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RELIABILITY AND RISK ASSESSMENT OF NETWORKED URBAN INFRASTRUCTURE SYSTEMS UNDER NATURAL HAZARDS

by

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ABSTRACT

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Modern societies increasingly depend on the reliable functioning of urban infrastructure systems in the aftermath of natural disasters such as hurricane and earthquake events. Apart from a sizable capital for maintenance and expansion, the reliable performance of infrastructure systems under extreme hazards also requires strategic planning and effective resource assignment. Hence, efficient system reliability and risk assessment methods are needed to provide insights to system stakeholders to understand infrastructure performance under different hazard scenarios and accordingly make informed decisions in response to them. Moreover, efficient assignment of limited financial and human resources for maintenance and retrofit actions requires new methods to identify critical system components under extreme events.

Infrastructure systems such as highway bridge networks are spatially distributed systems with many linked components. Therefore, network models describing them as mathematical graphs with nodes and links naturally apply to study their performance. Owing to their complex topology, general system reliability methods are ineffective to evaluate the reliability of large infrastructure systems. This research develops computationally efficient methods such as a modified Markov Chain Monte Carlo

simulations algorithm for network reliability, and proposes a network reliability framework (BRAN: Bridge Reliability Assessment in Networks) that is applicable to large and complex highway bridge systems. Since the response of system components to hazard scenario events are often correlated, the BRAN framework enables accounting for correlated component failure probabilities stemming from different correlation sources. Failure correlations from non-hazard sources are particularly emphasized, as they potentially have a significant impact on network reliability estimates, and yet they have often been ignored or only partially considered in the literature of infrastructure system reliability.

The developed network reliability framework is also used for probabilistic risk assessment, where network reliability is assigned as the network performance metric. Risk analysis studies may require prohibitively large number of simulations for large and complex infrastructure systems, as they involve evaluating the network reliability for multiple hazard scenarios. This thesis addresses this challenge by developing network surrogate models by statistical learning tools such as random forests. The surrogate models can replace network reliability simulations in a risk analysis framework, and significantly reduce computation times. Therefore, the proposed approach provides an alternative to the established methods to enhance the computational efficiency of risk assessments, by developing a surrogate model of the complex system at hand rather than reducing the number of analyzed hazard scenarios by either hazard consistent scenario generation or importance sampling. Nevertheless, the application of surrogate models can be combined with scenario reduction methods to improve even further the analysis efficiency.

To address the problem of prioritizing system components for maintenance and retrofit actions, two advanced metrics are developed in this research to rank the criticality of system components. Both developed metrics combine system component fragilities with the topological characteristics of the network, and provide rankings which are either conditioned on specific hazard scenarios or probabilistic, based on the preference of infrastructure system stakeholders. Nevertheless, they both offer enhanced efficiency and practical applicability compared to the existing methods.

The developed frameworks for network reliability evaluation, risk assessment, and component prioritization are intended to address important gaps in the state-of-the-art management and planning for infrastructure systems under natural hazards. Their application can enhance public safety by informing the decision making process for expansion, maintenance, and retrofit actions for infrastructure systems.

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Chapter 1

Introduction

Urban societies heavily rely on functional and dependable infrastructure systems for their well-being. With the urban population throughout the world on a sharp and steady rise, maintaining minimum standards for the satisfactory functioning of infrastructure systems is gaining more attention, as evidenced by some of the short and long term policies in cities around the globe (NIST, 2009). However, the amount of attention and funding allocated to maintain minimum levels of reliability for critical infrastructure systems such as the power grid, water distribution networks, and highway bridge systems is not proportional to their critical importance, even in developed countries (Amin, 2003; NIST, 2009; ASCE, 2009). In the United States, professional communities have continuously tried to raise concern over the condition of infrastructure networks in recent years. For example, the American Society of Civil Engineers (ASCE) report card on infrastructure systems gave an overall grade point average of D to the condition of infrastructure in 2009, and estimated 2.2 trillion US Dollars must be invested during the next five years on all systems (ASCE 2009). A new report card published recently in 2013 shows only marginal improvements, and gives an overall average of D+ to the current state of infrastructure systems (ASCE 2013). The 2009 report, for example, labeled more than 26% of bridges in the highway transportation system as structurally deficient or functionally obsolete. The expansion of the power grid, on the other hand, is not proportional to growing demand, which may result in similar scenarios to the 2003 North America blackout (Andersson et al. 2005). The same situation is echoed in other parts of the world; for example, see EU Commission (2006) for a green paper on European Union's state of energy systems.

Estimating the reliability of infrastructure systems against natural or man-made hazards is also of interest to system stakeholders and policy makers alike for the insights it provides for maintenance and expansion planning while ensuring public safety. Infrastructure systems are expected to maintain adequate functionality during normal operational conditions throughout their design lifetime; nonetheless, they must also provide the service required in the aftermath of extreme events, such as earthquakes and hurricanes (Chen et al., 2002). Accordingly, system reliability in the context of this thesis is defined as the probability that the system satisfactorily fulfills its performance objective(s) given a specific hazard scenario. Equation 1.1 formulates the concept of reliability by defining its complement, the system failure probability:

$$P_f = \mathrm{P}[system\ failure \mid h] = \int_{g(\boldsymbol{x})<0} f_{\boldsymbol{X}}(\boldsymbol{x})\, d\boldsymbol{x} \qquad 1.1$$

where P_f is the failure probability of the system, *h* stands for a given hazard scenario event, $\boldsymbol{x}$ is the vector of variables influencing system reliability, $f_{\boldsymbol{X}}(\boldsymbol{x})$ denotes the joint probability density function of the input variables, and $g(\boldsymbol{x}) = 0$ represents the *limit state function*, a hyper surface which separates regions of system failure and survival in the space identified by $\boldsymbol{x}$. Equation 1.1 can be used to evaluate the reliability of a single structure such as a bridge, or a portfolio of structures as in highway bridge networks. The system performance metrics which are used to define the limit state function are specific to the type of system under study. For instance, an appropriate performance metric for electrical power transmission networks may be the number of customers who remain connected or the amount of available megawatts after a seismic or hurricane event. Furthermore, the system failure may be associated with a variety of scenarios, from the structural failure of a few key components, such as bridges of road transportation networks, to cascading failures triggered by a chain of events, as possible for power transmission systems. For most reliability problems, the limit state function $g(\boldsymbol{x}) = 0$ is not available in explicit form. Therefore, computing the system failure probability in Equation 1.1 often requires point estimations or a surrogate model to replace $g(\boldsymbol{x})$ for numerical integration. Evaluating the system failure probability for complex systems is the first major objective of this research. Specifically, this thesis develops efficient methods to evaluate the system reliability for complex systems comprised of numerous components where the limit state function is too contrived or unavailable in closed form. Application of the developed methods is demonstrated for three types of urban infrastructure systems: highway bridge networks, water distribution networks, and the power transmission grid. Most of the developed methods are focused towards highway bridge systems; however, they are applicable to other networked infrastructure systems as well with appropriate reliability objectives.

System reliability evaluations can be integrated into a probabilistic risk analysis framework to estimate the exceedance rate of system failure probabilities. Evaluating the system failure probability by Equation 1.1 is contingent upon a given hazard scenario, which informs the joint probability density function $f_{\mathbf{X}}(\mathbf{x})$. As the result, the estimated system failure probability is conditioned on a specific hazard scenario. In this regard, the risk analysis framework provides an opportunity to evaluate the unconditional probability of exceeding system failure probabilities, which is achieved by estimating the system reliability for multiple hazard scenarios, and account for the hazard scenarios' annual rate of exceedance. The resulting risk curves can inform appropriate site-specific decision making for system stakeholders once the consequences of events in monetary or social terms are quantified. However, probabilistic risk assessment poses a computational challenge for infrastructure systems since system reliability evaluations must be performed multiple times. This challenge leads to the second major objective of this thesis: developing an efficient framework for probabilistic risk assessment of large, complex infrastructure systems. Accordingly, achieving the first stated objective is a pre-requisite of the second research objective.

With limited resources at their disposal, the owners of infrastructure systems often need to prioritize the system components for maintenance and retrofit actions against natural hazards in order to achieve the targeted risk and reliability goals. For example, in a highway transportation system, the stakeholders must give priority to bridges which are located on the most critical routes and are most vulnerable to the concerned hazard. Devising a prioritization scheme gives rise to an optimization problem which can be very complicated to solve without simplifying assumptions. As the third and final major research objective, this thesis develops methodologies which rank the system components based on different criteria, both for a given hazard scenario and in a probabilistic framework. The developed methods do not require solving the contrived optimization problem, and instead rely on importance measures to rank component criticalities.

1.1. Scope of Research

This study focuses on the reliability and risk assessment of spatially distributed infrastructure systems against natural hazards such as seismic and hurricane loads, and develops computationally efficient methods to make such studies feasible for large and complex networks. Although essential for urban planning and public safety, evaluating infrastructure system performance and subsequent reliability estimation often requires large-scale and complicated computations which may be prohibitive in practice (Chen et al. 2002; Dueñas-Osorio and Rojo 2011; Frangopol and Bocchini 2012). However, reliability and risk assessments are critical for future infrastructure operation, maintenance, and renewal, thus highlighting the need for methods that can efficiently apply to networked systems without over simplification. Moreover, system level assessments need to consider correlated component failures and interdependence with other systems, which add to the problem complexity.

Most infrastructure systems are spatially distributed over large areas with many components that interact to fulfill the objectives of the system. Network theory offers appropriate tools to model the behavior of infrastructure systems and study their reliability against a range of natural or man-made hazards. In their simplest forms, networks are modeled as a collection of nodes (vertices) connected together by links (edges). Networks are represented by either directed or undirected graphs denoted as $G(N, L)$, where N denotes the set of nodes in the network and of L is the set of links (Newman 2010). As an example, the set of nodes in the power grid may contain power generation plants, substations, and final consumption nodes such as residential homes, while the power lines connecting those nodes at the transmission and distribution level constitute the set of links. This research also adopts network models to study the performance of infrastructure systems at the component and system levels, and applies pertinent methods that balance efficiency and accuracy for system reliability and risk assessment of critical systems, including highway bridge networks, water distribution systems, and the power transmission grid. However, the application of the developed methods is not limited to the three mentioned networks, as they may be generally employed for networked systems.

The choice of performance metrics and reliability objectives are often specific to the type of the infrastructure system under study, but they can also be similar across different systems. Maintaining connectivity between source and consumption nodes, for example, is a relevant reliability objective among many infrastructure systems. This research considers a range of relevant performance metrics and reliability objectives for the different systems under study. Both structural failure of system components and the functional loss in the network performance as the result of component failures are emphasized. For instance, a highway transportation system may fail if critical destinations are inaccessible because the connecting brides are closed, or if the remaining path after the closure of some bridges is longer than an acceptable threshold (Chen et al. 2002; Liu et al. 2006; Stergiou and Kiremidjian 2010; Bocchini and Frangopol 2011a). As another example, even if pipes and pump station structures in water distribution networks are likely to survive a hurricane event, the system may fail to provide the necessary water pressure for the consumption nodes due to blackouts which leave the pumps without power. This example highlights the significance of considering interdependent infrastructure systems for reliability and risk analysis, as the reliability of one system may depend on other systems (Dueñas-Osorio et al. 2007; Dueñas-Osorio et al. 2007; Hernandez-Fajardo and Dueñas-Osorio 2011a; Hernandez-Fajardo and Dueñas-Osorio 2011b; Poljanšek et al. 2012; Hall et al. 2012).

The response of components of infrastructure systems to natural hazards is often correlated in a probabilistic risk analysis framework for a variety of reasons. For seismic hazard, many researchers have demonstrated that the intensity of excitations a portfolio of structures experience is correlated due to the geographical proximity of their locations (Wesson and Perkins 2001; Bocchini and Frangopol 2011b; Bommer and Crowley 2006; Jayaram and Baker 2009; Lee and Kiremidjian 2007). Neglecting these correlations can lead to underestimation of the system's failure probability, as the mentioned studies have shown. In addition to the hazard-induced correlations, there are other factors which also influence the correlated response of components by affecting the resistance capacity of structures. Such factors include similar structural detailing and similar environmental conditions among other sources, and have been the subject of only a few studies (e.g. Lee and Kiremidjian 2007). Specifically, they can impose a correlation structure on the failure probabilities of system components, which can subsequently impact the system reliability. This research also proposes a methodology to quantify the correlations from non-hazard sources, and integrates them into a framework along with hazard-induced correlations for efficient reliability and risk assessment of large infrastructure systems. The resulting framework is called Bridge Reliability Assessment in Networks (BRAN), and enables exploring the impact of different correlation levels on the reliability of networks with varying topological characteristics. Such an exploration enables communicating the importance of considering common cause effects in infrastructure reliability studies more effectively.

Even with efficient network reliability methods, probabilistic risk assessments often become a computational challenge for large networks since many hazard scenarios need to be considered. In structural reliability problems, surrogate models developed by methods in statistical learning have made reliability and sensitivity analysis of large structures accessible with manageable errors (Dai et al. 2012; Dubourg et al. 2011; Echard et al. 2011; Hurtado 2004, 2011). However, surrogate models, even in simple forms, have not been applied to network reliability and risk evaluations. This research employs advanced surrogate models to significantly relax the computational expense of seismic risk evaluations of networked systems, not by reducing the number of hazard scenarios, but by replacing costly simulations for each scenario to evaluate the network performance by a predictive model. The surrogate models in this work are developed by random forests (Breiman 2001), which are shown to be well suited for network reliability applications, and exemplified through synthetic and real systems. Establishing the surrogate models requires simulations on only a subset of hazard scenarios, and their application to large highway bridge networks is shown to produce results which are close to benchmark Monte Carlo simulations. Moreover, surrogate models produce even more accurate predictions if used along with hazard scenario reduction methods such as importance sampling (Jayaram and Baker 2010). Besides developing surrogate models by random forests, this research employs Fisher's Discriminant Analysis, a linear model, in order to visualize the limit state function of high dimensional network reliability problems in two dimensions. The proposed methods to develop surrogate models and visualization in networks make seismic risk evaluations accessible for large highway bridge systems, and can help network stakeholders concerned with efficient resource allocation.

Finally, efficient ranking methods are pursued to prioritize system components for maintenance and retrofit actions. Prioritization is a relevant problem in practice for developing effective policies to ultimately mitigate risks from natural hazards (Fussell 1975; Ramirez-Marquez and Coit 2005; Lee et al. 2011). Comprehensive ranking approaches need to consider the system reliability objectives along with the component vulnerabilities, and must measure the importance of components in fulfilling system-level objectives. This thesis reviews the existing approaches to address the problem of efficient resource assignment, and develops new importance measures to enhance upon the current state-of-the-practice, e.g. Buckle et al. (2006) for highway bridge networks, which often ignores system-level performance of components and solely focuses on component replacement costs in case of their failure.

1.2. Summary and Research Objectives

Reliability and risk assessment of urban networked infrastructure systems enables system stakeholders to make informed decisions regarding system maintenance and future expansions in order to protect public safety and optimize available resources. However, those assessments are often computationally expensive, which makes them impractical to implement for large and complex networks. On the other hand, the existing methods for reliability and risk assessment of networked systems do not consider all correlation sources that influence the response of system components during natural hazards such as earthquakes, which can potentially lead to either over or underestimating the system reliability and thus, waste resources or put the public safety in danger. The research proposed in this thesis addresses those concerns by developing efficient frameworks for reliability and risk analysis of networked systems, and proposing novel prioritization methods to optimize resource allocation. The developed frameworks are applied to case study networks of existing infrastructure systems, and the results are compared against state-of-the-art methods to highlight their efficiency.

Based on the discussions presented in this chapter, the objectives of this thesis may be summarized as follows:

1. Develop efficient network reliability methods which are applicable to large, complex infrastructure systems. Such methods must be able to accommodate correlated component failure probabilities from various sources of correlations.

2. Develop a framework for probabilistic risk assessments by fitting a surrogate model to the limit state function of networked systems. The surrogate model is instrumental to evaluate the annual exceedance rate of network reliability levels based on multiple hazard scenarios that enable risk quantification.

3. Develop efficient methods to prioritize network components under natural hazards by considering their vulnerabilities as well as role within the system.

Based on the stated research objectives, the thesis is organized as follows. Chapter 2 reviews the existing literature on the reliability and risk assessment of networked systems. Chapter 3 presents the relevant and established methods in complex network reliability assessment, re-states the gaps in the literature, and introduces the BRAN methodology, which enables integrating correlations into the network reliability framework. Chapter 4 describes forming surrogate models for network reliability assessments, which can be used for probabilistic risk evaluations. Chapter 5 introduces the developed importance measures to prioritize system components, and describes the specific applications of each metric. The developed methodologies are all exemplified through case study networks in Chapter 6, which also offers discussions on the insights from those practical applications. Finally, Chapter 7 provides the concluding remarks, and lists the future research needs in the field.

Chapter 2

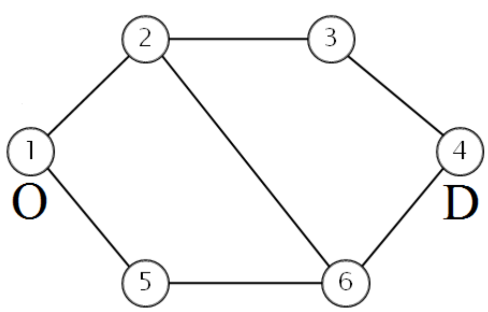
Review of the Existing Literature on the Reliability and Risk Assessment of Infrastructure Systems

This chapter reviews the advances in the reliability and risk evaluation of urban infrastructure systems, and summarizes the existing state-of-the-art methods for network reliability assessments and importance measures. Since infrastructure systems are modeled as networks, a brief introduction to network theory and its application to technological networks is presented first. The literature review consists of three subsections; each describing the advances for one of the infrastructure systems under study. Studying these systems (highway bridge networks, water distribution systems, and power transmission grid) requires system-specific performance metrics and reliability objectives, which are elaborated in their respective subsections. However, the reviews on the existing reliability and risk evaluation methods mainly focus on highway bridge networks because advanced bridge fragility models exist in the literature which are developed based on the results of dynamic analysis of structures. Fragility models are presented as functions relating the probability of a structure being in a particular state to the intensity of hazards, and are used to estimate the bridge failure probabilities given a hazard scenario. In contrast, fragility models for the components of the other two systems have not received the same amount of attention in the literature.

2.1. Network Models of Infrastructure Systems

Mathematical networks or graphs are widely used in the natural and social sciences to model the interaction of systems with many components (Albert and Barabasi 2002). The new applications by researchers over many fields of science (physics, mathematics, engineering, biology, social sciences, etc.) continue promoting new ideas and methods to model and analyze the behavior of networked systems (Newman 2010). Accordingly, network models of infrastructure systems have appeared in numerous recent studies (e.g. Albert et al. 2004; Cardillo et al. 2006; Dueñas-Osorio and Vemuru 2009; Hines et al. 2010; Yazdani and Jeffrey 2010).

For network modeling, each system is represented by a directed (e.g. highway bridge network) or undirected (e.g. water distribution system, power transmission grid) graph $G(N, L)$, with N and L denoting the sets of nodes and links, respectively. The adjacency matrix ($\boldsymbol{A}$) is one way of describing the connections between nodes in the network, besides other representations such as the edge list or the adjacency list (Newman, 2003). The adjacency matrix is a square matrix of size equal to the number of nodes in the network, where each entry A_{ij} is equal to 1 if there is a direct link connecting node j to node i, and 0 otherwise. The size of set N which is the number of nodes in the network is called the network order (n), while the number of links denotes the network size (l). Infrastructure systems are typically spatially distributed networks for transporting goods (data, commodities, humans, cars, etc.) across different nodes. Therefore, they often have special nodes as origin and destination (or source and sink) among which the transport takes place. Figure 2.1 represents a network of order six and size seven with two end nodes along with its adjacency matrix. Since this thesis is mainly concerned with the number of nodes in infrastructure systems, the term size is interchangeably used to refer to the network order (i.e. number of nodes).



$$\boldsymbol{A} = \begin{bmatrix} 0 & 1 & 0 & 0 & 1 & 0 \\ 1 & 0 & 1 & 0 & 0 & 1 \\ 0 & 1 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 & 0 & 1 \\ 0 & 1 & 0 & 1 & 1 & 0 \end{bmatrix}$$

Figure 2.1. Schematic six node network. O and D identify the origin and destination nodes, respectively.

Since infrastructure systems are designed to transport goods between origin and destination nodes, those nodes must remain connected in order for the network to function satisfactorily. Therefore, the performance metric in many network reliability studies against extreme hazards is connectivity, which examines for the existence of a path from the origin to the destination node(s). Connectivity is the minimum necessary condition for the network to function, preceding more sophisticated measures such as travel time or flow capacity. In the depicted example network of Figure 2.1, the network connectivity may be lost by removing Nodes 2 and 5, 3 and 4, or 3, 5, and 6, for instance, among other combinations. Examining connectivity is straightforward for small networks; however, efficient path finding algorithms are required for larger systems. Dijkstra (1959) presented one such algorithm, which finds the shortest path between two nodes in $\mathrm{O}(l + n\log(n))$ operations, where $\mathrm{O}(\cdot)$ denotes the asymptotic worst case computational complexity.

From the system reliability point of view, networks with simple topology (i.e. simple networks) can be reduced to sets of series and parallel sub-systems which provide paths from the origin to the destination nodes. The reliability of those series and parallel subgraphs can be readily identified given their components' failure probabilities before combining for the system reliability evaluation. Accordingly, the reliability of simple networks can be evaluated by established methods such as network reduction or event-tree analysis (Billinton and Allan 1992; Todinov 2007). Complex networks are not reducible to series and parallel sub-systems (e.g. Figure 2.1); however, regular decomposition algorithms can be used for small networks to extract simple network structures (Todinov 2007). Nonetheless, such methods are infeasible to apply to large networks since the number of computations quickly increases with the size of the network under study. Therefore, specific methods exist for complex networked systems (Section 2.2) which may be categorized in two main classes of closed-form and approximate methods.

Network reliability evaluations required component failure probabilities. The network components are typically assumed to have binary states (survival or failure), although problems with multiple component states can also be addressed with a few adjustments. The probability of a component being at either state is assessed by the component's response to the subjecting hazard, and is determined from the component's fragility model. For example, the failure probability of a bridge inside a bridge network under a seismic scenario may be the probability of exceeding a certain threshold displacement in its columns. Regardless of the method of choice, the network reliability is a function of component fragilities (probability of failure), topology of the network, and correlations among component responses to the hazard. In terms of Equation 1.1, the component fragilities and the correlation structure define the joint probability distribution $f_{\boldsymbol{X}}(\boldsymbol{x})$, and the network topology affects the limit state function $g(\boldsymbol{x})=0$. The developed *Bridge Reliability Assessment in Networks* (*BRAN*) methodology which is elaborated on in Chapter 3 provides more details on solving the complex network reliability problem with correlated component failures.

2.2. Review of Methods in Network Reliability Evaluations

Since complex infrastructure networks are not reducible to subsets of series and parallel systems, specific closed-form and simulation-based methods have emerged in the literature to evaluate their reliability. The reliability of networks depends on component failure probabilities and correlations among them, as well as the network topology. In highway bridge networks, for instance, the location of origin and destination nodes, the number of paths connecting them, the reliability of bridges on those paths, and the correlations among bridge failure probabilities determine the network-level reliability. A brief review of the most recognized methods in complex network reliability assessment follows.

2.2.1. Shortest Paths, Minimum Cut-Set Methods

This class of methods is concerned with finding the minimum cut-sets and shortest paths from the origin to destination nodes to solve the connectivity reliability problem in networks. For unweighted graphs that are commonly used in network reliability studies, the shortest path is a path that goes over the minimum number of links between the origin and destination nodes, which is also the path with the minimum weight. A cut-set is a set of several nodes or links in a network whose removal separates the origin and destination nodes into two disjoint sub-graphs. The minimum cut-set contains the minimum number of components to disconnect origin and destination nodes. Finding all disjoint shortest paths and cut-sets in a network determines the network reliability and probability of failure, respectively; resulting in an exact solution to the network reliability problem.

However, the number of paths and cut-sets grows exponentially with the number of components in a network, causing long computation times even for not very large networks (Billinton and Allan 1992; Todinov 2007). The Recursive decomposition algorithm or RDA (Li and He 2002; Liu and Li 2009; Liu and Li 2012) is an attempt to address this concern by recursively identifying and removing exclusive paths until the remaining network is not complex anymore. The same strategy is also applicable by finding and removing exclusive cut-sets. Since the number of paths and cut-sets are very large in a system with hundreds or thousands of nodes, RDA approximates the network reliability by decomposing the network up to a desired level, leaving out the rest of paths and cut-sets for computational efficiency. Recently, Lim and Song (2012) further improved the method into a Selective Recursive Decomposition Algorithm where the most reliable path is sought after at each stage of the decomposition. This method has performed satisfactorily for small to medium size test networks; although its efficiency has not been examined for large infrastructure networks yet. Originally, methods based on recursive decomposition were applicable to a single pair of origin and destination nodes. Recently, Kim and Kang (2013) developed a framework to extend the recursive decomposition algorithm to multiple origin and destinations; however, their application may become intractable for larger networks.

In summary, a major practical shortcoming of shortest path, minimum cut-set class of methods emerges in their decreased efficiency in application to large networks over multiple origin-destination (O, D) pairs. However, they are more computationally efficient when applied to small networks compared to simulation based methods, particularly for extremely high or very small network reliability levels.

2.2.2. Matrix-Based System Reliability (MSR) Method

Matrix-based system reliability (MSR) is an improvement upon original work on bounds on system reliability by Song and Der Kiureghian (2003), and provides a closed form solution to the network connectivity reliability problem. MSR establishes the power set of events (i.e. the complete set of are mutually exclusive and collectively exhaustive (MECE) events), and examines the connectivity among origin and destination nodes for each event. If a system comprises *n* components, $m = 2^n$ is the number of events in the power set. As for the MECE events, the system failure probability can be computed as:

$$\mathrm{P}\left(E_{sys}\right) = \boldsymbol{c}'\boldsymbol{p} \qquad 2.1$$

Where E_{sys} is the event of system failure, $\boldsymbol{c}_{m\times1}$ is a column vector of 0 and 1 associated with MECE events leading to system survival and failure, respectively, and $\boldsymbol{p}_{m\times1}$ represents the probabilities associated to each component of each event associated to $\boldsymbol{c}'$. Song and Kang (2009) present methods to efficiently produce vectors $\boldsymbol{c}$ and $\boldsymbol{p}$, and apply MSR to evaluate the seismic reliability of multi-member bridge structures where safety factors of the structural members are dependent due to respective correlations in their associated seismic demands. They also propose a method to analyze the sensitivity of system reliability estimates. MSR has also been applied to reliability assessment of bridge networks with simplified layouts (e.g. Kang et al., 2008). The major challenge for MSR lies in its computation complexity for large networks, where the number of events in the power set grows exponentially with the number of components in the network and become intractable. Similar to the recursive decomposition algorithm, bounds on system reliability may be established to relax the computations; however, the most probable events may not be identified (Der Kiureghian and Song 2008). MSR has also been used in a bridge seismic network reliability analysis with a simple flow-based reliability objective (Lee et al., 2011).

2.2.3. System Reliability Method for Radial Topologies

Special network topologies can enable increased computational efficiency in reliability assessment studies. Accordingly, a new combinatorial method was recently proposed that provides closed form solutions when applied to networks with radial topology. Since power distribution systems have tractable radial layouts, they are well-suited for the application of this method (Dueñas-Osorio and Rojo 2011). For power networks application, the method examines the connectivity of the source node to all other nodes (one to all). The methodology used in this approach reduces the number of computations for a system with n components from $O(2^n)$ to $O(n^3)$ by relying on recursion principles. While the combinatorial closed-form method could account for correlated component failures by $O(2^{n-1})$ computations, the complexity can still be reduced to $O(n^2)$ if correlations are ignored (Rojo and Duenas-Osorio 2011).

To apply the closed-form recursive reliability assessment methodology to risk assessment problems, Dueñas-Osorio and Rojo (2011) used the number of the served consumers as the network performance metric, and provided the probability mass function (PMF) of the served consumers based on service nodes connected to the source. Further improvements upon the uncorrelated version have provided approximate methods to compute the PMF of more general systems very efficiently, making it desirable relative to Monte Carlo based simulations for this application while providing component and event importance measures.

