactions between households and producers. Households provide labor and capital to producers in exchange for income. The producers, on the other hand, provide the households with goods and services by the use of not only that labor and capital, but also other types of materials and services. Generally, two types of economic theories exist in the literature that can be utilized in order to model interdependencies between critical infrastructures: the input-output (I-O) model and the computable general equilibrium (CGE) model. The I-O models represent the interdependencies between different sectors of a national economy or different regional economies (Dietzenbacher and Lahr, 2004). The fist I-O model was proposed by Leontief (1986), which was a static and linear model. Since then various researchers have developed more complicated I-O models (e.g. Haimes et al., 2005; Haimes and Jiang, 2001). CGE models are an extension of the I-O models and inherit the main features of I-O models, including the consideration of interdependencies between economic sectors, while they overcome most of their limitations, such as linear interdependencies among sectors, lack of consumers' and producers' behavioral responses to markets and prices subject to labor, as well as resource and capital constraints (Rose, 1995 and 2004; Ouyang, 2014). Extending the capacities of the I-O models, CGE models have been used by researchers in order to model interdependencies between infrastructures (e.g. Zhang and Peeta, 2011).

NETWORK-BASED APPROACHES

Interdependent critical infrastructures can also be modeled as networks, where components of the networks can be represented as nodes, and the physical and relational connections between these nodes can be represented by links. Network-based approaches model each infrastructure by networks and then describe the interdependencies between these networks by inter-links, providing intuitive representations along with detailed descriptions of their topologies and flow patterns if desired. Network-based approaches also provide the opportunity to evaluate response of critical infrastructures under different hazards by modeling the component failures at component level first, and then simulating the cascading failures within and across the infrastructures at system level. Depending on whether the modeling procedure includes particle flow of the infrastructures, network-based approaches can be broadly divided into topology-based and flow-based methods.

Topology-based methods

In order to investigate the performance of interdependent critical infrastructures under natural hazards, topology-based simulation methods can be used. A topology-based model, which has also been adopted in this dissertation, defines the interdependencies between the infrastructures based upon their topologies, with discrete states of functionality for each component (i.e. nodes and links), and generally with considering two states: functional or failed. Failure of a component might happen directly due to the failure of the component itself, or indirectly due to the failure of other components in the network that result in disconnections from its source nodes.

In this methodology, a number of different metrics can be defined in order to evaluate the performance of the networks, such as the number of normal or failed components (e.g. Johansson and Hassel, 2010), the inverse characteristic path length (e.g. Ouyang et al., 2009), the connectivity loss (e.g. Dueñas-Osorio et al., 2007a), as well as the redundancy ratio and cluster related metrics (e.g. Dueñas-Osorio et al., 2007b). Furthermore, by incorporating the level of service provided to the customers and system-level performance, some other metrics can be defined such as lost service hours (e.g. Johansson and Hassel, 2010) or the fraction of customers affected (e.g. Poljanšek et al., 2012). The topology-based methods mainly capture topological features of the interdependent infrastructures and can be used to provide suggestions on robustness improvements from the topological perspective.

Flow-based methods

The key difference between topology- and flow-based methods is that in flow-based methods, the flow and the amount of services provided by the critical infrastructures is also taken into account. In this context, some capacities are defined for each component in the networks that should be produced, loaded and delivered to the end users. Flow-based models capture the flow characteristics of interdependent infrastructures, and are capable of providing realistic descriptions on their operation mechanisms. This type of methods can also identify critical infrastructures' components and provide emergency protection provisions against natural hazards.

INTERDEPENDENCE APPROACH FOR NGN AND OTHER SYSTEMS

As the world struggles to find new sources of energy, natural gas plays a key role in the foreseeable future. Natural gas is used in different sectors – including residential, commercial, industrial, and electrical power sectors. The residential sector uses natural gas for heating buildings, heating water, cooking, and also for drying clothes. The commercial sector uses natural gas to heat buildings, heat water, operate refrigeration and cooling equipment, dry clothes and provide outdoor lighting. The industrial sector uses natural gas as a fuel for process heating as well as for combined heat and power systems, and as a raw material to produce different products. Finally, the electric power sector uses natural gas to generate electricity.

In particular, both natural gas and electric power networks show strong interdependency which is well recognized (Portante et al., 2017). For example, EPNs with gas-fired power plants need natural gas to produce electricity. An interruption or pressure loss in gas network systems may lead to a loss of multiple gas-fired electric generators, which can substantially decrease the supplied power and endanger the power system security (Shahidehpour et al., 2005). EIA's January 2018 Short-Term Energy Outlook (STEO) estimates that natural gas will remain the primary source of electricity generation in the United States, for at least the next two years, and it is likely that the use of natural gas as a fuel source for electricity will continue to grow (https://www.eia.gov). On the other hand, electricity is essential for natural gas processing plants and sometimes for other stations such as electric-driven compressor stations. Interruption of electric service to such facilities can have significant negative safety and financial consequences observable long after the electric power network has recovered (EAC, 2011).

It is worth mentioning that, the issues related to interdependencies between natural gas and electric power networks are not only limited to those described above, but these interdependencies can also have a negative impact on the economic and social systems within a community. For example, in severe weather situations, the natural gas and electricity demands may reach the highest point together, which in turn, can result in a spike in energy prices. In such situations, gas price hikes can push up the marginal cost of gas-fired generating units, which would directly transform into higher market prices for electricity (Shahidehpour et al., 2005). For example, in the 2000-2001 winter, gas and electricity markets in California reached their capacity limits simultaneously, and the result was a dramatic increase in energy costs (Pope, 2002).

Therefore, it is important to consider the interactions between the natural gas and electric power networks in restoration modeling and recovery of a community in the aftermath of a disaster. On the other hand, natural gas has a crucial role in maintaining continued occupancy as a disruption in the natural gas network may disturb the functionality of residential, commercial, and industrial sectors, and consequently result in population dislocation and outmigration, especially during cold weather.

Modeling the interdependencies between different networks can be accomplished via an adjacency matrix $\boldsymbol{A}$. As described in Wallace et al. (2003), a general network system k may be defined by $n^{(k)}$ nodes and $m^{(k)}$ links connecting the nodes, while the links are considered to be bidirectional (i.e. not pointing in a specific direction). In the case of K interdependent systems, each network can be represented as a symmetric $n^{(k)} \times n^{(k)}$ adjacency matrix, namely $A^{(k)} =$

$\left[a_{ij}^{(k)}\right]$, $(i,j \in k;\ i,j = 1, \dots, n^{(k)})$, where $a_{ij}^{(k)}$ is equal to 1 if there is a link (element) between nodes i and j, and is 0 otherwise. The K adjacency matrices representing each network can then be placed along the main diagonal of $\boldsymbol{A}$, and the off-diagonal matrices are used to represent connections between the nodes of different networks. For instance, considering two network systems p and q, the $n^{(p)} \times n^{(q)}$ matrix $A^{(p,q)} = \left[a_{ij}^{(p,q)}\right]$ represents the connections between the nodes of the two networks, where $a_{ij}^{(p,q)}$ is equal to 1 if there is a link between node i of network p and node j of network q, and is 0 otherwise. The adjacency matrix $\boldsymbol{A}$ can be represented as follows:

$$A = \begin{bmatrix} A^{(1)} & \cdots & A^{(1,p)} & A^{(1,q)} & \cdots & A^{(1,K)} \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ A^{(p,1)} & \cdots & A^{(p)} & A^{(p,q)} & \cdots & A^{(p,K)} \\ A^{(q,1)} & \cdots & A^{(q,p)} & A^{(q)} & \cdots & A^{(q,K)} \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ A^{(K,1)} & \cdots & A^{(K,p)} & A^{(K,q)} & \cdots & A^{(K)} \end{bmatrix} \qquad (3-1)$$

In essence, in the connectivity matrix $\boldsymbol{A}$, if $a_{ij}^{(k)} = 1$, then a failure of node i in the network results in a certain failure of node j, assuming that there is no redundancy in the network and that is the only connection between the nodes. It should be noted that, however, the dependency between two nodes in a network may not be mutual (Guidotti et al., 2016).

CHAPTER 4: MODELLING EARTHQUAKE HAZARD

Earthquakes are one of the most devastating disasters and can result in considerable loss of life and damage to property. As an example, the 1906 San Francisco earthquake caused more than 3,000 deaths and left 225,000 people homeless (USGS, n.d.). In general, earthquakes were responsible for 1.87 million deaths in the twentieth century and resulted in an average of 2,052 fatalities per event between 1990 and 2010 (Doocy et al., 2013; Wisner et al., 2003). Events such as the 1994 Northridge and 1995 Kobe earthquakes are reminders that losses to a community are not limited to the immediate aftermath of an earthquake only. In fact, socioeconomic losses accumulate over, as the recovery process gets longer and more complex (Miles and Chang, 2006). On the other hand, despite the sustained efforts on "earthquake prediction", which can be defined as issuing a science-based alarm of an imminent damaging earthquake with enough accuracy and reliability in order to justify measures such as evacuations, there is still no scientifically plausible way to predict the occurrence of earthquakes (Mulargia et al., 2017).

Two commonly used approaches for seismic hazard analysis include deterministic and probabilistic methods (Gupta, 2007). Both approaches are commonly used in the field and one has different advantages over another, but the question of what method should be used in a particular situation depends on the basic notion of the problem to be solved. In particular, factors affecting this choice include the decision to be made (i.e. the goal of the hazard and risk assessment), seismic environment (i.e. seismicity level of the location), and the purpose of the assessment (i.e. whether one is evaluating the risk at a site, a multi-site, or a region) (McGuire, 2001).

In the deterministic approach, different intensity measures are estimated for a specific considered earthquake scenario (Krinitzsky, 2002). An earthquake scenario can be a representative of a potential future earthquake by assuming a particular magnitude, location, and fault-rupture geometry. The shaking maps from that earthquake scenario can be estimated using ground motion prediction models. The deterministic approach can be used for generating realistic earthquakes that are considered likely to happen, or are a desirable measure to use in design and analysis of infrastructure. Further, these can be used to conduct training exercises, and can be used by local government, utility companies and other organizations for disaster preparation and emergency response planning. The USGS Earthquake Hazards Program has a product known as ShakeMap that provides near-real-time maps of ground motion and shaking intensity following significant earthquakes, and can also be used as a tool for scenario-based earthquake modeling. Although convenient and easy to model, deterministic approaches might not be able to provide a realistic picture of seismic hazard at a specific site, as there is a great deal of uncertainty about the location, magnitude, and resulting shaking intensity of future earthquakes.

Probabilistic seismic hazard assessment (PSHA) aims to account for the uncertainties in the occurrence and intensity of future earthquakes, essentially their location and magnitude, and combines these uncertainties in order to produce an explicit description of the distribution of future possible earthquakes that may occur at a specific site (Baker, 2008). The concept of PSHA was first introduced by (Cornell, 1968). Since then, various researchers have used the methodology proposed by Cornell (1968) as a basis to develop more advanced models for PSHA (e.g. Abrahamson, 2000; Akkar et al., 2018; Baker, 2005; Delavaud et al., 2012; Jayaram and Baker, 2010; Jibson et al., 2000; Lapajne et al., 2003; Refice and Capolongo, 2002; Shahi and Baker, 2011; Stein et al., 2003; Tothoug and Cornell, 2007; Visini et al., 2019). While performing a PSHA may add some complexity to the seismic hazard assessment procedure due to incorporation of uncertainties into the calculations, the results will be much more reliable especially in engineering decision-making applications (Baker, 2008).

FORMULATION OF PSHA

The PSHA considers all possible earthquake events and resulting ground motions, in addition to their associated probabilities of occurrence. The final output of a PSHA is a full distribution of levels of ground motion intensities along with their associated rates of exceedance. These results can later be used to identify a ground motion intensity having a certain probability of exceedance. The steps for performing a PSHA at its most basic level are explained in the following subsections (Baker, 2008).

Identifying seismic sources

The first step in performing a PSHA is to identify all earthquake sources capable of producing damaging ground motions. In contrast to the deterministic approach, in PSHA the interest is in all earthquake sources capable of producing ground motions. Ideally, the sources are faults, which are typically planar surfaces identified using various means such as by observations of past earthquake locations and geological evidence. However, if individual faults are not identifiable due to lack of knowledge about all the faults, then earthquake sources may be represented as areas that encompass several faults and are associated with a specific geological structure such as uplifts, rifts, folds, or volcanos that localize the seismic activity within that area. On the other hand, if there is no information on either active faults or geological structures (this may happen in less seismically active areas), then another type of seismic source referred to as “tectonic province” can be used in practical applications (Gupta, 2007). In this case, the area can be represented as a large geographic area of diffused seismicity with no identifiable active faults or geological structures, and earthquakes can occur anywhere within the considered area.

Seismicity sources in a region are usually identified based upon geological, geophysical, geodetic and seismotectonic data (Gupta, 2007). Nonetheless, if the available data is not adequate in most cases, expert knowledge and judgment will play an important role in identifying seismic sources for the region of interest. Once all possible sources of seismicity are identified for the region, one can identify the distribution of magnitudes and source-to-site distances associated with potential earthquakes from each source.

Characterizing the distribution of magnitudes

After the source of damaging earthquakes are identified, the next step is to identify the distribution of magnitudes for the potential earthquakes (i.e. the rates at which earthquakes with various magnitudes are expected to occur). Different seismic sources are capable of producing earthquakes with various magnitudes. The annual rate of occurrence for these earthquakes can be defined using recurrence relationships. Gutenberg and Richter (1944) first studied the magnitudes of earthquakes and noted that in general the number of earthquakes in a region greater than a given size follows a particular distribution as shown in Equation (4-1):

$$\log_{10} \lambda_m = a - bm \qquad (4-1)$$

where a and b are constants and λ_m represents the rate of earthquakes with magnitudes greater than m. In this formulation, constant a represents the overall rate of the earthquakes in a region, and constant b indicates the relative ration of small and large magnitudes. These constants can be estimated using statistical analysis of historical observations, with additional constraining data provided by other types of geological evidence (Hainzl et al., 2006; Baker, 2008).

Equation (4-1) can be used in order to compute the cumulative distribution function (CDF) for magnitudes of earthquakes that are larger than a minimum magnitude m_{min}. The minimum magnitude is used as a condition as earthquakes with magnitudes smaller than m_{min} may not have any engineering importance (Baker, 2008). By defining $\beta = b \ln(10)$, the cumulative distribution function for magnitudes can be written as:

$$F_M(m) = p(M \leq m \mid M > m_{min}) = 1 - 10^{-b(m-m_{min})} \qquad (4-2)$$

In practice, it is necessary to consider an upper limit on earthquake magnitudes, m_{max}, due to the finite size of the source faults. If a maximum magnitude is determined, then equation (4-2) can be rewritten as follows:

$$F_M(m) = p(M \leq m \mid m_{min} < M < m_{max}) = \frac{1 - 10^{-b(m-m_{min})}}{1 - 10^{-b(m_{max}-m_{min})}} \qquad (4-3)$$

In PSHA equations, the continuous distribution of magnitudes can be converted into a discrete set of magnitudes. Later, the former equation should be used in order to calculate the probabilities of occurrence for different magnitudes, as follows:

$$P(M = m_j) = F_M(m_{j+1}) - F_M(m_j) \qquad (4-4)$$

where m_j shows the discrete set of magnitudes, ordered in the way $m_j < m_{j+1}$. So long as the discrete magnitudes are finely spaces, the approximation will be accurate enough (Baker, 2008). It should be noted that, other alternative recurrence relationships exist in the literature that may be used instead of Gutenberg-Richter model (e.g. Burroughs and Tebbens, 2002; Kagan, 1991, 2002b, 2002a; Kijko, 2004; Lomnitz-Adler and Lomnitz, 1979; Main, 1996; Main and Burton, 1984; Merz and Cornell, 1973; Schwartz and Coppersmith, 1984; Youngs and Coppersmith, 1985). Some of these models have a faster decay for larger magnitudes and propose that some faults have repeated occurrences of a characteristic earthquake with a reasonably consistent magnitude (Gupta, 2007; Baker, 2008). This characteristic magnitude occurs more often than predicted by the Gutenberg-Richter model (Baker, 2008).

Characterizing the distribution of source-to-site distances

The PSHA also accounts for the differing probabilities of observing earthquakes at different locations. For this purpose, after the sources and corresponding earthquake magnitudes are determined, the distribution of source-to-site distances should be identified. It is usually assumed that earthquakes can occur with equal probability at any location within the earthquake source. Based on this assumption, the distribution of source-to-site distances can be identified using only the geometry of the sources. It is important to mention that there are different definitions of distance that are commonly used in PSHA (e.g. distance to epicenter or hypocenter, distance to the closet point on the rupture surface, distance to the closest point on the surface projection of the rupture, etc.). Although some of the distance definitions consider the distance from the surface projection of the rupture only, some definitions account for the depth of the rupture. The choice of distance definition will depend upon the required input to the ground motion prediction model. For example, in some models, it is required to assume ruptures occur over a plane rather than at a single point in space, and the definitions should account for the depth of the rupture (e.g. Campbell and Bozorgnia, 2014).

Predicting the resulting distribution of ground motion intensity

The next step involves using ground motion prediction models in order to predict the resulting distribution of desired ground motion intensity as a function of many parameters such as earthquake magnitude, distance, faulting mechanism, the near-surface site soil conditions, the potential presence of directivity effects, and so on. These prediction models are developed mainly by statistical regression analysis of thousands of observed ground motion intensities from dozens of previous earthquakes. For example, Campbell and Bozorgnia (2014) used 11,125 records from 245 earthquakes of $3.0 \leq M < 5.5$ and 4,396 records from 77 earthquakes of $5.5 \leq M < 7.9$, as a subset of the PEER NGA-West2 database (Ancheta et al., 2013 and 2014) updated to include earthquakes that occurred through 2011. Figure 4-1 shows the distribution of the recordings with respect to moment magnitude and rupture distance.

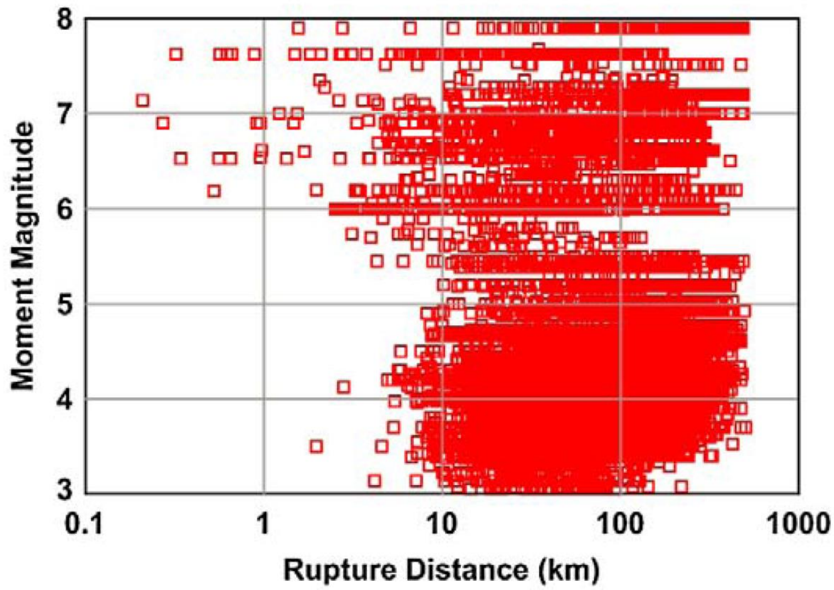

Figure 4-1: Distribution of recordings of the NGA-West2 database with respect to moment magnitude and rupture distance (excerpted from Campbell and Bozorgnia (2014))

As shown in Figure 4-1, there is- significant scatter in observed ground motions, and therefore, the ground motion prediction models need to provide a probability distribution for intensities rather than simply identifying a single intensity. This is important as PSHA calculations need to account for the possibility of unlikely events including those with extreme intensities much larger than the predicted mean values (Baker, 2008; Bommer and Abrahamson, 2006). In order to describe this probability distribution, ground motion prediction models take a general form as shown in Equation (4-5):

$$\ln IM = \overline{\ln IM}\,(M, R, \theta) + \sigma(M, R, \theta)\,.\,\varepsilon \qquad (4-5)$$

where $\ln IM$ shows the natural logarithm of the desired ground motion intensity measure, which is modeled as a random variable with a normal distribution, and $\overline{\ln IM}\,(M, R, \theta)$ and $\sigma(M, R, \theta)$ are the mean and standard deviation of $\ln IM$, respectively. These terms are functions of earthquake magnitude (M), distance (R), and other parameters referred to as θ. Moreover, ε is a normal random variable that captures the variability in $\ln IM$. Campbell and Bozorgnia (2014) proposed the following predictive model for the natural logarithm of PGA, PGV, and PSA:

$$\ln Y = \begin{cases} \ln PGA; & PSA < PGA \; and \; T < 0.25 \; sec \\ f_{mag} + f_{dis} + f_{flt} + f_{hng} + f_{site} + f_{sed} + f_{hyp} + f_{dip} + f_{atn}; & otherwise \end{cases} \quad (4-6)$$

where Y is the IM of interest and the f-term represent the scaling of ground motion with respect to earthquake magnitude, geometric attenuation, style of faulting, hanging wall geometry, shallow site response, basin response, hypocentral depth, fault dip, and anelastic attenuation, respectively (Campbell and Bozorgnia, 2014). The reader is referred to Campbell and Bozorgnia (2013) for detailed explanations of the abovementioned terms used in Equation (4-6).

The probability of exceeding any IM level can be estimated using the standard normal cumulative distribution function, as follows:

$$P(IM > x \mid m, r) = \int_{x}^{\infty} f_{IM}(t) dt \quad (4-7)$$

where $f_{IM}(t)$ is the probability density function of PGA, given m and r. The next step will be to combine all the information from previous steps in order to find the full distribution of levels of ground motion intensities along with their associated rates of exceedance.

Combining uncertainties using the total probability theorem

The final step in performing a PSHA is to combine all the uncertainties associated with the earthquake size, location, and ground motion intensity, using a calculation known as the total probability theorem. Having the probability distributions for distance and magnitude and assuming that the magnitudes and distances of events are independent, equation (4-7) can be written as:

$$P(IM > x) = \int_{m_{min}}^{m_{max}} \int_{0}^{r_{max}} P(IM > x \mid m, r) \, f_M(m) \, f_R(r) \, dr \, dm \quad (4-8)$$

where $P(IM > x \mid m, r)$ is calculated from the ground motion prediction model, $f_M(m)$ and $f_R(r)$ are the probability distribution functions for magnitude and distance. Equation (4-8) represents the probability of exceedance given an earthquake happens and does not include any information about how often earthquakes occur based on the considered sources. In order to calculate the rate of exceedance (instead of probability of exceedance), Equation (4-8) can be written as follows:

$$\lambda(IM > x) = \lambda(M > m_{min}) \int_{m_{min}}^{m_{max}} \int_{0}^{r_{max}} P(IM > x \mid m, r)\, f_M(m)\, f_R(r)\, dr\, dm \qquad (4-9)$$

where $\lambda(M > m_{min})$ shows the rate of occurrence of earthquakes bigger than m_{min}, and shows the rate of $IM > x$. Acknowledging the fact all seismic sources contribute to the rate of $IM > x$, Equation (4-9) will look like as follows:

$$\lambda(IM > x) = \sum_{i=1}^{n_{sources}} \lambda(M_i > m_{min}) \int_{m_{min}}^{m_{max}} \int_{0}^{r_{max}} P(IM > x \mid m, r)\, f_{M_i}(m)\, f_{R_i}(r)\, dr\, dm \qquad (4-10)$$

where $n_{sources}$ shows the number of sources included in hazard analysis, and M_i and R_i represent the magnitude and distance distributions of source i. In practice, the distributions of magnitude and distance are discretized Equation (4-10) can be rewritten as follows:

$$\lambda(IM > x) = \sum_{i=1}^{n_{sources}} \lambda(M_i > m_{min}) \sum_{j=1}^{n_M} \sum_{k=1}^{n_R} P(IM > x \mid m_j, r_k)\, P(M_i = m_j)\, P(R_i = r_k) \qquad (4-11)$$

where n_M and n_R show the range of possible M_i and R_i, respectively. The abovementioned equation is the most common formulation used in PSHA and integrates the knowledge about occurrence rates of earthquakes, possible magnitudes and source-to-site distances from those earthquakes, as well as distribution of ground shaking intensity due to the possible earthquakes.

The result can be represented as a graph known as a hazard curve, which represents the rate of exceeding different IM levels at a certain site. Figure 4-2 represents the hazard curve in Los Angeles downtown, for an earthquake with 10% probability of exceedance in 50 years (Return Period = 475 years), which is generated using the USGS Unified Hazard Tool (USGS, 2017). The results derived from a PSHA can be useful for engineering decision-making purposes.

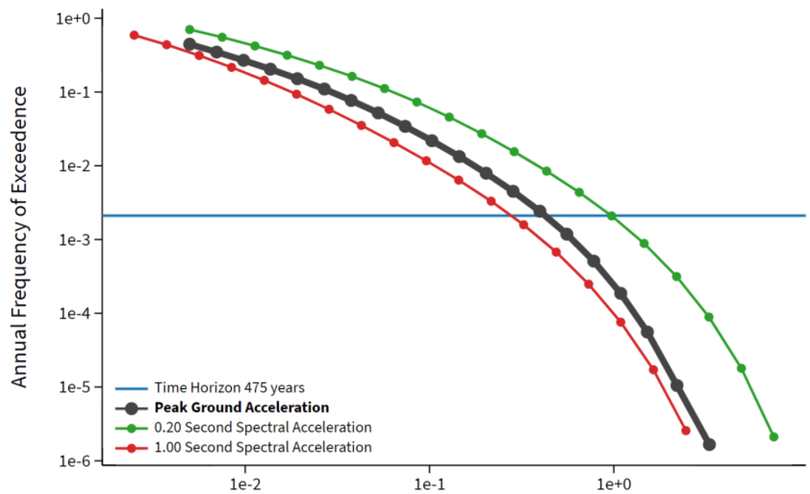

Figure 4-2: Hazard curve for Los Angeles downtown (generated by Unified Hazard Tool)

PSHA DEAGGREGATION

Despite the advantage PSHA provides by accounting for all possible earthquake sources in an area when computing seismic hazards, the contribution of each earthquake scenario in the hazard is not immediately obvious after all scenarios are aggregated together in the PSHA calculations. Perhaps the bigger issue is that the spatial correlations of the intensities over a community or region are lost since hazard intensity collects contributions from different sources. Nonetheless, the question of which earthquake scenario is most likely to result in exceedance of a prescribed level of earthquake ground shaking at a site can be answered through a process known as deaggregation (Baker, 2008; Bazzurro and Cornell, 1999). Deaggregation of seismic hazard helps to understand the contribution of different possible earthquakes to the hazard at a point location, by partitioning the earthquake sources into bins of distance and magnitude. The conditional joint distribution of magnitudes and distances can be found using the following equation:

$$P(M = m, R = r \mid IM > x) = \frac{\lambda(IM > x, M = m, R = r)}{\lambda(IM > x)} \qquad (4-12)$$

The numerator of the above equation can be computed using the basic PSHA equation but not summing over the magnitude or distance, as follows:

$$\lambda(IM > x, M = m, R = r) = \sum_{i=1}^{n_{sources}} \lambda(M_i > m_{min})\, P(IM > x \mid m_j, r_k)\, (M_i = m)\, P(R_i = r) \qquad (4-13)$$

An example of this conditional distribution of M and R given $IM > x$ is shown in Figure 4-3, for an earthquake with 10% probability of exceedance in 50 years (Return Period = 475 years) in Los Angeles downtown, which was generated using the USGS Unified Hazard Tool (USGS, 2017).

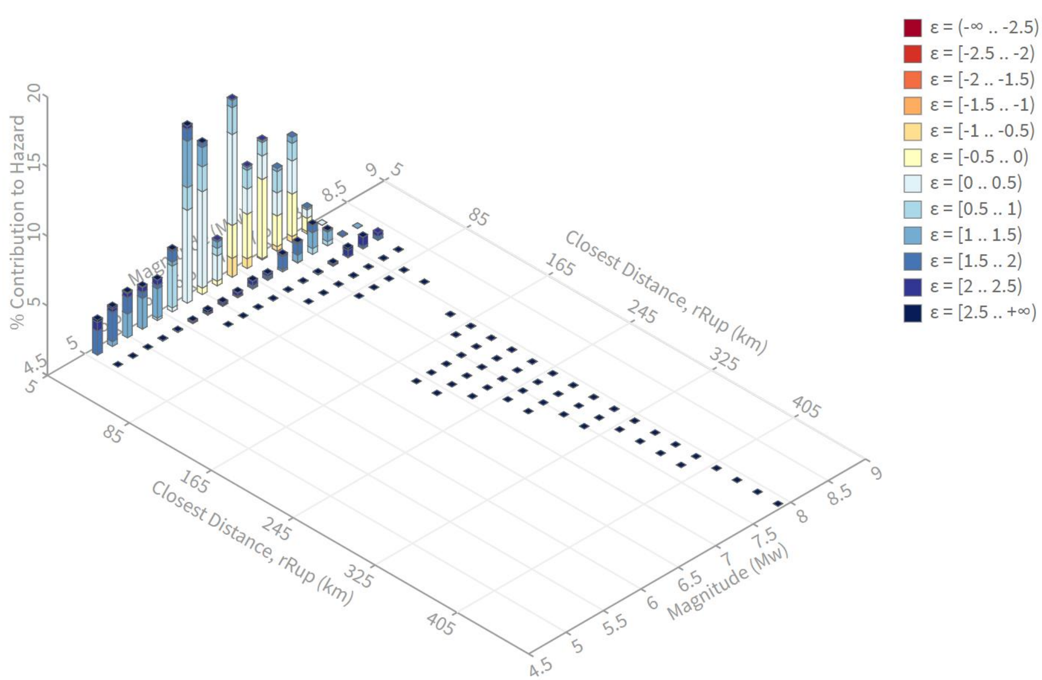

Figure 4-3: PSHA deaggregation for Los Angeles downtown (generated by Unified Hazard Tool)

The seismic hazard deaggregation is an essential part of many PSHA analyses and deaggregation results should be provided as part of the output from any PSHA calculations (Baker, 2008).

CAUSE OF DAMAGE TO NATURAL GAS COMPONENTS

Damage to the natural gas components from earthquakes occur due to either 1) ground shaking associated with traveling seismic waves, or 2) large permanent ground deformations. The former is often referred to as transient ground deformation (TGD), while the latter is generally known as permanent ground deformation (PGD). It should be noted that permanent ground deformations are usually the result of liquefaction, landslides or surface fault ruptures. The relative influence of different earthquake-induced PGDs on a natural gas network system may depend on different soil features such as morphologic, geological, and geotechnical conditions of the subsoil (Esposito et al., 2015). In general, fault displacement can be evaluated through semi-empirical equations that correlate displacement with earthquake magnitude (e.g. Petersen et al., 2011). Meanwhile, for liquefaction and landslide, the ground displacement can be estimated by using models that relate the ground displacement to a certain ground motion intensity measure. The approach of HAZUS-MH can be utilized for the purpose of risk assessment of large networked systems such as natural gas networks, as this methodology requires limited information about the geotechnical characterization of the region. In that methodology, the first stage for evaluating liquefaction hazard is to determine the liquefaction susceptibility, and then calculate the probability of liquefaction (i.e. the likelihood that the earthquake will initiate the phenomenon). Eventually, given that liquefaction occurs at certain locations, the amount of PGD (i.e., displacement) is calculated using predictive graphs. Similarly, the calculation of downslope displacement starts by first evaluating the landslide vulnerability, which is related to the morphologic and groundwater conditions of the area, in addition to the geologic source and the strength characteristics of soils. These factors contribute to the determination of the critical acceleration (which is known as k_c), which is defined as the minimum shaking intensity needed to overcome the slide resistance of the slope.

CHAPTER 5: RESTORATION ANALYSIS

Rapid recovery and restoration is a vital element of community resilience. Communities are composed of complex systems and highly coupled networks, and therefore, failure of one network or any of its key components can result in malfunction of other systems and loss of functionality of all or parts of the community. For example, the Rhode Island gas outage of 2019 resulted in a potentially dangerous loss of pressure caused by a supplier's faulty valve in a single natural gas pipeline, and left thousands of people without heat resulting in school closures (U.S. News, 2019). The Northeast blackout of 2003 that started from a single point source also affected approximately 50 million people in both U.S. and Canada (Farmer and Allen, 2006). These examples highlight that in addition to the direct losses such as injuries, fatalities, and property damage, indirect losses that are indeed the consequence of cascading failures need to be accurately addressed in community resilience assessment, as they play an important role in economic vitality and the social well-being of people. Various researchers have studied the damage to infrastructure systems and cascading failures resulting from damage in the aftermath of disasters (e.g. Argyroudis et al., 2015; Dong and Frangopol, 2017; Fang and Zio, 2019; Heracleous et al., 2017; Javanbakht and Mohagheghi, 2014; Shafieezadeh et al., 2014; Wu et al., 2016; Zanini et al., 2017; Zhang et al., 2016). Nonetheless, the duration of these failures within the community is of significant importance on the amount of indirect losses and can be quantified by modeling the restoration analysis of the community (Masoomi and van de Lindt, 2018a).

Restoration analysis in community resilience has received significant attention because of its critical role, but it is perhaps the least understood part of the recovery process for a community. Various researchers have modeled the post-disaster recovery of different infrastructure systems in order to estimate the expected restoration time for systems (e.g. Francis and Bekera, 2014; Guikema et al., 2014; Liu et al., 2007; Nateghi et al., 2011; Shinozuka et al., 2003). Some researchers have also compared different restoration strategies (e.g. Buzna et al., 2007; Çağnan et al., 2006). Ouyang et al. (2012) evaluated the performance of an electric power network under hurricane hazards and investigated the effect of the number of recovery resource units on the restoration process. Çagnan et al. (2004) categorized lifeline restoration models into two theoretical approaches known as Markov processes and network models, as well as two empirical approaches called statistical curve fitting and deterministic resource constraint. Moreover, they proposed a simulation-based model for post-disaster restoration process and called it the discrete event simulation (DES) method, which was built based upon past studies yet overcame some of their limitations. The method is capable of considering rules, constraints, and decisions from utility companies for restoration process including recovery prioritization plans, mutual aid agreements, as well as number of available repair crews and materials. The method also captures uncertainties associated with the parameters such as inspection time, repair time, and amount of available resources by defining these parameters as random variables with specific probability distributions. Cagnan and Davidson (2007) used the DES method to simulate the post-earthquake restoration process for Los Angeles Department of Water and Power (LADWP) electric power system and simulated the restoration curve for the Northridge earthquake. Çağnan et al. (2006) used the DES approach and investigated several restoration improvement strategies to improve the seismic resilience of the LADWP electric power system. Tabucchi et al. (2010) also used the DES approach to the water supply system of LADWP in order to simulate the restoration curve and spatial distribution of the restoration in the aftermath of Northridge earthquake. D'Uffizi et al. (2015) used the DES as decision support for planning different strategies of action to apply in emergency and risk situations due to man-made threats and natural hazards. Huling and Miles (2015) used the DES for modeling home reconstruction in the aftermath of disasters and stated that the DES is a novel approach that can be utilized to support pre- and post-disaster decision making for improved community disaster resilience.

The recovery pace of a network system is a function of different parameters such as the recovery strategy and the amount and prioritization of resource allocation (Guidotti et al., 2016; Jia et al., 2017; Sharma et al., 2017). In order to evaluate the system functionality and recovery after the occurrence of an earthquake, a reliability approach should be used that includes both hazard modeling and physical and functional models of the damaged network system (Ameri and van de Lindt, 2018b). Moreover, the possibility of multiple component failures and the cascading effects due to different internal and external network dependencies and interdependencies should be taken into account for understanding the functionality assessment of a damaged network. In this dissertation, the DES approach is combined with network-based approach and is applied to a virtual community known as Centerville (Ellingwood et al., 2016). The methodology used enables considering the effect of cascading failures in the analysis such that if a component has no damage due to the disruptive event or is already physically repaired, it remains non-functional until all its supplier nodes are recovered and back to functionality. Furthermore, the methodology allows taking into account dependencies and interdependencies, as well as priorities for repair among networks and network components using evolutionary algorithm optimization techniques.

METHODOLOGY AND PROCEDURE

The methodology proposed herein combines the methods previously described with damage, functionality, and recovery models. Specifically a damage model refers to the simulation of physical damage to network components and a network functionality model represents an analysis used to investigate the damage impact on the network. Finally, a recovery model refers to the restoration process of the damaged network. The methodology is also capable of modeling network dependencies and interdependencies. Figure 5-1 depicts the flowchart of the methodology.

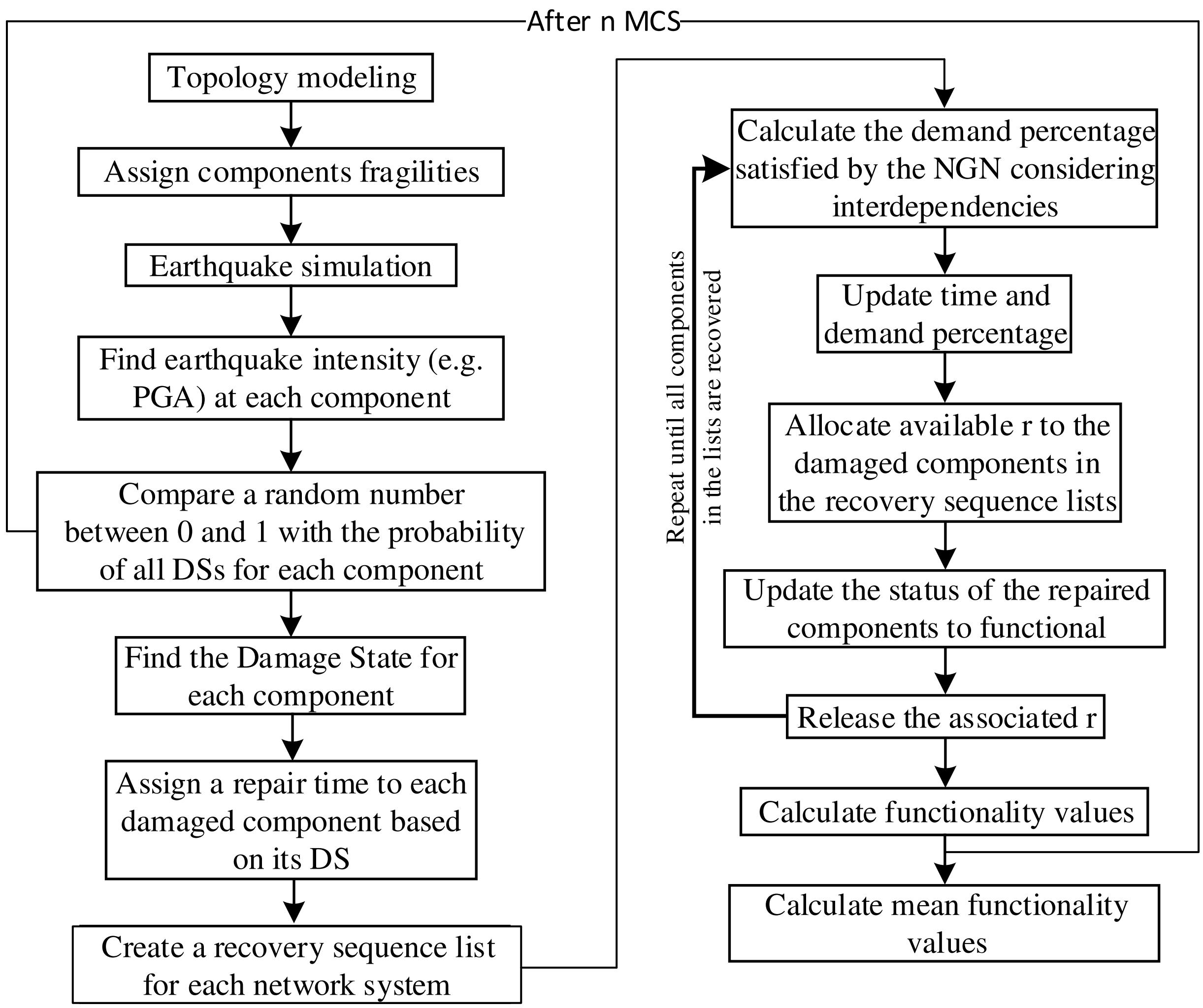

Figure 5-1: Flowchart for calculating functionality fragility and restoration process

The entire process can be summarized in six steps as follows:

1) Network modeling: The first step in resilience assessment of network systems is to model different networks components, including their internal and external dependencies and

interdependencies throughout the networks. This is worth-mentioning that different levels of resolution may be considered for modeling the networks based on the scale of interest and desired computational complexity.

2) Hazard modeling: The second step of the procedure is to create the hazard model with spatial variations in intensity for different components of the networks. Seismic hazard ground motion prediction models can be used for generating desired spatial maps of intensity measures. These include maps of peak ground acceleration (PGA), peak ground velocity (PGV), and peak ground displacement (PGD).

3) Direct damage assessment: Once the community topology and hazard are defined, the next step is to measure the physical damage that occurs to networks' components. This is evaluated probabilistically through fragility curves and *RR* equations for nodal and link elements, respectively. Fragility curves represent the conditional probability of exceeding a predetermined performance level for a given level of hazard intensity measure (e.g. Ditlevsen and Bjerager, 1986; Gardoni et al., 2003; Masoomi et al., 2017; Masoomi et al., 2018; Memari et al., 2017). *RR* equations, on the other hand, represent the expected number of leakage and breaks per unit length of the pipe, for a given hazard intensity measure (e.g. ALA, 2001; O'Rourke and Ayala, 1993; O'Rourke and Deyoe, 2004; Pitilakis et al., 2014).

4) Indirect damage assessment: In order to determine the damage states for each network system as a whole, the cascading effects due to internal dependencies of the network components as well as the interdependencies between different networks should be

included in the process. This step determines the damage status of the networks' components by including both the direct damage (from the previous step), in addition to the cascading effects due to dependencies and interdependencies.

5) Functionality assessment: In this step, natural gas network functionality is evaluated in the immediate aftermath of the earthquake. Functionality assessment of an NGN can be carried out at two different levels: a) connectivity-based analysis, and b) flow-based analysis. The former method concentrates on finding paths connecting source nodes to supplier nodes, and allows the serviceability assessment in terms of, for instance, the number of supplier nodes that remain accessible from at least one supply node after the occurrence of an earthquake. The flow-based method focuses on the network's capacity and considers extra constraints/factors in the serviceability evaluation; e.g., the minimum gas pressure at each supplier node.

6) Restoration analysis: The time duration that component failures remain within the community can have a dramatic effect on indirect losses, and can be estimated by performing a community restoration analysis. After determining the functionality status of the network following the seismic event, the next step is to evaluate the level of functionality at each time step t after the earthquake. The recovery time of a certain component in the network is a function of both its recovery time and that of the supporting elements through different networks. For each time step t, the method implemented herein updates the functionality status of the elements in the network based on the initial damage state and corresponding restoration functions. It should be noted that in the literature, there

are different examples of restoration functions that are either postulated (e.g. Bocchini et al., 2012; Titi et al., 2015), or obtained based on more fundamental recovery activities (Sharma et al., 2017).

In the restoration analysis in this dissertation, it is assumed that the recovery process of all networks are started immediately after the disaster occurs and simultaneously. This simultaneous assumption is felt to be logical as each network has its own crews for inspection, assessment, and repair.

MITIGATION STRATEGIES

Mitigation refers to measures that can be taken in order to minimize the destructive and disruptive effects of hazards, and thus reduce loss of life and property and lessen the impact of hazards in general. It includes some advance measures taken in order to avoid, decrease, or eliminate the risk that natural or man-made hazards impose to human lives and property. Mitigation strategies can be of different types, ranging from structural measures such as retrofitting the infrastructure components that are vulnerable to disasters, to non-structural measures such as developing and implementing education and outreach programs to increase public awareness. Although mitigation most often refers to actions against potential disasters before they happen, mitigation activities can take place at any time before the disaster, during an emergency, or after the disaster and during recovery and reconstruction (Maskrey, 1989).

The structural measures are important as immediate injury and damage results from the physical infrastructure systems failure (Godschalk, 2003). Structural measures focus on protecting people, property, and the environment from disruptive events in a number of different ways. Examples of structural measures include identifying hazards and risks in order to perform smart urban growth by directing new developments away from hazardous areas, retrofit and strengthen vulnerable buildings and lifelines, as well as other activities such as flood control works, slope stabilization, and shoreline hardening.

Various researchers have focused on mitigation strategies for community resilience. Albert et al. (2004) studied the power grid from a network perspective and determined its ability to transfer power between generators and customers when certain nodes were disturbed. They realized that disturbances affecting key transmission substations substantially reduced its ability to function, and that increasing the redundancy and capacity of the existent structure can be used as an effective mitigation strategy to increase resilience and reduce blackouts effects on the population. Pitilakis et al. (2006) proposed a methodology for seismic risk assessment of utility systems and transportation infrastructures. Their proposed methodology provided a uniform basis for the reduction of the consequences of lifeline damage in urban areas and an efficient mitigation strategy and periodization for pre- and post-earthquake actions. Davis (2008) summarized practices implemented as well as other practices identified as needing to be implemented by operational water systems worldwide in order to improve their seismic resilience. He presented several mitigation strategies for reducing component damage and effects on system functionality, such as providing normal and backup seismic resistant power supply, implementing block distribution system, as well as providing system redundancy to expected damage areas. Bana e Costa et al. (2008) developed a multi-criteria value model that enabled the prioritization of bridges and tunnels according to their structural vulnerability and strategic importance as a mitigation strategy in the case of seismic events. The model was subsequently explored to prioritize the bridges and tunnels of a zone in Lisbon, Portugal with high seismicity. Kishawy and Gabbar (2010) summarized typical threats to pipeline integrity and techniques used in management and monitoring pipelines, and presented a pipeline integrity management system design for failure prevention, inspection and repair, which allowed for risk mitigation and long-term optimized performance of pipeline systems. Zulfikar et al. (2016) described a real-time risk mitigation system for Istanbul natural gas distribution network. The system is capable of providing integrated ground shaking and damage maps for the natural gas network components immediately after an earthquake, which can be used for dispatching rapid response teams to high damage areas.