2.2.4. Simulation Based Methods

Monte Carlo based methods are widely used for reliability assessment of large networks, due to their general applicability (e.g. transportation networks: Kiremidjian et al. 2007 and Jayaram and Baker 2010; power networks: Allan and Billinton 2000). Since network reliability evaluations by Monte Carlo simulations do not require enumerating paths and cut-sets or decomposing the system into MECE events, they are relatively simple to implement. However, simulation based methods face two challenges: 1) their computational complexity may limit the size of the network that can be analyzed (although less limiting than most closed form solutions), and 2) they are computationally inefficient in evaluating low system failure probabilities. Nevertheless, algorithms based on Monte Carlo simulation coupled with other stochastic and heuristic techniques may efficiently solve the network reliability problem with thousands of nodes, and help overcome some of the noted limitations within reasonable accuracy. Moreover, Monte Carlo based methods can seamlessly integrate correlated component failures for network reliability assessment, and, therefore, they are the method of choice in this thesis. Since crude Monte Carlo simulations are often computationally inefficient, particularly to evaluate extreme probabilities, variance reduction techniques are used throughout this thesis to increase their efficiency. Accordingly, quasi Monte Carlo sampling (Korobov 1957; Halton 1960; Niederreiter 1992; Lemieux 2009) and importance sampling are discussed in Chapters 3 and 4, respectively, for reliability and risk assessment. Furthermore, simulation based network reliability assessment allows for parallelization algorithms, which enables using cluster computing to significantly reduce the computation time. The case studies (Chapter 6) also highlight the efficiency gained by reducing the number of simulations. The literature offers other methods to increase the efficiency of the simulations as well, most notably the subset simulations (Au and Beck 2001).

As the most basic form of simulation based methods, Naïve Monte Carlo simulations can be applied to evaluate the reliability of networked systems, with any number of origin and destination pairs. Component failures are realized based on their reliability in each Monte Carlo simulation, and the reliability of the remainder of the network is evaluated by the performance metric of choice (which is connectivity here). Table 2.1 presents the steps to evaluate the connectivity reliability in a network with n components.

Generating the n-dimensional uniform random variable $\boldsymbol{u}$ by quasi-random sequences such as the Sobol sequence or Latin Hypercube sampling can greatly enhance the efficiency of the Naïve Monte Carlo method. Although the Naïve Monte Carlo method provides a simple implementation, its efficiency decreases when several (O, D) pairs are considered and the reliabilities in $\boldsymbol{b}$ are high. The BRAN methodology employs a different simulation based method, the Markov Chain Monte Carlo simulations, which is more efficient for multiple origin and destinations, as discussed in Chapter 3.

Table 2.1. Pseudo-algorithm of naïve Monte Carlo method for network connectivity reliability

1	**START**
2	INPUT
3	Component reliabilities $\boldsymbol{b} \in [0,1]^n$; N_{MC}: number of Monte Carlo simulations; origin and destination nodes (O, D)
4	$r = 0$
5	for $k = 1{:}N_{MC}$
6	Simulate $\boldsymbol{u} \in [0,1]^n$
7	Set $\boldsymbol{t} = \boldsymbol{u} > \boldsymbol{b}$
8	For all i where $t(i) > 0$: remove component i from the network
9	Run an algorithm such as Dijkstra (1959) to examine (O, D) connectivity
10	If the connectivity is lost, set $r = r + 1$
11	end
12	$P_f = r / N_{MC}$
13	**END**

2.2.5. Summary and Research Gaps

Monte Carlo based methods for system reliability, particularly by variance reduction techniques, can be applied to estimate the network reliability of large infrastructure systems with correlated component failures. However, the computational efficiency of the Naïve Monte Carlo method for network reliability assessment decreases over multiple (*O*, *D*) pairs, particularly to estimate extreme failure probabilities. When computationally intensive tasks such as sensitivity analysis for network reliability assessment is intended, such constraints may become limiting in application to large networks. Similarly, probabilistic risk assessment requires many network reliability evaluations, which suggests more computationally efficient methods are required for such applications. Among closed form solutions for general network topology, recursive decomposition algorithms have shown promising results over small networks. However, their application to large networks with correlated component failures and multiple (*O*, *D*) pairs becomes intractable. Therefore, the BRAN methodology focuses on simulation based methods, and employs variance reduction techniques and more efficient algorithms to relax the computational complexity.

2.3. Advances in Reliability Evaluations of Critical Infrastructure Systems

This section reviews the existing literature on reliability evaluations of the three critical infrastructure systems studied in this thesis along with their applicable performance metrics and reliability objectives. Literature review on the highway bridge networks also includes probabilistic risk assessment and importance measures. The reviews identifie gaps in the existing research and areas in need of improvement.

2.3.1. Highway Bridge Networks

Bridge structures are vulnerable against natural hazards such as earthquakes and hurricanes. The fragility of bridges against natural hazards depends on many factors such as bridge type, material, proximity to deteriorating agents and environments, soil-structure interaction, and fatigue loading from crossing traffic, among others (Weyers et al. 1994; Nielson and DesRoches 2007; Choe et al. 2008; Ghosh and Padgett 2010). Advanced bridge fragility assessment frameworks (e.g. Ghosh et al. 2013; Rokneddin et al. 2013) consider most of these factors to evaluate the vulnerability of aging highway bridges under extreme hazards such as earthquakes, and provide bridge specific models to estimate their failure probability for spectral accelerations or displacements induced by a given hazard scenario. Moreover, these models can take advantage of data from bridge instrumentation of a select number of bridges to update the expected value of the deterioration parameters throughout the network and enhance the fragility estimates (Ghosh et al. 2013). The developed BRAN methodology employs time-dependent fragility models by Ghosh et al. (2013) to estimate the present-day reliability of bridges in the network.

At the network level, highway networks must maintain connectivity among critical nodes in the network as a minimum objective in the aftermath of a seismic or hurricane event (Chen et al. 2002; Rokneddin et al. 2012). The necessary connectivity condition is satisfied if the path between the critical origin and destination nodes remains connected after an extreme event, during which a number of bridges are expected to reach a damage state requiring short or long term closure to repair or replace. Reaching the extensive damage state is considered failure in this thesis, resulting in the unavailability of the bridge in the aftermath of natural disasters. To maintain an acceptable level of service, the remainder of the highway network must have enough paths and redundant traffic capacity to keep the average travel time below an acceptable threshold. Accordingly, most highway system reliability studies consider either connectivity or traffic flow metrics under seismic hazards (e.g. Liu et al. 2006; Lee and Kiremidjian 2007; Kang et al. 2008; Stergiou and Kiremidjian 2010; Bocchini and Frangopol 2011a; b; Chang et al. 2012; Rokneddin et al. 2012, 2013). The same reliability objectives and performance metrics are applicable for hurricane-induced loads as well; however, most of the existing literature of bridge network reliability evaluations focuses on the seismic hazard, as bridge fragility models under hurricane loads have only emerged very recently (e.g. Padgett et al. 2012; Ataei and Padgett 2013).

This thesis elects network connectivity as the reliability objective for highway bridge networks, similar to Lim and Song (2012) and Liu and Li (2012), as connectivity satisfies the minimum necessary condition for network functioning in the event of an extreme hazard. The network reliability methods reviewed in Section 2.2 are also consistent with this reliability objective. Accordingly, the computational complexity posed by the size of the network (highway bridge networks may contain hundreds or thousands of bridges) emphasizes the need for computationally efficient methods.

Until recently, the prevalent practice in seismic reliability studies of bridge networks assumed independent bridge failures for reliability and risk evaluations (e.g. Liu et al., 2006). The independence assumption can simplify the computations, but recent research has revealed that it can lead to unrealistic reliability or seismic loss estimates (e.g. Lee and Kiremidjian 2007; Jayaram and Baker 2010; Bocchini and Frangopol 2011b; Lim and Song 2012). However, the majority of the existing literature highlights the significance of correlated bridge responses to seismic intensities in a probabilistic risk assessment, and little has been done in formulating correlated responses due to other factors (Kiremidjian et al. 2007). Seismic intensity correlations are triggered by factors such as the geographical proximity of the bridges in a transportation network, which result in correlated structural response and subsequently correlated bridge failure probabilities which affect the network reliability evaluations. Intensity correlations in spatially distributed networks arise from inter- and intra-event dependencies carried by ground motions and included in attenuation models (Wesson and Perkins 2001; Crowley and Bommer 2006; Jayaram and Baker 2009). Equation 2.2 presents the general form of ground motion models with the two error terms combined that capture the observed dependence:

$$\ln(im) = f(\boldsymbol{arg}) + \varepsilon_{\ln(im)} \qquad 2.2$$

where *im* is the intensity measure at the location of network bridges, ***arg*** is a vector representing the arguments of the attenuation relationship (such as the earthquake magnitude, distance to the seismogenic rupture area, and subsurface conditions), and $\varepsilon_{\ln(im)}$ is the combined error term, which is normally distributed with mean zero. To conduct a probabilistic risk assessment, the performance of the network must be evaluated for multiple hazard scenarios, each specifying the intensity level at the location of all bridges. The proximity of bridge locations imposes correlations among the intensity they experience, which defines the normal distribution of the error term. The hazard intensity scenarios which are generated by simulating the intra- and inter-event error terms are called *network-consistent* in this thesis, and used for probabilistic risk assessment, as described in Crowley and Bommer (2006). However, if the network reliability evaluation is desired for one scenario only, the error term in Equation 2.2 can be set to zero, i.e., its mean value (Wesson et al. 2009).

Unlike intensity correlations, the impact of bridge failure correlations originating from correlated bridge structural capacities and network location has not received much attention. The structural vulnerabilities of bridges may be correlated due to factors such as the structural conditions of the bridges, similar construction detailing, traffic flows through the network, fatigue, and proximity to deteriorating environments, amongst others (Kiremidjian et al. 2007). The impact of such sources on correlated seismic response of structures is not always known, nor have all potential sources of correlations been identified. The BRAN methodology introduced in Chapter 3 quantifies the impact of correlations that stem from known factors different from hazards, while the case study application presented in Chapter 6 highlights the significance of accounting for the resulting correlations among bridge failure probabilities.

2.3.1.1. Probabilistic Seismic Risk Assessment

Some of the existing literature on the risk assessment of highway bridge networks is not concerned with network models. Those studies consider the bridge system as a spatially distributed portfolio of bridge structures, and are only concerned with the direct repair and replacement cost of bridge structures and no regard for the indirect costs from delayed or lost travels (e.g. Lee and Kiremidjian 2007). However, many studies suggest that the cost of delayed traffic and lost travels in the aftermath of a seismic event surpasses the direct loss due to structural repair and replacement of bridges (e.g. Luna et al. 2008; Enke et al. 2008). Accordingly, the majority of recent risk assessment studies consider the role of transportation system components in networks. Those studies, consequently, evaluate the systemic risk using metrics such as travel time or connectivity, either in addition to the structural repair cost or in solitary (e.g. Stergiou and Kiremidjian 2010; Jayaram and Baker 2010; Bocchini and Frangopol 2011; Lim and Song 2012).

Chapter 5 offers a probabilistic risk assessment framework, in which the network performance metric is the network failure probability, which is related to indirect costs from lost travels. Since risk analysis corresponds to evaluating the probability of exceeding different system performance levels, performing a probabilistic risk assessment requires estimating $\mathrm{P}[P_f > P_{f0}]$ for multiple values of $P_{f0} \in [0,1]$. Therefore, risk assessment requires multiple network reliability evaluations for different hazard scenarios, which is computationally intensive for large and complex networks. The use of advanced surrogate models, such as those formed by methods in statistical learning, relaxes the computational complexity by developing a predictive model of $g(\boldsymbol{x})$ to replace network reliability evaluations by Monte Carlo analysis. The surrogate models are formed by fitting a model to a subset of the hazard scenarios to be analyzed. As the result, network reliability evaluations can be performed using the predictive model (i.e. direct evaluation) instead of Monte Carlo simulations for the seismic scenarios not included in the model developing subset.

The seismic risk assessment literature for transportation networks offers other techniques to reduce the number of scenario analyses as well. For example, importance sampling may be employed to perform the network reliability assessments on a select number of scenarios (Jayaram and Baker 2010). Hazard-consistent probabilistic scenarios have also been proposed for this application (Chang et al. 2000; Vaziri et al. 2012). The surrogate model approach proposed by this thesis provides an alternative to enhance the computational efficiency, not by reducing the number of hazard-induced events, but by developing a surrogate model of the complex system at hand. Nevertheless, the proposed method can be also applied in conjunction with the existing methods to further enhance the computational efficiency. The application of surrogate models for network reliability evaluations is exemplified through several synthetic networks in Chapter 5 as well as by the case study bridge network in South Carolina, US (Chapter 6). While the synthetic networks show the applicability of the proposed method, its application to the existing highway bridge network in South Carolina highlights the improved efficiency which can be achieved by adopting a surrogate model and further enhanced with employing hazard scenarios generated by importance sampling.

2.3.1.2. Importance Measures for Bridge Retrofit Prioritization

Due to its significance, seismic retrofit prioritization has been the subject of many studies in highway bridge networks. Prioritization studies have either focused on optimizing the retrofit and replacement costs in bridge networks, or developing importance measures that can rank the criticality of bridges without solving a full combinatorial optimization problem. Stergiou and Kiremidjian (2010) proposed a two stage stochastic programming methodology to find the optimal set of bridges and minimize system damage given a set available budget. Although many simplifications are made, their presented method may be overly complex in practical applications due to the size of the problem. Moreover, since bridges are grouped into classes based on the type and cost of replacement, the results only identify clusters of bridges rather than individual ones with maximum impact. One reason for this shortcoming is that their study is mainly concerned with minimizing the overall retrofit cost rather than prioritizing the bridges, and a more detailed prioritization scheme would add to the complexity of the problem.

Methods evolving from importance measures are generally preferred in large highway bridge networks for their computational advantages. A review of the existing importance measure methods is presented by Song and Der Kiureghian (2005) and Rokneddin et al. (2012). Chapter 5 also presents the most widely used metrics to rank the seismic criticality of bridges in highway bridge networks. In practice, the *Seismic Retrofit Manual for Highway Structures* (Buckle et al. 2006) provides empirical methods to identify the most critical bridges in a network. These methods consider individual bridge vulnerabilities and the replacement cost of bridge structures; however, they fall short of taking the topology and system-level reliability of networks into consideration. On the other hand, the network theory literature also offers purely topological metrics which can be considered a first order proxy to flow in networks (i.e. traffic in highway networks). The *Betweenness Centrality* (*BC*) (Freeman 1977) is a prime example of the topological metrics used to rank component criticalities. However, topological measures do not consider bridge fragilities and are not conditional on the extreme events either. To address these concerns, conditional importance measures (*CIM*) are introduced in the literature to incorporate individual component fragilities with their role in fulfilling the network objectives (Ramirez-Marquez and Coit 2005; Song and Kang 2009; Rokneddin et al. 2012). *CIM* rankings are more comprehensive than empirical methods in practice or topological metrics, but they are more computationally intensive as they require solving the non-reducible network reliability problem for complex networks. Their dependence on network reliability also implies that *CIM* rankings are sensitive to the choice of origin and destination nodes, which makes them highly adapted to specific reliability objectives. Moreover, the rankings provided by *CIM* only apply to the hazard scenario considered for network reliability.

Rokneddin et al. (2012) developed Bridge Rank (*BR*), an importance measure which combines component fragilities with their topological significance in the network. Bridge Rank produces a ranking which does not depend on the choice of origin and destination nodes, and therefore, virtually considers all existing path in the network (i.e. an all to all ranking). However, and similar to *CIM*, *BR* rankings also applies only to the hazard scenario considered to estimate component fragilities. For a probabilistic ranking, another method is developed in this thesis which ranks bridge criticalities based on the impact of their failure on network reliability objectives in probabilistic risk assessments. This importance measure is developed using surrogate models for the network's limit state function by statistical learning methods, and is explained along with the other discussed methods in Chapter 5.

2.3.2. Water Distribution Networks

Components of water distribution networks (e.g. pump stations, water tanks, pipes and junctions) are directly vulnerable against seismic loading and aging; however, direct damage from other phenomena, such as wind-induced loads and flooding, is relatively negligible since most of the infrastructure in buried underground. Nevertheless, interdependency with the power transmission network results in indirect loss of performance, as hurricane-induced outages in the power system is followed by subsequent failure of source nodes in the water systems (i.e. pump stations). Evidence of interdependence-induced vulnerability against recent hurricane events such as Katrina in 2005 and Ike in 2008 is well documented in the literature (e.g. Comfort 2006; Miller et al. 2011).

The performance of water distribution networks under different hazards may be studied by different metrics, such as maintaining connectivity from source to consumption nodes, or providing a minimum water pressure for system customers. Regardless of the metric of choice, the impact of interdependencies between water distribution networks and electrical power systems must be included in the analysis, as it may have a significant impact on water network reliability estimates (Rinaldi et al. 2001; Lee et al. 2007; Adachi and Ellingwood 2008; Hernandez-Fajardo and Dueñas-Osorio 2011; Poljanšek et al. 2012).

Traditionally, the performance of water distribution networks is studied by deterministic hydraulic models such as EPANET (U.S. Environmental Protection Agency (USEPA) 2000) with defined topology, geometry, demand levels, and water sources (e.g. Fujiwara and Jun Li 1998; Li and Lence 2007; Raad et al. 2010). Where probabilistic approaches are considered for reliability analysis, the majority of the existing literature adopts connectivity-based metrics to estimate the network reliability, and often ignore the interdependence effects for simplicity and computational efficiency. On the other hand, studies that consider hydraulic analysis are not generally concerned with high consequence and low probability extreme events such as earthquakes and hurricanes, and focus on normal operational conditions (Wagner et al. 1988; Bao 1990; Wu et al. 1993).

To address the inadequacy of performance metrics in the literature of reliability assessment in water distribution networks, a new methodology is presented in Chapter 6 for the reliability analysis of a case study water distribution network under hurricane hazard with a hydraulic-based reliability objective. This study also highlights the impact of considering interdependencies between power and water systems on water network reliability. To simplify the procedure, the damage propagations in water and power systems are addressed separately; resulting in a two stage framework that is elaborated later.

2.3.3. Power Transmission Networks

The power transmission grid is arguably the most critical urban infrastructure system with high interdependencies with many other systems such as water distribution, telecommunications, the Internet, transportation networks, etc. (Rinaldi et al., 2001; Lee et al., 2007). Despite their critical importance, power transmission networks have expanded at a rate much slower than the increase in electricity demand during the past couple of decades which has left them more vulnerable to disruptions from natural hazards and targeted attacks (EU Commission 2006). Furthermore, even though the power grid in the United States is estimated to function with around 99.9% reliability, the blackouts and power cuts still cost the economy tens of billions of dollars annually when aggregated from its distribution level (Pipattanasomporn et al. 2005; Thornton and Monroy 2011).

Power transmission systems are comprised of power generation stations, voltage transforming substations, and power lines carried by transmission towers. Both nodes and links in power transmission networks are vulnerable against a wide range of natural (seismic, hurricane, tornado) and man-made (terrorism, vandalism, cyber attack) hazards, which complicates reliability studies in real systems. Moreover, and similar to other infrastructure networks, the topology of power transmission systems makes them complex.

The performance of power transmission systems under hazards has been studied by network topological indices (Albert et al. 2004) as well as various power flow metrics such as the Direct Current (DC) power flow model (Dobson et al. 2007) with different modeling complexities. Cascading failures in power transmission networks, which account for the fact that a few component failures in power distribution networks may lead to disproportional failure propagation in the system and result in large scale failures, is a critical consideration in power network reliability (Wang and Rong 2009). Furthermore, interdependence with other infrastructure systems makes reliability analysis of power transmission networks a challenging study (Ouyang and Dueñas-Osorio 2011a).

A major obstacle in evaluating the reliability of power transmission systems is that the reliability of system components is not always known. Furthermore, although the literature offers many reliability indices to evaluate the performance of power transmission systems, they are becoming less adequate in the environment created by deregulation of the power grid in recent years (Kropp 2006; Allan and Billinton 2000). Deregulation has introduced new challenges by causing deviation from centrally planned and operated power systems which resulted in separate entities being responsible for power generators, transmission, and distribution (Allan and Billinton 2000). Additionally, the increasing availability of renewable energy and the emergence of the smart grid are changing the old power grid models. Therefore, reliability estimates may be poor due to insufficient data or assumptions that are not accurate in the new environment (e.g. neglecting cyber attacks). Moreover, unforeseen events may happen as surprises for which the system was not analyzed for (Aven 2008).

A different approach to study the performance of the system against undesirable events is to systematically evaluate system weaknesses against all possible contingencies, known or unknown. This approach is known as vulnerability analysis, and has been applied to study the performance of both synthetic networks (Crucitti et al. 2004; Grubesic et al. 2008) and real power systems (Solé et al. 2008) in the recent past. A vulnerability analysis is particularly suited for power transmission systems since it does not require knowledge on the nature of hazards. Instead, it provides estimates of the negative consequences associated with all possible states the system can be subject to, due to any possible hazard. Moreover, reliability studies mostly focus on contingencies involving the failure of power lines; however, the performance of power transmission systems is also affected by the failure of power generation plants and substations. Albeit rare compared to transmission lines failure, their loss can cause considerable direct risks and cost to users, as well as indirect failures in interdependent systems (US–Canada Power System Outage Task Force

2004). A simple form of vulnerability analysis, the $N-1$ criterion, is widely used in reliability studies of power networks. $N-1$ criterion states that the system must provide enough redundancies to be able to function satisfactorily in case any single component of the system fails. The vulnerability analysis expands that concept to $N-2$, $N-3$, and further combinations.

Although network reliability methods reviewed in this chapter are also applicable to estimate the reliability of power transmission systems under natural hazards, the application shown in Chapter 6 adopts a vulnerability approach. Rather than direct reliability evaluation against a specific hazard scenario, topologically-informed bounds are established on system performance against all possible failure scenarios in a vulnerability analysis. Such bounds can provide an approximate solution to network reliability for all types of hazards, and therefore, can complement the reliability analysis as a screening tool for rapid assessments.

2.4. Summary

The review of the literature on infrastructure reliability and risk evaluation against extreme hazards highlights the significance of the three research objectives enlisted in Chapter 1 of this thesis, which are: 1) Developing a computationally efficient network reliability framework applicable to large and complex networked systems, 2) Developing an efficient risk assessment framework to combine network reliability evaluations with probabilistic hazard analysis, and 3) Developing new importance measures which account for both component vulnerabilities and the function of components within the network.

The existing network reliability methods are not efficient to apply to large complex infrastructure systems, especially with correlated component failures. Moreover, the existing literature is focused on correlations induced by hazard intensity levels, and does not provide a framework to consider other factors affecting the structural capacity of system components against natural hazards. Furthermore, probabilistic risk assessment requires multiple network reliability evaluations, a task which may become intractable with the existing methods. However, network surrogate models developed by statistical learning methods can significantly enhance the analysis. Finally, more advanced importance measures are required to prioritize system components for retrofit and maintenance actions against natural hazards. Such importance measures must account for component fragilities and their significance in fulfilling the network reliability objective. At the same time, they must provide a balance between the computational complexity required for ranking and applicability in practice.

Chapter 3

BRAN Methodology: Bridge Reliability Assessment in Networks

The Bridge Reliability Assessment in Networks (BRAN) is developed as a general framework for reliability evaluations of large bridge networks with complex topology and correlated bridge failure probabilities (Ghosh et al. 2013; Rokneddin et al. 2013). This framework improves upon the state-of-the-art in two ways: 1) by evaluating seismic fragilities for aging highway bridges in a network after Bayesian updating of spatially interpolated/measured deterioration parameters; and 2) by estimating the network reliability of large systems considering correlated bridge failures. This integrated methodology is summarized in Table 3.1, and is explained throughout this chapter. The application of the BRAN methodology is also exemplified in Chapter 6 on a case study highway bridge network in South Carolina, US.

The BRAN methodology focuses on quantifying the impact of correlations that stem from bridge structural capacities under joint seismic and aging threats. While the previous chapter reviewed the literature of seismic intensity induced correlations, little has been done to assess the impact of factors correlating the bridge structural capacities, and hence, their failure probability. Some of factors affecting the structural vulnerability of bridges (such as the effects of the corrosive agents) are directly modeled in bridge fragility models (Stage 1 of Table 3.1). This study, therefore, is concerned with the significant contributing factors which are not integrated into bridge fragility models. The resulting correlations among bridge failure probabilities are referred to as "extra correlations" in this thesis.

Table 3.1. The BRAN methodology to assess bridge network reliability

1	Determine the bridge failure probabilities from their respective seismic fragility model
2	Evaluate correlations among bridge failure probabilities and set up the correlation structure
3	Simulate bridge failure scenarios according to their joint probability distributions by the Dichotomized Gaussian Method
4	Estimate network reliability by the modified Markov Chain Monte Carlo simulations method

Individual bridge failure probabilities are determined in Stage 1 by a parameterized fragility formulation approach which updates the statistical distributions of the deterioration parameters using available data from bridge instrumentations (Ghosh et al. 2013). While BRAN provides a general framework for network reliability evaluations, Stage 2 proposes methods to determine the correlation values when direct estimates are not available. Finally, Stages 3 and 4 estimate the bridge network reliability by simulated bridge failure scenarios drawn from their joint probability distribution, which is consistent with bridge failure probabilities and the correlation matrix.

Generating realizations of correlated bridge failures is equivalent to simulating samples from an *n*-dimensional (*n* being the number of bridges in the network) binary random variable as the state of each bridge is a binary random variable with values equal to 0 for survival and 1 for failure. The expected value of the *n*-dimensional binary random variable, therefore, is also the vector of marginal probabilities (bridge failure probabilities from Stage 1), while its covariance matrix can be established from the correlation matrix (***R***) across failure probabilities. The process of forming the correlation matrix and simulating samples from the *n*-dimensional binary random variable are explained in detail throughout this chapter; after the next section clarifies how the network reliability is affected by accounting for correlated bridge failure probabilities.

3.1. Impact of Extra Correlations on Network Reliability Assessments

The connectivity reliability of bridge networks depends on the bridge failure probabilities, the correlation structure among failures, and the topology of the network which defines the paths from the origin to the destination. To illustrate the correlation effects, first consider a network consisting of merely two nodes where both nodes must survive for the network to remain functional. The network probability of failure may be written as:

$$P_f = \mathrm{P}\left(\mathrm{F}_1 \cup \mathrm{F}_2\right) = \mathrm{P}\left(\mathrm{F}_1\right) + P\left(\mathrm{F}_2\right) - \mathrm{P}(\mathrm{F}_1 \cap \mathrm{F}_2) \qquad 3.1$$

where F_i denotes the failure event of node *i*. A positive correlation between the two failure events has a favorable effect on network reliability as it increases $\mathrm{P}(\mathrm{F}_1 \cap \mathrm{F}_2)$, and therefore, reduces the network failure probability (P_f). A negative correlation, on the other hand, increases the vulnerability of the network. Before expanding the problem, consider the following two equalities on two given events A and B:

$$\mathrm{P}\left(\overline{\mathrm{A} \cap \mathrm{B}}\right) = \mathrm{P}\left(\bar{\mathrm{A}} \cup \bar{\mathrm{B}}\right) = 1 - \mathrm{P}(\mathrm{A} \cap \mathrm{B}) \qquad 3.2$$

$$\mathrm{P}\left(\overline{\mathrm{A} \cup \mathrm{B}}\right) = \mathrm{P}\left(\bar{\mathrm{A}} \cap \bar{\mathrm{B}}\right) = 1 - \mathrm{P}(\mathrm{A} \cup \mathrm{B}) \qquad 3.3$$

Equations 3.2 and 3.3 state De Morgan’s law, and can also be visually derived using a Venn diagram. It is readily inferred that a positive correlation among events A and B increases the probability of their joint union event which in turn induces an increase in the left hand side (L.H.S) of Equation 3.2 and a decrease in the L.H.S. of Equation 3.3 by the same amount. Consider now the network presented in Figure 3.1. The network failure probability may be expressed by mutually exclusive collectively exhaustive events as in Equation 3.4:

$$P_f = \mathrm{P}\left(\mathrm{F}_1 \cup \mathrm{F}_4\right) + \mathrm{P}\left(\overline{\mathrm{F}_1 \cup \mathrm{F}_4}\right)\mathrm{P}\left(\mathrm{F}_2 \cup \mathrm{F}_3\right) \qquad 3.4$$

Equation 3.4 may be derived by a recursive decomposition algorithm, similar to that presented in Liu and Li (2012). Based on Equations 3.2 and 3.3, the network reliability in Figure 3.1 is favorably affected by a positive correlation between events F_1 and F_4, and a negative correlation between F_2 and F_3. The first term in the right hand side

(R.H.S.) of Equation 3.4 decreases and the increase in $P\left(\overline{F_1 \cup F_4}\right)$ is weighted by $P\left(F_2 \cup F_3\right)$ (which decreases itself); inducing an overall reduction in P_f. Accordingly, the worst correlation scenario for the example network happens when events F_1 and F_4 are negatively correlated while F_2 and F_3 are positively correlated at the same time.