For the case of a natural gas network resilience against earthquakes specifically, using high-density polyethylene (HDPE) pipelines in the distribution network is one effective mitigation strategy, as the absence of damage in these pipelines in the Canterbury earthquake (O'Rourke et al., 2012) leads to a reasonable assumption of very good performance of HDPE pipelines in earthquakes. HDPE pipelines are a type of flexible plastic pipe that can carry portable water, wastewater, hazardous wastes, as well as oil and compressed gases (Sajwan et al., 2008). They are built from polyethylene, which is a very strong and durable, yet flexible material. Due to their lower life cycle costs (e.g. corrosion resistance and leak tight) and their reduced installation costs, HDPE pipes are being used more in new gas distribution networks as well as in replacement of aging steel pipes (Pitilakis et al., 2014). In this dissertation, the effect of replacing steel pipes with ductile HDPE pipelines has been investigated as part of an effective mitigation strategy against seismic hazard.

Optimized Network Recovery

Resources are usually limited and scarce in the immediate aftermath of an earthquake. Therefore, developing optimized network recovery plans in order to effectively allocate available resources to damaged components of a disrupted network can speed up the restoration process, and hence, enhance the community resilience. Various studies have focused on optimized restoration of disrupted lifelines for a faster and more efficient recovery. Bryson et al. (2002) used a mixed integer programming approach for selecting a set of restoration plans, with the aim to give the greatest benefit to business operation and maximize the total value of the coverage provided by the set of selected plans. Casari and Wilkie (2005) discussed sequencing lifeline repairs after an earthquake and represented ways to integrate economic inventive into the management of natural disasters. The proposed decisional procedures could be employed by a planner in order to set repair priorities and help to coordinate lifeline firms in the post-earthquake reconstruction. Lee et al. (2007) proposed a model for minimizing the operating costs involved in temporary emergency restoration of highly interconnected lifelines. The model allowed representation of infrastructures under different conditions of normal operation, post-disruption impact assessment, as well as restoration, and permitted the development and use of algorithms for identifying solutions to problems associated with disruption of interdependent infrastructures. Xu et al. (2007) developed a methodology to determine how to schedule inspection, damage assessment, and repair tasks in order to optimize the post-earthquake restoration of the LADWP electric power system. The objective of the optimization was to minimize the average time each customer was without power, and a genetic algorithm was used to solve the problem. Matisziw et al. (2010) proposed a multi-objective optimization approach for network restoration during disaster recovery. The goal of the optimization was to ensure that facility restoration was prioritized so that system performance was maximized over a planning horizon. The proposed model permitted tradeoffs between two objectives to be evaluated and was applied to a telecommunication network to illustrate significance of optimization. Nurre et al. (2012) proposed an integrated network design and scheduling problem that modeled optimized restoring of infrastructure systems after an extreme event. They used integer programming to formulate the problem and utilized residual network optimality conditions in order to create a disputing rule and solve the problem. Applying the models and algorithms on different testbeds, they indicated the developed dispatching rule can be utilized in real-time restoration planning activities. González et al. (2016) developed a model that optimized the reconstruction strategy of a damaged system of interdependent infrastructure networks, considering the existence of limited resources including budget, time, and manpower among others, as well as interdependencies between the networks, such as physical and geographical, among others. Maya Duque et al. (2016) developed a dynamic programming algorithm as well as an iterated greedy-randomized constructive procedure to solve the problem of network repair crew scheduling and routing problem during the aftermath of disasters. Vodák et al. (2018) introduced a modified ant colony optimization algorithm in order to increase the speed of the road network recovery process in the aftermath of disasters. Fang and Sansavini (2019) investigated the effects of uncertain repair time and resources on the post-disruption restoration of critical infrastructure. They proposed a stochastic programming for infrastructure restoration under uncertainty by developing a multi-mode component repair model, and proposed a tailored Benders decomposition to effectively solve the model.

In case of a disruptive event, utility companies start taking actions immediately after the disaster in order to recover their systems and its service. The number of available resource units for repairing the network is a crucial factor in this process. Meanwhile, the way in which these resources are being allocated to the damaged components in a network is another important factor that can substantially alter the entire recovery process. For a damaged network, different repair sequences can be defined based on the number of available resources, which can result in different restoration times and resilience. Accordingly, optimizing the restoration sequence to minimize the resilience loss is a good strategy to recover faster from a disaster.

Bruneau et al. (2003) proposed a deterministic static metric for measuring the resilience loss of a community in the aftermath of an earthquake as follows:

$$RL = \int_{0}^{t1} [100 - Q(t)] dt \qquad (5-1)$$

where t_1 is the time when the infrastructure is completely recovered, and $Q(t)$ represents the functionality of the infrastructure in percent. In this context, the performance of the damaged infrastructure system is compared to the target infrastructure performance during the recovery process. Resilience Loss (RL) can be illustrated simply as the shaded area in Figure 5-2. Accordingly, a larger RL value means a lower resilience while a smaller value of RL indicates higher resilience. Herein, this definition is used in order to measure community resilience in the aftermath of an earthquake.

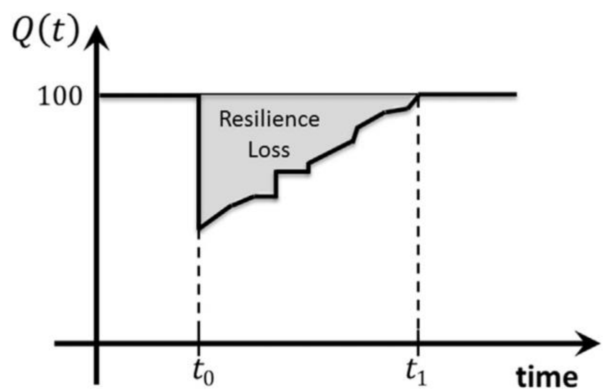

Figure 5-2: Resilience loss measurement (excerpted from Bruneau et al. (2003))

It is usually difficult for standard optimization techniques to solve such problem due to the complicated cascading effects within and across multiple systems (Ouyang et al., 2015). Nonetheless, a Genetic Algorithm (GA) is a powerful optimization technique and has been successfully used in the literature for optimizing restoration sequences of damaged components (Xu et al., 2007; Ouyang and Wang, 2015). A Genetic Algorithm methodology has been used in this dissertation in order to study the effect of optimized network recovery on recovery pace of natural gas network.

Genetic Algorithms, inspired by Darwin's theory of natural selection and initially developed by Holland (1975), is a well-known and accepted optimization method. In this method, a population of candidate solutions (aka individuals) is evolved to find a better solution for the problem. Each individual has a set of properties and is encoded as a string which represents a chromosome. The evolution begins by randomly generating a population of individuals, and it is a repetitive procedure, with the population at each iteration being called a generation. In each generation, a fitness value – which is usually the value of the objective function in the optimization problem being solved – is calculated for each individual in the population. Forming a new population takes place using three main operators: selection, crossover, and mutation. The selection operator chooses individuals based on their fitness values, meaning that the more fit an individual is, chances are higher they are selected. Two selected individuals (parents) then produce two descendants (offspring) by using the crossover and mutation operators. Crossover operator exchanges substrings of the chromosomes in the chosen individuals based on a crossover probability. Mutation operators alter the chromosomes of the offspring with a mutation probability. This process is repeated until enough offspring are available to create the next generation. The new population of candidates is then used in the next iteration to seek better solutions. It should be noted that, the algorithm usually terminates after a certain maximum number of generations has been reached, or after a satisfactory level of fitness is achieved. The procedure to optimize the restoration sequence for damaged components is shown in Figure 5-3.

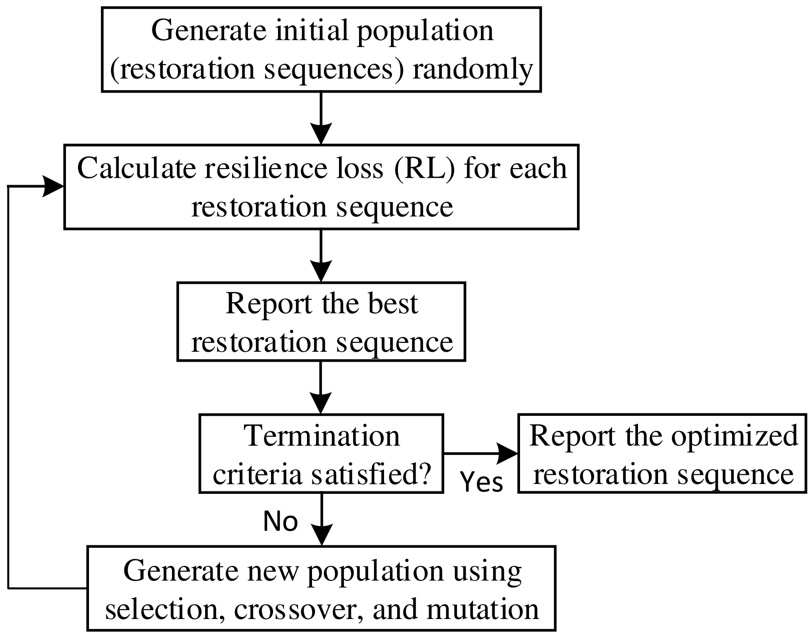

Figure 5-3: Flowchart for fiinding the optimized restoration sequence

The procedure can be described in five steps as follows:

1) Generate candidate solutions: The first step in this procedure is to number the damaged components in the network. Then, a restoration sequence may be expressed as a string composed of those numbers. For example, if five components are damaged in the network and the restoration sequence is in the order of 1 → 2 → 3 → 4 → 5, a chromosome such as 12345 represents that specific restoration sequence. It is obvious that in this context, the length of the chromosome is equal to the number of damaged components.

2) Calculate fitness values: The second step of the procedure is to evaluate the fitness value for each of the individuals built in the previous step. For this purpose, for each chromosome which corresponds to a restoration sequence, the restoration process is simulated and the RL is calculated. Then, a linear normalization technique is used in order to calculate the fitness values. In this formulation, after calculating the RL for each of the candidate

solutions, the RL values are arranged by the order starting from the smallest RL to the biggest one. Then, the fitness value for the i-th individual can be calculated as $f(i) = max(a - bi, 1)$, in which i is the order of the chromosome, a is the maximum fitness value, and b is the reducing ratio (Ouyang and Wang, 2015). The values for a and b can be set to 100 and 2.5, respectively.

3) Selection: The roulette wheel selection techniques can be utilized in order to select superior chromosomes based on their fitness values. In this technique, a cumulative sum of all fitness values is calculated in order to make a summing fitness value sequence. Then, a uniformly distributed random number *r* is chosen between 0 and the total sum of fitness values. This random number is then compared with the elements of the summing sequence, and the first individual with its element in the summing sequence exceeding *r* is chosen.

4) Crossover: For a pair of selected individuals in the previous step, if a uniformly distributed random number is less than the crossover probability, then this operator is called into action. In this context, a number between 1 and the length of the chromosome is randomly selected as the cutting point. The first offspring inherits the longer substring from the first parent and replaces the genes of the shorter substring in the order they appear in the second parent. The second offspring inherits the longer substring from the second parent and replaces the genes of the shorter substring in the order they appear in the first parent. For example, if 63281745 and 24876153 are the selected parents, assuming a cutting point 5 is considered, the first offspring inherits the genes 63281 from the first parent, and the remaining substring of 745 is replaced by 475, which is the order of genes, appeared in the

second parent. Hence, the first offspring will be 63281475 and the second offspring will be 24876315. This is shown in Figure 5-4.

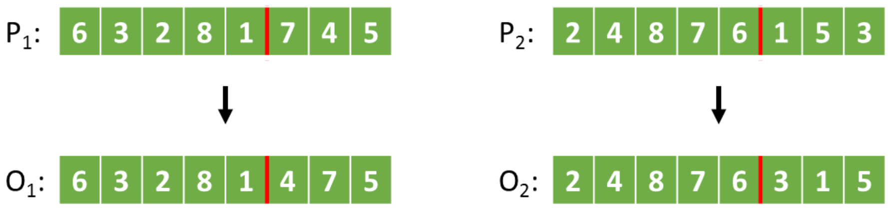

Figure 5-4: Example of crossover operator application in optimizing repair sequence

1) Mutation: For each offspring generated in the previous step, if a uniformly distributed random number is less than the mutation probability, then this operator is called into action. In this context, two randomly selected genes in the chromosome of an offspring are replaced with each other. For examples, if 63281745 is the selected offspring for mutation, assuming that the 3rd and 6th genes are selected to be replaced, then the mutated chromosome will be 63781245. This is shown in Figure 5-5.

Figure 5-5: Example of mutation operator application in optimizing repair sequence

Steps 3 to 5 are repeated until enough number of offspring individuals are made for the next generation. The whole process is repeated until a certain maximum number of generations has been reached. Finally, the chromosome with the minimum RL corresponds to the optimal restoration sequence for recovery of the network system.

CHAPTER 6: ILLUSTRATIVE COMMUNITY MODEL AND SIMULATIONS

To illustrate the application of the probabilistic procedure described before, the natural gas and electric power networks of a virtual community known as Centerville are considered and subjected to two different earthquake scenarios. The Centerville virtual community was developed as a testbed for the NIST–funded Center of Excellence for Community Resilience (van de Lindt et al., 2015) with the goal for examining procedures and methodologies (Ellingwood et al., 2016). Centerville is a typical mid-size community with a population of 50,000, located near an earthquake fault in the United States, and approximately 8 km by 13 km (5 miles by 8 miles) in size. The physical infrastructure of the Centerville built environment was initially modeled with four physical infrastructure components/systems – buildings, transportation system, water system, and electric power system. A natural gas network was later designed and added to the community (Ameri and van de Lindt, 2018a). The Centerville building portfolio contains about 30,000 buildings with residential, commercial, and industrial occupancies. It also includes critical facilities such as fire stations, hospitals, schools, and government offices. These are distributed in in seven residential zones (including a mobile home park), two commercial zones, and two industrial zones (one light and one heavy industry). All of the systems are essential to the health and welfare of a community, and play a significant role in the community resilience assessment, regardless of community size or its location. The schematic view of the Centerville is shown in Figure 6-1.

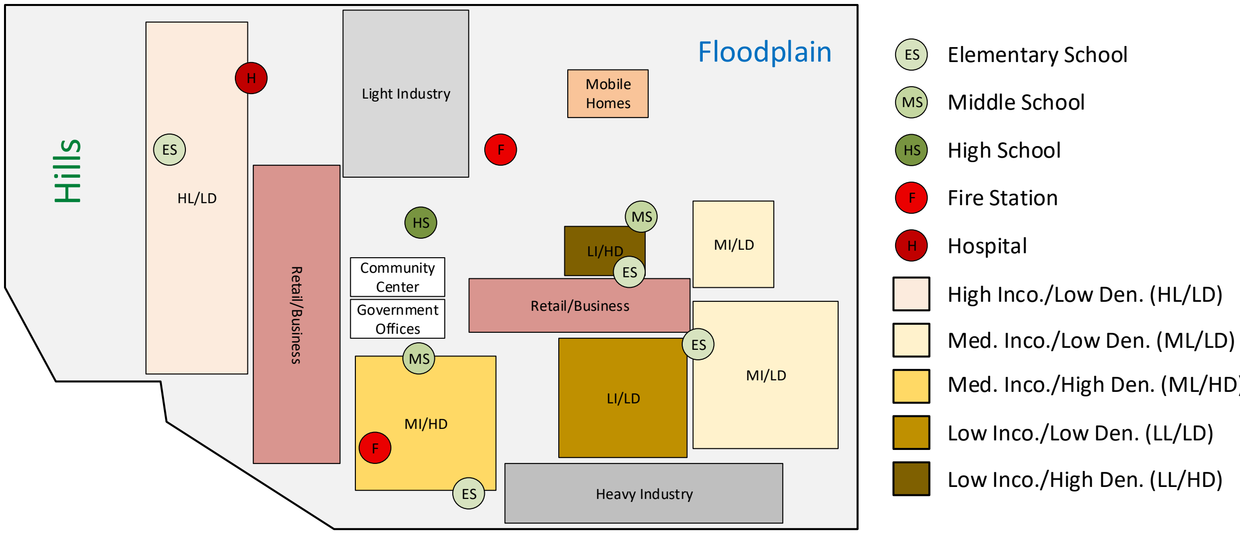

Figure 6-1. Plan of Centerville (after Ellingwood et al., 2016) [Inco. = Income; and Den. = Density]

The Centerville NGN and EPN

The natural gas network of the Centerville supports residential, commercial, and industrial sectors of the community through subsystems that include supply, transmission, and distribution (Ameri and van de Lindt, 2018a). These subsystems are modeled using graph theory with nodal elements (e.g. processing plant, city gate stations, etc.) and link elements (i.e. the transmission and distribution pipelines). The network is characterized by a natural gas processing plant, which is the major source of natural gas for Centerville, two compressor stations, two city gate stations, one local distribution company, 20 district regulating stations, and steel pipelines that connect these components together. The model of the natural gas system is illustrated in Figure 6-2. Among the 20 DR stations, one provides natural gas for the electric power processing plant, two stations deliver gas to the industrial sectors (heavy and light), and each of the other stations support two main sectors as well as their nearby critical facilities. It is noteworthy that even though the DR stations demand the natural gas from the transmission networks, herein they are considered supplier nodes as they supply the natural gas for different sectors of the Centerville. The map of regions supported by each DR station is shown in Figure 6-3.

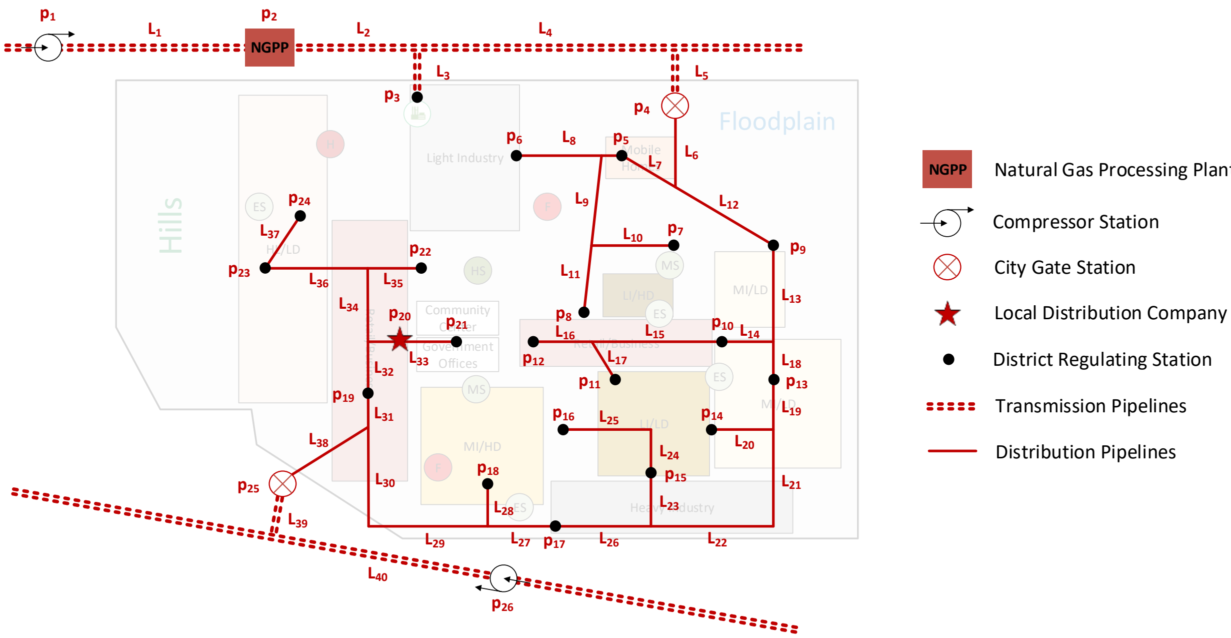

Figure 6-2. Centerville Natural Gas Network

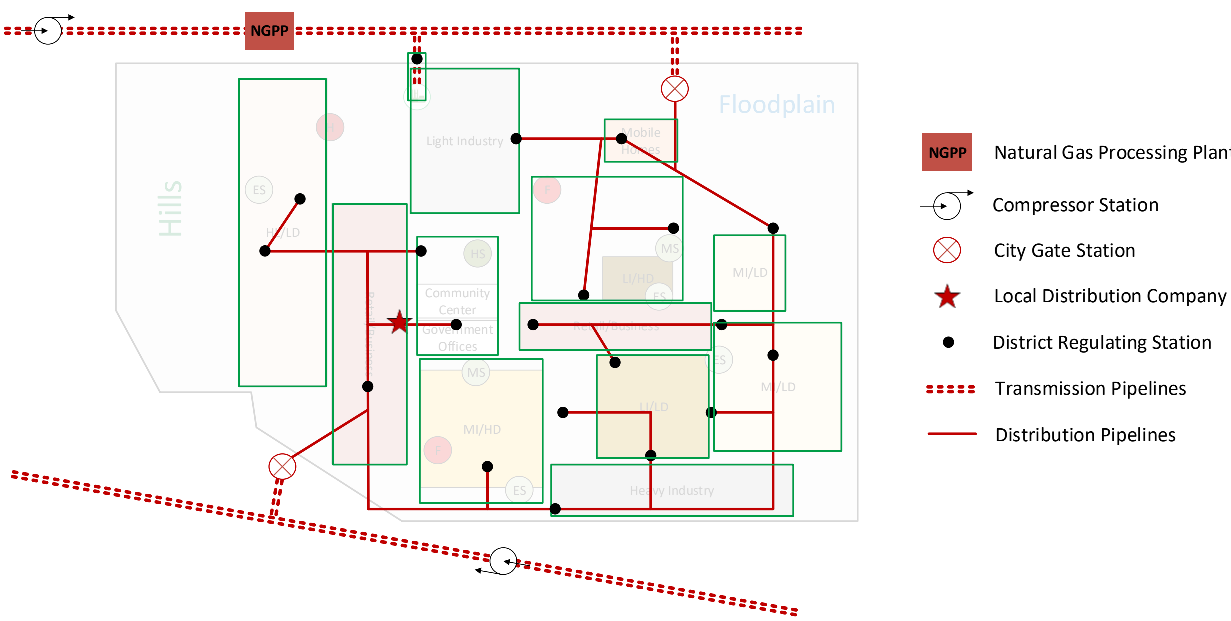

Figure 6-3. Supported Zones by each District Regulating Station

Only large diameter transmission and distribution pipelines are represented in the model, as this simplified modeling is felt to be of sufficient resolution for assessing the system performance at the community level. Moreover, in designing the natural gas network system it was assumed that the natural gas system would be congruent to the major roadway system (Ameri and van de Lindt, 2018a). It is common practice in urban development in the U.S. to utilize the right-of-way for transportation systems to locate other distributed infrastructure systems (Ellingwood et al., 2016).

The electric power network of the Centerville includes one power plant, one transmission substation, one main grid substation, two distribution substations, three sub-distribution substations and 24 overhead poles (Unnikrishnan and van de Lindt, 2016) These are connected via transmission, distribution, and sub-distribution lines. The model of the electric power system is illustrated in Figure 6-4. As mentioned earlier, in case of a seismic event, damage occurs primarily to power plants, substations and buried power lines. Thus, in Centerville, the power plant and the substations are the only components of EPN that are prone to earthquakes.

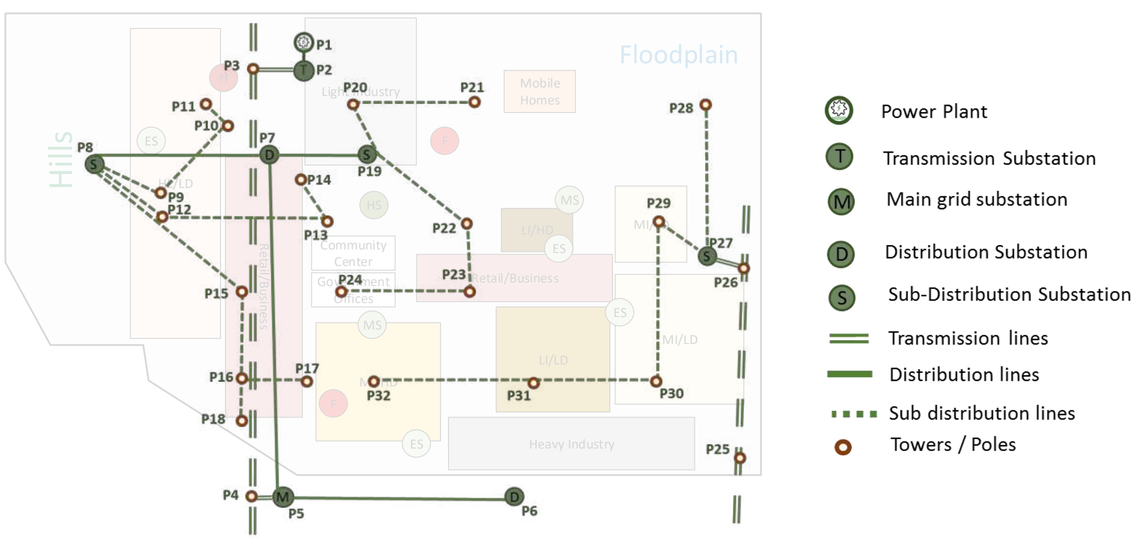

Figure 6-4. Centerville Electric Power Network

ILLUSTRATIVE SCENARIOS

The methodology described in Section 2 was applied to Centerville in order to estimate damage and simulate recovery of the natural gas network when subjected to earthquakes. In order to evaluate the functionality and restoration of the natural gas network in the community, two earthquakes of magnitude 6.5 and 7.9, both located approximately 10 km northwest of the Centerville, were considered as two separate examples. Figure 6-5 to 6-8 show the PGA and PGV maps for each simulated earthquake from the attenuation relationship developed by Campbell and Bozorgnia (2014).

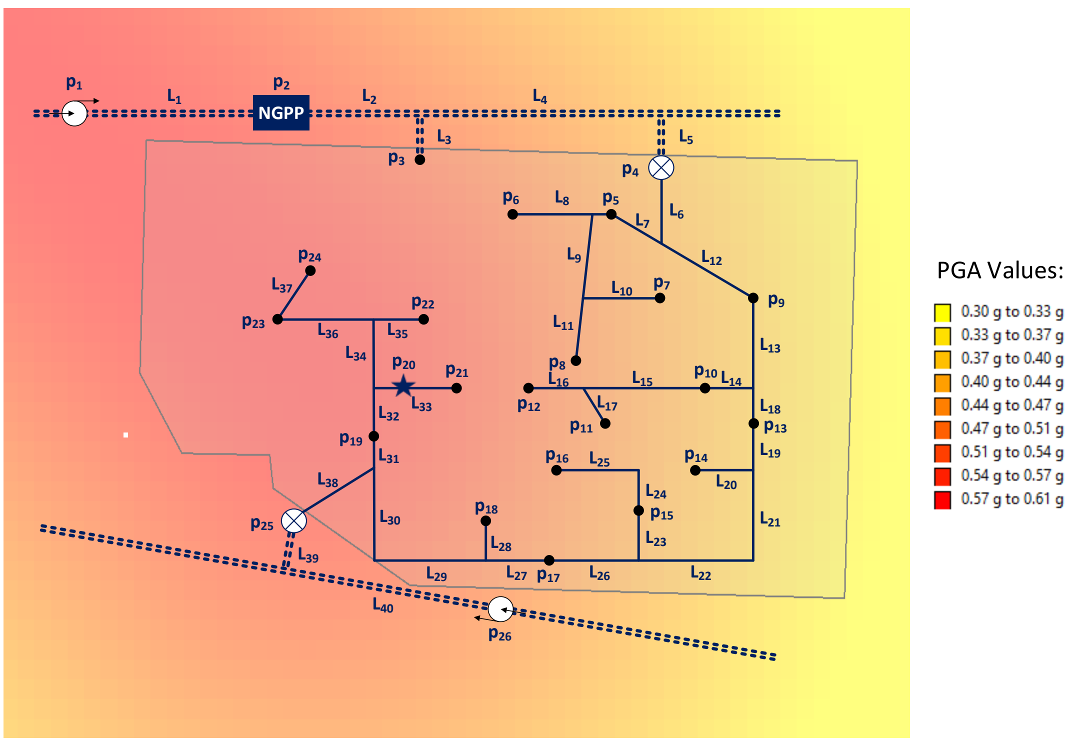

Figure 6-5. PGA map for the simulated 6.5 magnitude earthquake

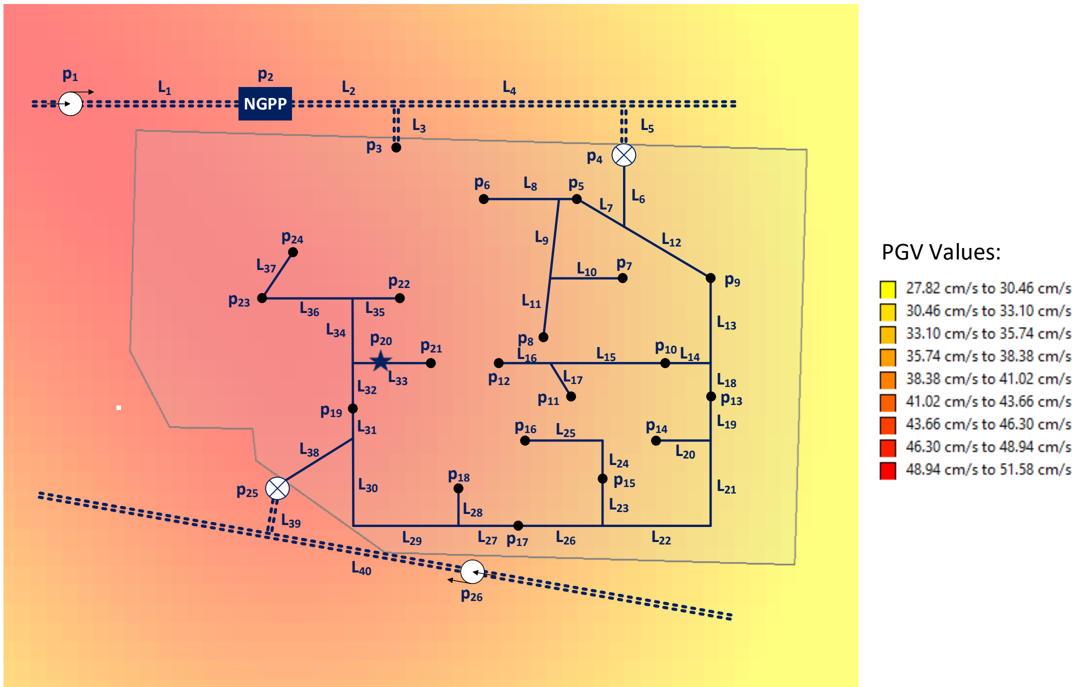

Figure 6-6. PGV map for the simulated 6.5 magnitude earthquake

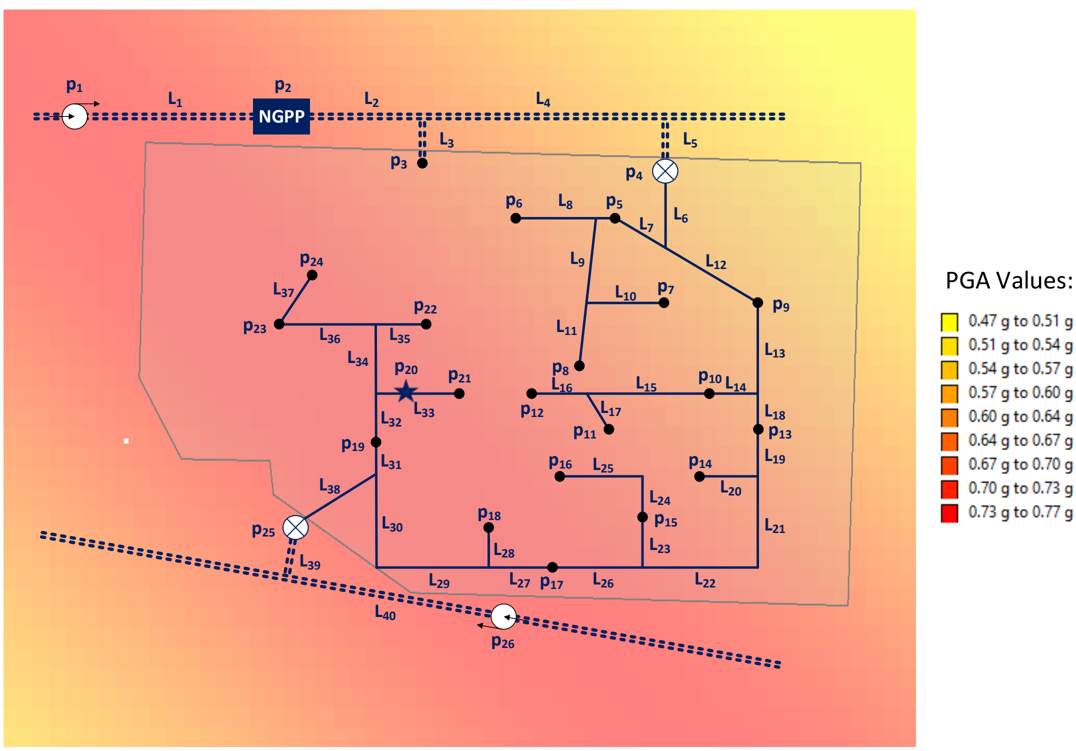

Figure 6-7. PGA map for the simulated 7.9 magnitude earthquake

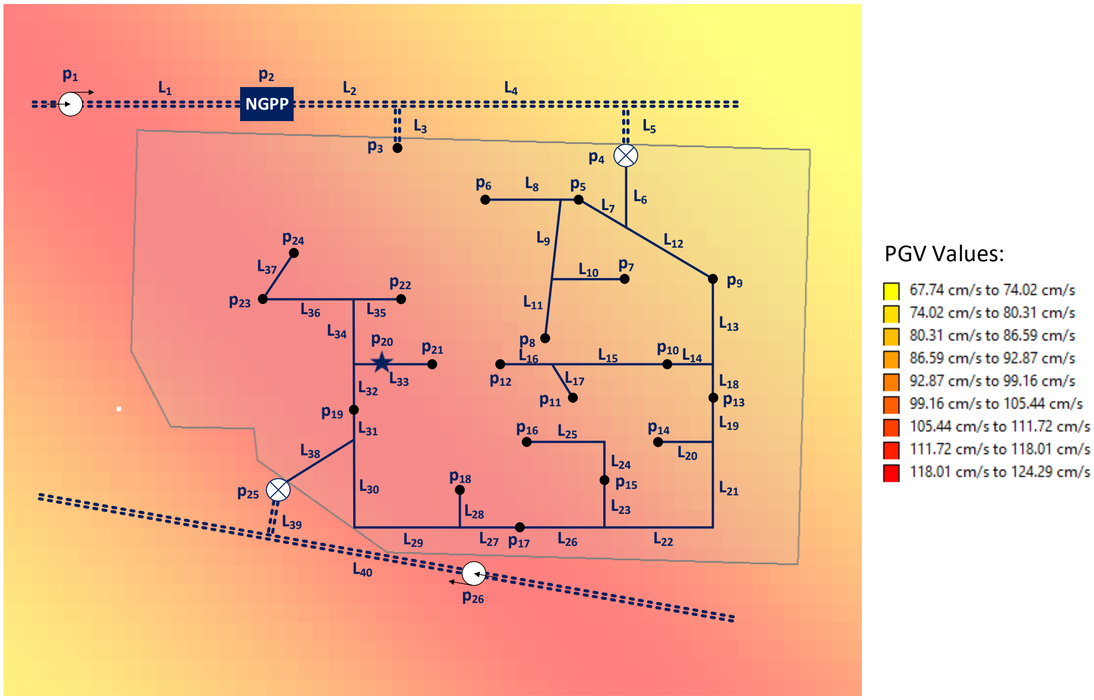

Figure 6-8. PGV map for the simulated 7.9 magnitude earthquake

The simplified methodology explained in HAZUS-MH was adopted in order to simulate liquefaction effects. As was mentioned earlier, the first step for liquefaction hazard evaluation is to determine the relative liquefaction susceptibility of the soil and geologic conditions of the region. Based on the age, depositional environment, and soil properties in the area, a relative liquefaction susceptibility rating – that can range from very low to very high – can be assigned to each soil type in the region. The liquefaction susceptibility map assigned to Centerville is shown in Figure 6-9. Based on this map the PGD values can be determined for each location within Centerville for each hazard scenario.

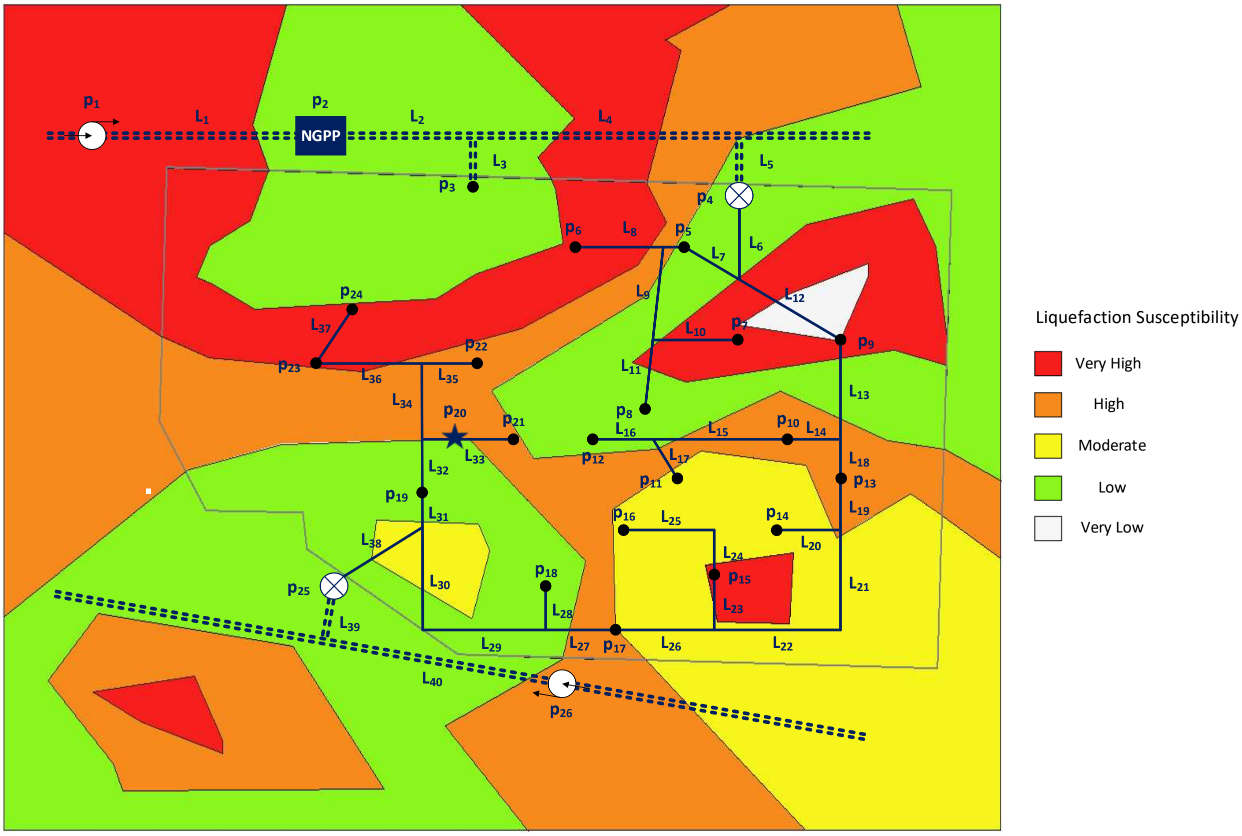

Figure 6-9. Liquefaction susceptibility map for Centerville

The purpose of the natural gas network is to deliver gas from transmission systems to the distribution system, and then from there to the supplier nodes (i.e. DR stations), thus the network performance is evaluated under the simulated earthquakes. Two different scenarios are considered:

1) Independent NGN: In this case, it is assumed the natural gas network is independent from the electric power network. In a connectivity-based analysis which is the scope of this dissertation, it is assumed the DR stations remain functional if they are properly connected to a source node. In this context, for nodal elements, it was assumed that the connectivity between the source and supplier node is lost if these components are in extensive damage stations according to the adopted fragility curves.

2) Interdependent NGN and EPN: In this case, the bi-directional interdependencies between the natural gas and electric power networks are considered. In this context, for the DR stations to remain functional, not only they need to be properly connected to the source nodes, but also the natural gas processing plant and the city gate stations need to be properly connected to and fed by the electric power network system.

The bi-directional interdependency between the NGN and EPN is represented in Figure 6-10. As shown in Figure 6-10, the required natural gas for electricity production is first produced in the natural gas processing plant (NGPP) and then delivered to the EPN power plant through NGN transmission pipelines. The NGPP also depends on EPN power plant for electricity. The city gate stations in the NGN depend on the nearby substations for electricity as shown in Figure 6-10.

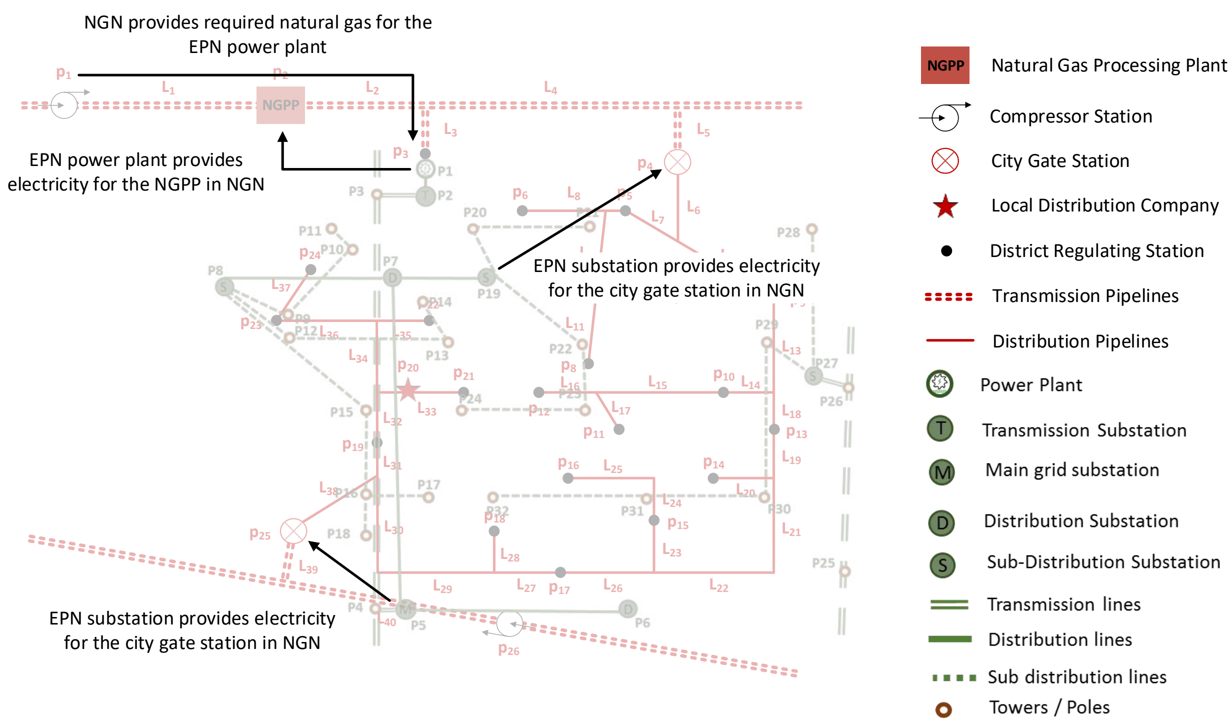

Figure 6-10. Bi-directional interdependency between NGN and EPN

In the case of link elements it is assumed that a pipeline cannot supply gas to the DR stations if it has at least one break. The compressor stations and the local distribution company were removed from the model for fragility analysis as the natural gas can still flow through the network without these components being functional (although unquestionably a failure in the compressor station will result in lower pressures, but pressure alteration is not the scope of this dissertation). The susceptibility of DR stations were also neglected which is consistent with the work done by Esposito et al. (2015).

Accordingly, the NGPP, CG stations, and pipelines were considered as the vulnerable elements for the natural gas network. The CG stations were assumed to be modeled with the same fragility as of unanchored compressor stations (e.g. Chang and Song, 2007; Esposito et al., 2015). Moreover, for NGPP, the fragility curves for small oil refineries were adopted from HAZUS-MH in terms of lognormal cumulative distribution functions. For the electric power network, the power plant and the substations were considered as the vulnerable elements of the network, and the fragility curves were adopted from HAZUS-MH accordingly.

For buried pipelines, the RR equations were adopted from Pitilakis et al. (2014) for steel pipelines as functions of PGV and PGD as follows:

$$RR = K_1\, 0.002416\, PGV \qquad (6-1)$$

$$RR = K_2\, 2.5829\, PGD^{0.319} \qquad (6-2)$$

where RR is given in $1/km$, PGV and PGD are expressed in cm/s and cm, respectively, and K_1 and K_2 are coefficients that are selected based on the pipe diameter and material. In order to calculate the RR for each pipeline, the pipe is first divided into separate segments. The RR for each segment is evaluated at the end nodes for both PGV and PGD intensity measures, and the mean RR is calculated by taking the average values at the end points of the pipe segments. Finally, the calculated RRs are multiplied by 0.2 and 0.8 for PGV and PGD, respectively, as only breaks are considered in a connectivity-based analysis, and the largest number is taken as the final RR. It is noteworthy that, the probability of having n repairs in a pipe segment with length L can be evaluated using a Poisson probability distribution as in Equation (6-3):

$$P(N = n) = \frac{[(RR)(L)]^n}{n!} e^{-(RR)(L)} \qquad (6-3)$$

There are different indicators that can be used in a connectivity-based analysis for performance assessment of natural gas networks, among which is the serviceability ratio (SR) (see Esposito (2011) for other possible performance indicators and more details). The SR indicator, originally defined for water supply systems (see e.g. Adachi and Ellingwood, 2008), is associated with the number of supplier nodes in the distribution network that remain accessible from the supply facilities in the transmission network after the hazard occurrence. The SR may be calculated as:

$$SR = \sum_{i=1}^{n} (w_i \,.\, x_i) \bigg/ \sum_{i=1}^{n} w_i \qquad (6-4)$$

where w_i is the weighting factor for the supplier node i, x_i represents the functionality status of the supplier node i (which is modeled as the outcome of a Bernoulli trial, i.e., it is one if the supplier node is functional and it is zero otherwise), and n is the number of the supplier nodes. The weighting factor for each supplier node is calculated based on the amount of natural gas consumed by the buildings supported by that certain DR station (Ameri and van de Lindt, 2018a). For this purpose, the amount of natural gas consumption for each building archetype in Centerville was estimated based on the available data from the U.S. Energy Information Administration (EIA) (https://www.eia.gov). Table 6-1 shows the amount of natural gas consumption for each building archetype in Centerville.