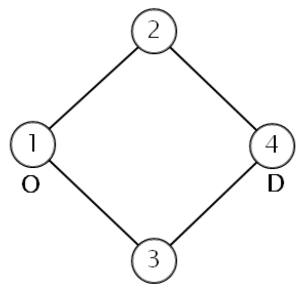


Figure 3.1. Example of a reducible network topology

These arguments may be expanded to more complicated networks. The network connectivity reliability is favorably affected by negative correlations among nodes on a cut-set (e.g. Nodes 2 and 3 in Figure 3.1) as well as positive correlations among nodes on a chain which include the origin and destination nodes. In small networks where full network decomposition can be carried out to identify all cut-sets and shortest paths in the network, the impact of correlations on the network reliability may be qualitatively assessed by examining correlations among nodes on cut-sets or chains. In actual bridge networks with hundreds or thousands of nodes, a full decomposition may not be practical, but simulations-based methods can quantify the impact of correlations, as presented in the case study in Chapter 6.

3.2. Estimating the Extra Correlations (Stage 2)

Stage 2 of the BRAN methodology forms correlation matrix ***R***, which along with the bridge failure probabilities (Stage 1) define the joint probability distribution of bridge failures, which is in turn used at Stage 3 to simulates bridge failure scenarios for Monte Carlo analysis. The extra correlations must ideally be estimated from sufficient number of detailed post-earthquake reconnaissance reports that offer correlations among bridge failures based on similarities in factors such as maintenance and retrofit schedule, construction methods, and traffic loads. However, unlike correlations among seismic intensities for probabilistic seismic hazard analysis, extra correlations are often overlooked in the literature of transportation network reliability, and data-driven estimates are not currently available due to lack of sufficient reliable data. Therefore, forming the correlation matrix must depend on network owners' discretion and the availability of auxiliary data sets in lack of explicit correlation estimates (Rokneddin et al. 2013). Accordingly, the estimated correlations may not accurately represent the actual correlation values, and therefore, a sensitivity analysis with various levels of correlations among bridge failure probabilities is conducted in this research to investigate the impact of extra correlations on network reliability estimates.

This thesis evaluates the parameters contributing to extra correlations from available data on bridge structural conditions and network characteristics. In particular, the correlation matrix is set up from three sources: the current condition ratings of bridges from inspection records, the Functional Road Class (FRC) of the route the bridges are carrying, and the topological characteristics of the bridge network. This section describes the procedure of constructing the correlation matrix (***R***) from these three sources (the original estimate) as well as deriving correlation matrices with different values for sensitivity analysis.

The condition ratings of bridge structures are qualitative scores (from 0 at worst to 10 at best) assigned to bridges based on their structural condition by bridge inspectors (Federal Highway Administration 2013). The FRC refers to the classification of the roads carried on bridges, and is adopted from TELEATLAS (TELEATLAS 2010) highway maps. Table 3.2 lists the road classes considered for this research. Finally, the topological characteristics of the highway network refer to the indices that characterize its topology as a graph. Network theory offers metrics to evaluate the level of topological similarities between pairs of nodes in a network, among which a degree-based similarity metric, the degree assortativity, is used in this thesis since it directly provides a correlation ratio. The degree assortativity establishes pair-wise bridge correlations based on the node degree (i.e. the number of highway segments directly connected to a bridge), and the similarity of their immediate neighboring bridges. The evaluated similarity between two nodes within the network is compared to that in a random network where connections are arbitrary.

The effects of corrosion and environmental agents, bridge types, and common structural detailing on bridge failure probabilities are considered in bridge fragility models, and therefore, the evaluated bridge failure probabilities (Stage 1) are conditionally independent of them. Hence, the three mentioned proxy data sources can represent the majority of the unaccounted factors in extra correlations among bridge failures. For instance, the effects of construction methods and maintenance are reflected in the condition ratings of bridges; and a combination of bridge condition ratings and the

FRC may represent the impacts of traffic loading. The correlations among bridges stemming from the network topology (such as the degree assortativity) may indicate patterns for long term maintenance and retrofit prioritization. Specifically, the topological metric is a better predictor of the level of correlations than the geo-location of the bridges for factors such as live traffic loading, allocation of maintenance segments to contractors, etc. since topology concerns with connectivity of bridges while close by bridges may not be directly connected or even accessible from one another. In addition, the topological metrics may capture sources of correlation not yet modeled or even unknown to analysts as topology influences network functionality.

Table 3.2. Functional Road Classes (FRCs) as per TELEATLAS classification. Local roads and collectors (below Class 5) are not considered in the transportation nework.

FRC	Description
0	Motorway, freeway, or other major road
1	A Major road less important than a motorway
2	Other major road
3	Secondary road
4	Local connecting road
5	Local road of high importance

Stage 2 of the BRAN methodology forms separate correlation matrices from bridge condition ratings ($\boldsymbol{R}_1$), the FRC data ($\boldsymbol{R}_2$), and the degree assortativity ($\boldsymbol{R}_3$) before combining them to establish the overall correlation matrix ($\boldsymbol{R}$). Forming $\boldsymbol{R}_3$ is straightforward, while establishing $\boldsymbol{R}_1$ and $\boldsymbol{R}_2$ requires additional steps. The degree assortativity is equivalent to the Pearson correlation coefficient among node degrees, as described by Equation 3.5:

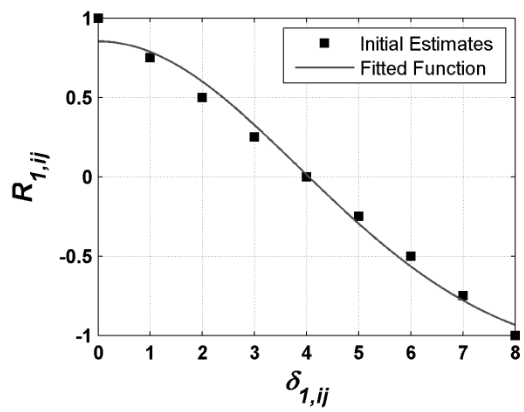
$$r_{ij} = \frac{\sum_k (A_{ik} - \bar{A}_i)(A_{jk} - \bar{A}_j)}{\sqrt{\sum_k (A_{ik} - \bar{A}_i)^2}\sqrt{\sum_k (A_{jk} - \bar{A}_j)^2}} \qquad 3.5$$

where r_{ij} is the similarity metric's value between nodes i and j, and $\bar{A}_i$ denotes the mean of values on the i^{th} row of the adjacency matrix. The value of r varies in [-1, 1], presenting a correlation ratio that is readily applicable to form the topological correlation matrix.

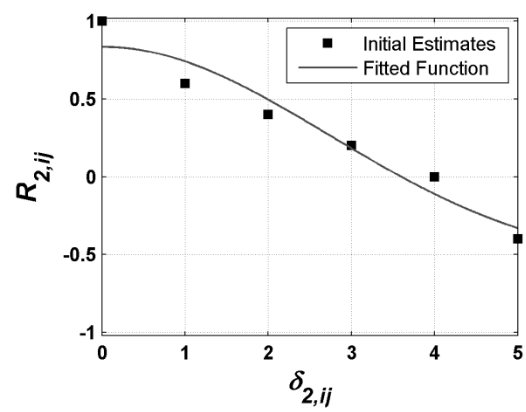
Correlation ratios in $\boldsymbol{R}_1$ and $\boldsymbol{R}_2$ are informed by the National Bridge Inventory and TELEATLAS databases, respectively, and require a function to transform the perceived similarities between two bridges into a correlation ratio. To be consistent with the existing research, which generally prefers an exponentially decaying function to capture correlations among bridge locations as a function of distance (e.g. Bocchini and Frangopol 2011b), this thesis elects a function in the form of Equation 3.6, reflecting user discretion rather than real data analysis:

$$R_{q,ij} = ae^{-b(\delta_{q,ij})^2} + c \qquad q = 1, 2 \text{ and } i, j = 1, ..., n \qquad 3.6$$

where $R_{q,ij}$ is the correlation ratio between bridges i and j in constituent matrix $\boldsymbol{R}_q$; $\delta_{q,\,ij}$ is the difference in values associated with those bridges (in condition rating or the FRC); and a, b, and c are model parameters to be estimated. Equation 3.6 maps the difference between bridges' condition ratings or FRCs into the [-1, 1] range. Parameters a, b, and c are evaluated by the following procedure: First, initial values of $R_{q,ij}$ (in [-1, 1]) are assumed for different δ_{ij}'s based on user's discretion on the level of correlations between bridges with various levels of similarities. Then, a function in the form of Equation 3.6 is fitted to the initial values by the Least Square Error method. Figure 3.2 demonstrates the initial values assumed in this study and the fitted curves to evaluate the entries of $\boldsymbol{R}_1$ and $\boldsymbol{R}_2$. For instance, Figure 3.2(b) associates the maximum and minimum differences in the FRC levels with correlation ratios of -0.4 and 1, respectively. The fitted function reduces correlation levels at the limits to -0.33 and 0.83.



(a)



(b)

Figure 3.2. Estimated correlation ratios between bridges *i* and *j* for a) the difference in condition ratings, and b) the difference in the Functional Road Class. The differences between the condition ratings in the NBI database vary from 0 to 8, while the FRCs differ by 0 to 5 levels (Table 3.2). The fitted function is derived by Equation 3.6 fitted to the initial estimates.

Finally, the three constituent matrices combine to form the correlation matrix. The user has the flexibility of choosing the form of combination as well as assigning weights in order to establish the correlation matrix. In the absence of further information on the relative importance of the three sources on correlation levels, the correlation matrix is formed by averaging the correlation values from the constituent matrices. The established matrix, which averages the originally estimated correlation values from the three sources, is not yet ready for simulating bridge failures, as it might not be compatible with the failure probabilities of bridges. The roots of compatibility conditions and the procedure of examining for compatibility are discussed in the next section.

3.3. Adjusting the Correlation Matrix for Compatibility Conditions

Since the estimates used to form the correlation matrix $\boldsymbol{R}$ do not emerge from actual post-earthquake reconnaissance data analysis, the correlation values may be incompatible with the marginal probabilities (i.e. bridge failure probabilities). The compatibility conditions arise from basic rules of probabilities and limit the range of admissible values for the correlation ratio between pairs of marginal probabilities. Equations 3.7and 3.8 state the necessary compatibility conditions among probabilities of failure:

$$\max\left(0, P_i + P_j - 1\right) \leq P_{ij} \leq \min\left(P_i, P_j\right), i \neq j \qquad 3.7$$

$$P_i + P_j + P_k - P_{ij} - P_{ik} - P_{jk} \leq 1, i \neq j \neq k \qquad 3.8$$

where P_i is bridge i's probability of failure, and P_{ij} is the joint probability of failure between bridges i and j. In order to check for compatibility conditions, the probability matrix $\boldsymbol{P}_{n\times n}$ may be established from the marginal probabilities and correlation matrix $\boldsymbol{R}$ in which the diagonal entries are the marginal probabilities and off-diagonal entries are the joint probabilities computed from Equation 3.9:

$$P_{ij} = P_i P_j + R_{ij}\sqrt{P_i\left(1-P_i\right)P_j(1-P_j)} \qquad 3.9$$

where R_{ij} is the correlation ratio between the failure probabilities of bridges *i* and *j*. Equation 3.9 is derived from the definition of the correlation ratio between two binary random variables where the expected values are P_i and P_j and the variances are $P_i(1-P_i)$ and $P_j(1-P_j)$, respectively.

If the joint probabilities in the probability matrix do not satisfy the necessary compatibility conditions (Equations 3.7 and 3.8), they need to be modified accordingly to be within the admissible range, which is a range of values that comply with the compatibility conditions. Equation 3.9 may then be used to back calculate the admissible ranges for the correlation ratios when solved for R_{ij}. The incompatibility of estimated correlation values with the admissible range has been reported in the literature, for example in Bocchini and Frangopol (2011), for other types of correlations. However, the literature does not offer a settled solution to address the incompatibilities, especially for large systems. The proposed approach in this thesis, therefore, offers a systematic solution to this problem which can be used for related problems as well.

The compatibility modification is performed by mapping the elements of the correlation matrix into their respective admissible range. Two auxiliary matrices, $\boldsymbol{R}_{\min}$ and $\boldsymbol{R}_{\max}$, store the minimum and maximum allowable correlation ratios, respectively, for every element of the correlation matrix. The modification, therefore, involves linearly mapping the correlation ratios R_{ij} from their original range to $[R_{\min}(i,j), R_{\max}(i,j)]$. The modified correlation matrix $\boldsymbol{R}_0^{'}$ is constructed by Equation 3.10 and is compatible with the marginal probabilities, and therefore, ready to be used in simulating samples from the multi-dimensional binary random variable:

$$\boldsymbol{R}_0^{'} = \boldsymbol{R}_{\min} + \frac{\boldsymbol{R}_{\max} - \boldsymbol{R}_{\min}}{\max(\boldsymbol{R}) - \min(\boldsymbol{R})}(\boldsymbol{R} - \min(\boldsymbol{R}).\mathbf{1}) \quad 3.10$$

where min($\boldsymbol{R}$) and max($\boldsymbol{R}$) are the overall minimum and maximum correlation ratios in the correlation matrix, respectively, and $\mathbf{1}_{n\times n}$ denotes a matrix of ones. The zero subscript in $\boldsymbol{R}_0^{'}$ indicates that the modified correlation matrix is mapped from the originally estimated correlation matrix.

To investigate the sensitivity of network reliability estimates to the correlation values, the elements of the original correlation matrix are shifted towards either min($\boldsymbol{R}$) or max($\boldsymbol{R}$), resulting in more negative or positive correlation levels, respectively. Since Equation 3.11 represents a linear mapping, any shift towards the boundaries in the original correlation ratio range results in a proportional shift in the modified correlation matrix towards $\boldsymbol{R}_{\min}$ or $\boldsymbol{R}_{\max}$, as:

$$\boldsymbol{R}_\lambda^{'} = \begin{cases} \boldsymbol{R}_0^{'} + \lambda\left(\boldsymbol{R}_{\max} - \boldsymbol{R}_0^{'}\right) & \lambda \in [0,1] \\ \boldsymbol{R}_0^{'} + \lambda\left(\boldsymbol{R}_0^{'} - \boldsymbol{R}_{\min}\right) & \lambda \in [-1,0] \end{cases} \quad 3.11$$

where $\boldsymbol{R}_\lambda^{'}$ is the shifted modified correlation matrix and λ is the level of overall deviations from the original correlation estimates.

Although modifying the correlation matrix to satisfy the compatibility conditions is necessary for its applicability, such modifications may result in considerable deviations from the originally estimated values. The difference in correlation matrix 2-norm before and after the compatibility adjustments offers a metric to quantify the level of modifications. Equation 3.12 introduces the error metric based on matrix 2-norm:

$$E = \frac{\| \boldsymbol{R} - \boldsymbol{R}^{'} \|}{\max(\| \boldsymbol{R} - \boldsymbol{R}_{\min} \|, \| \boldsymbol{R} - \boldsymbol{R}_{\max} \|)} \qquad 3.12$$

where E denotes the normalized change in the 2-norm of the correlation matrix, and $\boldsymbol{R}^{'}$ is the modified correlation matrix, either from the original correlation estimates or the shifted values (Equation 3.11or 3.12, respectively).

The admissible range for P_{ij} (and consequently R_{ij}) can be very tight for extreme probabilities of failure. In particular, the difference between P_{ij} and $P_i.P_j$ becomes negligible in extreme cases and therefore, the binary random variables representing bridges i and j can be treated as independent random variables. Appendix A provides a proof for the rationality of this independent treatment when the failure probabilities are either very large or very small. Accordingly, failure probabilities larger than 0.95 or smaller than 0.05 are assumed to be statistically independent.

3.4. Generating Realizations of Correlated Bridge Failures (Stage 3)

With a correlation matrix compatible with the marginal probabilities, samples of the n-dimensional binary random variable can be simulated. Among the different established methods in the literature to simulate samples from binary random variables (e.g. the use of Copulas (Nelsen 1999); Emrich and Piedmonte 1991; Park et al. 1996; Lunn and Davies 1998), this thesis adopts an algorithm based on the general Dichotomized Gaussian Method (DGM). The DGM is preferred over the other methods for its general applicability, especially when negative correlations exist. The DGM procedure forms an associated n-dimensional normal random variable from the binary random variable. The covariance matrix (**$\boldsymbol{S}$**) of the associated normal random variable is derived from the marginal probabilities and the correlation matrix for the binary random variable (***R***). To generate samples from the original binary random variable, simulated samples from the normal random variable are dichotomized based on their signs. The details of DGM may be found in Emrich and Piedmonte (1991) and Bocchini and Frangopol (2011b).

The independent treatment of extreme failure probabilities reduces the dimensionality of the binary random variable (which is originally *n*) since the correlated samples only need to be generated for correlated bridge failures. In addition to enhancing the computational efficiency, the reduction of dimensionality prevents the numerical errors produced by the narrow admissible ranges in establishing matrix ***S*** in DGM. In real bridge networks with large number of bridges, such size reduction may vastly improve the applicability of DGM by polynomially reducing the computation time. Finally, matrix ***S*** must be checked for positive-definiteness before it can be used in DGM to simulate correlated bridge failures. In high dimensional problems such as networks with many components, evaluating matrix ***S*** often incurs numerical errors (e.g. from numerical integration of the multivariate normal density). Moreover, and since satisfying the compatibility conditions does not guarantee the modified correlation matrix to be strictly positive-definite, the computed matrix ***S*** may have a few small negative eigenvalues. A straightforward routine to solve this problem is setting the erroneously produced negative eigenvalues of ***S*** equal to zero in its eigenvalue decomposition.

Table 3.3 illustrates the pseudo-algorithm to simulate correlated bridge failures. The open source statistical package *Bindata* (Leisch et al. 1998) in statistical analysis software R (R Core Team 2012) is used to simulate samples of correlated binary failures after forming matrix $\boldsymbol{S}$. The result is N_{MC} records of realized failures (0 for survival, 1 for failure) for n bridges in the network (a data-frame of N_{MC} rows and n columns) which are directly applicable for Monte Carlo simulations.

Table 3.3. Pseudo-algorith to generate realizations of correlated bridge failures for Monte Carlo simulations

1	**START**
2	Input
3	Bridge failure probabilities (P_i, $i = 1, 2, \ldots, n$) from Stage 1
4	The originally estimated correlation matrix $\boldsymbol{R}$
5	If $\exists i, \ (P_i < 0.05) \ or \ (P_i > 0.95) \rightarrow$ Treat bridge i as independent
6	Compute the admissible range for the elements of $\boldsymbol{P}_{d \times d}$ from Equations 3.7 and 3.8, where d is the number of correlated bridges
7	Determine the admissible range for the elements of the correlation matrix from Equation 3.9
8	Modify the elements of correlation matrix for compatibility with the admissible range
9	Establish the modified correlation matrix from Step 8 ($\boldsymbol{R}'$), and compute the normalized change in the 2-norm from Equation 3.12
10	Set up $\boldsymbol{S}$, the covariance matrix for the associated d-dimensional normal random variable, from $\boldsymbol{R}'$ and the bridge failure probabilities (using *Bindata* package), and check for its positive-definiteness
11	Simulate N_{MC} samples from the d-dimensional binary random variable by DGM (*Bindata* package)
12	Independently simulate N_{MC} binary samples for (n – d) independent bridges. Put the records in a dataframe together with the records of Step 11
13	**END**

3.5. Network Reliability Assessment by Markov Chain Monte Carlo Simulations (Stage 4)

The dataframe of correlated bridge failure samples from Stage 3 are used to evaluate the network reliability by Monte Carlo simulations. This study evaluates the connectivity reliability of the aging bridge network subjected to seismic loading by the Markov Chain Monte Carlo simulations approach (MCMC). The MCMC system reliability method is described in detail in Ching and Hsu (2007) and Rokneddin et al. (2012), although for independent failures. For each Monte Carlo simulation, MCMC simulates the state of the network by a Markov Chain whose transition probability matrix $\boldsymbol{T}$ is given by Equation 3.13. Each entry T_{ij} in the transition probability matrix is the probability that a random walker can move from node i to node j in one step ($i \neq j$).

$$T_{ij} = \begin{cases} \dfrac{1}{k_i}\left[\max\left(0,1-\dfrac{w_j}{b_j}\right)\right], & nodes\, i\, and\;\, j\, are\, directly\, connected \\ 0, & i\, and\;\, j\, not\, directly\, connected, or\, k_i = 0 \end{cases} \qquad 3.13$$

In Equation 3.13, k_i is the out-degree of node i, b_j is the reliability of node j (i.e. 1 – P_j), and w_j denotes a simulated sample from a uniform distribution in [0, 1]. Moreover, $T_{ii} = 1 - \sum_{j \neq i} T_{ij}$ since the sum of probabilities on each row of T must be one. For each Monte Carlo simulation, the connectivity is retained if the random walker starting from the origin node has non-zero probability to reach the destination. The network connectivity reliability is then computed by dividing the number of simulations in which the network remains connected over the total number of simulations.

The original MCMC algorithm requires modification in order to accommodate correlated binary samples simulated by the DGM. The modified algorithm is summarized in Table 3.4. In particular, simulating w_j in Equation 3.13 is modified to comply with the correlated failures:

$$w_j = \begin{cases} u_j \in [b_j, 1], \text{ bridge } j \text{ fails} \\ u_j \in [0, b_j], \text{ bridge } j \text{ survives} \end{cases} \quad 3.14$$

where u_j is a uniform random variable. This modification ensures $T_{ij} = 0$ if bridge j fails according to the correlated binary samples generated by DGM.

Compared to the naïve Monte Carlo method for network reliability with the computational complexity of $\mathrm{O}(l^2 n^2 \log(n))$, MCMC offers a superior efficiency with the complexity of $O(ln^3)$. Furthermore, and in its application to highway bridge networks, the computational complexity of MCMC is even less than $O(ln^3)$ for the general case. The reason is that the state transition matrix $\boldsymbol{T}$ is very sparse, and therefore, computing V_{OD} and V_{DD} (Step 7 of Table 3.4) only requires a select number of entries in $\boldsymbol{V}$, and often does not involve a full conversion (as in Step 6 of Table 3.4).

The network probability of failure (P_f in Table 3.4) represents the outcome of applying the BRAN methodology and helps the stakeholders of the transportation system to assess risks to the functionality of the network in the event of a strong ground motion. The network reliability method with correlated failures also enables ranking the criticality of bridges with conditional importance measures, as elaborated on in Section 5.4. Assessing such criticalities enables owners to make more informed decisions in allocating funds for necessary maintenance and seismic retrofitting actions.

Table 3.4. Pseudo-algorithm of MCMC network reliability method with correlated bridge failures

1	**START**
2	Generate N_{MC} correlated bridge failures by DGM
3	$r = 0$
4	for $k = 1:N_{MC}$
5	Set up the transition matrix $\boldsymbol{T}$ from Equations 3.13 and 3.14
6	Create matrix $\boldsymbol{V} = (\boldsymbol{I} - \boldsymbol{T})^{-1}$
7	Compute $f_{OD} = \frac{V_{OD} - \delta_{OD}}{V_{DD}}$
8	If $f_{OD} \neq 0 \rightarrow r = r + 1$
9	End
10	$P_f = r / N_{MC}$
11	**END**

$\boldsymbol{I}$ stands for the identity matrix, O and D are the origin and destination nodes in the network reliability objective, and δ_{ij} denotes the Kronecker Delta function assuming the value of 1 if $i = j$ and zero otherwise. V_{OD} and V_{DD} in Line 7 are elements of matrix $\boldsymbol{V}$ (Line 6).

3.6. Summary

The BRAN methodology offers a comprehensive framework for reliability assessment of large and complex infrastructure systems which accounts for correlated bridge failures from different sources. The extra correlations, having not been formulated and quantified before, are considered in this methodology along with a general Dichotomized Gaussian Method (DGM) procedure to simulate samples of correlated bridge failures from a multi-dimensional binary random variable. Moreover, the BRAN methodology uses an advanced simulation based network reliability method in Markov Chain Monte Carlo simulations to achieve the efficiency required to analyze large and complex highway bridge networks.

Factors such as the structural conditions of bridges, type of the roads they carry, traffic, and topological implications of bridge networks impose extra correlations among the failure probabilities that are often impractical to include in the analytical bridge modeling, particularly on a structure-by-structure basis. Nevertheless, the impact of extra correlations on network reliability estimates may be significant, depending on specific correlation ratio signs and the topology of the network. Using a decomposition algorithm, it is shown that neglecting correlations may over- or underestimate network reliability assessments based on the correlation values and the topology of the network. The correlations shape the joint probability density function, while the network topology determines the limit state function. The decomposition method presented in Section 3.1 enables the user to qualitatively evaluate the impact of extra correlations on network reliability, even prior to performing a network reliability evaluation.

The BRAN methodology offers a practical approach to quantify the extra correlations and use them to simulate correlated bridge failures in large systems based on the DGM. Realizations of correlated bridge failures become the input for the modified Markov Chain Monte Carlo (MCMC) reliability method to assess network-level performance. Regardless of the approach to evaluate pair-wise correlations among bridge failure probabilities, the established correlation matrix, which is formed upon three auxiliary sources in this thesis, needs modifications to comply with the necessary conditions which impose an admissible range for the correlation ratios based on bridge failure probabilities. Accordingly, the elements of the correlation matrix are modified to comply with their respective admissible ranges. BRAN offers an error metric to measure the level of changes made to the estimated correlation values when modified for compatibility. This metric can be used to measure the quality of the original correlation estimates.

BRAN improves upon the existing methodologies in terms of efficiency and practical applicability. Its systematic modification of estimated correlation values is also applicable to other networks and types of correlations (e.g. hazard-induced correlations). The application of the BRAN methodology to large highway bridge networks is exemplified in Chapter 6. Although BRAN offers a method efficient enough for infrastructure reliability studies, probabilistic risk assessment still poses a computational challenge since reliability evaluations must be implemented multiple times. Therefore, the next chapter introduces the surrogate models for reliability evaluations. The surrogate models are developed by fitting a predictive model on network reliability evaluations by BRAN, and enable efficient risk assessment implementation.

Chapter 4

Network Surrogate Models for Probabilistic Risk Assessment of Bridge Networks

In network reliability problems, the random variables that populate $\boldsymbol{x}$ in Equation 1.1 represent the failure probability of system components. For instance, the reliability of a highway bridge network in a given seismic scenario depends on the failure probability of bridges given the intensity of seismic excitation at bridge locations. If the limit state function $g(\boldsymbol{x})=0$ is known in explicit form, the reliability problem may be solved by classical approximations such as first and second order reliability methods (Cornell 1967; Hasofer and Lind 1974; Ditlevsen 1979; Hohenbichler and Rackwitz 1983; Shinozuka 1983; Tvedt 1990; Ditlevsen and Madsen 1996; Melchers 1999). As previously discussed, however, explicit functional forms are often not available, and the limit state function must be numerically approximated to find the system failure probability by Monte Carlo simulations. Traditional structural reliability studies apply polynomial functions for this approximation, resulting in polynomial response surface methods

(Faravelli 1989; Bucher and Bourgund 1990; Rajashekhar and Ellingwood 1993; Kim and Na 1997; Guan and Melchers 2001). Although simple and transparent, the limitations of response surface methods in application to complex domains or problems with many components have been well documented by researchers in the field. For example, the number of point estimates of the limit state function and the location of these points have been shown to influence the outcome of the numerical integration (Guan and Melchers 2001). Moreover, the number of required analyses to estimate the failure probability significantly increases with the number of random variables in the problem (Hosni Elhewy et al. 2006). Therefore, other functional forms of the limit state function have been proposed, such as those based on artificial neural networks for implicit approximations (Adeli 2002; Papadrakakis and Lagaros 2002; Cardoso et al. 2008). More recently, advanced statistical learning techniques such as Support Vector Machines (SVM) and Kriging have been successfully applied to structural reliability problems (e.g. Dai et al. 2012; Dubourg et al. 2011; Echard et al. 2011; Hurtado 2004, 2011). In spite of such successful applications to set up surrogate models instructural reliability, statistical learning application to network reliability has not been explored to date.