Table 6-1. Average annual natural gas consumption for each building archetype in Centerville

Sector	Consumption (MCF*)
Residential - R1	60
Residential - R2	100
Residential - R3	135
Residential - R4	100
Residential - R5	2100
Mobile home	25
Retail/Businesses	1075
Government offices	1340
School	2980
Hospital	9420
Fire Station	400
Walmart/Home Depot	2500
Light Industrial	5000
Heavy Industrial	20000

*MCF = the volume of 1,000 cubic feet

Moreover, two different networks are considered for each of the aforementioned scenarios:

1) Normal networks: In this scenario the natural gas and electric power networks are modeled realistically, meaning that all of the components in the networks are reasonably susceptible to the earthquake hazard.
2) Fortified networks: In this scenario, the networks are considered to be more secured, in the way that the key elements in each network (i.e. natural gas processing plant in the NGN and electric power plant in EPN) are fortified, so that if they get damaged during the earthquakes they can be repaired much faster.

For each of the aforementioned scenarios, two different restoration strategies are considered: Random Restoration Strategy and Optimized Restoration Strategy. The different restoration strategies are being considered in order to evaluate how optimized resource allocation can speed up the recovery process. Moreover, in order to perform a thorough community resilience assessment, the effect of having different numbers of resource units on the restoration process are also taken into account. For natural gas network restoration, a number of available resource units, *r*, as generic work teams including repair crews, vehicles, equipment and replacement components are considered for assignment to damaged components (Ameri and van de Lindt, 2018a; Masoomi and van de Lindt, 2018; Ouyang et al., 2012). For electric power network restoration, two available resource units are considered, as this number seems reasonable according to the number of components in the EPN. It is assumed that only one resource unit is needed to repair each damaged component in the networks. When the repair is completed for a certain component, the resource unit is immediately shifted to the next damaged component in the network until the entire network is restored. Moreover, the effect of the industrial makeup of a community on its natural gas recovery following an earthquake, as well as the influence of replacing conventional steel pipes with high-density polyethylene (HDPE) ductile pipelines as part of the mitigation strategy plan has been examined for the case of an independent normal network with random restoration.

RESULTS

Effects of industrial makeup and HDPE pipelines

Considering the independent normal network under random restoration, in order to investigate the effect of the industrial makeup of a community on the natural gas recovery and the influence of replacing conventional steel pipes with high-density polyethylene (HDPE) ductile pipelines, three scenarios were considered in this dissertation for functionality assessment of the natural gas network of the Centerville:

<u>Scenario A: General</u>

In this scenario, the natural gas is realistically distributed between different buildings and sectors (i.e. residential, commercial, and industrial) of Centerville based on the number and size of buildings.

Scenario B: Residential

In this scenario, the natural gas is still realistically distributed among different buildings/sectors, however, the focus is on residential building (including mobile homes) restoration only. Therefore, the results in this simulation will represent the pace at which natural gas is restored to residential buildings as the measure being tracked for recovery.

Scenario C: Industrial

In this scenario it is assumed that the main portion of the natural gas (about 70%) is consumed by the industrial (both heavy and light) sectors of Centerville.

Furthermore, two different cases were considered for each of the abovementioned scenarios. First, it is assumed all the pipelines are made of steel and the fragilities are adopted accordingly. In the second case, the distribution network pipelines are assumed to be made of high-density polyethylene (HDPE) pipelines, which are being used more in new gas distribution networks due to their high ductility (K Pitilakis et al., 2014). There are no fragilities available for HDPE pipelines but the absence of damage in these pipelines in the Canterbury earthquake (O'Rourke et al., 2012) leads to a reasonable assumption of very good performance of HDPE pipelines in earthquakes. Therefore, in this dissertation it is assumed that HDPE pipelines in Centerville do not break in an earthquake due to their high ductility. Table 6-2 presents a summary of the 12 analyses presented in this dissertation for evaluating the effect of industrial makeup and HDPE pipelines.

Table 6-2. Summary of analyses types and corresponding analysis number

Earthquake	Scenario	Pipeline	
		Steel	HDPE
$M_w = 6.5$	Scenario A	1	4
	Scenario B	2	5
	Scenario C	3	6
$M_w = 7.9$	Scenario A	7	10
	Scenario B	8	11
	Scenario C	9	12

For each scenario considered in Table 6-2, the intensity measures for simulated earthquakes were applied to each element of the natural gas network and their damage state and repair time were calculated using the methodology described in Chapter 5. The network damage and functionality status are then updated from the previous time step. The reader is reminded that even if a component has no damage or is physically repaired, it remains non-functional until all its supplier components are recovered and become functional, consistent with a standard network analysis. A Monte Carlo Simulation (MCS) was used to propagate uncertainties with simulations. In essence, the whole procedure described in Figure 5-1 in Chapter 5, is a single run within the MCS. In each run of the MCS, a uniformly random number between 0 and 1 is generated and used to sample from the statistical distributions for each component within the network models. Each run provides a probability of being in one of four damage states for each component. A repair time is then assigned to each damaged component based on its damage state and the demand percentage satisfied by the network in the immediate aftermath of the earthquake is calculated. Subsequently, a recovery sequence list is generated and the available resources (crews) are allocated to the damaged components in the generated recovery sequence list. After the first components in the list are repaired, the status of the repaired components is updated to functional, the new demand percentage satisfied by the network is calculated, and the associated resources are released and assigned to the next damaged components in the recovery sequence list. The process continues until the system is fully recovered and the restoration curve can be determined. This whole process is repeated for 10,000 times and the mean result is eventually presented as the final answer.

The results for recovery of the natural gas network under the magnitude 6.5 earthquake are illustrated in Figures 6-11 (Analyses 1-3) and 6-12 (Analyses 4-6) for steel and HDPE pipeline cases considered. Figures 6-13 (Analyses 7-9) and 6-14 (Analyses 10-12) show the results for the magnitude 7.9 earthquake with r indicating the number of resource units in the analysis.

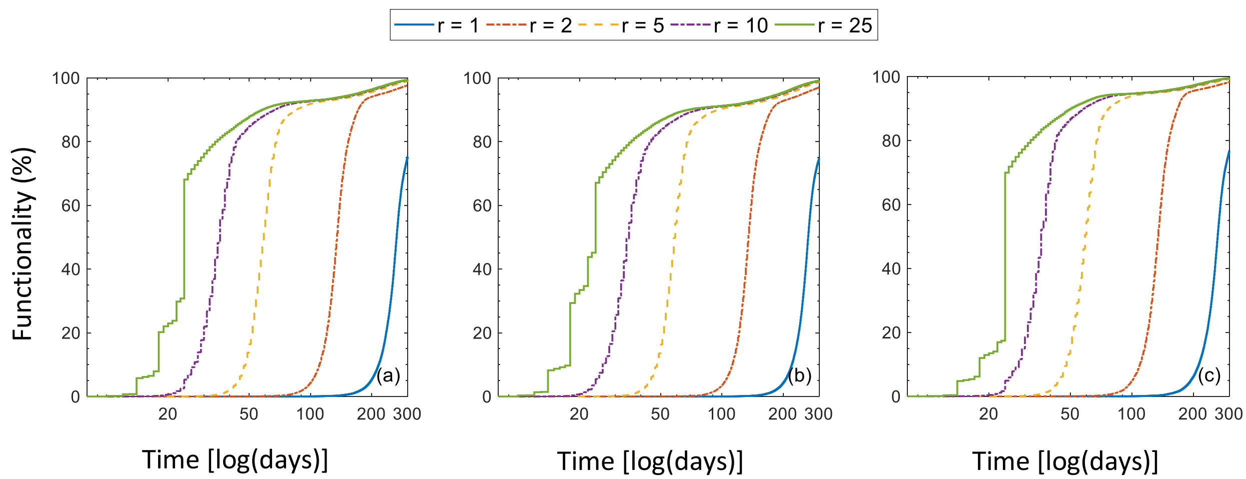

Figure 6-11. Restoration curves for the natural gas network with steel distribution pipes in case of magnitude 6.5 earthquake: (a) Scenario A: General, (b) Scenario B: Residential, and (c) Scenario C: Industrial

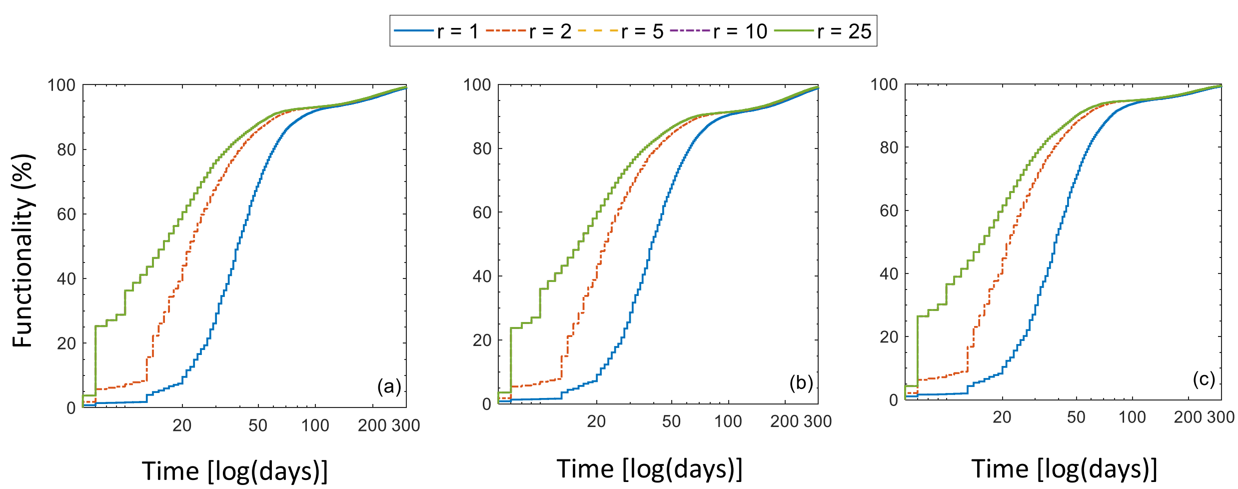

Figure 6-12. Restoration curves for the natural gas network with HDPE distribution pipes in case of magnitude 6.5 earthquake: (a) Scenario A: General, (b) Scenario B: Residential, and (c) Scenario C: Industrial

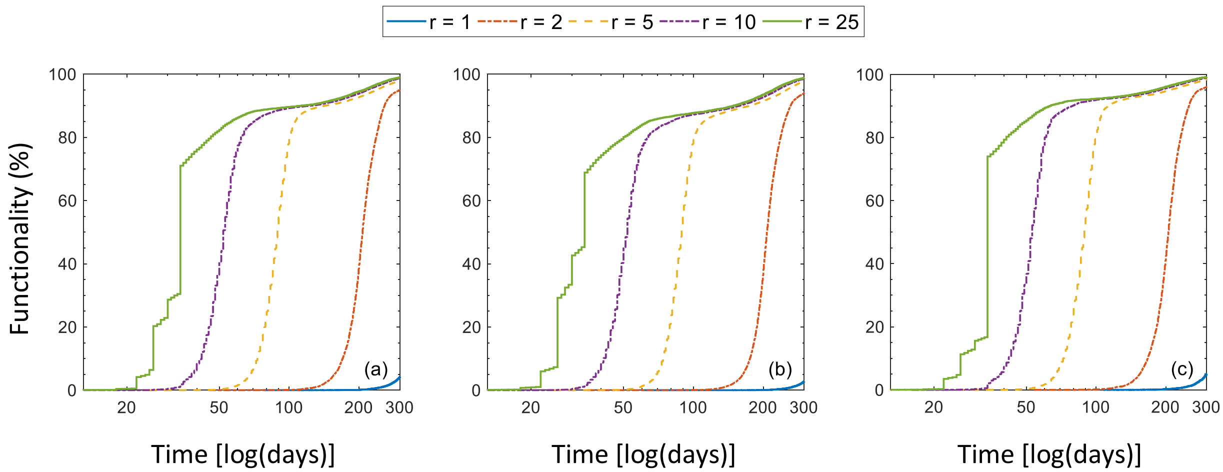

Figure 6-13. Restoration curves for the natural gas network with steel distribution pipes in case of magnitude 7.9 earthquake: (a) Scenario A: General, (b) Scenario B: Residential, and (c) Scenario C: Industrial

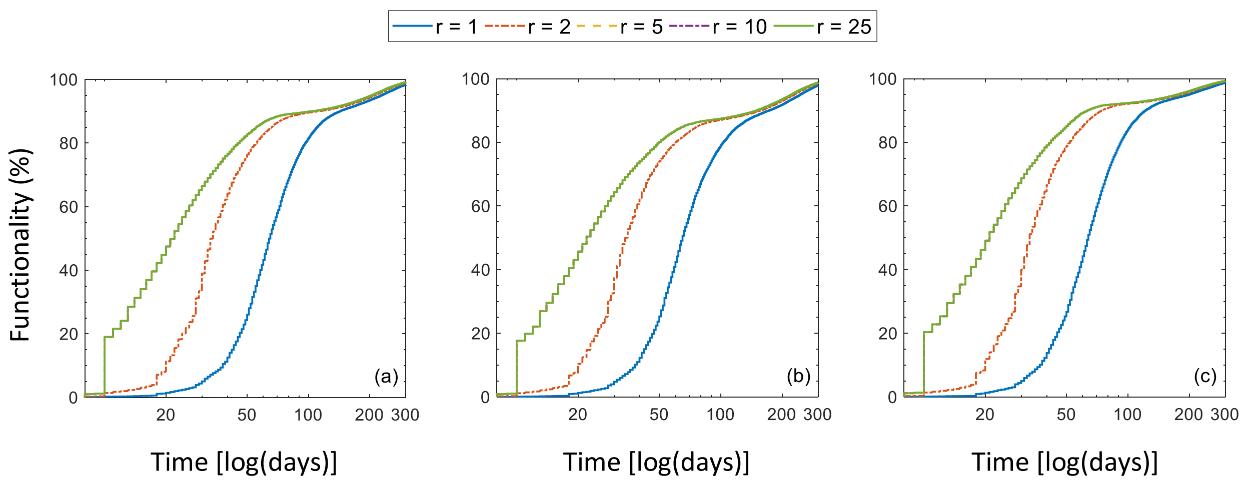

Figure 6-14. Restoration curves for the natural gas network with HDPE distribution pipes in case of magnitude 7.9 earthquake: (a) Scenario A: General, (b) Scenario B: Residential, and (c) Scenario C: Industrial

As shown in the figures, utilizing a different number of crews (resource units) was considered in the recovery process models. It is assumed that each crew for the natural gas network is capable of working on two damaged components simultaneously. For Scenario A in the 7.9 magnitude earthquake with steel pipelines (Analysis 7), for instance, the natural gas network will be 50% operational after 321 days (on average) if only one resource unit (r) is available. Obviously, having only one work crew available after a major earthquake is unreasonable but is included with each scenario to serve as a benchmark. Increasing r from one to five significantly decreases the functionality time to 70 days for 50% functionality. It should be noted that increasing the number of crews beyond r = 10 does not considerably improve the recovery process. This is due to several factors. Namely, in the case where one of the damaged components has a higher repair time in comparison to the other network components. In the cases where the HDPE pipelines are used for distributing (Analysis 10) the natural gas network will be 50% operational after 64 days if only one resource unit is available. Increasing r from one to five decreases the functionality time to 21 days with HDPE. Meanwhile, increasing the number of crews beyond five does not have any influence on the recovery process if HDPE pipeline is used due to the same reasons explained earlier.

A basic resilience metric was able to be defined as the ratio of the area under the restoration curve to the area under the fully functioning curve corresponding to the fully functional system in line with Bruneau et al. (2003). Table 6-3 represents the approximate mean value of the resilience metrics for each scenario that are normalized to the maximum amount of resilience metric observed among all scenarios for each earthquake.

Table 6-3. Resilience metrics for the studied scenarios

Earthquake	Scenario	Relative Resilience Index (%)					
		Steel Distribution Pipes			HDPE Distribution Pipes		
		r = 1	r = 5	r = 25	r = 1	r = 5	r = 25
$M_w = 6.5$	Scenario A	25	88	97	92	99	99
	Scenario B	25	87	97	91	98	98
	Scenario C	26	88	98	93	100	100
$M_w = 7.9$	Scenario A	2	79	96	86	98	98
	Scenario B	1	78	94	85	97	97
	Scenario C	2	80	96	87	100	100

Note: the results for r = 2 and r = 10 are not shown in the table for brevity.

As shown in Table 6-3, and as expected, the most resilient system is the system with the HDPE pipelines for the distribution portion of the network. This is clear from the table that for such a system using more than five resource units does not have any influence on the recovery process as also noted earlier. However, for the system with steel pipes, increasing the number of crews can have a significant influence on the recovery process. Such a resilience index could be used to assist in community-level decisions regarding the replacement of steel NGN pipeline in high seismic regions. Each resilience index can be tied to a cost for a community, thereby supporting scenario-based decision.

Effects of bi-directional interdependencies and optimized network recovery

In order to investigate the effect of bi-directional interdependencies between natural gas and electric power networks on recovery rate of natural gas network system, as well as evaluating the effect of optimized resource allocation on recovery and restoration of natural gas network, several scenarios were considered. Table 6-4 presents a summary of the analyses performed for this purpose. In this context, "I" and "ID" stand for independent and inter-dependent scenarios, "N" and "F" stand for normal and fortified networks, and "R" and "O" stand for random and optimized restoration strategies, respectively. Also, "65" and "79" stand for 6.5 and 7.9 magnitude earthquakes, respectively.

Table 6-4. Summary of analyses types and corresponding analysis IDs

Earthquake	Scenario	Network	Restoration Strategy	
			Random	Optimized
$M_w = 6.5$	Independent	Normal	INR-65	INO-65
		Fortified	IFR-65	IFO-65
	Inter-dependent	Normal	IDNR-65	IDNO-65
		Fortified	IDFR-65	IDFO-65
$M_w = 7.9$	Independent	Normal	INR-79	INO-79
		Fortified	IFR-79	IFO-79
	Inter-dependent	Normal	IDNR-79	IDNO-79
		Fortified	IDFR-79	IDFO-79

Figure 6-15 shows the functionality of the natural gas network under the magnitude 7.9 earthquake, when five crews are utilized. In Figure 6-15, the vertical axis represents different scenarios under study, the horizontal axis shows the day (time), and the colors represent the functionality of the network according to the color bar at the top of the figure.

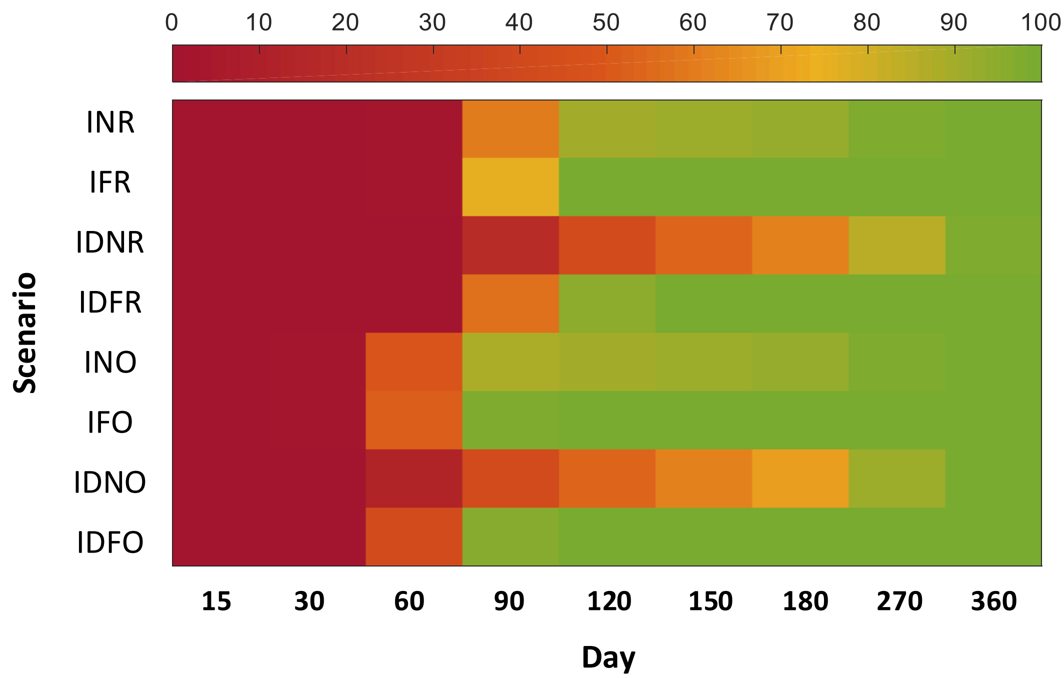

Figure 6-15. Functionality of the natural gas network under the magnitude 7.9 earthquake in case of using five crews

As shown in Figure 6-15, implementing an optimized recovery process for the natural gas network is beneficial in almost every single scenario considered. For example, in the case of an independent normal network, using an optimized recovery process will result in achieving around 90% functionality after 90 days, whereas the absence of an optimized recovery process reduces functionality to about 60% (compare INR and INO) in the same time horizon. In the case of an interdependent normal network, however, optimization does not have a significant influence on network recovery, as in this case interdependencies dominate the entire recovery process regardless of how the resources are being allocated to the damaged components (compare IDNR and IDNO). Moreover, fortifying the networks has a significant advantage and accelerates the entire recovery process. This is especially important in the case of interdependent networks, as fortifying the key elements in the networks will result in more resilient systems. For example, in the case of using optimized restoration strategy for interdependent networks, a fortified network will be 95% recovered after 90 days; meanwhile a normal network will recover up to around 40% during that time frame (compare IDNO and IDFO). The results for other scenarios are shown in Figures 6-16 to 6-20.

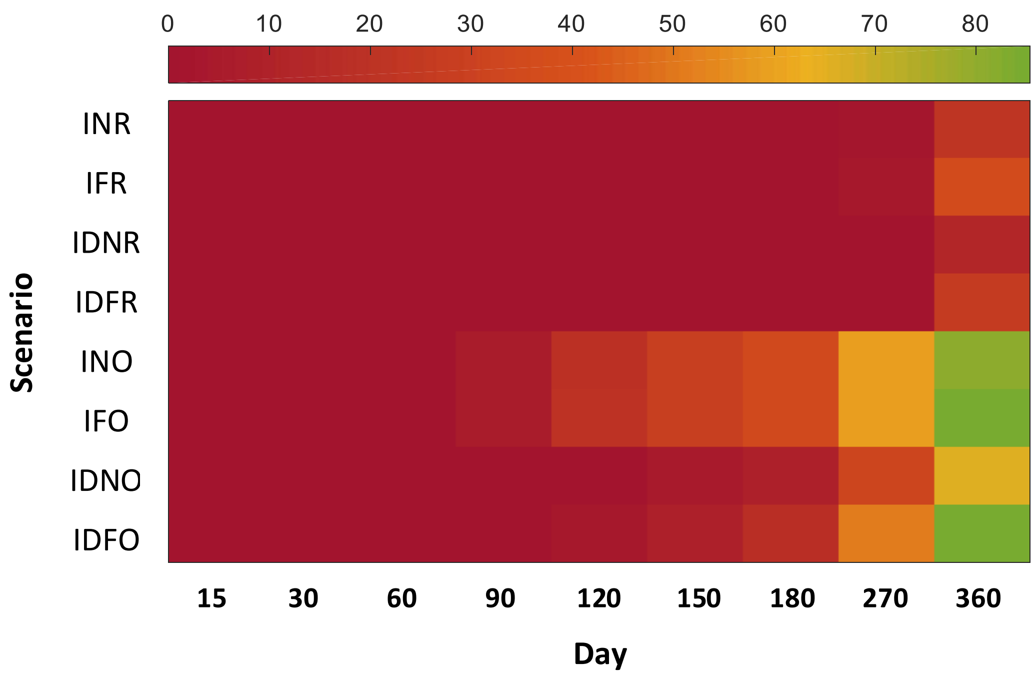

Figure 6-16. Functionality of the natural gas network under the magnitude 7.9 earthquake in case of using one crews

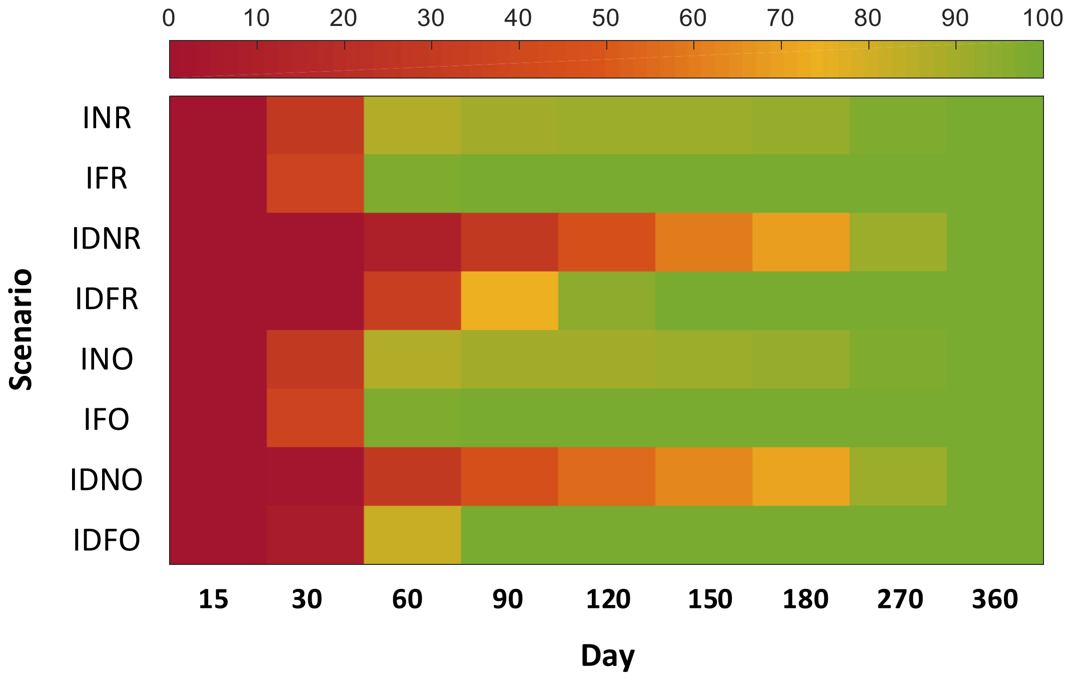

Figure 6-17. Functionality of the natural gas network under the magnitude 7.9 earthquake in case of using 25 crews

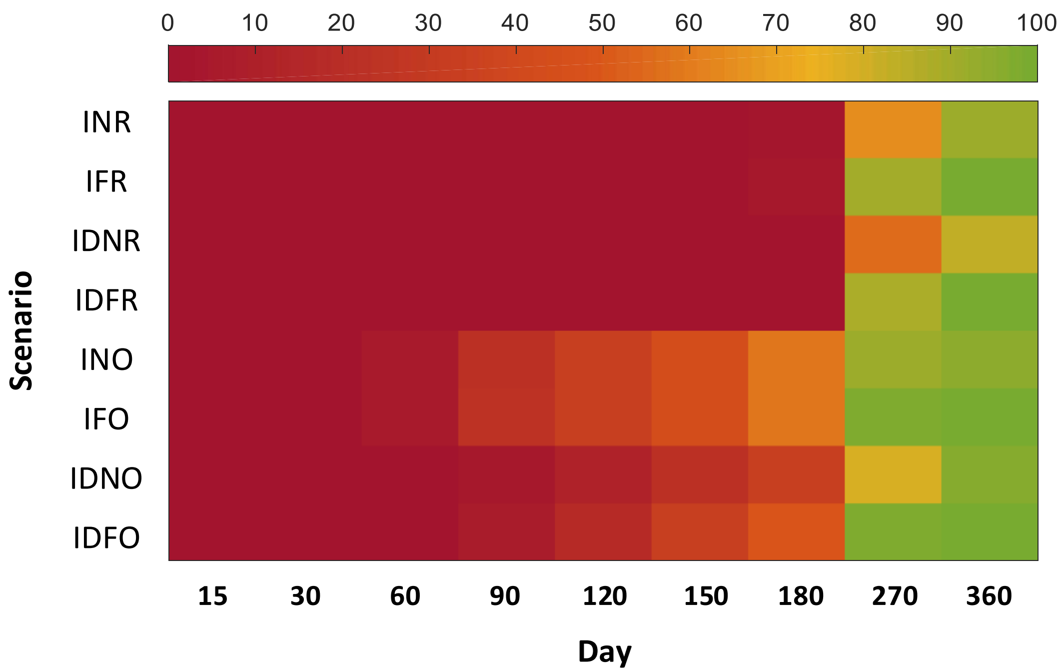

Figure 6-18. Functionality of the natural gas network under the magnitude 6.5 earthquake in case of using one crews

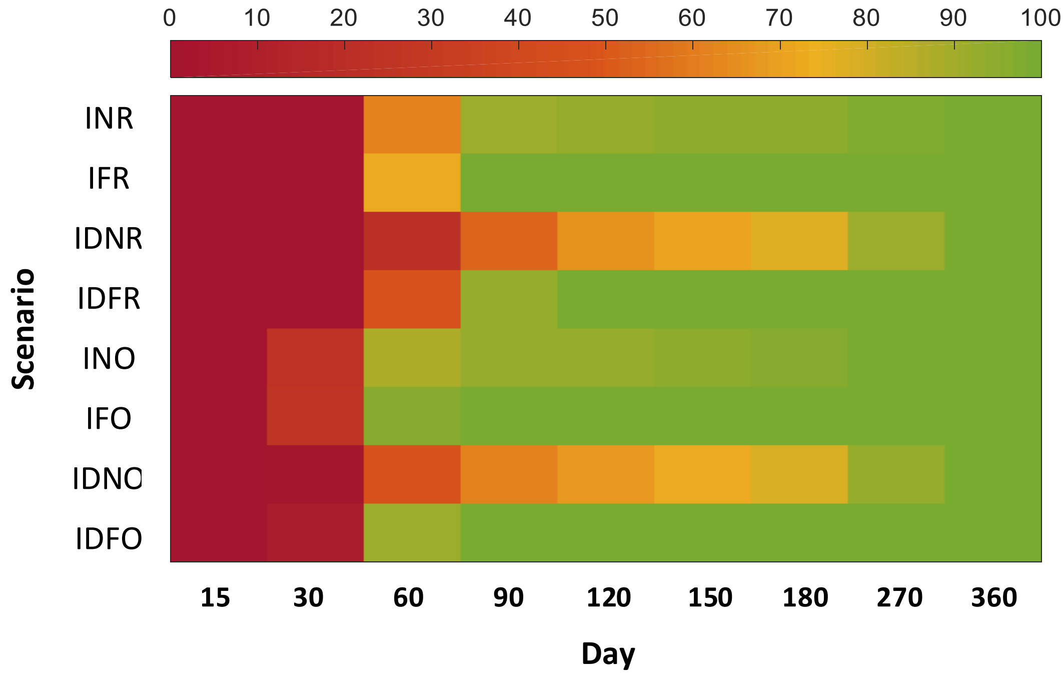

Figure 6-19. Functionality of the natural gas network under the magnitude 6.5 earthquake in case of using five crews

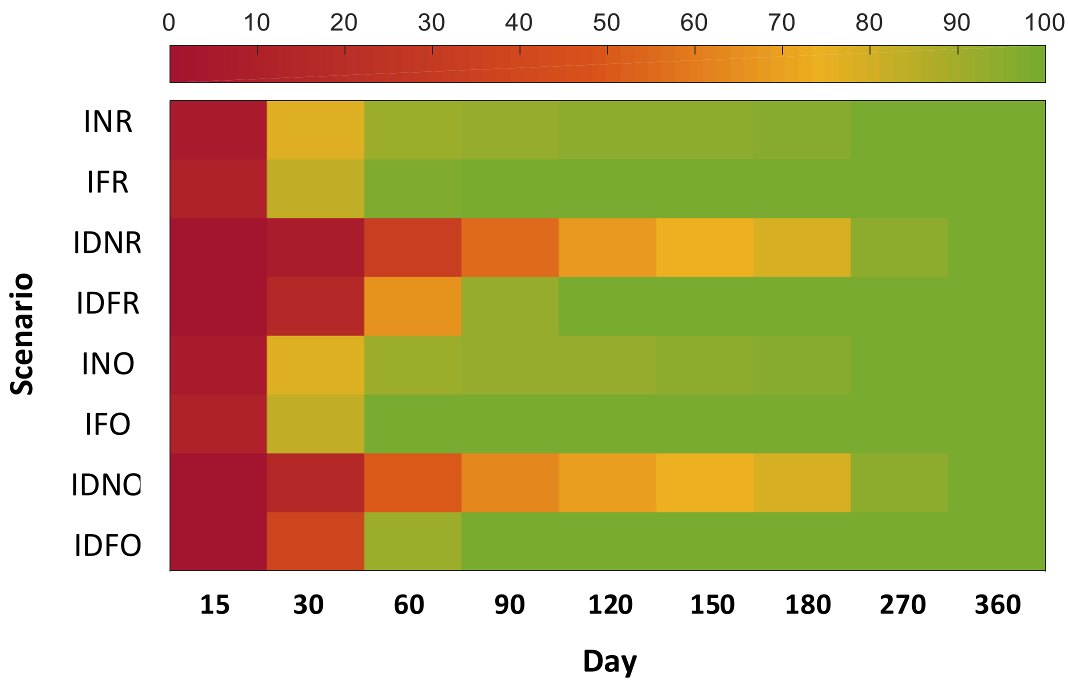

Figure 6-20. Functionality of the natural gas network under the magnitude 6.5 earthquake in case of using 25 crews

As shown in these figures, using only one repair crew following a 7.9 magnitude earthquake is ineffective, regardless of the type of network (i.e. normal or fortified) and the method of restoration (i.e. random or optimized). Furthermore, in the case of using 25 repair crews, there is not much difference between random and optimized restoration methods; although in the case of the interdependent fortified networks, implementing an optimized restoration strategy can still be beneficial to some extent (compare IDFR and IDFO).

Figure 6-21 compares the different types of restoration curves for the natural gas network following a magnitude 7.9 earthquake, with 25 repair crews.

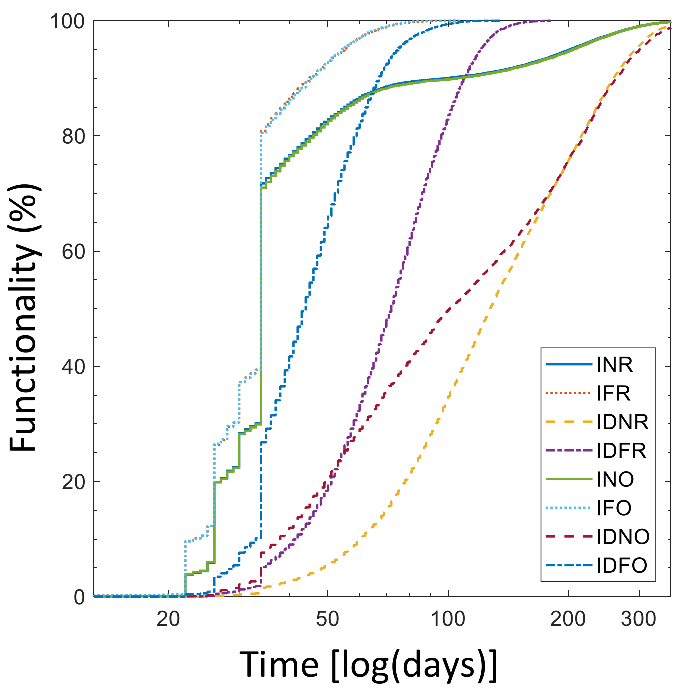

Figure 6-21. Restoration curves for the natural gas network under the magnitude 7.9 earthquake in case of using 25 crews

As shown in Figure 6-21, using an optimized recovery strategy does not have any influence on the recovery process for the independent NGN. Nevertheless, a fortified independent network has a better performance than a normal independent network as one would expect. In the case of interdependent networks, however, using an optimized recovery strategy always improves the recovery process. It should be noted that fortified interdependent networks have better performance when comparison to normal interdependent networks, even if a random restoration strategy is adopted for network recovery. In addition, in the case of interdependent normal networks, even though the systems eventually become functional at the same time (the graphs merge at a functionality of about 70%), the optimized restoration strategy still provides a better recovery curve and reduces the amount of resilience loss.

Finally, Figure 6-22 shows the data for resilience loss generated via Monte Carlo Simulations for the natural gas network under magnitude 6.5 earthquake while using five crews for recovery of the network. The unit for resilience loss is functionality-days

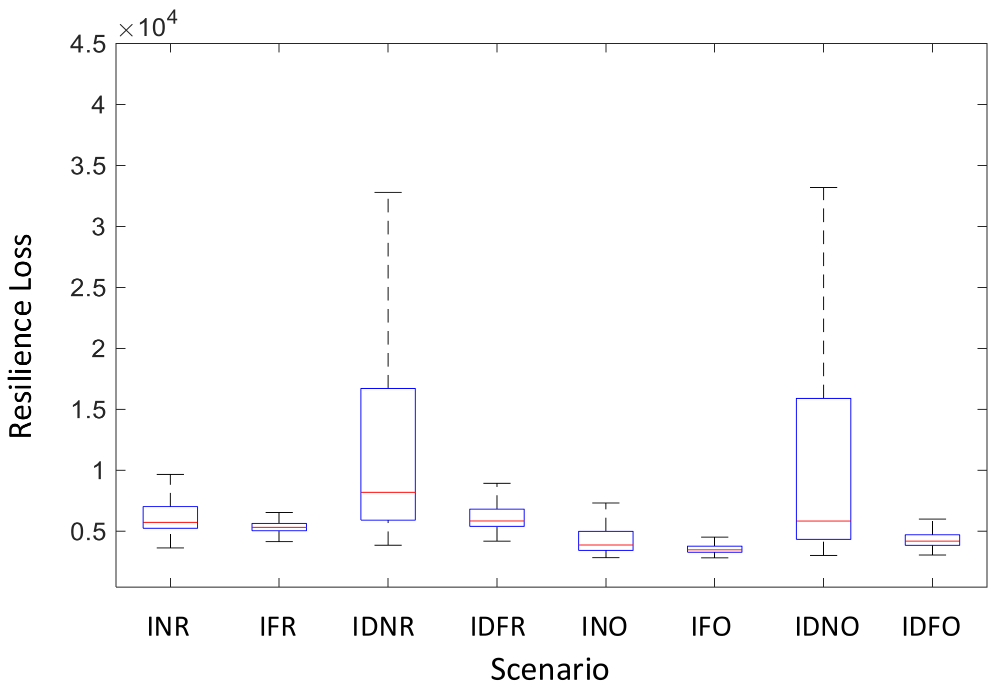

Figure 6-22. Resilience loss for the natural gas network following a magnitude 6.5 earthquake in using five crews

As can be seen from Figure 6-22, the average resilience loss is minimum for the independent fortified network when using an optimized restoration strategy; meanwhile, the average resilience loss is maximum for the interdependent normal network with a random restoration strategy, which follows intuition but can now be quantified for the NGN. It is worth mentioning that the high variation in resilience loss for the interdependent normal network is due to the fact that for such systems, when both the natural gas processing plant and electric power plant are severely damaged during the earthquake, it can take a long time for the natural gas network to return to being functional. Of course, this means the resilience loss will be substantial. Meanwhile, in scenarios where the electric power plant - or generally the electric power network - is slightly damaged, then the natural gas network can function quite independently, meaning that the amount of resilience loss will be much lower and similar to that observed in the independent normal network.

The results provided here propose that considering bi-directional interdependency between the natural gas and electric power networks can alter the entire recovery process of the natural gas network in the aftermath of an earthquake. Fortifying the key elements in the natural gas and electric power networks can guarantee a much more resilient system and accelerate the recovery process, specifically when interdependencies are included in the analyses. Moreover, using an optimized network restoration strategy can speed up the recovery process of the natural gas network. Increasing the number of crews does not necessarily improve the recovery process post a certain number of crews, and in case of having sufficient number of repair crews, using an optimized recovery strategy does not necessarily enhance the recovery process. The failure of only one component in any of the natural gas or electric power network may impair the functionality of a large number of other components consistent with network analysis. Therefore, functionality cannot be used by itself in the decision-making process and should be considered in addition to the restoration process. The methodology proposed here can be utilized for weighing the cost of fortifying key elements in the networks or replacing steel distribution pipelines with HDPE compared with the summation of direct and indirect losses for different scenario events and decision making under uncertainty. The ability to quantify the effect of investment in improving the seismic performance of buried lifeline networks is key to deciding where these investments should be made for overall community resilience strategies. The methodology can be implemented to investigate the use of different decisions and policies by a community for a disaster scenario in order to prioritize disaster planning and mitigation, and for pursuing strategic decisions regarding whether to proactively retrofit or reactively repair steel pipelines in the distribution network of a NGN, with the objective of minimizing the network functionality loss, and therefore, disruptions in the society and economy. These will be further discussed in the next chapter.

CHAPTER 7: OPTIMAL DECISION MAKING UNDER UNCERTAINTY

In the context of risk management and community resilience, critical decisions should be made not only in the aftermath of a disaster in order to immediately respond to the event and properly repair the damage and restore services, but preventive decisions should be made in order to mitigate the adverse impacts of disasters before they happen. This usually involves significant uncertainty related to the basic notion of the hazard itself as well as disaster realization, and usually involves mitigation strategies such as strengthening components or preparing required resources for post-event activities. In essence, instances of risk management problems that encourage a framework for coupled decisions before and after disasters include how to allocate resources before the disruptive event so as to maximize the efficiency for their distribution in order to repair damage in the aftermath of the disaster, and how to determine which network components require preemptive investments in order to enhance their performance in case of a disaster (Gomez and Baker, 2019; Gomez et al., 2015).

A number of researchers have worked on addressing decision-making and optimization problems within risk assessment and management of complex infrastructure systems. Lim and Song (2012) proposed an efficient reliability assessment approach for complex infrastructure networks and introduced an algorithm called the selective recursive decomposition algorithm, which preferentially identified critical disjoint cut sets and link sets to calculate the probabilities of network disconnection events with a significantly reduced number of identified sets. Baroud et al. (2014) defined network resilience along dimensions of reliability, vulnerability, survivability, and recoverability, and proposed a framework to optimize network resilience strategies using a non-parametric stochastic ranking technique. Hu et al. (2015) developed a framework in order to determine optimal maintenance plans for large networks with many bridges, with the objective to minimize the extra travel distance caused by potential bridge failures over a planning horizon and under a budget constraint.

Frangopol and Bocchini (2011) proposed a methodology that used resilience as an optimization criterion for bridge rehabilitation, considering the maximization of the transportation network resilience in addition to minimizing the total rehabilitation cost, relying on bi-objective genetic algorithms for constructing an efficient Pareto front. Pereira et al. (2016) used multi-objective evolutionary algorithms to find resilient routing configurations that are robust to changes in traffic demands and are able to maintain desired performance in the case of arc failure events. Alderson et al. (2017) investigated the resilience of the transportation network in the San Francisco Bay Area based on a sequential game strategy and from the perspective of users. The model was used to quantify the operational resilience of the system, as well as for characterizing trade-offs in resilience considering different investments. Fan et al. (2009) proposed a stochastic programming model in order to optimize retrofit decision for highway systems so that damage caused by future earthquakes would be minimized. Liao et al. (2018) proposed a mathematical model to optimize transportation network resilience in case of a disaster. The model was used in order to prioritize preparedness and recovery activities under the constraints of budget and traversal time.

Peeta et al. (2010) addressed a pre-disaster planning problem that sought to strengthen a highway network whose links were subject to random failures due to a disaster. Considering the goal to select the links to invest in under a limited budget with the objective of maximizing the post-disaster connectivity and minimizing traversal costs between the origin and destination nodes which was modeled using a stochastic programming approach. Chang et al. (2012) proposed a methodology to find the optimal bridge retrofit program that aimed to maximize the post-disaster network evacuation capacity, addressing the uncertainties of earthquake intensity, bridge structural damage, as well as bridge traffic-carrying capacities using a Monte Carlo simulation. Zhang et al. (2019) addressed the problem of evacuating residents out of affected areas in the aftermath of a natural disaster, and formulated a mathematical optimization model with the goal of maximizing the transportation network resilience and minimizing the total travel time for all users through different network reconfiguration schemes.

MULTI-OBJECTIVE OPTIMIZATION

Multi-objective optimization has a remarkable practical importance as almost every real-world optimization problem can be logically developed by considering multiple conflicting objectives. In the past, in order to solve a multi-objective optimization problem (MOOP), these problems used to be converted to a single-objective problem using weighting factors due to the lack of suitable solution techniques (Deb, 2014). The difficulty arises due to such problems giving rise to a set of trade-off optimal solutions known as Pareto-optimal solutions. Nevertheless, various methods have been proposed that are capable of solving such problems without the need to simplify and convert them to a single-objective problem (e.g. Deb et al., 2002; Fonseca and Fleming, 1993; Zitzler and Thiele, 1999).

In general, a multi-objective optimization problem can be defined as follows:

$$Optimize\ F(x) = \left(f_1(x), f_2(x), \ldots, f_n(x)\right);\ \ x \in D \qquad (7-1)$$

where n is the number of objectives ($n \geq 2$), $x = (x_1, x_2, \ldots, x_k)$ is the vector of decision variables, D is the set of feasible solutions and $F(x)$ is the function to be optimized. Each variable x_i in the feasible decision space can be mapped to a point in objective space defined as $F(x_i)$ as shown in Figure 7-1. It should be noted that although Figure 7-1 is in two-dimensional space to simplify visualization, in practice mapping usually takes place from a k-dimensional decision vector to an n-dimensional objective vector.