The review of the literature on probabilistic risk assessment of bridge networks revealed that such studies may require prohibitively large number of simulations for real infrastructure systems, as they involve evaluating the network reliability for multiple hazard scenarios. However, if the implicit function $g(\boldsymbol{x})$ in the system reliability formulation is replaced by an explicit, surrogate model, network reliability evaluations can be performed in closed form, which can save computation time. Such surrogate models developed in this chapter by non-parametric data fitting using statistical learning methods. In order to form the surrogate models, network reliability evaluations are performed (for example, using the BRAN methodology) on a subset of the total required hazard scenarios for risk assessment. Once a model is fitted to the data generated by those reliability simulations, network reliability evaluations can be performed using this surrogate model (which is direct evaluation rather than Monte Carlo simulations) for the seismic scenarios not included in the model developing subset. Therefore, the proposed approach provides an alternative to enhance the computational efficiency of risk assessments: rather than reducing the number of hazard scenarios to analyze by hazard consistent scenario generation (e.g. Vaziri et al. 2012) or importance sampling for hazard scenario selection (e.g. Jayaram and Baker 2010) as mainly pursued today, it develops a surrogate model of the complex system at hand.

This thesis employs random forests to develop the surrogate models for network reliability evaluations. While the application of other statistical learning methods such as SVM to structural reliability has steadily risen in recent years, random forests (Breiman 2001) have not been explored in this field. Nonetheless, random forests have been extensively used in other engineering fields from image recognition to bioengineering (e.g. Mao and Kelly 2007; Homenda and Lesinski 2011; Zhao et al. 2011; Latifi and Koch 2012; Vibrans et al. 2013), and have emerged as one of the most powerful data mining tools for their robustness to outlier data (Hastie et al. 2009). Additionally, random forests are able to detect significant random variables amongst a mixture of irrelevant input variables or features to build a predictive model. This characteristic is especially desirable for application to network reliability, where the state of the system is primarily governed by a small subset out of many constituent components. Application of statistical learning methods to reliability problems are sometimes presented as classification instead of regression (Hurtado 2004). Rather than fitting a surrogate model to $g(\boldsymbol{x})=0$, which is a regression approach, the classification approach finds whether $g(\boldsymbol{x}_0<0)$ or $g(\boldsymbol{x}_0>0)$ given an input vector $\boldsymbol{x}_0$. This thesis pursues both approaches for network reliability assessment.

Seismic reliability and risk assessment of bridge networks can also benefit from visualizing the failure surface, in which the limit state function is visually placed either in the original or transformed feature space defined by the vector of random variables $\boldsymbol{x}$, and separates the failed and safe samples in the classification problem. The benefits of failure surface visualization include easy determination of the seismic scenarios leading to systemic failure (which can be used to compute the integral in Equation 1.1), and identification of the worst case scenarios in seismic risk assessment (Hlavácek et al. 2004; Takewaki 2007; Hurtado 2011). In order to visualize the failure surface in network reliability problems, a separate statistical learning method, Fisher's Discriminant Analysis (FDA), is also applied to two example networks. Although FDA approximates the failure surface by a linear function and hence is not as well suited as more advanced methods such as random forests to solve the nonlinear network reliability problems, it provides a visualization of the estimated failure surface that has not been previously explored for networks.

The next section formally defines the network reliability problem to be solved in the context of seismic risk assessment via statistical learning. Then, an introduction to random forests is provided which lists some of their most desirable characteristics for network reliability application, and describes the process of model selection. Finally, the proposed method is applied to form surrogate models for three synthetic networks, and provide the prediction error for different sizes of training sets. One of the example synthetic networks also involves FDA application in order to visualize the failure surfaces in network reliability. The real application to the case study bridge network in the state of South Carolina is presented in Chapter 6.

4.1. Network Reliability as a Statistical Learning Problem

In order to formulate the problem of statistical learning for a network with *n* bridges, first assume that the BRAN methodology is applied to evaluate the network reliability of the bridge system for *ns* seismic scenarios. For seismic scenario *i*, the bridge failure probabilities form a row vector $\boldsymbol{x}_i^T = \begin{bmatrix} x_1^{(i)} & x_2^{(i)} & \dots & x_n^{(i)} \end{bmatrix}$ where $x_j^{(i)}, j = 1, \dots, n$ is the failure probability of bridge *j* given scenario *i*. The input matrix $\boldsymbol{X}_{ns \times n}$ is subsequently set up as follows for *ns* seismic scenarios:

$$\boldsymbol{X} = \begin{bmatrix} \boldsymbol{x}_1^T \\ \boldsymbol{x}_2^T \\ \dots \\ \boldsymbol{x}_{ns}^T \end{bmatrix}$$

Network failure probabilities for those *ns* seismic scenarios form the output vector $\boldsymbol{Y}_{ns \times 1}$. Note that the input and output values are all probabilities, and hence are in [0, 1]. A regression model fitted to input $\boldsymbol{X}$ and output $\boldsymbol{Y}$ for *ns* seismic scenarios can predict the outcome (i.e. network failure probability) for future different scenarios and save computation time, as the network reliability evaluations only need to be implemented to form the training set output vector $\boldsymbol{Y}$. A related classification problem could also be defined when the output vector $\boldsymbol{Y}$ becomes categorical, taking values in {0, 1} instead of continuous values in [0, 1]. Formulating the reliability problem as classification may be achieved by adopting a threshold value for network failure probability P_f, so that a P_f greater than the threshold value is considered a failure for that seismic scenario (network state = 1) and survival otherwise (network state = 0). The threshold value of tolerable network failure probability may be set by network managers, and has been selected to be 0.8 in this paper.

The appropriate statistical learning method to solve a regression or classification problem must be selected based on the nature of the problem and the involved random variables. Network reliability has a deterministic underlying physical model in either classification or regression cases (i.e. the MCMC algorithm) to compute the outcome $y^{(i)}$ (the i^{th} component of $\boldsymbol{Y}$) given the input bridge failure probabilities $\boldsymbol{x}_i^{\mathrm{T}}$ for scenario i. As a result, the regression model produces a clear hyperplane for the limit state function and the classification problem brings about perfect separability between classes. By having an underlying physical model, network reliability problems are similar to those in structural reliability. The functional form of the failure surfaces in network reliability problems must also be examined to select a suitable statistical learning method. Figure 4.1 depicts two simple networks and presents their computed failure probability. The presented formulae for network failure probabilities given the input bridge failure probabilities (x_j) are straight forward to derive, since the selected network topologies are not complex and hence, the example networks can be reduced to sets of series and parallel nodes. The computed closed form functions for these two examples confirm that the failure surfaces are strictly nonlinear functions of the input features, even for simple topologies. Furthermore, polynomial functions which are commonly used in structural reliability do not properly represent the failure surfaces in networks, due to the existing interaction terms $x_i x_j$. Therefore, polynomial response surface methods are not appropriate for network reliability problems. In fact, some response surface models consider the interaction terms, but they often restrict terms to secondary interactions, which does not suffice for larger complex networks. Nonetheless, the form of the failure surfaces imply that one must not be concerned about large local errors in the numerical integration of Equation 1.1 when those functions are replaced with surrogate models as the derived functional forms are relatively smooth.

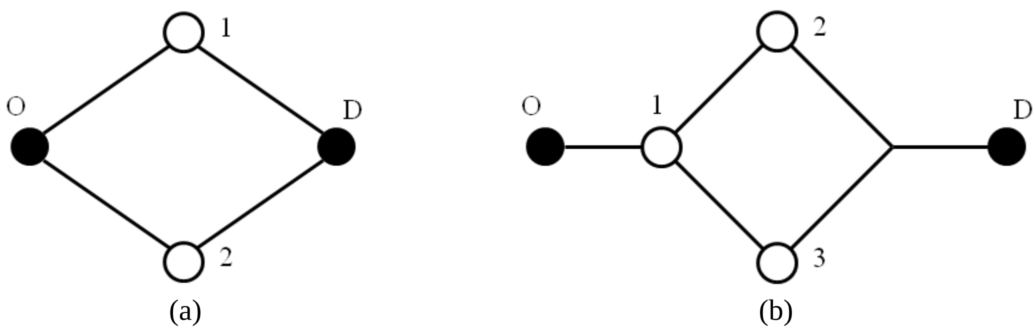


Figure 4.1. Network failure probabilities of schematic network topologies with independent component failures: a) $\boldsymbol{P_f} = \boldsymbol{x}_1\boldsymbol{x}_2$, and b) $\boldsymbol{P_f} = \boldsymbol{x}_1 + \boldsymbol{x}_2\boldsymbol{x}_3 - \boldsymbol{x}_1\boldsymbol{x}_2\boldsymbol{x}_3$. Hollow nodes represent bridges while dark nodes are used to show origin and destination nodes. Links show the connecting highways between bridges, and are assumed to be invulnerable.

Actual bridge networks have complex topologies which prevent explicit representation of their limit state function. Predictive models formed by statistical learning methods such as random forests can approximate such complicated functions using a limited number of training samples, and therefore, should be considered strong candidate tools for risk assessment applications where many failure scenarios must be analyzed. Random forests, which are extensively used for data mining, are introduced in the next section in the context of network reliability along with their identified advantages for network reliability problems.

4.2. Random Forests in Network Reliability Evaluations

The fundamentals of statistical learning are presented here prior to describing the random forest surrogate model. In any statistical learning problem, classification or regression, the *ns* available data points (i.e. bridge failure probabilities from the seismic scenarios and their associated network reliabilities) to establish the predictive model must be divided into two disjoint sets for *model selection* and *model assessment* (Table 4.1). The predictive model is fitted to the data points in the model selection set without using any data from the other set. Table 4.1 also helps to explain the process of model selection. Each statistical learning method, including random forests, has several *tuning parameters* which need to be set in order to establish the best predictive model. The values for the tuning parameters are determined by randomly splitting the data points in the model selection set into two other sets, *training* and *validation*. The predictive model is fitted to the training set using some assumed values for tuning parameters, and is then applied to the validation set to estimate its prediction error. This prediction error can be the root of mean squared error (RMSE) in a regression problem or the percentage of misclassified data points in classification, among other possible metrics. The validation error is estimated for models established with different values of the tuning parameters, and the values resulting in the minimum validation error are selected to form the optimal model. The evaluated error consists of two terms, bias and variance, which are defined by Equation 4.1 for regression:

$$
\begin{aligned}
MSE(\boldsymbol{x}_0) &= \mathrm{E}[f(\boldsymbol{x}_0) - \hat{y}_0]^2 \\
&= \mathrm{E}[\hat{y}_0 - \mathrm{E}(\hat{y}_0)]^2 + [\mathrm{E}(\hat{y}_0) - f(\boldsymbol{x}_0)]^2 \\
&= Var(\hat{y}_0) + Bias^2(\hat{y}_0)
\end{aligned} \quad 4.1
$$

in which, *MSE* refers to the mean squared error in a regression model, $f(\cdot)$ is the true function (here, the network failure probability, as exemplified in Figure 4.1) relating the input variables in $\boldsymbol{x}_0$ to the output in y_0, and $\hat{y}_0$ is the predicted output from the predictive model. The bias term in a model measures the difference between the expected (mean) prediction value for a data point and its given value in the model selection set. The variance term refers to the variance of the prediction values around their mean. Since the decrease in one term results in an increase in the other term, finding the optimal tuning parameters for model selection is equivalent to forcing a balance between those two terms (Hastie et al. 2009). Although classification problems measure the prediction error with different metrics such as misclassification or exponential loss, those error metrics can be described by bias and variance error terms as well. The examples later in this chapter use RMSE and misclassification error for regression and classification problems, respectively. Other L_1 error measures such as the mean absolute error are also applicable for regression to enhance the interpretability of the measured errors.

Table 4.1. Splitting the available data points into separate sets for model selection and model assessment

Model Selection		Model Assessment
Training	Validation	Test

The selected model from the model selection process is finally applied to the test set for model assessment, which provides the expected prediction error for future data points which are not in the considered data set (also known as *out of sample* data). To obtain an unbiased estimation of the prediction error, the data points in the test set must not be used for model selection. However, the majority of the available data must be used for model selection in order to reduce the model's bias from the training data, limiting the size of the test set to 20-30% of total data points for practical applications.

Random forests average the outcomes of a large collection of decision trees for their output (Hastie et al. 2009); therefore, trees are briefly explained next. As one of the most basic models in statistical learning, trees are mostly popular for their interpretability, robustness to irrelevant (insignificant) input variables, and invariance under monotonic variable transformations. Figure 4.2 demonstrates sample regression and classification trees for classification with five random variables x_1 to x_5. Such trees can be employed to predict the failure probability of a five-bridge network (the state of the system for the classification problem).

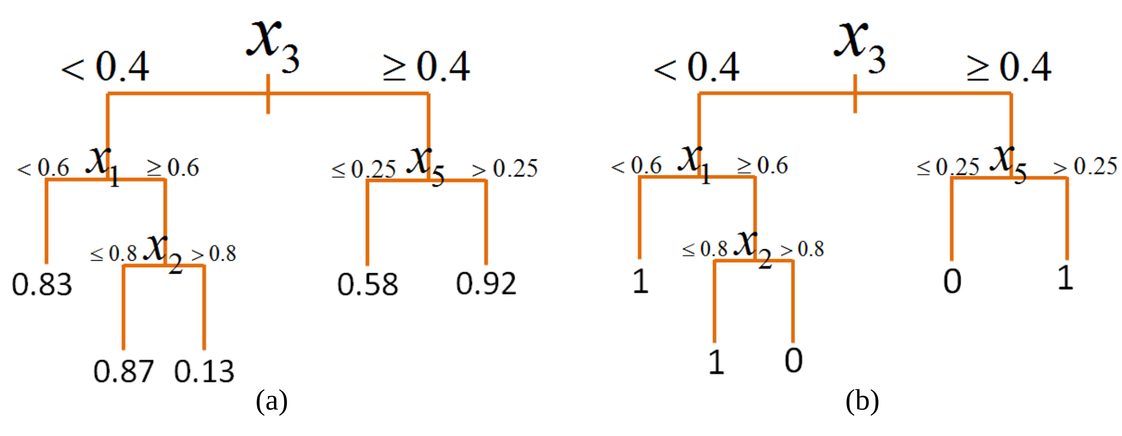


Figure 4.2. Sample regression (a) and classification (b) trees for a problem with five predictors (x_1, …, x_5) and five terminal nodes. Note that x_4 was not selected as a dividing variable in setting up these trees

Classification trees divide the feature space into *ns*-dimensional cuboids, with data points in each cuboid categorized as one class in the classification problem. The number of cuboids is equal to the number of terminal nodes in the tree; for example, the tree in Figure 4.2(b) divides the feature space into five regions (for example, the first region is where $x_3 < 0.4$ and $x_1 < 0.6$). If the number of terminal nodes in a classification or regression tree increases (i.e. the tree grows larger), the model fits more closely to the data points in the training set, and therefore, the model's bias from data points (training error) decreases. However, overfitting is likely to occur in larger trees, resulting in a large variance and large overall prediction error which makes them less suitable for future, out of sample predictions. As previously described, each statistical learning method aims at balancing the bias and variance error terms in order to present a model that is representative of the training set, yet general enough to generate reasonable predictions for out of sample data points in the test set. Random forests achieve that balance by forming many *de-correlated* trees, and averaging their outcome as in Equation 4.2:

$$\hat{f}_{rf}^{B}(\boldsymbol{x}) = \frac{1}{B}\sum_{b=1}^{B} T_b(\boldsymbol{x}) \qquad 4.2$$

where $\hat{f}_{rf}^{B}(\boldsymbol{x})$ denotes the outcome of random forest prediction from a total of B trees, and $T_b(\boldsymbol{x})$ is a decision tree formed upon m randomly selected variables (out of n variables) from the input vector $\boldsymbol{x}$. Unlike individual trees, large-sized trees in a random forest rarely lead to overfitting, and therefore, one may let the trees grow large to decrease the bias without concern for a major increase in variance. The overfitting is avoided by selecting m variables at random for each tree, which results in minimal correlations among their outcomes even if the trees are large. In order to show how de-correlation avoids overfitting by limiting the variance term, assume B random variables each corresponding to the outcome of one tree in the random forest for a data point in the model selection set. Those random variables are identically distributed as all of them estimate the outcome of one particular data point. Moreover, they are not strongly correlated since each tree is established using only *m* input random variables randomly chosen out of total *n* variables. The selective variable assignment limits the correlation coefficient between the *B* random variables to a small ρ value. The average of the *B* described random variables, as used in Equation 4.2 to estimate the outcome of the random forest, will have the variance presented by Equation 4.3 (Hastie et al. 2009):

$$Var_B = \rho\sigma^2 + \frac{1-\rho}{B}\sigma^2 \qquad 4.3$$

where σ is the common standard deviation of the *B* random variables. A large *B* value eliminates the second term, while the first term is governed by the correlation coefficient. The specific algorithm used in random forests minimizes ρ as described above while preventing σ from growing large in the process. A full explanation of the random forest algorithm may be found in Breiman (2001) or Hastie et al. (2009). An efficient implementation is presented by the randomForest package in R language (R Core Team 2012).

Random forests have strong advantages over most widely used statistical learning and data mining methods in application to network reliability evaluations, both as classification or regression problems. While support vector machines offer a solid performance in classification problems, their prediction power in regression models is generally weaker. Another advantage over SVM emerges in the process of model selection. Random forests have *m* as their only tuning parameter compared to two parameters for support vector machines, resulting in a shorter model selection process.

Other parameters of random forests are not critically important since the size of the tree is often not an issue in selecting optimized random forest models, while the average personal computers can simulate many trees in minutes, letting the modeler choose a large value for parameter *B* to increase the accuracy of the model. Moreover, the value of *m* most likely to yield the best model is known (Hastie et al. 2009), making optimal model selection in random forests relatively fast. Assuming *n* random variables in the model, the search for the optimal value for *m* is performed around $\sqrt{n}$ for classification and $n/3$ for regression problems.

Other characteristics of random forests also underline their applicability to network reliability assessments for risk analysis. Random forests naturally select the significant features and understate the irrelevant random variables to form the surrogate model. In network reliability application, it is equivalent to identifying the more critical bridges in the system and using them to develop the model rather than considering many bridges whose failures have negligible effect on the network connectivity among origin and destination nodes. The existence of many insignificant features can deteriorate the performance of some other statistical learning methods such as SVM and *k*-nearest-neighbors (KNN). KNN splits the feature space into hyper spheres rather than cuboids and similarly requires only one tuning parameter: the number of nearest neighbors *k*. In fact, random forests may be thought of as KNN with weighted distances which are proportionate to the importance of the random variables. Weighting the distances per variable importance is the key to make random forests robust to problems with many irrelevant variables, where KNN often fails to form a reliable predictive model. As another advantage, random forests are well suited for studying the relationship between the input variables and the output. Since random forests are developed based on trees, the results are straight forward to interpret. They also provide insights on variable importance, and consequently, can be used for data mining. Such characteristics set random forests apart from the competing well established methods in statistical learning, and makes them uniquely desirable for the network reliability applications.

To rank input variables based on their relative importance, random forests assign criticality to random variables whose inclusion in a tree as dividing variables enhances the model accuracy more significantly. In other terms, inclusion of those variables reduces the *impurity* of the trees. This feature of random forests is used in Chapter 5 to develop a probabilistic importance measure for bridge retrofit prioritization, and will be elaborated in more details later.

4.3. Examples of Surrogate Models in Network Reliability

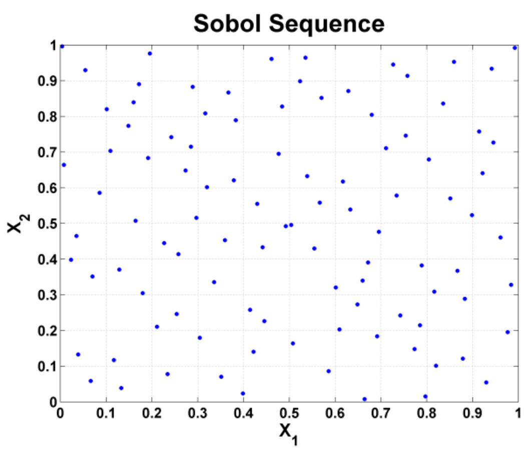
This section presents the application of random forests to form a surrogate model and predict the network failure probability in four synthetic bridge networks with different topologies (Table 4.2). Both regression and classification problems are presented, to estimate the network failure probability and determine the state of the system (failure or survival), respectively.

The data points in the input matrix $\boldsymbol{X}_{ns\times n}$ for training, validation, and testing are generated by an experimental design scheme using n-dimensional uniformly distributed quasi-random numbers in $[0,1]^n$, since the input random variables are bridge failure probabilities. Sampling from a uniform distribution replaces the bridge failure probabilities from actual seismic scenarios in this chapter, implying that there is no prior knowledge on the joint distribution of input random variables. However, the real case study in Chapter 6 describes a risk assessment application where it is possible to draw samples from a known joint distribution based on seismic hazard scenarios. The impact of that prior knowledge (i.e. the distribution of bridge failure probabilities resulting from the seismological study of the faults in the region) on the accuracy of predictions is demonstrated in the case study network of Chapter 6 by comparing the results of the two training schemes: one with independent uniform sampling similar to Examples 1-3 here, and the other by drawing samples from the joint distribution. The examples in this section, however, show that sampling with no prior knowledge on the joint distribution can still result in a satisfactory surrogate model. Note that the surrogate models developed in this chapter as well as Chapter 6 do not consider extra correlations in order to maintain focus on statistical learning methods. However, the extra correlations can be similarly included as hazard-induced correlations, since they also influence the joint probability distribution of the input variables.

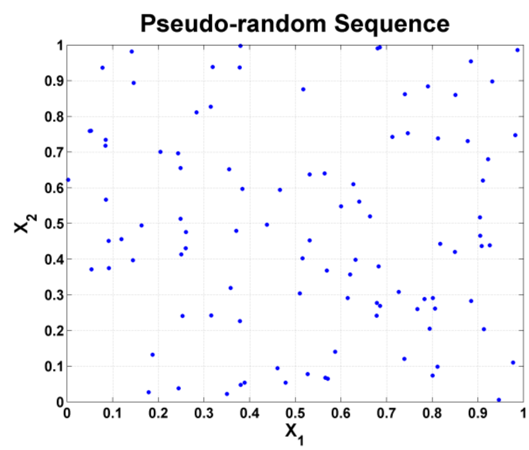
Table 4.2. List of example networks to predict the network failure probability (regression) or the state of the system (classification)

No.	Description
1	Simple five node synthetic network (three bridges). Network reliability is evaluated by closed form solution.
2	Complex six node synthetic network (four bridges). Network reliability is evaluated by MCMC.
3	Two complex synthetic lattice networks, with 16 and 20 nodes (14 and 18 bridges, respectively). Network reliability is evaluated by MCMC, and FDA is also performed for visualization.

Experimental design with independent uniform sampling is performed by using quasi-random numbers. Quasi-random numbers cover the feature space more uniformly compared to pseudo-random numbers, as demonstrated by Figure 4.3. The figure compares the distribution of 100 data points in a two-dimensional feature space (i.e. a network with two bridges). The left part of the figure shows the distribution of data generated by a Sobol sequence (Niederreiter 1992), a quasi-random number generator, while data points on the right figure are simulated by a pseudo-random number generator. Quasi-random number simulators are more structured than pseudo-random number generators, and leave less uncovered areas in the feature space.



(a)



(b)

Figure 4.3. Experimental design with 100 data points in two dimensions with a Sobol sequence (left) and a pseudo-random sequence (right). The two input random variables are bridge failure probabilities.

The network failure probability for model selection and assessment is evaluated by either closed-from solutions (where available, as in Example 1) or Monte Carlo simulations. For large and complex networks, therefore, the training size *ns* is limited by the available computational capacity since Monte Carlo simulations are computationally expensive for larger networks. The network failure probabilities for the presented examples have been evaluated for 0.01 allowed error with 95% confidence.

Example 3 uses Fisher's discriminant analysis (FDA) in addition to random forests to solve the classification problem in order to visualize the boundary separating the two classes. FDA is a linear classifier, and is used in spite of the fact that failure surfaces in networks are nonlinear (Figure 4.1). In theory it is possible to use linear models to solve network reliability problems by introducing new random variables formed by interaction of bridge failure probabilities, such as adding all secondary ($x_i x_j,\ i, j = 1, \ldots, n$) and other higher level interactions. However, such techniques are not suitable when *n* is already large, as is the case for real bridge networks. Therefore, FDA is mainly presented as a means to visualize the failure surface in networks rather than to form a predictive model. Direct visualization in network reliability problems is often troublesome because of the dimensionality of such problems (*n*, the number of bridges). FDA makes visualization possible by transforming the *n*-dimensional feature space into two proxy random variables most able to explain the variation in the data using some simplifying assumptions, and therefore, enables visualizing the class separation in two dimensions (Hastie et al. 2009).

4.3.1. Example 1

The simple network in Figure 4.1(b) is selected as the first example. This network contains three bridges, so *n* = 3. A closed-form solution exists in form of $f(\boldsymbol{x}) = x_1 + x_2 x_3 - x_1 x_2 x_3$ to evaluate the network failure probability as presented in Figure 4.1, and therefore, the desired number of training records depends on preference rather than computational power. One hundred data points (corresponding to 100 combinations of bridge failure probabilities generated at random) are used for this example, of which 70 are used to establish the predictive model (model selection) while 30 data points are reserved for testing to evaluate the prediction error relative to the closed-form solution. As the result, input matrix ***X*** has 100 rows and three columns. Both regression and classification predictive models are developed by a random forest of 500 trees with maximum allowable size, which means the trees may grow to have up to 70 terminal nodes (the number of data points in the training set), if desired. The optimal model was found using $m = 2$. Figure 4.4 shows the evolution of model selection and test errors in terms of root of mean squared error for the regression problem. The model selection error is also called the training error, since it results from the process of validation on a model which was fitted to the training data points. Note that the test error is even smaller than the training error, but is shown in a different scale to highlight its variations as trees are grown. The evaluated test error is an unbiased estimator of the expected prediction error for future data, while the training error is mainly used to find the optimal *m* value. The classification model results are also presented in Table 4.3 . Similar to the regression problem, a classification model established by the data points in the model selection set (with the same number of trees and *m* value) is tested by 30 data points which have not been used to train or validate the model. The resulting test error is hence an unbiased estimator of how reliable the surrogate model is to predict the outcome for future data points, such as actual seismic scenarios. Similar to the regression problem, the test misclassification error is smaller than training error, showing the accuracy of the developed model to predict the network failure probability for future, out of sample bridge failure records.

The prediction error estimates become very small after merely 50 trees are grown (Figure 4.4); suggesting the surrogate model properly fits the failure surface. However, even the best surrogate models cannot outperform a closed-form solution. Complex networks, as in the following examples, better emphasize the benefits of surrogate models since closed-form functions are not available or difficult to obtain.