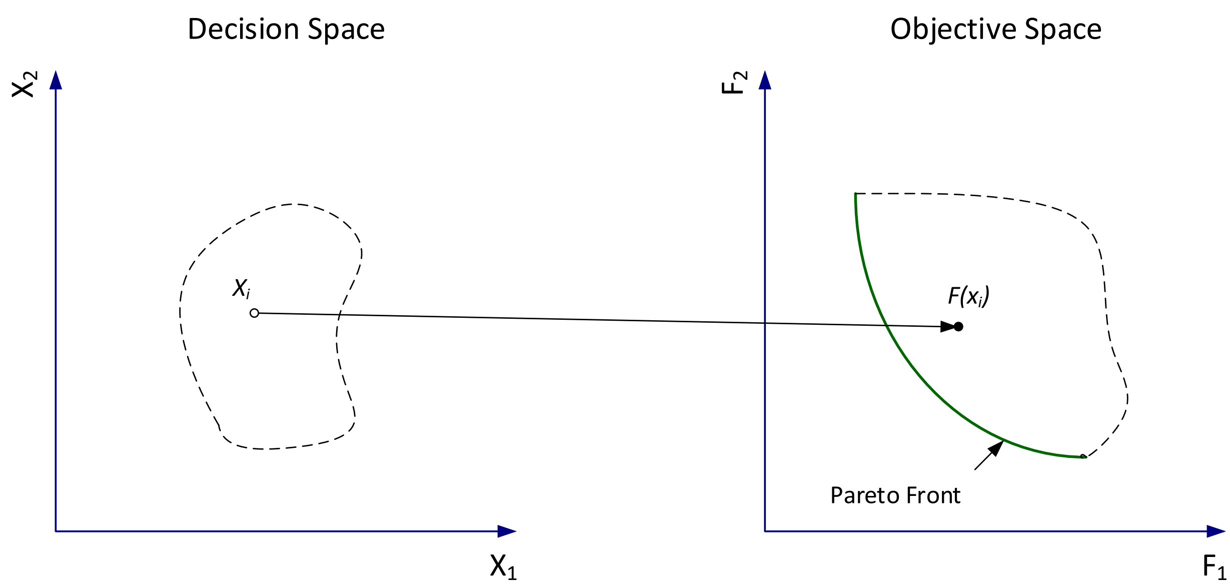

Figure 7-1. Mapping from decision to objective space

In contrast to a single-objective optimization problem, often there is no unique solution for a MOOP. Instead, there are usually a set of solutions representing the best possible trade-offs between the objectives. This set of solutions referred to as Pareto optimal solutions. Many researchers have developed algorithms to find the Pareto optimal solutions for MOOPs. As most MOOPs are mathematically complex (i.e. NP-hard), exact methods are usually effective for small-scale problems only. For medium- and large-size problems, it is necessary to use approximation methods such as metaheuristics. Multi-objective metaheuristics can be broadly classified into two categories:

- Scalar approaches: In this methodology, the MOOP is transformed into one or more single-objective problems. These methods require prior knowledge of the problem in order to define preferences among objectives, and most of the time they produce a single solution per each run. The aggregation method (Ishibuchi and Murata, 1998) and ε-constraint method (Hertz et al., 1994) are examples of scalar approaches.

- Population-based approaches: These methods use different candidate solutions in each run as a population that evolves in a way that guarantees some level of diversity among solutions. Among these methods, some are Pareto-based, in which the selection mechanism incorporates the concept of Pareto optimality. Some of the well-known methods in this category include: Pareto-archived evolution strategy (PAES) (Knowles and Corne, 1999), strength-Pareto evolutionary algorithm (SPEA) (Zitzler, 1999), and non-dominated sorting genetic algorithm (NSGA-II) (Deb et al., 2002).

It should be noted that a non-dominated sorting genetic algorithm (NSGA-II) approach has been used in this dissertation, and thus, this method is discussed in more details in the following sub-section.

Non-dominated Sorting Genetic Algorithm II (NSGA-II)

The non-dominated sorting genetic algorithm II (NSGA-II) proposed by Deb et al. (2002) is one of the most popular multi-objective optimization algorithms. With its three special and innovative features, i.e. a fast non-dominated sorting process, a fast crowded distance estimation procedure, and a simple crowded comparison operator, NSGA-II has been proved to outperform other contemporary multi-objective optimization techniques in terms of finding a more diverse set of optimal solutions (Yusoff et al., 2011; Deb et al., 2002). The aforementioned features are briefly explained in the following sub-sections.

<u>Fast Non-dominated Sorting Approach</u>

In order to sort a population into different non-domination levels in this methodology, at first two entities are calculated for each solution: 1) domination count n_p i.e. the number of solutions that dominate the solution p, and 2) S_p, a set of solutions that the solution p dominates. In this context, all solutions in the first non-dominated front will have their domination count as zero. For each solution p with $n_p = 0$, each member (q) of its set S_p is visited and the domination count for those members is reduced by one. In doing so, if the domination count becomes zero for any member q, that member is placed in a separate list Q, which represents the second non-dominated front. This procedure is repeated on each member of Q in order to find the third non-dominated front, and the process is continued until all fronts are identified.

Crowded Distance Estimation Procedure

Along with convergence to the Pareto-optimal solutions, it is also important to maintain a good spread of solutions in the Pareto front. For this purpose, a crowded comparison approach is used in NSGA-II. In this method, in order to estimate the density of solutions surrounding a specific solution in the population, the average distance of two points on either side of that solution is calculated along each of the objectives. This quantity, known as the crowding distance, can serve as an estimate of the perimeter of the cuboid formed by using the closest neighbors as the vertices. Figure 7-2 shows the crowding distance of the i-th solution in its front (marked in filled circles) as the average side length of the cuboid (showed as a dashed box). In order to compute the crowding distance for each solution, the population is first sorted in ascending order of magnitude according to each objective function value. Afterwards, for each objective function, the solutions with smallest and largest function values are assigned an infinite distance value. All other intermediate solutions are assigned a distance value equal to the absolute normalized difference in the values of two adjacent solutions. This calculation is then repeated for other objective functions and the overall crowding distance is reported as the sum of individual distance values corresponding to each objective. The estimated crowding distance is then used in the crowded comparison operator that guides the selection procedure at various stages of NSGA-II algorithm.

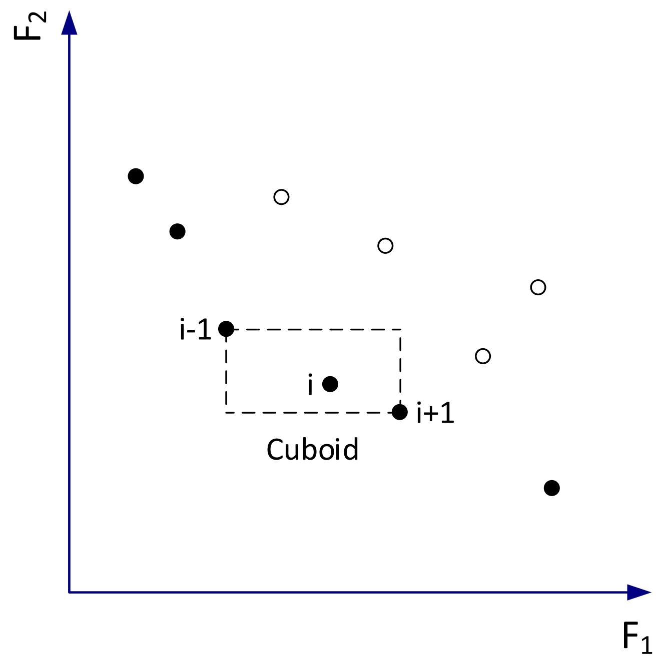

Figure 7-2. Crowding-distance calculation

<u>Crowded Comparison Operator</u>

After all members in the solution population are assigned a crowding distance, the crowded comparison operator directs the selection of candidate solutions toward a uniformly spread-out Pareto optimal front. In this context, between two solutions selected from different fronts, the one with a better rank is desired; nonetheless, if the solutions have the same ranking (i.e. they belong to the same front), the solution with a bigger crowding distance is desired, as a bigger crowding distance represents a lesser crowded region.

NSGA-II Procedure

In this methodology, a random parent population P_0 with size N is initially created and sorted based on the non-domination ranking. Each random solution in the population P_0 is assigned a ranking based upon its level of fitness. Using this initial population, a set of offspring population Q_0 is generated using the typical binary tournament selection, crossover, and mutation operators. The parent and offspring populations are then combined together in order to embrace the concept of elitism for generating next populations. From there, the process to generate next offspring populations using NSGA-II is shown in Figure 7-3.

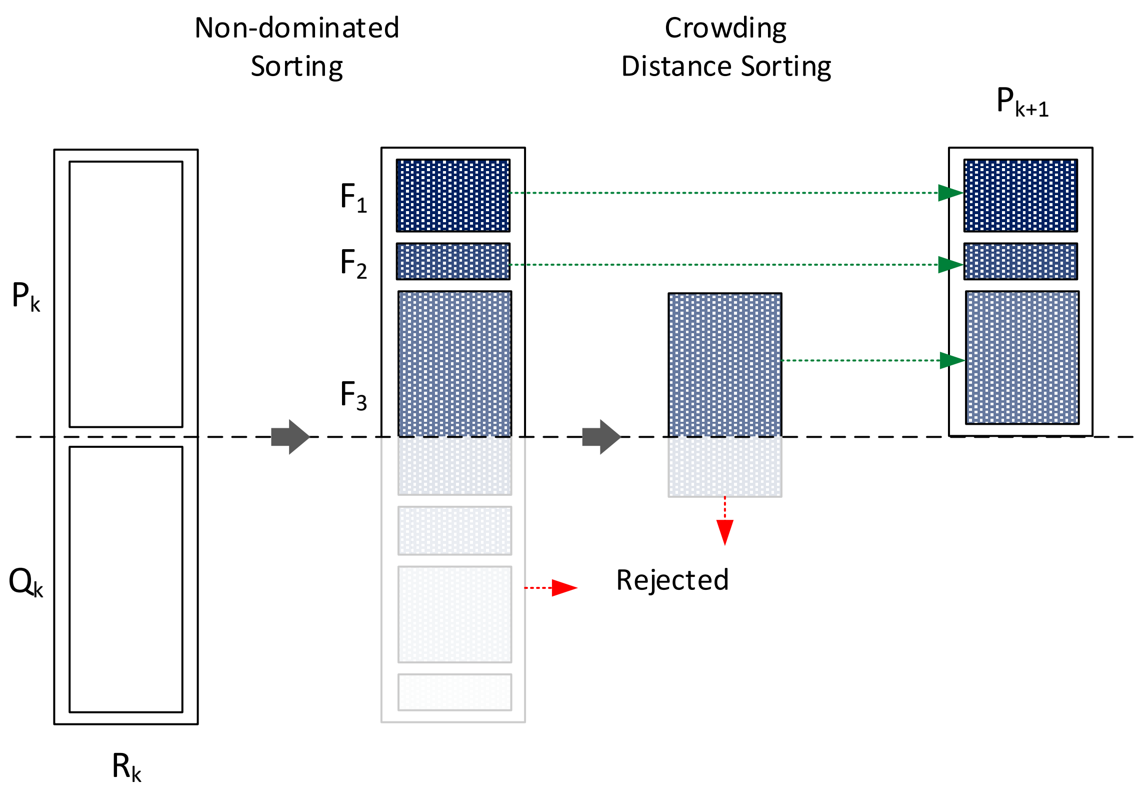

Figure 7-3. NSGA-II procedure

As shown in Figure 7-3, in order to create a new population P_{k+1} (of size N), the parents and offspring from previous generations need to be combined first in order to ensure elitism ($R_k = P_k \cup Q_k$). The combined population R_k (of size $2N$) is then sorted according to non-domination, and solutions that belong to the best non-dominated fronts are transferred to the new population P_{k+1} based on their rankings (i.e. the solutions are transferred first from set $F1$, then $F2$, and so on). Considering that the new population should have exactly N members, the process is continued until no more sets can be completely transferred to the new population. In this case, the members of the last set that cannot be completely transferred to the new population and will be sorted using the crowded-comparison operator, and then the best solutions from that last front will be selected in order to fill in the population P_{k+1}. The new population P_{k+1} will then be used for selection, crossover, and mutation in order to create another population Q_{k+1}. This process is usually repeated until a satisfactory level of non-dominated solutions are found for the specific multi-objective problem under study.

DECISION MAKING FRAMEWORK FOR DISASTER PREPAREDNESS AND RECOVERY

As described before, in order to improve the resilience of an infrastructure component or system, courses of action might be taken either before the event occurs (preparedness) or in the aftermath of the event (repair/recovery). Moreover, the actions that are taken in the aftermath of a disaster are often dependent upon the preceding actions that are taken beforehand. For example, a typical decision before an event occurs is to whether or not invest in strengthening a system's components in order to prevent or lessen the negative consequences of a potential future disaster, and how these investments are made will affect the repair and recovery process in the aftermath of the event. In this dissertation, an optimization framework that integrates probabilistic risk assessment of coupled infrastructure systems and evolutionary algorithms is proposed in order to determine cost-optimal decisions before and after a seismic event, with the objective of making the network recovery faster, and thus the community more resilient. Specifically, strategic decisions are pursued regarding which distribution pipelines should be retrofitted in the Centerville natural gas network under limited budgets, considering the objectives of minimizing the number of people without natural gas in the residential sector, as well as minimizing the business losses due to the lack of natural gas in non-residential sectors. MCS is used in order to propagate uncertainties with simulations and PSHA is adopted in order to capture uncertainties in the seismic hazard. A non-dominated sorting genetic algorithm (NSGA-II) approach was utilized to solve the multi-objective optimization problem in the present study, and the results can provide risk-informed decision support as will be shown later.

Risk Assessment Methodology

The decision-making framework proposed in this dissertation adopts a methodology that combines probabilistic and deterministic seismic risk assessment methodologies. As mentioned in Chapter 4, the results from a PSHA are much more reliable due to incorporation of uncertainties into calculations, especially in engineering decision-making applications. Nevertheless, using the results of a PSHA merely may not be a suitable option for evaluating the serviceability of spatially distributed infrastructure networks, as the variation in spatial intensity in seismic demand from a particular earthquake is lost through the aggregation process (McGuire, 2001; Miller and Baker, 2015). In contrast to PSHA, a deterministic scenario-based hazard assessment has the ability to better capture the spatial correlation in seismic intensity, as it is based upon a single earthquake rather than an aggregation of earthquakes. Nonetheless, using a single earthquake scenario with a very low and unknown rate of occurrence cannot provide sufficient information for estimating losses due to a spectrum of possible future earthquakes, or for determining proper investments in retrofit of existing infrastructures (Adachi and Ellingwood, 2009). Therefore, implementing a method that includes desirable features of both PSHA and scenario-based seismic hazard assessment is required. For this purpose, the methodology developed by Adachi and Ellingwood (2009) is adopted in this dissertation. In this context, all possible earthquakes affecting the serviceability of an infrastructure at a stipulated seismic hazard should be included in the analyses.

For the case of the Centerville coupled NGN and EPN systems, it is assumed the seismicity in the Centerville is affected by earthquakes that can occur from two separate seismic source zones. One seismic zone is located with its center at a distance approximately 15 km from the northeast side of Centerville, and with the potential to generate magnitude 7.0 to 8.0 earthquakes that occur at a rate of $\lambda = 0.002$ times per year. The other seismic zone is located with its center at a distance approximately 10 km from the southwest of the Centerville, with potentially producing magnitudes 6.0 to 7.0 earthquakes that occur at a rate of $\lambda = 0.01$ times per year. Accordingly, in order to evaluate the serviceability of the interconnected NGN and EPN of the Centerville under a specified seismic hazard, both of the abovementioned seismic sources should be taken into account.

Two different return periods of 475 and 2475 years are considered in this dissertation. The first step in the process of seismic hazard assessment for Centerville - that combines both PSHA and scenario-based methodologies together, is to deaggregate the seismic hazard at each return period of interest, as explained in Chapter 4. Next, the performance of the networks under all possible earthquake scenarios is evaluated in order to capture the spatial variation in intensity values accurately. Finally, the components' functionality and the networks' serviceability are determined by re-aggregating the seismic damage, weighted by the relative contribution of each earthquake at each return period of interest.

Optimization Problem and Objective Functions

Considering the coupled NGN and EPN in Centerville, the goal is to minimize the adverse consequences due to the unavailability of natural gas in the case of an earthquake, by retrofitting the most vulnerable components of the natural gas network under limited budgets before the seismic event, and effectively allocate the limited resources available for repairing the damaged components of the network in the aftermath of the earthquake. Thus, acknowledging the limited budgets for retrofit and scarcity of available resources for repair, strategic decisions need to be made regarding how to proactively retrofit beforehand, and then reactively repair the damaged components afterwards, in order to maximize community resilience. For this purpose, two different objective functions are considered for minimization: 1) the number of people affected by unavailability of natural gas in the residential sectors, and 2) the amount of business losses due to unavailability of natural gas in the non-residential sectors. In order to calculate the business losses, the same concept of resilience loss proposed by Bruneau et al. (2003) is utilized in this dissertation, as described in Chapter 5. In this context, the business loss can be evaluated using the following equation:

$$BL = \int_0^{t_T} [100 - F_2(t)]dt \qquad (7-2)$$

where t_T is the target time i.e. the time until when the business losses are being calculated, and $F_2(t)$ represents the functionality of the non-residential sectors as a percent. This metric can be later transformed to a monetary measure, by evaluating the amount of money that is lost due to unavailability of natural gas in the non-residential sectors. For the case of Centerville, it is assumed that 100% unavailability of natural gas in non-residential zones can result in losses equivalent to $1,000,000 per day. The reader is reminded that this amount is just an assumption made in this dissertation for illustrative purposes only, and one may require performing a detailed investigation of exact amount of monetary losses due to unavailability of natural gas in non-residential sectors.

Retrofit and Repair Strategy for the Centerville NGN

As shown in Chapter 6, replacing steel pipes with HDPE pipelines in the natural gas distribution network can effectively increase the resilience of the system. Hence, retrofitting the steel pipes with HDPE pipelines can be regarded as an effective mitigation strategy. In order to find what combinations of retrofit and repair strategies result in the Pareto optimal solutions based on the defined objectives in this dissertation, a random population of retrofit parents (i.e. retrofit schemes) is first generated. Each retrofit parent is built such that steel pipelines are randomly selected from the distribution network to be replaced with HDPE pipes, until there is no money available for retrofitting more steel pipelines. Afterwards, for each retrofit parent, NSGA-II is implemented in order to find the best repair strategies that result in Pareto optimal solutions for that specific retrofit scheme. Considering the limited number of available repair crews, selection, crossover, and mutation operators are used as described earlier in Chapter 5 in order to find the best repair sequences for each retrofit scheme. After the best combinations of retrofit and repair strategies are found, a new population of retrofit parents needs to be generated. In this dissertation, in order to generate new retrofit offspring populations, only selection and mutation are used. The reason is that the retrofit optimization problem considered in this dissertation is not a sequential problem (i.e. the order of selected pipelines for retrofitting does not matter in the optimization process), and therefore, exchanging different segments of retrofit chromosomes does not necessarily result in a more diverse population. Moreover, there is also the danger of violating budget constraints in swapping different segments of selected retrofit chromosomes. Therefore, using only selection and mutation operators seems to be a better option for the specific problem defined herein. Therefore, in this dissertation, a mutation operator is designed with the aim to guarantee building a more diverse population for next generations. In this context, first a number (p) between 1 and half of the length of the selected chromosome is randomly selected. Then, p elements of the selected retrofit chromosome are randomly selected and substituted with other pipelines that do not already exist in the chromosome. Combining this mutation operator with the selection methodology used in NSGA-II algorithm, the retrofit parents for next generations can be built. Then, for each newly built retrofit parent, the procedure explained above is repeated again, in order to find the best repair strategies for each retrofit parent. This whole process is repeated until enough number of non-dominated Pareto optimal solutions are found. It should be noted that NSGA-II has already been used by other researchers adopting a selection and mutation operator only (e.g. Coello et al., 2009). Moreover, it is proven that depending on the basic notion of the problem under study, a search strategy that is merely based upon selection and mutation can be used as a powerful search procedure (Michalewicz, 2013). It is also noteworthy that technically, an algorithm that only works based upon selection and mutation operators is no longer considered a genetic algorithm, but may be referred to as an evolution strategy or evolutionary programming (Simon, 2013).

Results

In order to show the results of the multi-objective optimizations, it is important to capture the bi-directional interdependencies between the NGN and EPN systems. Moreover, as the results from Chapter 6 proved the importance of functionality of key elements (i.e. natural gas processing plant in the NGN and electric power plant in EPN) in the resilience of the natural gas network, retrofitting these key elements should be prioritized in any mitigation plan. Thus, a fortified interdependent natural gas network is selected in order to show the optimization results.

In terms of the costs for replacing the pipelines, Farahmandfar et al. (2016) obtained the cost of pipeline replacement from the literature. Assuming that pipe bursting technique is used for pipeline replacements, they used a cost of $1.04/mm/m ($8 in./ft.) for pipeline replacements, which was derived by adjusting the costs provided by Boyce and Bried (1998) for inflation from 1998 to 2014. In this dissertation, the same cost of $1.04/mm/m is used in order to calculate the costs of pipeline replacements. There are approximately 44 km of pipelines in the natural gas distribution network of the Centerville. In order to retrofit the natural gas network distribution pipelines, two different budgets of \$2.8 and \$5.6 million dollars are considered for illustrative purposes, which are sufficient for retrofitting approximately 25% and 50% of the total pipelines in the distribution network, respectively. Moreover, three different number of repair crews (two, five, and ten) are considered in the recovery process of the natural gas network, in order to capture the effect of having a different number of available resources for repair in the aftermath of an earthquake. Considering two different earthquakes with return periods of 475 and 2475 years, three different target days of 30, 60, and 90 days have been selected. These are used as a target in time domain, at which the objective functions are being optimized.

As an example, consider a retrofit budget of \$2.8 million dollars and two repair crews available to repair the damaged components under an earthquake with 475 years return period. After 30 days, both residential and non-residential sectors remain completely non-functional, regardless of how the gas distribution network is retrofitted before the earthquake and how the damaged components are repaired afterwards. Nonetheless, after 60 days, even though the sectors cannot reach 100% functionality, there are certain combinations of retrofit and repair that can produce some optimal solutions. Figure 7-4 shows the process of moving toward optimal solutions via millions of simulations for the considered scenario. The Pareto front for these simulations is also plotted in Figure 7-5. As shown in Figure 7-5, each dot on the plot represents a certain policy (P) of retrofit and repair that results in Pareto optimal solutions. The retrofit schemes for these policies (i.e. P_1 to P_5) are depicted in Figures 7-6 to 7-8. The green lines in the figures show the pipelines that have been retrofitted. It is noteworthy that the retrofit schemes for Policies 2, 4, and 5 are similar, and the difference in the results is due to adopting different repair strategies in the aftermath of the earthquake.

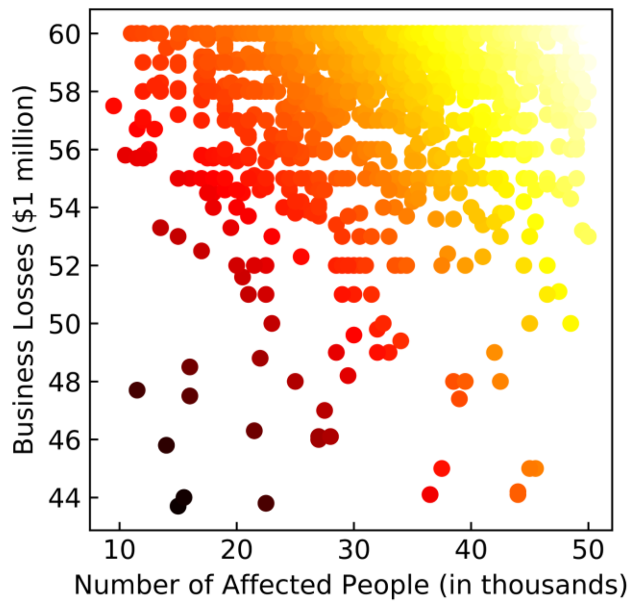

Figure 7-4. Simulations at day 60, for the case of an earthquake with a return period of 475 years, a retrofit budget of $2.8 million dollars, and two available repair crews

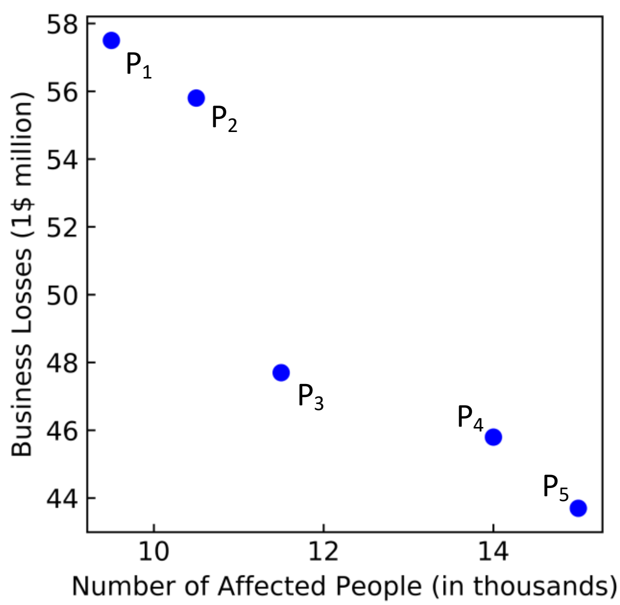

Figure 7-5. Pareto optimal solutions at day 60, considering an earthquake with a return period of 475 years, a retrofit budget of $2.8 million dollars, and two available repair crews

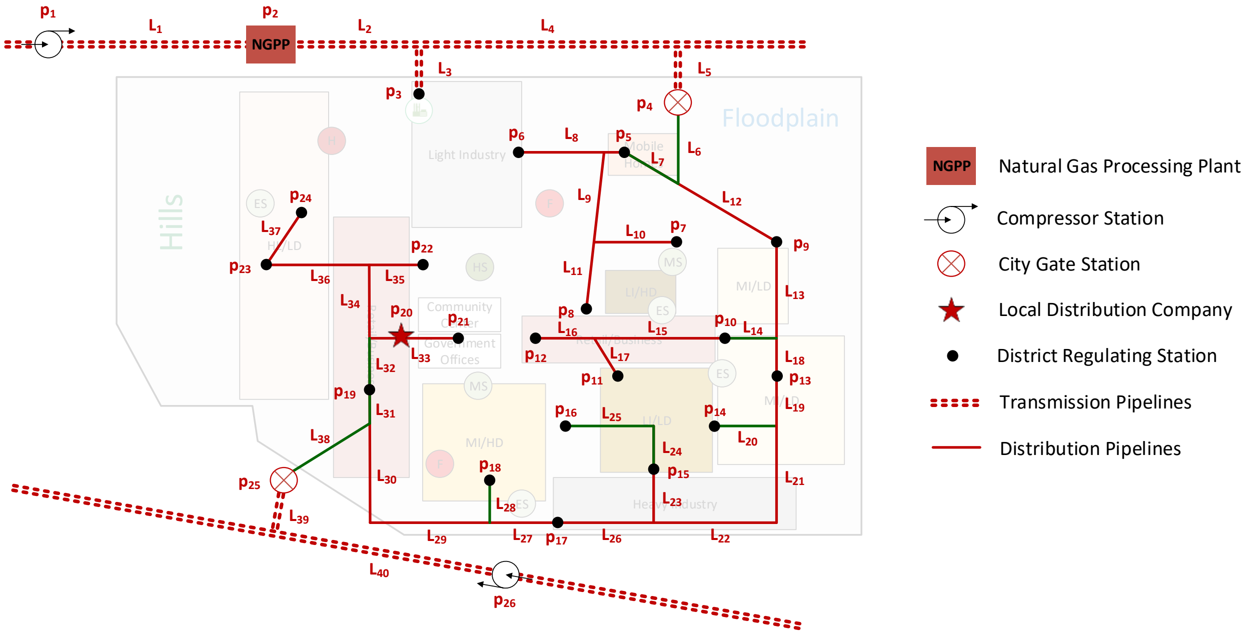

Figure 7-6. Retrofit scheme for Policy 1 (green lines indicate retrofitted pipelines)

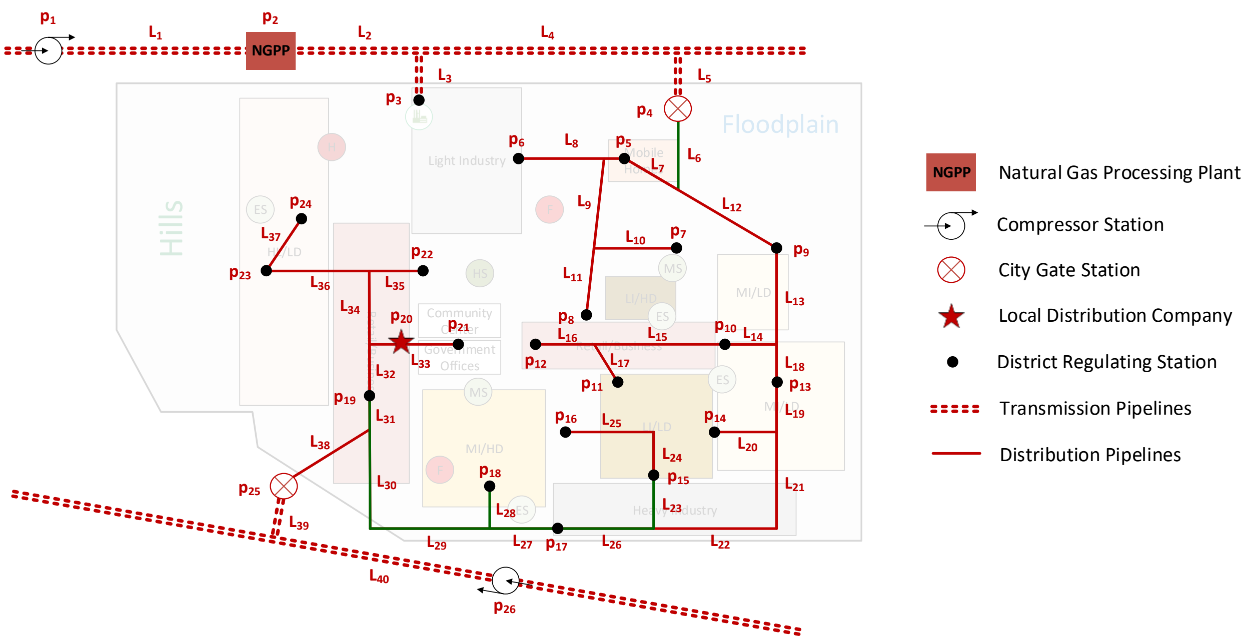

Figure 7-7. Retrofit scheme for Policy 2, 4, and 5 (green lines indicate retrofitted pipelines)

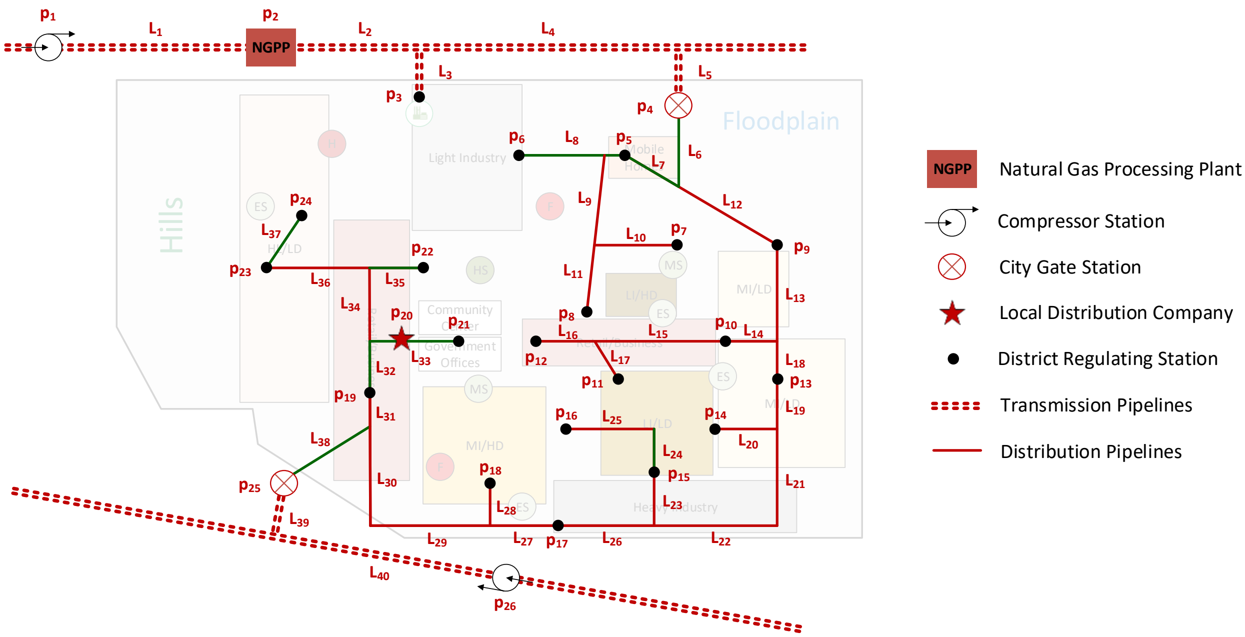

Figure 7-8. Retrofit scheme for Policy 3 (green lines indicate retrofitted pipelines)

It should be noted that after 90 days, there are certain combinations of retrofit and repair strategies that can provide 100% functionality in both residential and non-residential sectors. Figure 7-9 shows one of the retrofit schemes that provides complete functionality of the sectors, considering that an optimized network recovery will be done after the earthquake.

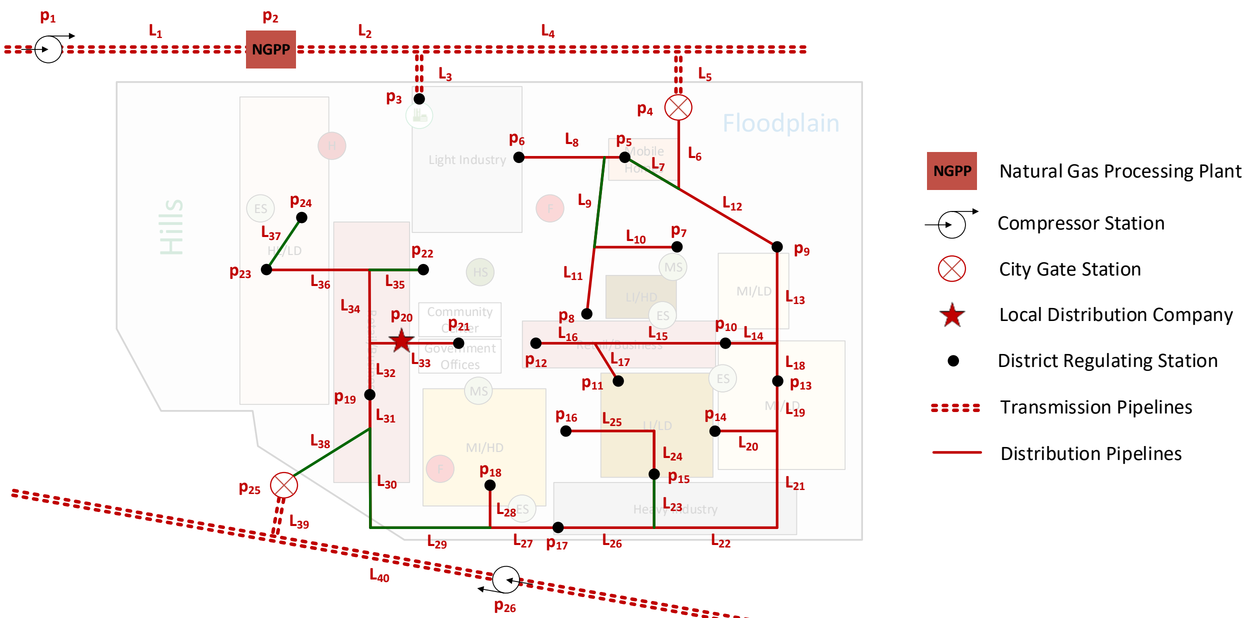

Figure 7-9. Retrofit scheme that results in 100% functionality in both sectors after 90 days for the considered scenario

Tables 7-1 and 7-2 show several polices that represent different combinations of retrofit and repair schemes for the Centerivlle NGN under all scenarios considered in this dissertation. For simplifications, for each scenario, at most three Pareto optimal solutions have been selected to be shown in the tables as possible solutions for policy-makers to consider: one that minimizes the number of people affected, one that minimizes the amounts of business losses, and one that is in-between the two.

Table 7-1. Results for the earthquake with 10% chance in 50 years (RP = 475 yrs)

Retrofit Budget	Repair Crew	Policy	Day					
			30 days		60 days		90 days	
			People	BL	People	BL	People	BL
$2.8	R = 2	P1	50,000	$30	11,500	$47.7	0	$49.6
		P2	50,000	$30	9,500	$57.5	0	$62.4
		P3	50,000	$30	15,000	$43.7	0	$44.2
	R = 5	P4	15,500	$30	13,500	$33.6	0	$33.8
		P5	50,000	$30	0	$42.2	0	$42.2
	R = 10	P6	13,500	$30	0	$43.8	0	$44.3
		P7	50,000	$30	0	$38.7	0	$38.7
$5.6	R = 2	P8	26,500	$28	13,000	$43.4	0	$43.5
		P9	50,000	$30	0	$44.3	0	$44.5
		P10	50,000	$28	2,500	$43.4	0	$43.4
	R = 5	P11	13,500	$28	0	$33.5	0	$33.5
		P12	0	$30	0	$38.6	0	$38.6
	R = 10	P13	13,500	$28	0	$33.5	0	$33.6
		P14	0	$30	0	$38.6	0	$38.6

Note: the retrofit budget and business losses (BL) are in million dollars

Table 7-2. Results for the earthquake with 2% chance in 50 years (RP = 2475 yrs)

Retrofit Budget	Repair Crew	Policy	Day					
			30 days		60 days		90 days	
			People	BL	People	BL	People	BL
$2.8	R = 2	P15	50,000	$30	50,000	$60	28,500	$76.3
		P16	50,000	$30	50,000	$60	21,500	$89.9
		P17	50,000	$30	50,000	$60	44,500	$72.1
	R = 5	P18	50,000	$30	15,500	$55.2	13,500	$65.3
		P19	50,000	$30	37,500	$47.1	0	$84.5
	R = 10	P20	50,000	$30	13,500	$51.1	0	$63.1
$5.6	R = 2	P21	50,000	$30	50,000	$60	17,500	$71.9
		P22	50,000	$30	50,000	$60	9,500	$83.1
		P23	50,000	$30	50,000	$60	48,500	$61.2
	R = 5	P24	50,000	$30	13,500	$56.3	0	$57.5
		P25	50,000	$30	29,500	$48.1	0	$49.8
	R = 10	P26	50,000	$30	13,500	$56.4	0	$57.7

Note: the retrofit budget and business losses (BL) are in million dollars

As shown in the tables, each policy (P) provides information with regard to the trade-offs between the number of people affected and the amount of business losses at different time frames, considering different budgets for retrofit, the number of repair crews, and two different design earthquakes. The results from these tables can provide useful information for decision making purposes. For example, consider policies P4 and P5, which represent the results for the case of an earthquake with 475 years return period, when a budget of $2.8 million dollars and five repair crews are available for retrofit and repair, respectively. Comparing these policies together, adopting policy P4 results in a smaller number of people being affected after 30 days (15,500 people instead of 50,000) and reduces the amounts of business losses in the long run ($33.8 million dollars after 90 days). Nonetheless, using this policy results in 13,500 people not having access to natural gas after 60 days. Therefore, if the goal is to have 100% functionality of natural gas network in the residential sectors by the day 60, then policy P5 should be implemented, even though the amount of business losses after 90 days will increase for this case ($42.2 million dollars).

Furthermore, for the earthquake with 475 years return period, the results show that when a budget of 5.6 million dollars are available for retrofit, arranging more than five repair crews would be unnecessary for repairing the damaged components. Nontheless, considering five crews can be much more effective than two crews for this case. Moreover, if under certain circumstances only two crews can be arranged and devoted for repairing the damaged components in the aftermath of the earthquake, then doubling the retrofit budget to strengthen the natural gas distribution pipelines does not seem to be a reasonable option, as there is not much difference between the results for these cases. Instead, it may be more reasonable to save the extra budget and invest it in either increasing the number of available repair crews after the event, or fortifying the key elements of the networks more extensively before the event occurs. Similar reasoning can also be made for the case of earhtquake with 2475 years return period.

Moreover, the question for which earthquake the decisions should be made is completely up to the decion-maker. A risk-taker may only consider the results for the earthquake with a return period of 475 years. Nontheless, if the decision-maker is a risk-averse person, they may select planning for the earthquake with 2475 years return period, which is a low-probability yet high-consequence event. Regardless, for someone who is risk neutral, both of the above-mentioned tables can provide sufficient information for decision making purposes at the community committee level.

Finally, the methodology developed in this dissertation can provide decision makers with useful information in order to prioritize retrofit actions. For example, in most scenarios under study, pipelines L_6 and L_{38} have been selected for retrofit. This reveals the importance of these pipelines as the key connections between the transmission and distribution networks. Thus, the developed methodology is capable of recognizing the critical components in the network that need to be prioritized in retrofit and planning projects at the community level.

CHAPTER 8: SUMMARY, CONTRIBUTIONS, AND RECOMMENDATIONS

SUMMARY

In this dissertation, a methodology was proposed and described for optimizing resilience decision making for natural gas networks under uncertainty. An optimization framework that integrated probabilistic seismic risk assessment of coupled infrastructure systems and evolutionary algorithms was proposed in order to determine cost-optimal decisions before and after a seismic event, with the goal of making the network recovery faster and thus contributing to a more resilient community. Specifically, strategic decisions were pursued regarding which pipelines in the natural gas distribution network of a community should be retrofitted under limited budgets, and how the limited available resources should be allocated to damaged components, considering minimizing two competing objective functions: the number of people without natural gas in the residential sector, and business losses due to a lack of natural gas in non-residential sectors. The proposed methodology can be used to find the best mitigation and recovery policies or to master-plan a new community or network.

As a basis for the proposed decision-making methodology, component models for natural gas networks were discussed by defining the network components at the community level and their damage models in chapter 2. In order to model the interdependencies between the natural gas network and other networks, approaches for modeling these interdependencies were explained in chapter 3. In chapter 4, earthquake hazard modeling was discussed and deterministic and probabilistic seismic hazard assessment methodologies were explained including an approach to maintain spatial correlation while utilizing hazard with a specified return period. The causes of damage to natural gas network components were also discussed in chapter 4. Chapter 5 introduced a community restoration algorithm, primarily the natural gas network combined with electrical power, in order to model that portion of the recovery process in the aftermath of an earthquake. The developed algorithm was capable of representing the restoration process both spatially and temporally until full restoration of the network was achieved. Mitigation strategies and optimization of resource allocation processes were discussed in this chapter.

In order to illustrate the methodology proposed, chapter 6 represented a virtual community model that was used in this dissertation and subjected to earthquakes in order to examine the restoration of communities in the aftermath of an earthquake. The chapter discussed the topology and structure of the natural gas as well as electric power networks and described the bi-directional interdependency that should be considered across the networks. Finally, chapter 7 introduced a platform for optimal decision making, resilience assessment, seismic risk mitigation, and optimized recovery of natural gas networks, taking into account their interdependencies with other systems. An algorithm was developed in order to find the best locations for replacing the main steel distribution pipelines with earthquake-resistant HDPE pipelines for mitigation before the event and under limited budgets, as well as finding the best way to allocate the available yet limited repair crews to damaged components for recovery.

CONTRIBUTIONS

Modelling NGN at the community level

A robust simulation methodology was proposed for modeling natural gas networks including their interdependencies with other systems at the community level. The causes of damage to natural gas network components due to earthquakes were discussed and component damage models were provided. This simulation model can be coupled with any restoration model in order to investigate the recovery of natural gas networks under seismic hazards at the community level.

Optimized restoration analysis methodology

An algorithm was developed in this dissertation, which can model interdependencies between natural gas networks and other systems, and includes cascading failures in restoration of natural gas networks in the aftermath of an earthquake. The proposed restoration algorithm combines discrete event simulation (DES) and network-based approaches and can represent spatial and temporal depiction of the restoration process until the full restoration is achieved. Another advantage of the developed algorithm is its ability to perform optimized network recovery and prioritized resource allocation using genetic algorithms.

Optimizing resilience decision-making for NGN under uncertainty

A comprehensive approach for optimal decision making for resilience assessment, seismic risk mitigation, and recovery of natural gas networks, taking into account their interdependencies with other systems was developed. The optimization framework is capable of integrating sophisticated probabilistic descriptions of potential disruptive scenarios derived from seismic risk assessment with evolutionary algorithms in order to determine cost-optimal decisions before and after a seismic event. Using this platform, strategic decisions can be pursued regarding which pipelines in the natural gas distribution network in a community should be retrofitted under limited budgets before the hazard event, and how the limited available resources should be allocated to damaged components in the aftermath of the event, considering different competing objective functions. Therefore, the proposed methodology can be used for risk-informed prioritization of investments incorporating different levels of risk preferences.

Integrating the Platform into IN-CORE

The platform for optimal decision making under uncertainty has been developed in Python and can be integrated into the Interdependent Networked Community Resilience Modeling Environment (IN-CORE) in a straightforward fashion, in order to be coupled with other models for further analyses and investigations.

RECOMMENDATIONS

Incorporate community-level metrics as objective functions

Community-level metrics may be used as more comprehensive objective functions in the decision-making approach developed in this dissertation. Examples include using a socioeconomic resilience metric such as population outmigration as an alternative for the number of people not having access to natural gas.

Include direct and indirect business losses

The simplified methodology to evaluate business losses used in this dissertation can be replaced by a more complex model that can accurately relate the unavailability of natural gas to direct and indirect economic losses. Examples may include incorporating computable general equilibrium (CGE) models into the decision-making platform in order to make a more accurate estimation of the amount of business losses due to unavailability of natural gas in the community. It would also be appropriate to include other systems/networks in the community in the decision-making framework (e.g. water, food supply chains, etc.)

Combine additional mitigation approaches

In addition to the mitigation strategies adopted in this dissertation, other mitigation schemes may be added to the decision-making platform. One example is the installation of new pipelines in the natural gas distribution network in order to make the system more resilient by adding more redundancy to it.

Reduce computational costs

Despite the strength and capabilities of the algorithm developed in this dissertation, the amount of time it takes to converge to the optimal solution is lengthy. This is due to the stochastic nature of the models/methods (i.e. Monte Carlo simulation, probabilistic seismic hazard, and multi-objective genetic algorithm). It is therefore recommended to investigate other approaches that may reduce the complexity of the simulations. One suggestion may be replacing Monte Carlo simulation with Latin Hypercube sampling to reduce computational demand.

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