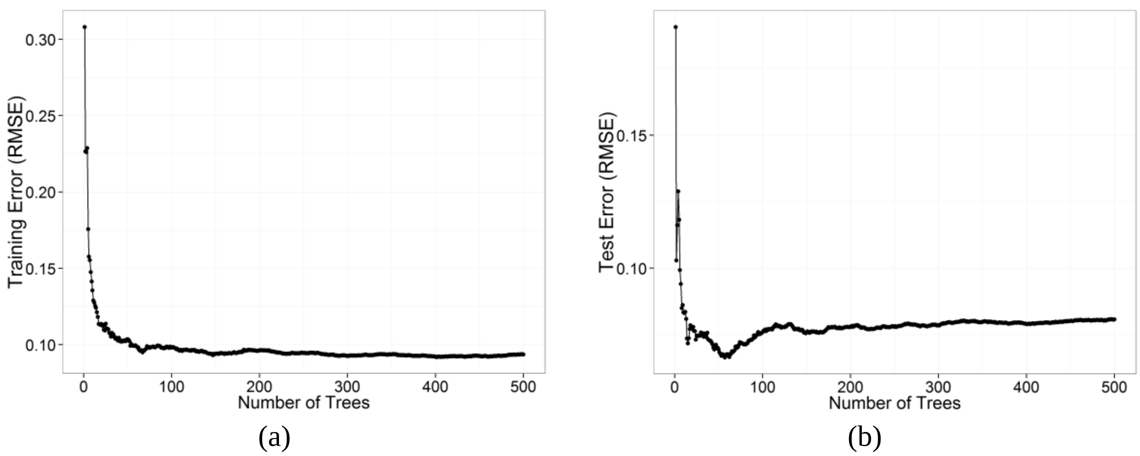


Figure 4.4. Root of mean squared error in fitting a random forest predictive model for the five-node network depicted in Figure 4.1(b), with 70 data points for training and validation, and 30 data points for testing.

Table 4.3. Training (left) and test (right) misclassification errors for the five-node network depicted in Figure 4.1(b), with 70 data points for training and validation, and 30 data points for testing. 0 = network survival, 1 = network failure.

Training error estimate = 7.14%

	0	**1**	**Class error**
0	48	3	0.06
1	2	17	0.10

Test error estimate = 6.67%

	0	**1**	**Class error**
0	19	1	0.05
1	1	9	0.10

4.3.2. Example 2

Figure 4.5 depicts a small complex network with four bridges. One hundred data points are generated according to the independent uniform sampling scheme, of which 80 are used for model selection and the remaining 20 for testing. Compared to Example 1, more data points are assigned to model selection due to the increase in dimensionality and complexity of the network topology. In lack of a closed-form solution, Monte Carlo simulations are employed to estimate the network failure probability for each of the 100 data points. This example represents a situation in which a surrogate model developed by random forests fits the failure surface of a bridge network with complex topology. The classification error estimates are presented in Table 4.4. The obtained predictive model with m = 3 perfectly separates the two classes in the test set (testing error is zero). The regression model is not presented for brevity, although based on the classification results and similar to Example 1, it is expected to produce a surrogate model with minimal RMSE error for the network reliability problem at hand.

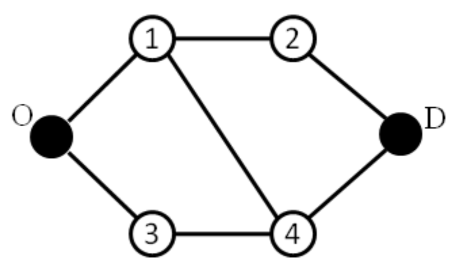


Figure 4.5. A complex six-node network (four bridges) for Example 2

4.3.3. Example 3

Two lattice networks are explored in this example, shown in Figure 4.6, with 16 and 20 nodes (14 and 18 bridges, respectively). Lattice structures pose a different challenge from the previous examples due to lack of bridge importance hierarchy. To clarify the differences, note that Bridge 1 is more critical than the other two in Example 1, since its failure results in certain network failure, while the failure of either Bridge 2 or Bridge 3 still leaves open the path from the origin and destination through the other bridges. Also in Example 2, Bridges 1 and 4 are more critical than the other two as their failure more adversely affects the network connectivity. However, the bridges in Figure 4.6 networks seem to have equal criticality other than four bridges directly connected to the origin and destination nodes (1, 4, 11, and 14), since there are many paths with equal length from the origin to the destination node and the loss of no single bridge has a significant impact on the network connectivity. Clearly, the percentage of more critical bridges reduces as the size of a lattice network grows.

Table 4.4. Training (left) and test (right) misclassification errors for the six-node network depicted in Figure 4.5, with 80 data points for training and validation, and 20 data points for testing. 0 = network survival, 1 = network failure

Training error estimate = 7.5%

	0	**1**	**Class error**
0	69	1	0.01
1	5	5	0.50

Test error estimate = 0%

	0	**1**	**Class error**
0	17	0	0.00
1	0	3	0.00

The lack of clear hierarchy in lattice structures makes it more difficult for random forests to form a successful predictive model. In hierarchical networks, the more important bridges emerge more frequently in trees within a random forest since they can explain more of the variance, and hence, become preferred random variables for dividing. Given lack of hierarchy, more trees need to grow to explain the same amount of variance and establish a dependable predictive model. Nevertheless, an increase in the number of

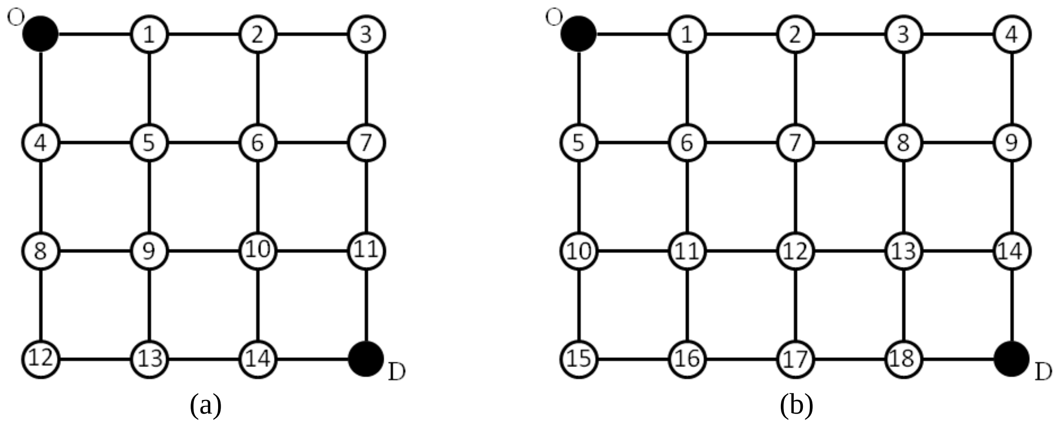


Figure 4.6. Lattice networks in Example 3: a) 16-node lattice, and b) 20-node lattice

trees is a manageable challenge for random forests as the implementation is fast in available software packages.

A more significant challenge compared to the previous two examples is the number of training samples, which needs to increase with the rise in dimensionality in order to preserve the prediction accuracy. In fact, the number of data points must increase exponentially with the number of random variables (bridges) to keep the density of data points constant in the feature space. However, the prediction accuracy does not deteriorate as fast by a reduction in the density of data points. The required density of data points for a desired level of accuracy cannot be predicted before the model is established, and the number of data points must be selected based on previous experience and judgment. This example uses 1,000 data points by the independent uniform sampling scheme for the two lattices in Figure 4.6, of which 800 are assigned to model selection. Similar to the previous example, the network failure probability for each of those data points is estimated by Monte Carlo simulations. The models are developed by growing 500 trees, although the error would stabilize with fewer trees as well. Figure 4.7 presents the regression test errors for the example networks. The projected test errors verify that model accuracies are comparable to those of Example 1 (Figure 4.4b) which only has three bridges, in spite of far less data point density in the lattice networks. The classification model is also formed, and confusion matrices are given in Table 4.5 (the training errors which are used to find the optimal model are not shown). The classification model for the 20-node lattice predicts failures (class = 1) perfectly, but misclassifies nearly half of survival cases (class = 0). The low accuracy in predicting survivals indicates the classification predictive model has not been sufficiently trained with data in that class. In fact, around 70% of 20-node network's 800 data points belong to the failure class. As a result, the established model is conservative, since it is far more likely to label network survivals as failures than vice versa. Nevertheless, most of those misclassified failures (false failures) lie close to the failure surface (i.e. network failure probabilities are close to 0.8) which explains the regression model's acceptable test error relative to the classification model's relatively low accuracy in predicting survivals.

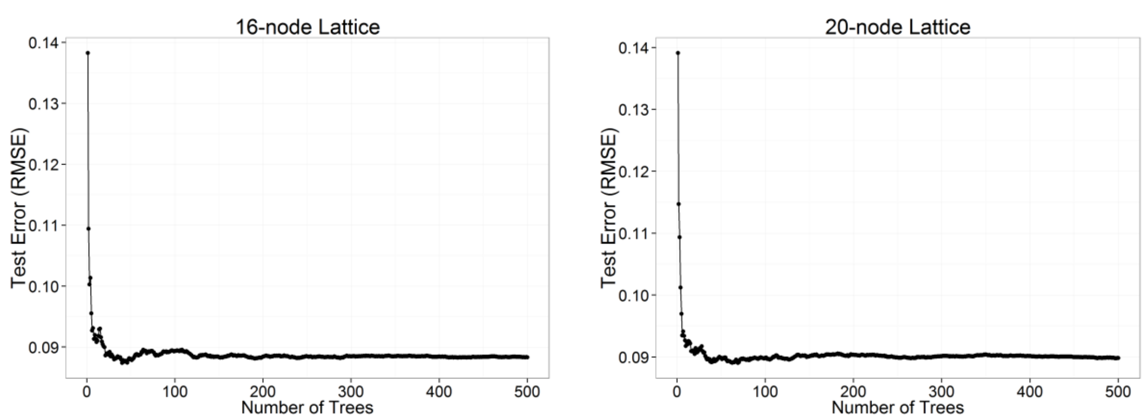


Figure 4.7. Root of mean squared test errors for Example 3 networks depicted in Figure 4.6. 800 data points are used for model selection, and the test is performed on 200 additional samples.

Table 4.5. Test misclassification errors for the Example 3 networks (Figure 4.6). 0 = network survival, 1 = network failure.

16-node network: Test error estimate = 13.5%

	0	**1**	**Class error**
0	79	21	0.21
1	6	94	0.06

20-node network:Test error estimate = 15%

	0	**1**	**Class error**
0	34	30	0.46
1	0	136	0.00

Using random forests ranking, the input variables corresponding to bridges 1, 4, 11, and 14 rank at the top as the most important input variables for the 16 node network. Similarly, bridges 1, 5, 14, and 18 come on top in the 18 node network. These rankings conform to the intuition from the network topology, as those are the bridges on minimum cut-sets.

In order to visualize the *n*-dimensional failure surfaces for the example lattice networks, Fisher's discriminant classifier is applied to the training set. FDA assumes the data points in each class are normally distributed with full rank covariance matrices, and categorizes data points based on the ratio of between and within class variances (Hastie et al. 2009). The between (Σ_B) and within (Σ_W) variance matrices are used to project the data points into two new dimensions which explain the most variability in the data, as shown by Component 1 and Component 2 in Figure 4.8. As observed, the application of a linear classifier which assumes normal data point distribution results in fuzzy separation surfaces where different classes are mixed at the boundary. Figure 4.9 replicates the visualization of the failure surface for tolerable network failure probability values other than 0.8 that is otherwise used throughout this chapter. As expected, the mixture at the boundary does not depend on the selected tolerable value. Nevertheless, FDA enables such data visualizations which are applicable to high dimensional data as in network reliability problems. Therefore, while random forests may provide superior classifiers of network performance for use in reliability and risk assessments, the use of FDA can render rapid visual screening of failed and safe domains feasible for bridge network reliability problems.

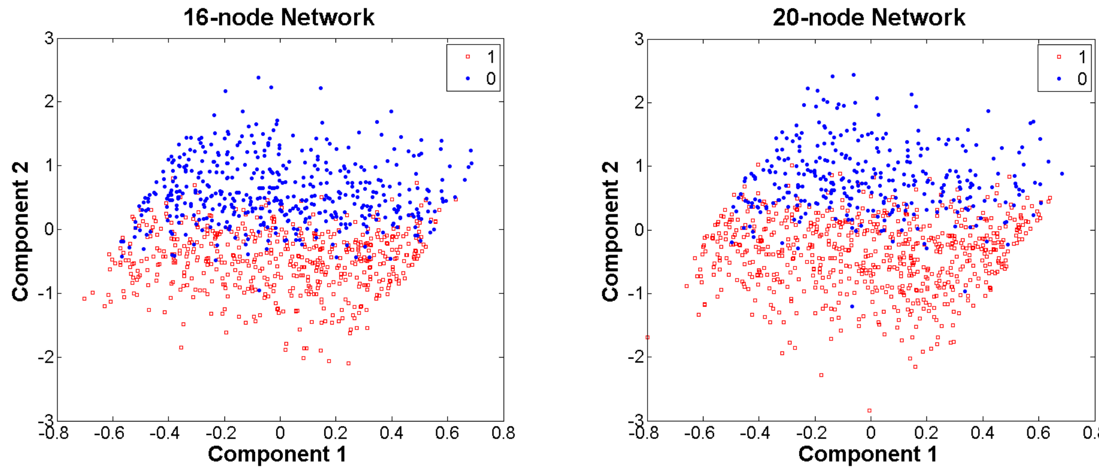


Figure 4.8. Failure surface visualization for the lattice networks in Example 3

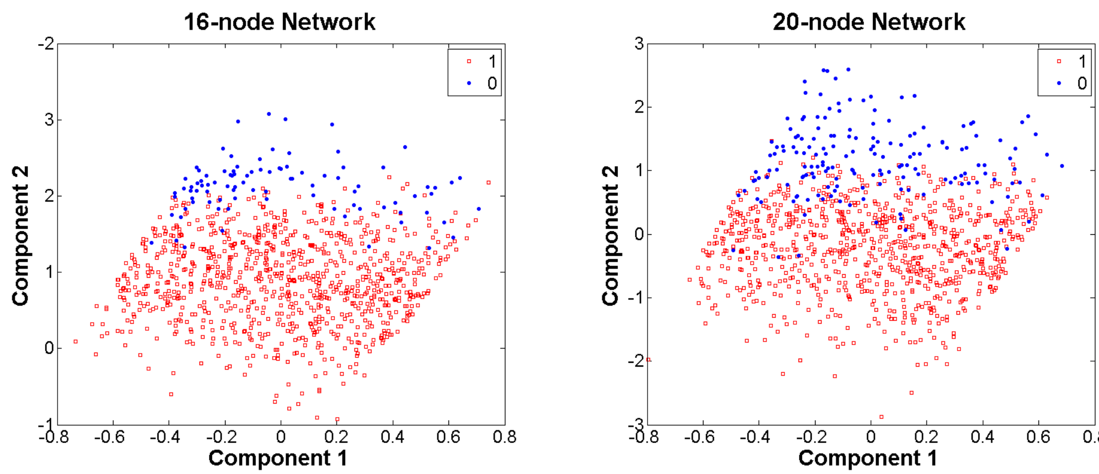


Figure 4.9. Failure surface visualization for the lattice networks in Example 3 using diffeent tolerable network failure probability values. The 16-node network uses 0.5 while the 20-node network uses 0.7.

Hurtado (2011) has also proposed a dimensionality reduction method to visualize the failure surface for problems in structural reliability using polar coordinates. However, the dimensionality reduction requires that the limit state function be expressed in explicit form and be differentiable around the design point. Since surrogate models of the limit state function developed by random forests are expressed by decision trees which are step functions (and therefore, not continuous), the requirements of the dimensionality reduction method limit their applicability to visualize the failure surface in network reliability problems.

4.4. Summary

Probabilistic risk assessment of urban infrastructure systems such as highway bridge networks enables network managers and stakeholders to make informed decisions for risk mitigation and emergency planning. However, assessment of risks owing to failures and natural hazards such as earthquakes requires extensive simulations, and can be limiting for large networks. This chapter proposed a new framework which uses a limited number of network reliability evaluations (for example, by BRAN) to develop surrogate models by random forests. Therefore, surrogate models do not replace methods to evaluate network reliability, but they rather build upon them for probabilistic risk assessment applications. The proposed method can reduce the simulations time to for multiple network reliability evaluations by orders of magnitude while incurring manageable errors compared to benchmark Monte Carlo simulations. The surrogate models in this chapter are developed using data points simulated by uniform independent sampling, and therefore, they don’t represent actual bridge failure records resulting from hazard scenarios (the actual risk assessment application is presented in Chapter 6). The examples presented in Section 4.3 verify that the application of random forests can develop proper surrogate models for networks with different simple and complex topologies. When the network topology does not offer a clear hierarchy among bridge criticalities, establishing surrogate models becomes more contrived and may required more data points for training as shown for two synthetic networks in Example 3. In addition to random forests, a linear classifier in Fisher's discriminant analysis has been presented to visualize the implicit high dimensional failure surfaces in networks projected into two auxiliary dimensions. The use of the linear classifier, however, is limited to visualization as it is not a suitable candidate for nonlinear network failure surfaces.

The application of surrogate models relaxes the computational demand at the network performance evaluation level rather than reducing the number of hazard scenarios to be analyzed for probabilistic seismic risk assessment, which is the state-of-the-art approach. However, network surrogate models formed by random forests may be trained by bridge failure scenarios generated by importance sampling after a seismological study of the region's fault systems to further enhance the model accuracy, as explained in Chapter 6. The improved accuracy is achieved by making use of the joint probability distribution (induced by hazard intensity or extra correlations) among random variables for training. Nevertheless, data points for model selection may also be generated by an independent experimental design without any knowledge on the joint probability distribution if seismic risk assessment is not the primary focus of the analysis.

The study of South Carolina bridge network in Chapter 6 reveals that components of real highway bridge systems often results in a hierarchical bridge importance, which makes the application of random forests to form surrogate models more desirable.

Moreover, although the surrogate models in this chapter are developed for network connectivity reliability, their application is not limited to that reliability objective, and can be readily extended to objectives such as the total travel time in the network.

Besides network reliability evaluations, the use of random forests to establish the network surrogate models also provides a prioritization scheme for input variables by ranking their potential to predict network failures. Example 3 of this chapter revealed that the provided ranking by random forests conforms to the bridge criticalities by studying minimum cut-sets. The next chapter uses the ranking feature of random forests to develop an importance measure which is not dependent on a hazard scenario, but rather can be used in a probabilistic risk framework.

Chapter 5

Prioritizing Network Components for Retrofit and Maintenance

Stakeholders of infrastructure networks face the challenge of optimizing the allocation of limited available resources (budget, personnel, etc.) to maximize the benefits to their systems and users. From the reliability perspective, resource allocation implies prioritizing the components of the network (e.g. bridges in a highway transportation system) for maintenance and retrofitting in order to optimize the network's ability to perform its intended function. While the resource allocation problem can be addressed by running an optimization scheme (e.g. Stergiou and Kiremidjian 2010), the size of the problem often poses practical limitations. Moreover, such optimizations require many simplifying assumptions which influence the validity of the produced results. In practice, therefore, importance measures are often preferred since they identify the criticality of components, either directly or as a by-product of reliability analyses, without solving an optimization problem. Thus, this chapter reviews the most widely used importance measures to rank the seismic criticality of bridges in highway bridge networks, and introduces two importance measures developed in this research: the Bridge Rank and random forests importance measure. The proposed importance measures are applied to the case study bridge network in South Carolina, US (Chapter 6), and the results are discussed and compared against the more traditional metrics. Although presented for highway bridge networks, the application of the two proposed importance measures is not restricted to highway bridge networks, as they can be generally applied to any networked infrastructure system.

5.1. State-of-the-Practice Methods for Ranking Highway Bridges

Traditionally, two different strategies are prevalent in practice for ranking bridges in a highway network, namely, the Indices Method and the Expected Damage Method, both of which are presented in the seismic retrofitting manual (Buckle et al. 2006). The Indices Method is the simplest of the ranking strategies and assigns a rank between 0 to 100 to each bridge following a qualitative assessment of bridge structural vulnerability against seismic and geotechnical hazards and the seismicity of the region, as well as socio-economic factors. Bridges are first assigned a score based on their vulnerability, which is later modified by their importance (cost, importance for neighborhood, etc.). The Expected Damage Method, on the other hand, ranks bridges by estimating direct monetary losses incurred to repair a bridge during the same earthquake. Bridges with the largest expected damage are then assigned the highest priority for retrofitting. In contrast to the Indices Method, the Expected Damage Method captures to a certain extent the uncertainty in ground motions and structural properties by using simple fragility functions to estimate the damage state probabilities. Despite similarities between the two ranking schemes, their bridge rankings can differ significantly, and their results often do not match those of the other methods (discussed in the following sections) either. Although the seismic retrofitting manual does not offer a method to consider the overall role of bridges to fulfill the objectives of the transportation network, it acknowledges the need to incorporate such aspects. Moreover, the simplified fragility models used to evaluate the structural seismic vulnerability do not account for environmental conditions (e.g. corrosion) or live load (traffic) effects.

5.2. Ranking by Time-Dependent Bridge Fragility Analysis

This method determines the probabilities of failure of each deteriorating bridge in the network using time-dependent seismic bridge fragility models (Rokneddin et al. 2012; Ghosh et al. 2013). Unlike simple fragility curves, these advanced models estimate the probability of a bridge being in a given damage state by accounting for the deteriorating effects of the corrosive agents in addition to seismic intensity levels at bridge location (in terms of peak ground acceleration or spectral acceleration). Figure 5.1 exemplifies a fragility model which accounts for the age of the bridge and provides the probability of reaching complete damage state conditioned upon Peak Ground Acceleration (PGA) at bridge location. The bridge fragility models are formed by structural reliability analysis under various strong ground motion records. Clearly, older bridges become more vulnerable against the same level of seismic intensity, as their fragility curve moves towards left (Figure 5.1).

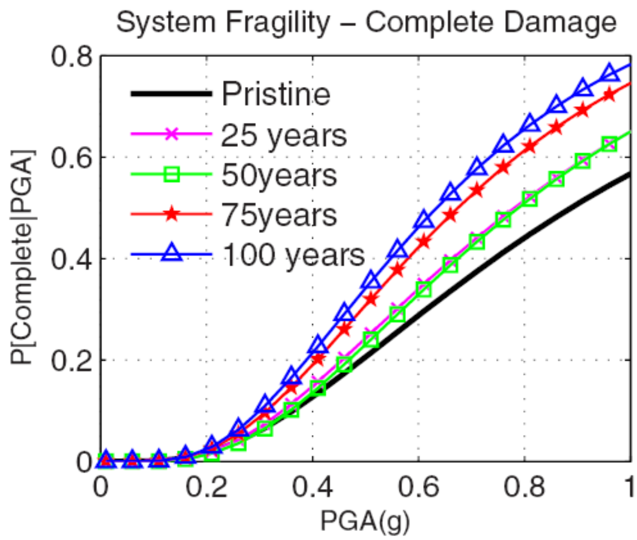


Figure 5.1. Sample bridge fragility model accounting for the age of the bridge

Ranking by Time Dependent Fragility Analysis (TDFA) assigns priority to bridges with the highest probability of failure (reaching the complete damage state) regardless of their significance inside the network. Therefore, TDFA ranking ignores the significance of bridges in fulfilling the network reliability, or the layout of the bridge network in general.

5.3. Topological Ranking

Although the importance of accounting for the topology of the network is highlighted in the *Seismic Retrofitting Manual for Highway Structures* (Buckle et al. 2006), the manual does not provide an explicit method to consider the impact of network layout. *Betweenness Centrality* (*BC*) is one of many centrality measures in network theory that has been extensively used in the literature to simulate the flow in complex networks under hurricane and seismic hazards (e.g. Kinney et al. 2005; Dueñas-Osorio and Vemuru 2009; Winkler et al. 2010). The *BC* of a given node in the network is defined as the number of paths passing through that node, as shown in Equation 5.1 (Freeman 1977):

$$BC(i) = \sum_{s,t} n_{st}^{i}, \; i = 1, \ldots, n \qquad 5.1$$

where *s* and *t* are pairs of all origins and destinations in the network and n_{st}^{i} is an indicator function assuming the value of one if node *i* is on the geodesic path from *s* to *t* and zero otherwise. Geodesic paths are the shortest paths between two nodes in terms of the number of links. The *BC* metric is often normalized for the size of the network, as in Equation 5.2 for directed networks:

$$BC(i) = \frac{BC(i)}{(n-1)(n-2)}, \; i = 1, \ldots, n \qquad 5.2$$

Since flow tends to follow the shortest path between any two nodes, *BC* can be considered as a first order proxy to the flow in networks (traffic in the case of transportation networks). Thus, high *BC* can be a measure of bridge importance since removing the nodes with high betweenness results in longer travel times or fast degradation of connectivity. For example, consider the network in Figure 5.2, in which nodes 1 and 2 each represent a one-node cut-set. Apparently, any flow from the origin to destination has to pass through nodes 1 and 2, and accordingly, they have the highest betweenness in the network.

Computing *BC* values for all bridges in the network is possible with a computational complexity of $O(ln + n(l+n)\log(n))$ for directed networks; implying that *BC* ranking does not require significant computational resources as it scales polynomially as a function of *n*. The *BC* may also be customized for transportation network applications by slightly modifying its definition. In the modified form, paths are only considered between predefined *O-D* pairs, to be consistent with the network reliability objective, rather than all the nodes in the network. As the result, the modified definition is more compatible with the network reliability objective. This thesis uses this modified definition on Betweenness Centrality in its application to the case study network in Chapter 6.

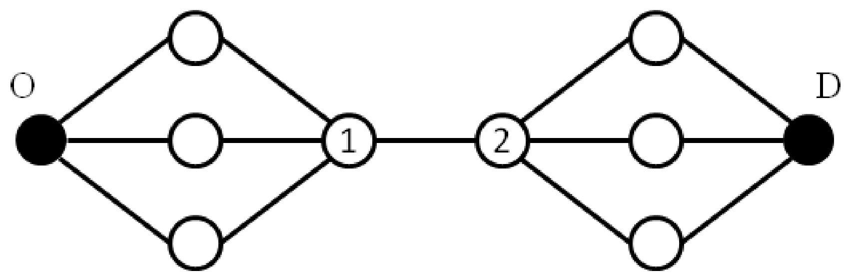


Figure 5.2. High betweenness nodes 1 and 2 are critical to facilitatating the flow in the network

5.4. Conditional Importance Measure

Conditional importance measures focus on the probability that a given component fails provided that the system has failed; for example:

$$CIM_i = \frac{\mathrm{P}(E_i E_{sys})}{\mathrm{P}(E_{sys})} \qquad 5.3$$

where CIM_i denotes the conditional importance measure of component *i*, and E_i and E_{sys} refer to the events of component *i* and system failures under a given hazard scenario, respectively. Therefore, *CIM* finds components whose failure triggers a high loss of connectivity between the predefined *O-D* pairs in the network (Song and Der Kiureghian 2005).

Ranking based on network reliability is the most comprehensive of the four proposed strategies so far since it relates the importance of a bridge not only to its vulnerability in terms of failure probability, but also to its impact on overall network reliability based on a network reliability objective, as Equation 5.3 considers the joint occurance of component and system failures. In the example network of Figure 5.2, bridges 1 and 2 may not appear at the top of the *CIM* ranking, depending on the considered seismic hazard event, if they are not vulnerable to the seismic excitations.

CIM provides a comprehensive method to evaluate network component criticalities; however, it requires solving the whole system reliability problem by one of the methods introduced in Chapter 2, which makes it more computationally expensive compared to the other reviewed importance measures. If the MCMC algorithm is followed for network reliability evaluation, *CIM* may be computed with computational complexity of $O(N_{MC}.m^2.n^2.log(n))$.

Equation 5.3 presents the most commonly used form of the conditional importance measure; although other forms have also appeared in the literature with slight differences (Der Kiureghian and Song 2008; Volkanovski et al. 2009). For example, the reciprocal form of the *CIM* formula introduced above is also used in some applications. However, this thesis evaluates the conditional importance measure by the form used in Equation 5.3.

5.5. The Newly Developed Importance Measures

5.5.1. Bridge Rank

To overcome the computational complexity of conditional importance measures, a novel ranking approach has been proposed by the author based on the original PageRank algorithm (Brin and Page 1998). PageRank is the metric used to rank web pages by the Google search engine, and combines the relevance of web pages with the importance of other pages linking to them to assess topological criticality in the network of the World Wide Web. PageRank is formulated to give importance to nodes that are themselves connected to important nodes, and is used in Google and many other search engines in response to search queries, as described below.

Search engines rely on internet bots (web crawlers), which are automated programs to browse the web and index web pages along with their incoming links to constantly update the network of internet websites. Then, PageRank or similar algorithms are applied to the network's graph to assess the topological criticality of webpage across the web. This criticality assessment is performed offline to identify important websites (nodes), which are well connected themselves and receive many incoming links from other important nodes. When a user enters a search query, the search engine evaluates the relevance of the indexed web pages to the query, and again ranks the web pages based on a specific combination of the topological criticality (e.g. by PageRank) and keyword relevance (Newman 2010). This process can be implemented fast, since the topological criticality ranking is already stored on the search engine's servers after offline evaluation.

Bridge Rank is developed by modifying the described process to assess the criticality of the components of urban infrastructure systems, specifically highway bridge networks. Rather than search queries, Bridge Rank combines the topological importance with bridge fragilities, as defined by Equation 5.4:

$$\boldsymbol{BR} = \boldsymbol{\beta}(\boldsymbol{I} - \alpha \boldsymbol{AD}^{-1})^{-1}1 \qquad 5.4$$

where $\boldsymbol{BR}$ is the Bridge Rank vector, $\boldsymbol{I}$ is the identity matrix, $\boldsymbol{A}$ is the adjacency matrix of the network, $\boldsymbol{D}$ is the diagonalized matrix of node out-degrees, and $\boldsymbol{\beta}$ denotes the diagonalized matrix of network component vulnerabilities. $1_{n\times1}$ represents a vector of ones (*n* being the number of brides in the network), while $\boldsymbol{D}$ and $\boldsymbol{\beta}$ are square matrices with zero entries except on the main diagonal. Parameter α denotes a scalar that is required to be less than the reciprocal of the maximum eigenvalue of $\boldsymbol{AD}^{-1}$. The original PageRank formulation assumes the diagonal entries of $\boldsymbol{\beta}$ to be 1, as it is performed in the offline stage of the search process, and is only concerned with the topological ranking. However, using bridge vulnerabilities for $\boldsymbol{\beta}$ in the Bridge Rank formulation eliminates the need for two-stage ranking as applied in the search engines, since vulnerabilities are available and can be combined with the topological ranking at once.

The introduction of $\boldsymbol{\beta}$ containing non-topological information enables tailoring the PageRank approach to other applications. Accordingly, using information on bridge fragilities for this purpose leads to a unique combination of network topology and structural vulnerability which is the basis for Bridge Rank. The component vulnerabilities in matrix $\boldsymbol{\beta}$ are derived by time dependent structural reliability analysis on system components, as in the BRAN methodology (Ghosh et al. 2013; Rokneddin et al. 2013).

The contribution from topology comes from degree centrality and connection to important nodes to form critical sectors in the network (Equation 5.4). The set of topologically important nodes (which are interconnected among themselves) facilitate global connectivity, and their failure impacts the system reliability more severely than the failure of less central nodes.

To have balanced contributions from the topological importance of components in the network and their structural vulnerability, the magnitude of component vulnerabilities in β must be scaled to the PageRank values (provided by setting the diagonal entries of β to one in Equation 5.3). Such scaling ensures uniform contributions from topology and vulnerability—thus averting unbalanced rankings that can arise from differences in magnitudes where modest differences in the topological importance may undermine significant contrasts in structural urgencies (and vice versa). Nonetheless, the formulation presented in Equation 5.4 also provides the flexibility to give more weights to the contribution from either topology or vulnerability to tailor the metric to different applications and stakeholder preferences.

Although *BR* accounts for the topological structure of the bridge network, it does not depend on the choice of network reliability objectives or the origin and destination nodes. In this regard, *BR* provides an all-to-all ranking, where connectivity is evaluated between every pair of nodes in the network. In the example network of Figure 5.2, *BR* disregards the specified origin and destination nodes; however, bridges 1 and 2 are still topologically important since both are well connected (with a node degree of 4), as well as connected to each other. Nevertheless, their *BR* rank also depends on their vulnerability to the seismic hazard.

The computational complexity of *BR* ranking is significantly less than that of the conditional importance measures as it averts the need for network reliability assessments. However, rankings from both methods are conditioned upon the considered hazard scenario to estimate bridge failure probabilities. The next method, informed by random forest surrogate models presented in Chapter 4, provides a ranking scheme which is not scenario dependent, and can be used in a probabilistic risk assessment framework. The application of *BR* is shown on a case study bridge network in Chapter 6.

5.5.2. Relative Component Importance by Random Forests

In fitting a surrogate model to $g(x)$, different input variables show different predictive capability. For example, consider the bridge network reliability problem of Figure 4.1(b). Losing bridge 2 does not affect the network connectivity as much as the failure of bridge 1, since bridge 1 is a minimum cut set for the considered origin to the destination nodes (note that removing bridge 2 still leaves the path to the destination connected through bridge 3). Similarly, bridges 1 and 2 each provide a one-node cut-set in the network of Figure 5.2; thus the failure of each disconnects the network. None of the remaining six bridges in the depicted network are as significant to the network connectivity. Accordingly, the number of variables which have a significant influence on the fitted surrogate model for bridge networks is often a fraction of n, the number of components in the system. Chapter 4 showed that the hierarchy of variable importance influences the accuracy of the developed surrogate model with the same training samples. Since each tree in a random forest is established via m random variables out of the possible n variables, those variables appearing in more trees can be considered to have higher predicting capability. Random forests consider the variable importance as the average gain in accuracy while splitting by the variable over all trees. This gain in accuracy may be defined either through the Gini splitting index or out-of-bag randomization (Hastie et al., 2009). However, this choice often has little influence on the final ranking, as both metrics generally assign importance by counting the number of times a variable is used for dividing in the random forest.

Variable importance measures for random forests are gaining in popularity in many scientific fields (e.g. Strobl et al. 2007; Archer and Kimes 2008); however, they are shown to be sensitive to differences in the scale of input random variables (Strobl et al. 2007). However, random forests importance measure rankings (referred to as *RFIM* hereafter) are well suited to the risk assessment of bridge networks since all input variables are bridge failure probabilities and therefore, have the same scale. Moreover, since the surrogate models are developed over multiple failure scenarios in a probabilistic risk assessment framework, the ranking scheme offered by random forests does not depend on a single hazard scenario, unlike *CIM* and *BR*. The probabilistic nature of *RFIM* ranking has important implications, as a bridge close to the earthquake epicenter is more likely to rank high based on event specific *CIM* and *BR* methods. *RFIM*, on the other hand, evaluates the bridge criticalities over multiple events, and thus, provides a more balanced ranking in which the role of bridges in fulfilling the network reliability objective is more emphasized than their single event vulnerability. Accordingly, one should expect similarities between *RFIM* and *BC* rankings. The application of *RFIM* alongside the other introduced metrics in Chapter 6 highlights the similarities and contrasts discussed in this chapter. The most important characteristics of the discussed methods are also summarized in Table 5.1. This table may be used to select an importance measure for bridge retrofit prioritization based on user preferences.

Table 5.1. Characteristics of the importance measures in Chapter 5

Importance Measure	**Considers bridge vulnerability**	**Considers role in network**	**Depends on (*O*, *D*) pairs**	**Provides probabilistic ranking**
Seismic retrofit manual methods	No*	No	No	No
BC	No	Yes	Yes**	No
TDFA	Yes	No	No	No
CIM	Yes	Yes	Yes	No
BR	Yes	Yes	No	No
RFIM	Yes	Yes	No	Yes

Seismic retrofit manual methods include the Indices method, and the Expected Damage method. BC: Betweenness Centrality. TDFA: Time Dependent Fragility Analysis. CIM: Component Importance Measure. BR: Bridge Rank. RFIM: Random Forests Importance Measure

* The Indices method ignores fragility, while the Expected Damage method uses old fragility models.

** The (O, D) dependent definition of BC is considered here.

5.6. Summary

Importance measures provide viable alternatives to optimization schemes to identify critical system components. Without the need to solve an optimization problem which can be costly for large networks, importance measures are either directly computed or evaluated as a by-product of network reliability analyses. Traditionally, importance measures focused on the repair or replacement cost of bridges, or their individual vulnerability against natural hazards, without considering their role inside the network.

Conditional importance measures (*CIM*) combine bridge vulnerabilities with their significance in fulfilling the network reliability objective. However, *CIM* ranking is more computationally demanding than most other methods, as it requires solving the network reliability problem. Bridge Rank is developed based on the PageRank sorting algorithm by Google, and provides a computationally efficient solution while considering both bridge vulnerabilities and network aspects. Additionally, Bridge Rank does not depend on the choice of (*O*, *D*) pairs in network reliability, and offers an implicit all-to-all approach. Both *CIM* and Bridge Rank, however, present rankings which depend on a specific hazard scenario. The second novel presented approach uses random forests' relative importance of input variables (i.e. bridges) to predict the network reliability outcome. In that regard, random forests ranking is similar to *CIM*, as both consider the network reliability objective and the role of bridges in maintaining connectivity. However, using the network reliability formulation by surrogate models in Chapter 4, random forests provide a probabilistic framework for ranking which does not depend on a particular hazard scenario.

Chapter 6 compares the ranking outcome of the different importance measures discussed in this chapter, and compares the results across different methods. The developed metrics give priorities to bridges very different from those by *Seismic Retrofit Manual for Highway Structures*; highlighting the significance of involving the network aspect for retrofitting and maintenance planning.

Chapter 6

Applications of Reliability and Risk Assessment Methods to Urban Infrastructure Systems

This chapter presents the application of the methods developed in the previous chapters to network reliability evaluation, probabilistic risk assessment, and component prioritization of highway bridge networks. In addition to bridge networks which have been frequently discussed in the precious chapters, this chapter presents case studies for two other infrastructure systems: the water distribution network and the power transmission grid. The same reliability and risk methods are applicable to study all networked infrastructure systems; however, water and power network applications are exemplified by focusing on less discussed aspects of interdependence and performance bounds to emphasize their significance in reliability and risk evaluations.

6.1. Highway Bridge Network

The case studies shown in this section exemplify the application of the BRAN methodology, risk assessment using surrogate models, and ranking by importance measures for part of the highway bridge system in South Carolina, US (Figure 6.1). An earthquake scenario is considered, for which the peak ground acceleration (PGA) contours are shown. The depicted seismic scenario results from a strong ground motion of M_w = 7.3, based on the largest contributing event to the 10% exceedance probability in 50 years seismic de-aggregation map of the region (USGS 2010). The event's epicenter coincides with the epicenter of the historic 1886 Charleston earthquake, which is 20 km away from the center of Charleston. The PGA contours are computed using HAZUS-MH MR4 (FEMA 2009) by an attenuation model for Central and Eastern US seismic zone (CEUS). This CEUS attenuation models is itself the weighted average of four attenuation relationships, namely Atkinson and Boore (1995), Toro et al. (1997), Frankel et al. (2002), and Campbell (2003), which present different models for that region. The case study network lies in the greater Charleston area and includes bridges and roads along freeways, highways, and main roads encompassing the counties of Charleston, Berkeley, Orangeburg, Dorchester, and Colleton between Interstate-95 and the Atlantic Ocean.

The network consists of 509 aging bridges from different bridge classes categorized according to structure, material properties, and construction type (Table 6.1). The bridge inventory is obtained from the National Bridge Inventory (Federal Highway Administration 2013) and integrated with the GIS map of the region's roadways from (TELEATLAS 2010). The majority (over 83%) of the bridges in the network belong to the category of non-seismically designed bridges (pre-1990 construction), and have been characterized by previous researchers as seismically vulnerable (Nielson and DesRoches 2007). Moreover, they are prone to the adverse effects of aging and deterioration given their age and proximity to the sea.

Previous studies on the seismic vulnerability of highway bridges in the region highlight potential bridge susceptibility to seismic loads (Wong et al. 2005; Padgett et al. 2010); however, they do not consider the effects of aging and network-level performance. Rokneddin et al. (2012) studied the seismic network reliability in the region considering the effects of aging bridge fragilities. Also, a later study highlighted the need for updating historical estimates of deterioration parameters from field-monitored data to develop bridge fragility models that reflect in situ conditions (Rokneddin et al. 2013).

For this case study, the destination node is selected to be in highly populated urban areas, which would be in need or urgent care in the event of the depicted seismic scenario. The origin node is on the perimeter of the network, which can be considered as a point of access from the outside through the Interstate-95 highway.

The bridge network of South Carolina is a large and complex network which provides an opportunity to showcase the capabilities of the developed methods in previous chapters. The BRAN methodology is first employed to evaluate the seismic reliability of the network under the depicted scenario (Section 6.1.1) taking into account the extra correlations among bridge failures, which do not stem from PGA correlations due to geographical proximity, but rather originate from the bridge structural conditions, topological characteristics of the network, and the effect of live traffic, among other factors. For probabilistic risk assessment, surrogate models are developed in Section

6.1.2 which are consistent with the network reliability objective and the identified origin and destination nodes. Finally, different importance measures are applied to the case study network, and the ranking outcomes are compared in Section 6.1.3.

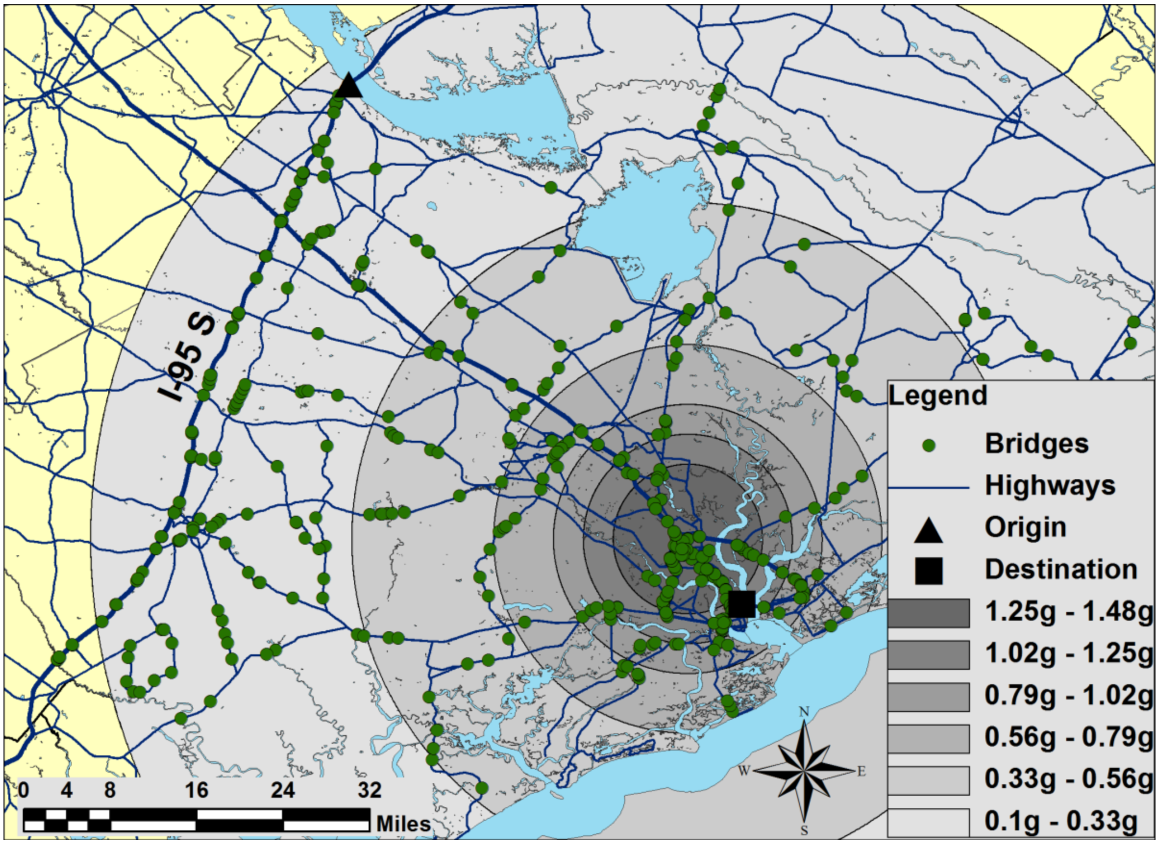


Figure 6.1 - The case study aging bridge network in South Carolina, US, along with intensity contours (PGA) of the seismic scenario (M_w = 7.3) and the choice of origin and destination nodes

6.1.1. Network Reliability Evaluation by BRAN methodology

6.1.1.1. Correlation Matrix and Monte Carlo Sampling

This section reviews the process of BRAN methodology with data from the case study network. The network failure probability is evaluated in the next section. BRAN offers the necessary algorithms to simulate samples from the *d*-dimensional binary random variable with mean $\boldsymbol{\mu} = [P_1, P_2, ..., P_d]^T$ and correlation matrix ***R***, where *d* is the number of correlated bridges in the network out of the total *n* bridges. Correlated bridges must have a failure probability between 0.05 and 0.95, since bridges with lower and higher failure probabilities can be treated independently, as detailed in Chapter 3 and Appendix A.

Table 6.1. Inventory of bridges in the case study transportation network showing the different classes

Bridge Classes	**Number**
MSSS Slab	159
MSSS Steel Girder	123
MSSS Concrete Girder	117
MSC Steel Girder	38
MSC Slab	17
SS Concrete	19
SS Steel	19
MSC Concrete Box Girder	15

MSC = Multi-span continuous, MSSS = Multi-span simply supported, SS = Simply supported

The case study network has 117 bridges (out of 509) with correlated failure probabilities, constituting 23% of the total. The remaining 392 bridges (77%) either have extremely high (110 bridges) or extremely low (282 bridges) failure probabilities which make them independent. The bridge failure probabilities (P_i's) are evaluated using a parameterized bridge fragility model, developed by Ghosh et al. (2013). The correlation matrix (***R***) is established by the three auxiliary data sources, i.e. bridge condition ratings, functional road classes, and the topological similarity measure, as per explanations in Section 3.2. Given lack of any information on the relative importance of the three sources, the entries of the correlation matrix are assumed to be the average value from the three data sources.

Next, the correlation matrix ($\boldsymbol{R}$) is transformed to $\boldsymbol{R}_0'$ whose correlation values are compatible with the evaluated bridge failure probabilities. In conjunction with the bridge failure probabilities, $\boldsymbol{R}_0'$ is used to simulate samples of the *d*-dimensional binary random variable. For the case study network, the contributions from bridge condition ratings and the functional road class mostly produce positive correlations. However, network topology results in some negative correlations across bridge pairs since nodes can be connected to very different neighboring bridges which produces negative correlation ratios according to Equation 3.5. Accordingly, the resulting $\boldsymbol{R}_0'$ includes both positive and negative entries.

Since the correlation values in $\boldsymbol{R}$ and consequently, in $\boldsymbol{R}_0'$ are derived from auxiliary data sources, they may not necessarily provide accurate estimates of actual correlation values. Therefore, the correlation values are varied within their respective admissible range for a sensitivity analysis which is used to examine the range of variations in the evaluated network failure probability. Section 3.3 presents the formulation of the varied correlation matrices $\boldsymbol{R}_\lambda'$, where positive and negative λ values represent the shift of correlation ratios towards minimum and maximum admissible values, respectively. For this case study, λ values vary from -0.5 to 0.5 in 0.1 intervals, producing a total of eleven correlation matrices for network reliability analysis.

The normalized error metric (E) introduced in Section 3.3 measures the level of changes from original correlation estimates in $\boldsymbol{R}$ when modified for compatibility by computing their normalized difference in matrix 2-norm. The value of E computed for the eleven formed correlation matrices is shown in Figure 6.2. For the mapped original estimates in $\boldsymbol{R}_0'$, E is computed to be 5%, which is small enough to support the choice of the three information sources to establish the correlation matrix. Although the correlation ratios from the three auxiliary sources are not estimated based on real post-earthquake data analysis, they at least show reasonable compatibility with bridge failure probabilities. Nevertheless, it must be noted that compatibility does not necessarily imply accuracy of estimates. Therefore, the impact of varying correlation levels on network reliability is investigated in the sensitivity analysis.

With correlation matrices R_λ' ready, the Dichotomized Gaussian Method (DGM) is used to simulate realizations of bridge failures from their correlated failure probabilities and the modified correlation matrix. The dimensionality reduction as the result of independent treatment of extreme bridge failure probabilities has significant computational consequences. In this case, forming the covariance matrix ($\boldsymbol{S}$) of the associated d-dimensional (here, d = 117) normal distribution requires far less computations compared to forming it for an n-dimensional (n = 509) variable. The remaining 392 bridges with independent failures do not depend on the DGM method to simulate correlated failure samples, as their failure can be simulated independently. To increase the efficiency of computations, independent failures are generated using quasi random numbers rather than common pseudo-random number generators.

Finally, realizations of correlated bridge failures are combined with independent failure realizations to form a dataframe consisting of N_{MC} realizations of the n-

dimensional binary random variable for each λ value. These eleven dataframes are used to evaluate the network reliability by the modified MCMC method, the results of which are presented in the next section.

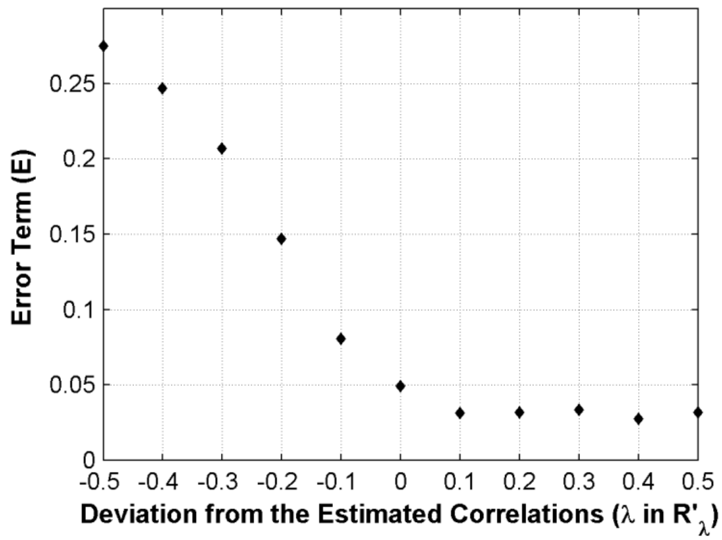


Figure 6.2. the error term associated with $\boldsymbol{R}'_{\lambda}$ for compatibility modifications

6.1.1.2. Results of BRAN's Application to the South Carolina Bridge Network

Figure 6.3(a) shows the frequency distribution of the conditional failure probabilities corresponding to the 509 bridges in the network under the scenario seismic hazard. Evidently, the majority of the bridges have extreme failure probabilities. A significant percentage of the bridges with very low failure probabilities are comprised of MSSS Slab, MSC Slab, SS Concrete, and SS Steel bridges which are found to be relatively non-vulnerable to the scenario seismic event owing to minimal bearing deformations and low column demands (for multi- span bridges). The low seismic vulnerability of these bridge types is in agreement with similar findings reported by a previous study (Rokneddin et al. 2012). Bridges with high failure probabilities tend to belong to the aging MSC Steel, MSSS Steel, and MSSS Concrete girder bridge classes characterized by high demands on column, bearing and abutment deformations and are primarily concentrated near the epicenter characterized by high PGA intensity and corrosive environment due to proximity to the sea splash zone.

Figure 6.3(b) compares the network reliability estimates as a function of the number of Monte Carlo simulations. Both independent and correlated (based on original estimates $\boldsymbol{R}_0'$) bridge failures are examined, and the simulations continue until the standard deviation of estimates falls below 0.005. Monte Carlo analysis for the independent failures shows superior efficiency as they have been sampled using quasi-random numbers. As the result, evaluating the network failure probability by independent failures only requires up to 20,000 simulations. The correlated scenario, on the other hand, needs 100,000 simulations to stabilize since it uses pseudo-random sampling, according to Equation 3.14. As for network reliability estimates, Figure 6.3(b) suggests that accounting for the original estimates of extra correlations among bridge failures improves the reliability of the case study network by reducing its failure probability from around 0.55 to 0.51.

Due to the size of the network, the arguments on the impact of extra correlations on network reliability estimates (Section 3.1) cannot be directly tested, as the network is too large to identify all paths and cut-sets. However, Figure 6.2 suggests that the correlation values in $\boldsymbol{R}_0'$ are closer to $\boldsymbol{R}_{\mathbf{max}}$ than $\boldsymbol{R}_{\mathbf{min}}$, since moving further towards $\boldsymbol{R}_{\mathbf{max}}$, by increasing λ, which means more positive correlations, has negligible influence on the error term. On the other hand, accounting for extra correlations has improved the network reliability (Figure 6.3b), suggesting more bridges on the shortest paths between the origin and destination nodes must be positively correlated. An examination of the shortest path reveals that six out of seven bridges on that path are in fact positively correlated.

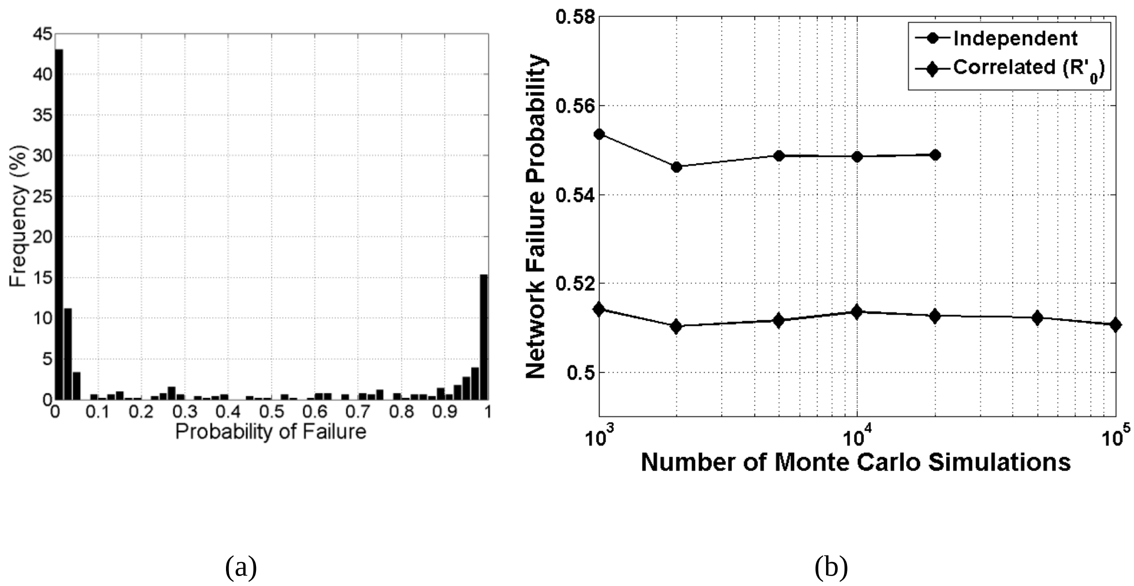


Figure 6.3. The results of network reliability evaluations corresponding the the network and seismic scenario depicted in Figure 6.1: a) Frequency distribution of the bridge failure probabilities, and b) Network connectivity reliability between origin and destination nodes versus the number of samples in Monte Carlo simulations.

Figure 6.4 presents the results of the sensitivity analysis, along with the associated error E for each $\boldsymbol{R}'_{\lambda}$. This figure confirms that overall, more positive correlations improve the reliability of the case study network. On the other hand, the failure probability generally increases as λ moves towards negative values before dropping at λ = -0.5 (this irregularity needs further investigation in future research). In spite of this increase, the failure probability does not reach that of the independent scenario. The range of failure probability variations is around 20% of the failure probability associated with the original estimates (0.51), which emphasizes the impact of extra correlations and underlines the need to develop post-earthquake-data-driven models to better estimate the extra correlations.

Several past studies on the seismic reliability of bridge networks have suggested that neglecting correlations results in underestimation of losses at the network level (e.g. Bommer and Crowley 2006; Lee and Kiremidjian 2007). It is important to note that those studies have considered different types of correlations (hazard intensities in terms of inter- and intra-event errors, and seismic response of structures) and present the results for a different limit state (loss in monetary terms rather than network connectivity). Neglecting the spatial correlations resulting from of inter- and intra-event error terms is commonly assumed to underestimate the assessed loss in a portfolio of structures. However, neglecting extra correlations may over or underestimate the network reliability depending on the correlation signs and the topology of the network. Therefore, the impact of extra correlations and may vary among different networks. Nevertheless, neglecting extra correlations may cause large deviations from the real network reliability value, as confirmed in this section.

To further investigate the impact of extra correlations on network reliability assessments, two different scenarios are studied in which the origin and destination nodes have changed to produce tail failure probabilities in the case study network. Figure 6.5 presents the results of the sensitivity analysis on the failure probability of these scenarios with the same range of λ values as before. To be consistent with the original case study, the simulations continue until the standard deviation of reliability estimates reaches 0.005. As expected, varying extra correlations has far less influence on extreme failure probabilities. Note that the trend observed in Figure 6.4 (i.e., reduction of network failure probability with overall more positive correlations) is not echoed in Figure 6.5, as the (*O*, *D*) pair and the resulting paths and cut-sets have changed. Nevertheless, changing correlation ratios has negligible effect when the network failure probability is either very large or very small, as confirmed by Figure 6.5.

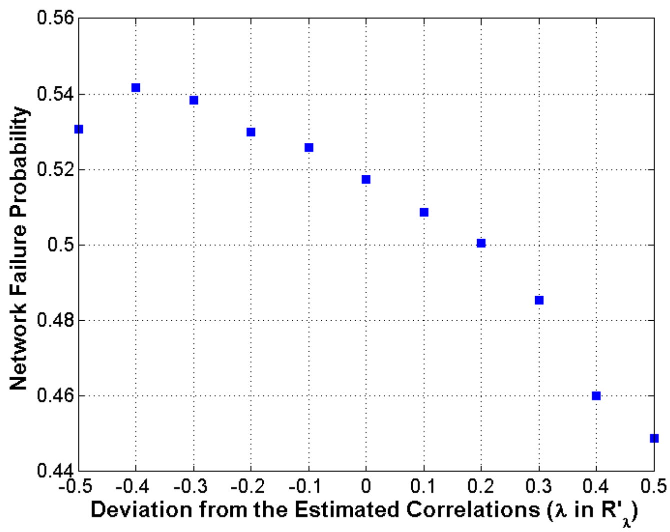


Figure 6.4. The impact of varying λ on the network failure probability of the South Carolina bridge network

In summary, the BRAN methodology is shown to be applicable for reliability assessment of large highway bridge networks. BRAN employs advanced bridge fragility models, which are used to evaluate the bridge failure probabilities. Several bridge classes, especially slab type and simply supported bridges, are relatively non-vulnerable to seismic events due to low seismic demands on bearings and columns. On the contrary, proximity to the epicenter of the earthquake makes many bridges highly vulnerable. Therefore, the majority of bridges (77%) in the network have either extremely high or low probabilities which make their failures independent.

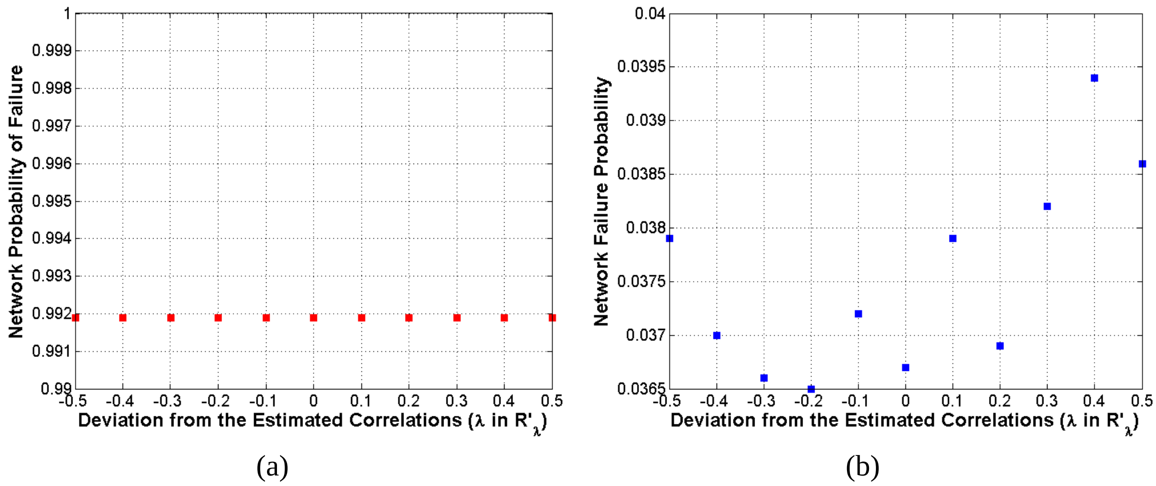


Figure 6.5. The impact of varying λ on the network failure probability with: a) an origin-destination pair resulting in extremely high failure probability, and b) an origin-destination pair resulting in a very low probability of failure.

Network reliability evaluation of the South Carolina bridge network revealed that the three auxiliary data sources can produce a viable the correlation matrix, a claim supported by around 5% change in matrix 2-norm after modification for compatibility. Furthermore, the sensitivity analysis examined the impact of accounting for different levels of extra correlations on network estimates. The evaluated network reliabilities showed up to 20% variation, which is significant enough to justify their inclusion in network reliability studies. The results also emphasize the need to derive post-earthquake data driven correlation estimates. Next, network reliability evaluations by BRAN are used in a probabilistic risk assessment.

6.1.2. Probabilistic Risk Assessment by Surrogate Models

Table 6.2 lists the required steps to evaluate the risk of exceeding given network reliability levels by the application of surrogate models. Step 1 involves creating n_{maps} hazard intensity maps, which are the input for risk assessment, and account for inter- and intra-event correlations (Crowley and Bommer 2006; Jayaram and Baker 2009). Bridge fragility models by Ghosh et al. (2013) are then employed to evaluate the bridge failure probabilities, which is the probability of exceeding the extensive damage state in this case study. The BRAN is subsequently employed to evaluate the network failure probability for *ns* (which is less than n_{maps}) hazard maps (Step 3), which along the bridge failure records corresponding to those *ns* maps are used to develop a surrogate model for network reliability evaluations (Step 4). The surrogate model is then applied to evaluate the network failure probability for the rest of hazard maps ($n_{maps} - ns$).Once the n_{maps} network failure probabilities are evaluated using Steps 1-4, Equation 6.1 can be used to evaluate the probability of exceeding network reliability levels (Jayaram and Baker 2010):

$$\mathrm{P}(P_f \geq p_0) = \frac{\sum_{i=1}^{n_{maps}} \mathrm{I}(P_f^{(i)} \geq p_0) w_i}{\sum_{i=1}^{n_{maps}} w_i} \qquad 6.1$$

where P_f is the network failure probability, p_0 specifies values for which the probability of exceedance is evaluated, and terms *w* and I stand for scenario weight and the indicator function, respectively. The weights are used for importance sampling, so that more hazard maps are generated corresponding to larger earthquake magnitudes. Moreover, and since the generated seismic intensity maps are associated with a return period, Equation 6.1 may be expressed in terms of the annual probability of exceeding network reliability levels.

Table 6.2. The risk assessment methodology using network surrogate models

Steps	Description
1	Generate n_{maps} hazard intensity maps
2	Evaluate the bridge failure probabilities for the generated hazard maps using bridge fragility models
3	Evaluate the network failure probability for *ns* (*ns* < n_{maps}) hazard maps by BRAN methodology
4	Form a network surrogate model by training with the *ns* scenarios of Step 3 using statistical learning methods. Evaluate the network failure probability using the developed surrogate model for the rest of the hazard maps
5	Evaluate the risk of exceeding network reliability levels using Equation 6.26.1

The presented methodology for risk assessment provides efficient methods which can save simulation time, as listed below:

1. The advanced bridge fragility models used in Step 2 are developed by surrogate demand models (Ghosh et al. 2013). Accordingly, they provide the fragility function without the need for extensive finite element analyses.

2. BRAN (Step 3) incorporates several methods to enhance the computational efficiency of network reliability simulations, as detailed in Chapter 3. The possible errors from independent treatment of extreme bridge failure probabilities are shown to be negligible. Moreover, MCMC allows for large number of Monte Carlo simulations to achieve the desired convergence level.

3. The use of surrogate models in Step 4 reduces the number of network reliability evaluations from n_{maps} to *ns*. The value of *ns* is determined by the desired level of

accuracy in the predictive model. Therefore, in cases where n_{maps} is large, the use of surrogate models can significantly reduce the simulation time of risk assessments.

4. Finally, the inclusion of weights for importance sampling in Equation 6.1 reduces the variance in evaluating the probability of exceedance, as elaborated on in Jayaram and Baker (2010). Accordingly, importance sampling results in narrower bounds around the estimated mean probability of exceedance from n_{maps} hazard maps.

This section describes the development of surrogate models for the South Carolina bridge network with the same choice of origin and destination nodes as in Figure 6.1. The risk assessment is then performed using n_{maps} = 1,000; however, the value for *ns* is to be determined. Comparing the dimensionality of this case study (i.e., 509) with the example networks presented in Section 4.3 may suggest the need for a large number of data points to train the random forest model, as 1,000 failure records were used for the model of the 20-node network. However, the bridge importance hierarchy in the South Carolina network differs from that of the lattice networks, and is governed by the shortest paths between the origin and destination sets, as is the case for most actual bridge networks. Since the failure of bridges lying on shortest paths affects the network connectivity more than the failure of the rest which results in unequal bridge criticalities, there is a clear hierarchy among nodes within the network and the predictive models are expected to train faster than lattice topologies. This clear hierarchy helps to avoid keeping up with the density of data points in actual bridge systems, which otherwise would make the simulations intractable.

The experimental design implemented for the synthetic networks assumes no knowledge on the distribution of random variables. However, for risk assessment applications, it is possible to find and make use of the joint distribution of bridge failure probabilities among random variables in order to generate the data points in the region of most interest for more accurate predictions. The joint distribution involves the intra- and inter-event correlations resulting from the hazard scenarios (Step 1 of Table 6.2), and is estimated by studying the fault systems in the area in order to simulate network consistent seismic scenarios for the network. Since this case study focuses on surrogate model development, extra correlations are excluded for simplicity. For each seismic scenario, the bridge failure probabilities are evaluated by bridge fragility models (Step 2). The resulting bridge failure probabilities follow a joint distribution which differs from independent uniform sampling in $[0, 1]^n$ which is used for the experimental design set up of example networks in Section 4.3. Researchers in structural reliability (e.g. Hurtado 2004) have reported improvement in prediction accuracy when samples are drawn from joint distributions which is often known for structures. Nevertheless, surrogate models by independent experimental design are also developed and their results are compared against those of the surrogate models developed according to the methodology in Table 6.1 (i.e. scenario-based sample generation).

The independent experimental design makes use of 1,000 data points (i.e. bridge failure records and their corresponding network failure probabilities), 800 of which are used for model selection. The scenario-based approach, on the other hand, employs ns = 350 seismic intensity scenarios. Although the methodology in Table 6.1 adopts hazard maps generation by importance sampling (Jayaram and Baker 2010), other importance sampling methods in the literature (e.g. Kiremidjian et al. 2007) are also applicable for this purpose, and can be used to derive the coveted joint probability distribution. Those *ns* seismic scenarios produce 350 bridge failure records resulting from bridge fragility models, of which 280 (i.e. 20%) are used for model selection. In order to evaluate the performance of the surrogate model on the depicted seismic scenario in Figure 6.1, the corresponding record of bridge failure probabilities resulting from that specific scenario is not included in the model selection dataset and reserved for the final prediction tests. This record corresponds to the network reliability study presented in Section 6.1.1.

Figure 6.6 compares the test error in the regression model for the two training approaches. Only the regression model is established, since this case study primarily intends to estimate the network failure probability for the scenario earthquake depicted in Figure 6.5, and therefore, a classification model is not necessary. Both training approaches have resulted in smaller test errors compared to the lattice networks (Figure 4.6) in spite of application to a problem with far higher dimensionality. Recall that surrogate models for lattice networks produced an RMSE error close to 0.09. The observed improved accuracy highlights the benefit of random forests to de-emphasize the contribution of irrelevant random variables (here, most bridges close to the perimeter of the depicted network). In comparing the two training approaches, the one trained by true hazard scenarios produces lower errors, while trained with only one third as many data points as the independent sampling approach. Approach 2 also requires more trees grown to stabilize the error, which has negligible impact on the computation time.

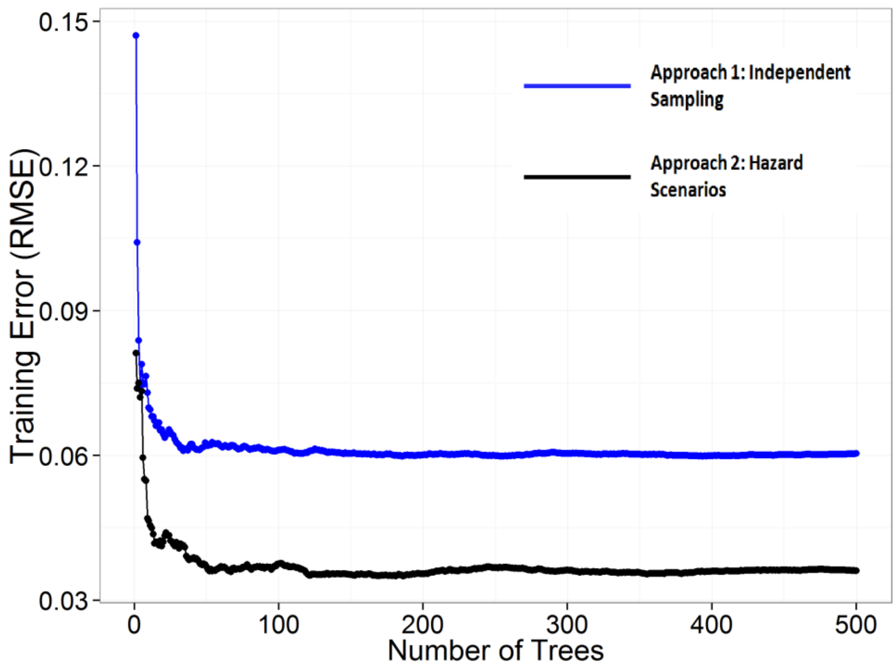


Figure 6.6. Root of mean squared test errors for the South Carolina network.The independent sampling approach uses 800 data points for training, while the network consistent scenario based approach uses 280.

The network reliability study for the demonstrated scenario in Figure 6.1 evaluates the network failure probability to be 0.55 for the case without extra correlations (Section 6.1.1). In comparison, Approach 1 (independent sampling) estimates that probability to be 0.58, which incurs a 5.4% deviation, while Approach 2 (sampling by hazard scenarios) evaluates it to be 0.57, resulting in an even smaller 3.6% relative error. The magnitude of those errors is in the admissible tolerance range of risk assessment studies, suggesting that random forests can significantly contribute to the computational efficiency of such applications.

Finally, the surrogate models developed by Approach 2 are employed to evaluate the seismic risk for the South Carolina network for the remaining 650 hazard maps. Figure 6.7 depicts the evaluated risk curve, which shows the annual probability of exceeding network failure probabilities. Although test error for network reliability evaluation confirms that the difference between computed network failure probabilities by surrogate models and BRAN is negligible, future work will confirm whether the two resulting risk curves match closely.

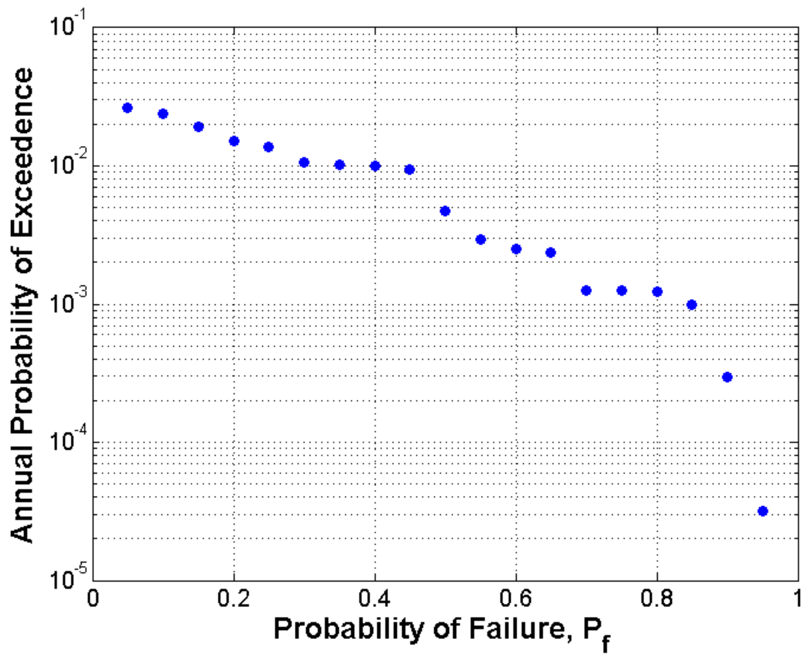


Figure 6.7. The risk evaluation curve for the South Carolina bridge network, showing annual probability of exceeding network failure probabilities. Network reliability evaluations are performed by the developed surrogate models.

The application of statistical learning surrogate models to risk assessment is especially emphasized as once a predictive model is established, the future network reliability predictions can be made almost instantaneously for many representative hazard scenarios. Since the computational complexity of forming the surrogate models by random forests is insignificant compared to the reliability evaluations, the computation time required for risk assessments is nearly proportional to the number of performed reliability evaluations. Accordingly, using surrogate models may cut the computation time proportional to the size of the model assessment set divided by the necessary number of reliability evaluations for risk assessment. In this case study, for instance, 350 seismic scenarios are used to set up the surrogate model, which is then used to form the risk curve of Figure 6.7 by 1,000 network reliability evaluations. The computational time, accordingly, is reduced by almost two thirds. Network stakeholders, as a result, can opt to simulate many more hazard scenarios after forming the model with a tractable number of them in order to develop more detailed risk curves.

6.1.3. Importance Measures

This section compares the ranking outcome from the importance measures discussed in Chapter 5 to rank bridge priorities for retrofitting or maintenance. The review of importance measures reveals that ranking of bridges within the network based on state-of-the-practice methodologies are cursory in nature and do not account for either the deteriorated bridge fragilities or the topological aspects of the network. The time-dependent fragility analysis (*TDFA*) improves the bridge ranking by accounting for the deteriorated bridge fragilities developed through rigorous nonlinear dynamic and probabilistic analyses. However, *TDFA* still ignores the role of bridges within the network. On the other hand, ranking by Betweenness Centrality (*BC*) is based solely on the topology of the network, without acknowledging the heterogeneity in their vulnerabilities. Conditional importance measures (*CIM*) consider both of these aspects; however, they require solving the network reliability problem, which makes them the most computationally intensive metric among the discussed methods. Chapter 5 also introduces two new importance measures, the Bridge Rank (*BR*) and the Random Forest

Importance Measure (*RFIM*), which account for bridge vulnerabilities and significance within the network. In comparison, *BR* is not limited to the choice of any specific reliability objective or the location of origin and destination nodes, as it implicitly accounts for all possible paths from every node to every other node in the network. However, *BR* ranking does depend on a specific hazard scenario to evaluate the bridge vulnerabilities. *RFIM*, on the other hand, evaluates the significance of bridge failures to predict the network failure probability based on its reliability objective. Moreover, it provides a probabilistic ranking which considers multiple hazard scenarios as required for probabilistic risk assessment.

Figure 6.8 identifies the location of ten top ranked bridges inside the South Carolina network according to the discussed metrics. The seismic scenario of Figure 6.1 is considered for *TDFA*, *CIM*, and *BR* importance measures. Accordingly, the rankings by these metrics tend to rank higher the bridges closer to the epicenter of the earthquake. In addition, for *CIM* and *RFIM* which account for the network reliability objective and (*O*, *D*) pairs, the origin and destination nodes also rank high. *RFIM* has both of the end nodes in the top ten, while *CIM* has the origin node in the top ten, and the destination node in the top 20 (not depicted). Moreover, three out of ten top ranked bridges based on *RFIM* lie on the shortest path from the origin to the destination, highlighting the importance of those bridges in maintaining the network connectivity.

As less complicated methods, *BC* and *TDFA* provide contrasting rankings. *TDFA* highlights the most vulnerable bridges, which unsurprisingly lie close to the seismic scenario's epicenter. Highly ranked bridges by *BC*, on the other hand, do not account for bridge vulnerabilities and are more scattered throughout the network, as it is a proxy for traffic flow. Two out of ten top ranked bridges by *BC* also lie on the shortest path from the origin to the destination.

BC and *RFIM* both rely on the choice of origin and destination nodes in the network. However, while the *BC* metric ignores the seismic hazard altogether, *RFIM* provides a probabilistic ranking, which does not depend on the depicted seismic scenario. This is a key difference, which becomes obvious by comparing the highly ranked bridges by the two methods. *BC* is concerned with key bridges facilitating connectivity, as those on the shortest path. However, *RFIM* accounts for their vulnerability as well, and does not include structurally safe bridges among those with priority for retrofitting. Nevertheless, their rankings may have a few bridges in common depending on the network topology and choice of origin and destination nodes.

Finally, the simple metrics of the Expected Damage method and the Indices method provide rankings which do not match any of the patterns by other importance measures. These metrics have been designed with replacement cost of bridges in mind (although the Expected Damage method considers old bridge fragility curves as well), and give priority to bridges with long spans. The highly ranked bridges by the state-of-the-practice methods have an important role to distribute traffic under normal operational conditions, but their impact on fulfilling the network reliability objectives in extreme events is not significant, particularly when compared to highly ranked bridges by more advanced methods.

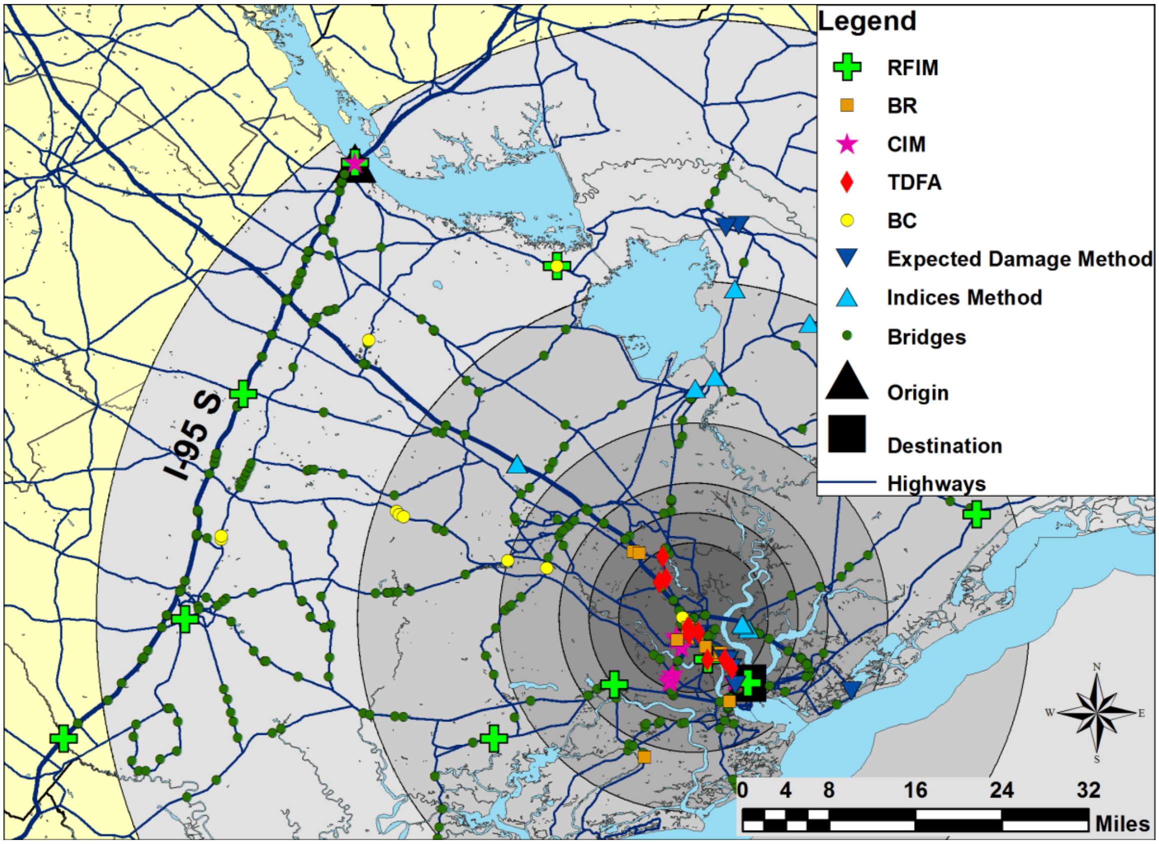


Figure 6.8. Bridge criticality rankings by importance measures: RFIM: Random Forest Importance Measure, BR: ridge Rank, CIM: Comditional Importance Measure, TDFA: Time Dependent Fragility Analysis, and BC: Betweenness Centrality. The Expected Damage and Indecis Methods are state-of-the-practice methods in the *Seismic Retrofit Manual* (Buckle et al. 2006).

In summary, the ranking outcomes by presented methods differ from one another based on their characteristics (Table 5.1). Nevertheless, there are clear similarities between them as well. Specifically, the three advanced metrics of *CIM*, *BR*, and *RFIM* identify the location of important bridges in the network, although by different criteria. Out of those methods, *BR* has the least analytical complexity, and provides the ranking scheme by far fewer computations. Therefore, it may be an appropriate metric for a probabilistic ranking framework similar to *RFIM*, since evaluating the *BR* rankings for multiple hazard scenarios can be done relatively fast. However, *BR* rankings from those multiple scenario analysis need to be combined in a systematic way, which is pursued in future research.

Before moving to the case study of other infrastructure networks, the following lists highlights from the case study on the South Carolina bridge network:

1. BRAN methodology is applied to evaluate the reliability of a large highway bridge network in South Carolina, US, with 509 deteriorating bridges from different bridge classes. The methodology presented to estimate and modify the correlation matrix for extra correlations efficiently produced samples of correlated bridge failures for Monte Carlo simulations. The efficiency is specially achieved by independent treatment of bridges with very high or very low failure probability (greater than 0.95 and less than 0.05, respectively).
2. Extra correlations have potentially significant impact on network reliability estimates, and therefore, they may not be ignored in reliability studies. Varying the correlation levels resulted in up to 20% change in the estimated network reliability of the case study network.
3. Probabilistic risk assessment in bridge network can greatly benefit from surrogate models for network reliability evaluations. Such surrogate models are developed by random forests after training with a manageable number of network reliability evaluations, and produce predictive models to replace Monte Carlo simulations for further reliability evaluations with negligible error.

4. Network surrogate models can combine with hazard scenario reduction methods prevalent in risk analysis, such as importance sampling, to further enhance the efficiency and accuracy of the risk assessment.
5. The newly introduced importance measures, Bridge Rank and Random Forests Importance Measure, enhance upon the state-of-the-art methods for bridge retrofit prioritization by accounting for bridge vulnerabilities and their role in the network at the same time. Bridge Rank focuses on computational efficiency, while Random Forests Importance Measure can provide a probabilistic ranking which does not depend on a specific hazard scenario.

While the developed frameworks for highway bridge network reliability and risk evaluation are transferable to other networked systems, the case studies for water distribution systems and power networks focus on reliability aspects which are more relevant to those networks. Those aspects, including interdependencies across different infrastructure systems and vulnerability analysis, are the subject of increased interest in recent years due to their significance in system reliability studies. The next two sections exemplify new approaches to implement interdependence and vulnerability analysis in water and power systems, respectively, for large and complex systems.

6.2. Water Distribution Network

Communities located along the U.S. Gulf of Mexico are uniquely vulnerable to disruptive events associated with hurricane activity in the Gulf. In 2005, landfall of Hurricanes Katrina and Rita on the Louisiana and Texas coasts brought public attention to the overwhelming destructive power of hurricane events and to the impacts they can have on local and regional infrastructure networks, such as the water distribution system. Similarly in 2008, Hurricane Ike hit the Texas coast resulting in heavy damage to major infrastructure systems. Analogous to the highway bridge networks, studying the vulnerabilities of water network components, and evaluating the systemic reliability enables the system stakeholders to make informed decisions for risk mitigation and network management.

While the majority of water system components, such as water pipes and fittings, enjoy protection from hurricanes because they are located underground, the dependence of water distribution network on the electrical grid to power its pumps make it vulnerable to hurricane demands. Equipping pumping sites with back-up power generators to provide emergency power may not fully address this vulnerability issue because of the limited amount of fuel that can be stored on-site, the likelihood of power outages lasting on the order of weeks, potential problems with securing dependable fuel sources in times of emergency and shortages, and the likelihood of transportation disruptions. Moreover, having a separate power generator at each pumping site requires a considerable investment, which is not always possible.

6.2.1. The Case Study Network

The case study network belongs to a small community (approximately 70,000 residents) located on the upper Texas, US, within the Greater Houston metropolitan area. Figure 6.9 shows the city’s actual water distribution network containing 5 to 107 cm (2 to 42 inch) diameter pipes with a total length of 502 km (312 miles), 9 ground storage/booster pump sites, and 3 elevated storage tanks. The depicted water distribution system, even though it serves a relatively small community, is a complex network with approximately 17,200 individual pipes. To facilitate the analysis, the actual water distribution network is simplified to only include the most important components, as represented by the network shown in Figure 6.10. This simplified version of the city's distribution system contains 316 links representing approximately 209 km (130 miles) of pipes connecting 221 vertices including the 12 supply nodes.

The network reliability is evaluated under the impact of five hurricane scenarios, each representative of a hurricane category in the Saffir-Simpson hurricane scale (National Hurricane Center). The State of Texas requires that each water system operator in the state develop an emergency preparedness plan that details steps the operator will take to provide a minimum operating pressure of 240 kPa (35 psi) under foreseeable emergency conditions, including natural disasters (Texas Administrative Code). The reliability analysis, therefore, require hydraulic pressure modeling in the network for each simulated state of the system by EPANET, which exemplifies a different reliability objective compared to the connectivity reliability for highway bridge networks. EPANET is a software cable of estimating water flux and pressure across pipes in the network by defining the geometry of the water network, pipe specifications, and source water pressures.

For the power grid in the study area, only the power system asset inventory of generators and transmission level facilities are identifiable from available data sources (Federal Emergency Management Agency 2008). The corresponding electric distribution network is typically not documented due to security concerns, but its layout is estimated by inspection through several site visits. A topological representation of the power grid serving the area is shown in Figure 6.11, where power load substations are modeled as nodes and power lines are shown as connecting links. Nine power distribution lines from the power substations to water pump stations (i.e., the interdependency lines) are also included in the system model.

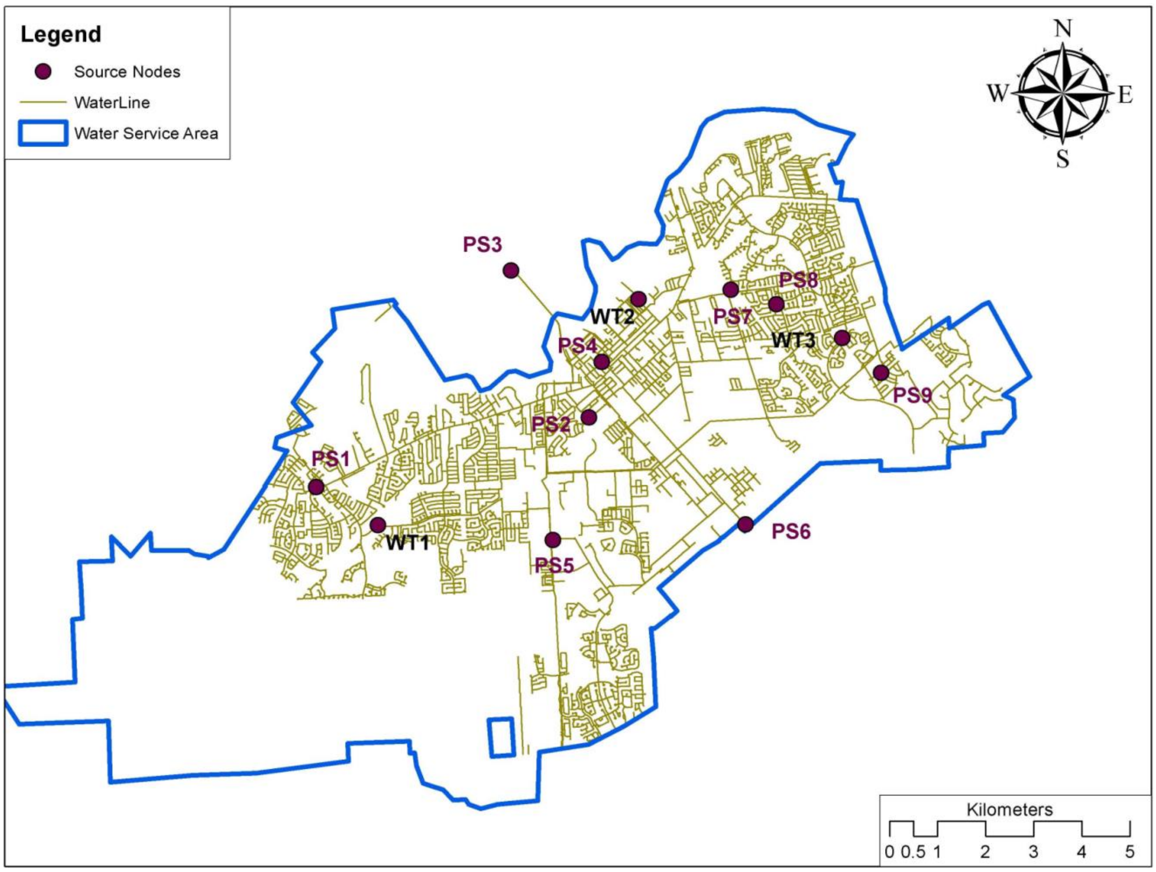


Figure 6.9 - Case study water distribution network in a small city in Texas, US. PS denotes pump station, and WT stands for water tank.

Studying the performance of two networks at the same time, as well as the flow based reliability objective of the water distribution system highlights the need for efficient models which are applicable to large systems. The next section presents a model developed for this study, which accounts for the interdependent response of water and power systems in a decoupled, two-stage framework.

6.2.2. The Decoupled Reliability Approach

A novel two-stage reliability assessment methodology is proposed for water distribution networks in coastal communities under hurricane hazard. A decoupled method is used to simulate the state of the components in the electrical and water distribution systems under hurricane scenarios, and hydraulic analysis by EPANET follows to estimate water pressures throughout the network. Figure 6.12 presents the flow chart of the decoupled method to simulate realizations of the state of the systems. The decoupled method assumes a unidirectional relationship between the power grid and the water network in which the latter is dependent upon the former for operating power, but no significant dependence exists in the other direction. Accordingly, failures in the electrical network can be simulated prior to failures in the water network. For the case study presented, cooling water for the electrical substations is acquired from surface water sources and not the potable water distribution system, so the unidirectional dependence assumption is reasonable. The decoupled strategy is justified because the response of power grid components to failures is significantly faster than water network components, and therefore, the spread of damage in the water network can be assumed to start after the power grid has reached a steady state. Decoupling the response of the two systems reduces the complexity of jointly simulating the state of the system, which in turn makes the reliability analysis more applicable and computationally feasible for real infrastructure systems, such as the water distribution system of this study. Evaluating the performance of utility systems by physics-based models is computationally intensive; however, the decoupled framework presented here provides a practical alternative.

6.2.2.1. Stage 1: Power Network Failure

Node Betweenness Centrality is employed in this case study to approximate the power flow (which in future research is replaced by DC flow models). As also explained in Section 5.3, betweenness is a proxy for the amount of current passing through network elements. The initial load of a substation equals its betweenness in the initial power network. A disruptive event can cause the failure of some power substations and alter the network topology, which further changes all substation betweenness values. If a substation betweenness exceeds its maximum capacity defined as the product of its initial betweenness and a tolerance parameter, the substation fails operationally due to overload. Stage 1 runs the betweenness model for each hurricane category to simulate the direct and operational failure of the power network components. Similar outage models have been used to analyze the cascading failure process of many real power transmission grids, such as the North American power grid (Kinney et al. 2005) and the Italian electric grid (Crucitti et al. 2004). The generated failure scenarios are used in Stage 2 to evaluate the hydraulic reliability of the water system by Monte Carlo simulations.

6.2.2.2. Stage 2: Water Network Failure

The components of the water network are assumed to be invulnerable to direct hurricane impact, especially in lack of trees which can uproot the underground pipes in the region. However, a sensitivity analysis is conducted that assumes reliabilities of 0.95, 0.98, and 0.99 for the water system components under wind load, in order to investigate the variations in network reliability estimates. Moreover, the state of water pump stations also depends on the state of their corresponding power load substation and the interdependency lines as simulated at Stage 1. Accordingly, water pumps fail if either of the corresponding load substation, the interdependency line, or the water pumping

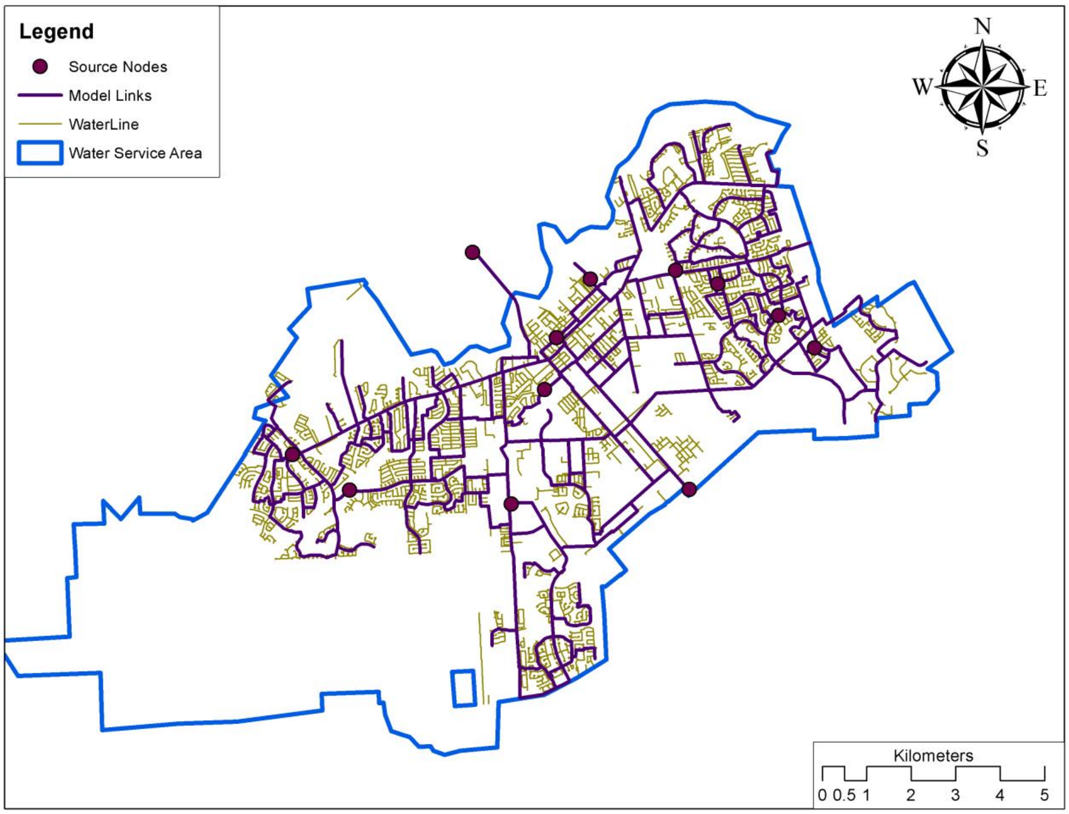


Figure 6.10. The simplified version of the water distribution network in Figure 6.9

structure fails. For each of the five hurricane categories, one hundred realizations of the state of water system components are generated by Monte Carlo simulations. The use of one hundred samples for Monte Carlo ensures that the coefficient of variation of the estimated network failure probabilities is limited to 5% with 95% confidence. For each realization, the layout of the water distribution network is updated to reflect the new state of the system considering both direct structural and interdependence-induced pump failures.

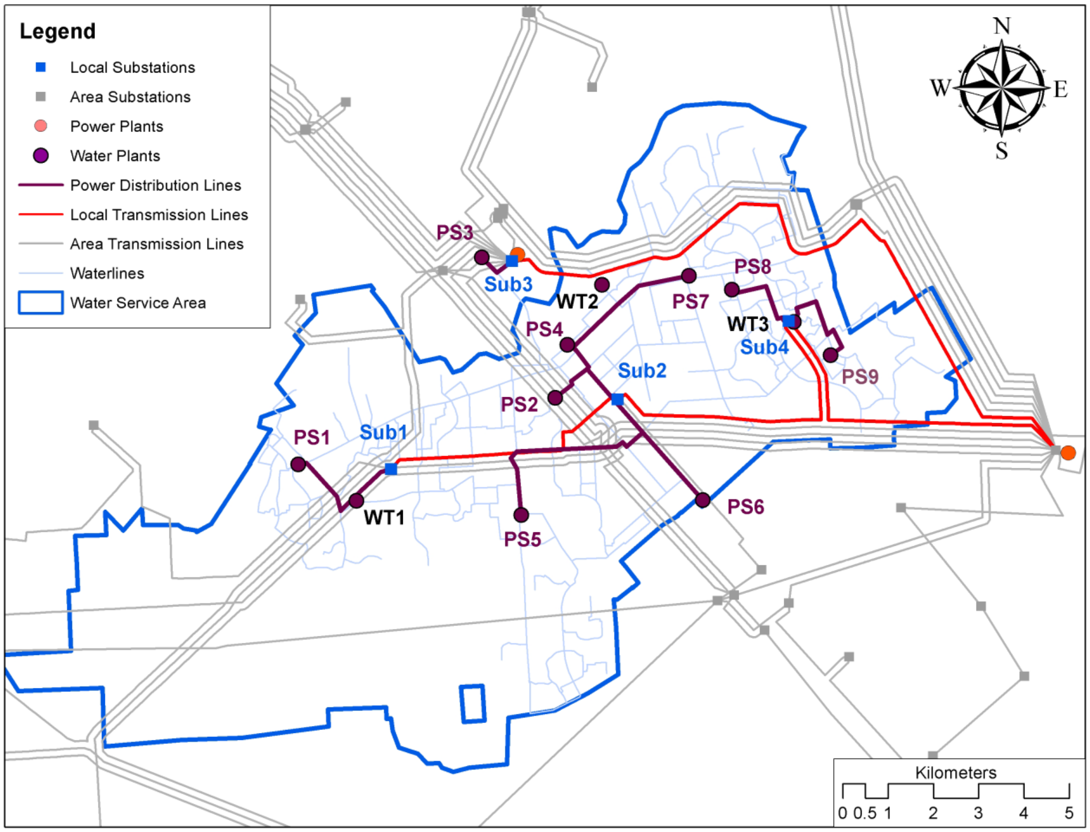


Figure 6.11. The approximate layout of the elecrical network in the case study region

Finally, to evaluate the system reliability, the water system's ability to satisfy the State's pressure requirement (i.e., 240 kPa throughout the system) is evaluated for each Monte Carlo simulation by hydraulic analysis (via EPANET). The results of the described two-stage reliability analysis are discussed in the next section.

6.2.3. Network Reliability Results by the Two-Stage Method

This two-stage, multi-system system reliability analysis estimates the water pressure throughout the network under five hurricane category events, each with one hundred failure realizations. For each hydraulic realization, the pressure at each node is calculated and compared against the minimum regulatory requirement. If all nodal pressures within the system are greater than 240 kPa (35 psi), the system is in compliance with the regulatory requirement for that realization and is classified as reliable. If some, or all, of the distribution nodes do not provide a pressure of 240 kPa (35 psi), the system is considered unreliable for that category of hurricane in that realization. Note that being classified as unreliable means that some portion of the network does not meet the minimum pressure requirements, and does not necessarily imply that the system suffers catastrophic failure. Upon completion of all realizations for each category of hurricane, a failure probability is estimated as the number of failed scenarios divided by the total number of model realizations (the failure probability is the probability that at least one node in the system does not meet the minimum pressure requirement). If the probability of failure is unacceptably high, the water system owner would then develop and implement system improvements to rectify the short-comings as required by regulation.

Figure 6.13 shows the pressure distribution contours across the case study water distribution network for Category 1 through 5 hurricanes. The reliability results suggest that the system fails to meet the reliability objective (the regulatory requirement of 240 kPa) for Categories 4 and 5, mainly due to loss of power at the water pumping sites. Figure 6.13 shows the results of the sensitivity analysis, implemented for Category 3 hurricane, where the reliability of water pipes is assumed to be 0.99, 0.98, and 0.95 to replace the invulnerability assumption. The system reliability is adversely affected as the result, and almost completely fails under all three reliability scenarios (Figure 6.14).

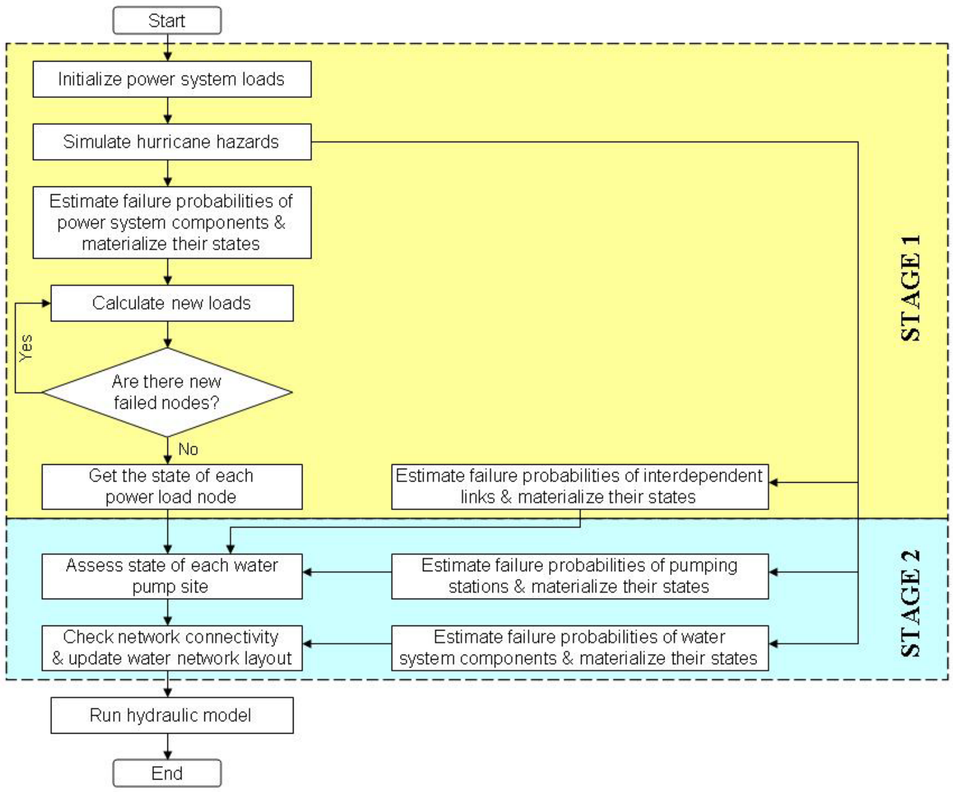


Figure 6.12. The flowchart of the decoupled method to evaluate the water network reliability by accounting for its interdependence with the power grid.

Access to such quantitative information can assist engineers, city planners and emergency managers in maintenance and retrofit plans against hurricane disasters by identifying the weaknesses not only in the water network itself, but also in the supplying power load nodes. The two-stage decoupled reliability approach presented in this section enables reliability and sensitivity analysis of large water distribution networks under hurricane hazard. It can also help developing and implementing a responsive and appropriate disaster management plan based upon the size of the approaching storm and the probability of the city's ability to provide basic services in the immediate aftermath.

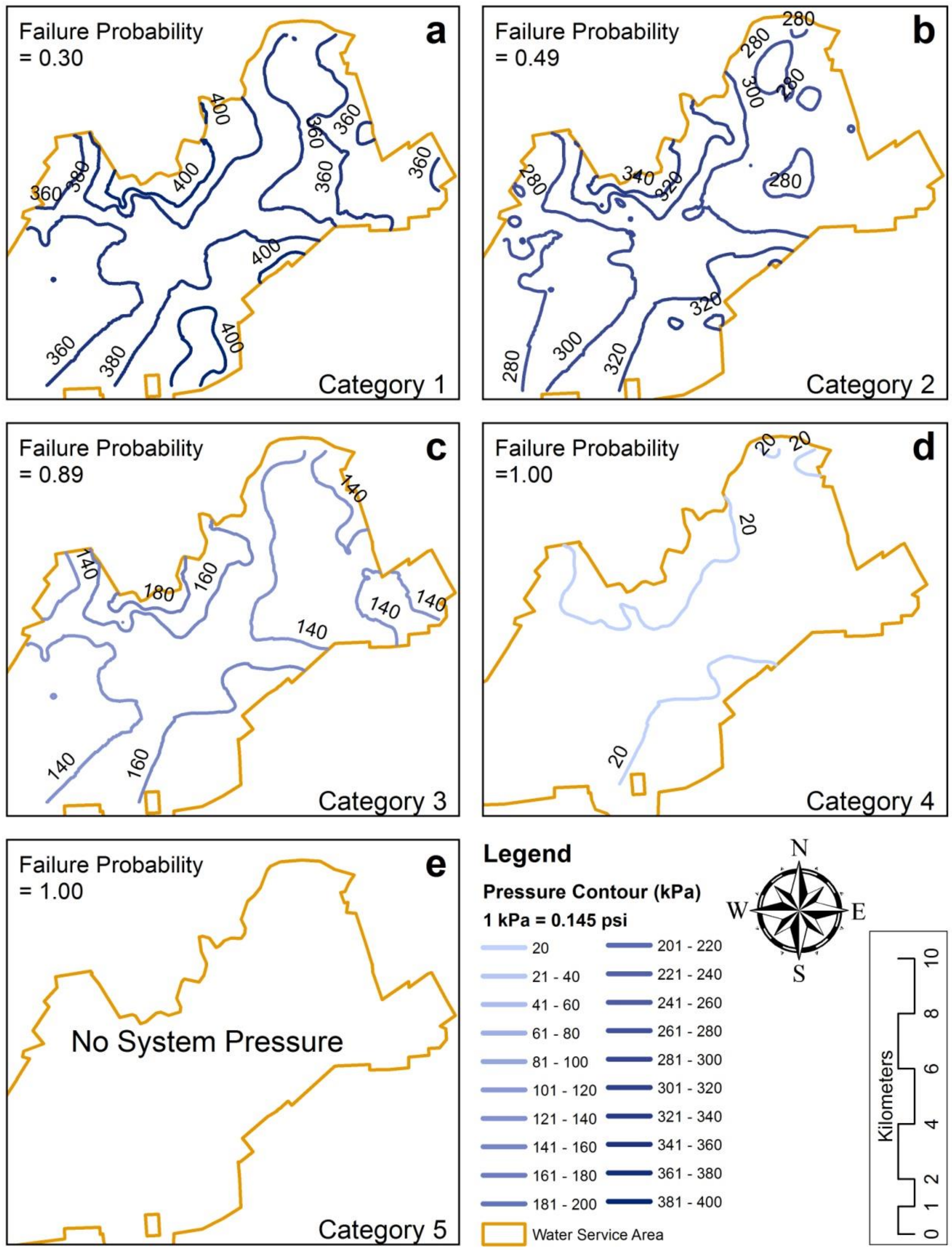


Figure 6.13. The results of the reliability analysis on the case study water distribution network. The contours of water pressure throughout the network are shown for five hurricane categories. Pipes are assumed to be invulnerable to hurricane.

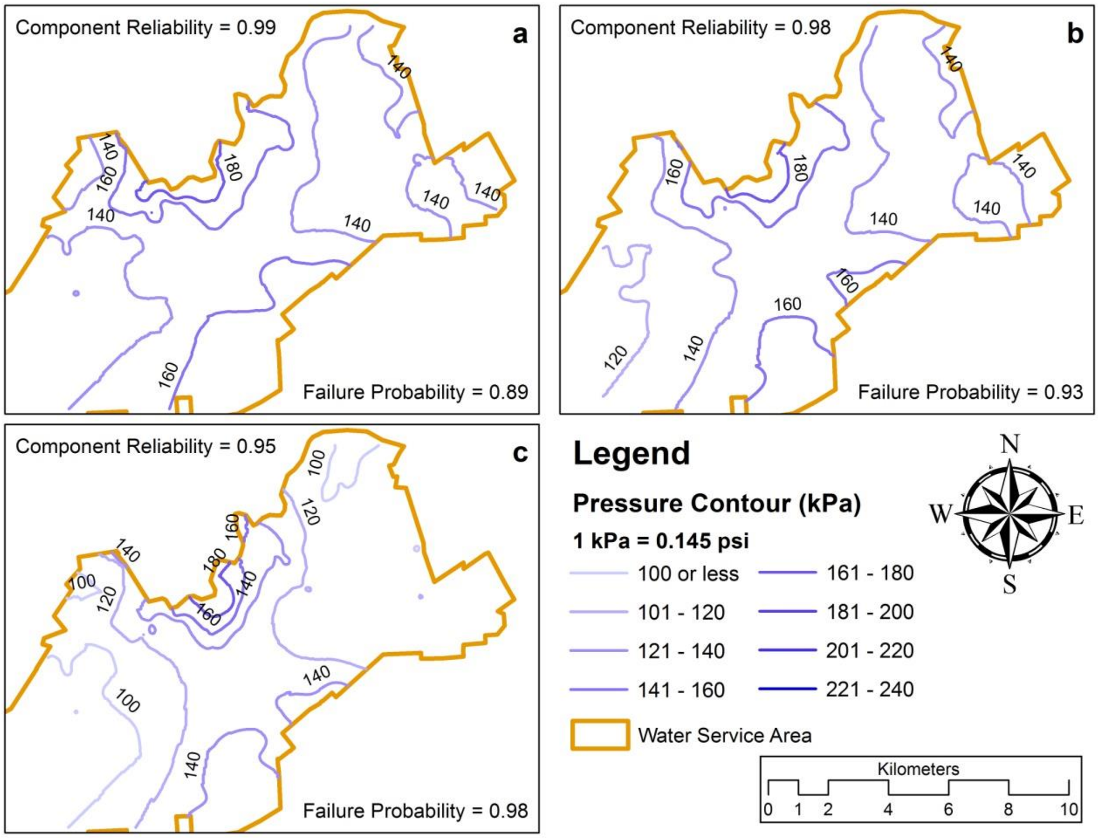


Figure 6.14. The sensitivity of network reliabilty estimates against Category 3 to varying pipe vulnerabilities

The same methodology used in BRAN for highway bridge networks can be applied to simulate correlated failures of the components in water and power systems once the sources of correlations are identified. Moreover, surrogate models can apply to predict the state of the system for risk assessment. Rather than predicting the connectivity reliability of the network, surrogate models fit to the outcome of hydraulic results, which are more computationally intensive for large systems than connectivity reliability simulations. Accordingly, the gained efficiency in risk analysis is even more substantial.

6.3. Power Transmission System

At the transmission level, the power grid consists of power plants (generators), substations, and high voltage transmission lines (over 37.5 kV). Network models of power transmission systems regard generator and electrical substations as nodes and the power lines as links. As an example, Figure 6.15 shows the layout of the power transmission grid in the state of Texas, US. This section investigates the performance of twenty five power transmission systems corresponding to major cities in Texas, California, and Southeastern states of Florida, Georgia, Tennessee, South Carolina, and North Carolina against various hazards. The selected systems represent a variety of characteristics in design and reliability since they were designed during different times and expanded with different growth rates.

The power transmission grid across some states or the country level is sparsely interconnected, and nodes are often distributed in clusters. This interface separation roots in the design of the grid to populate centers and also to mitigate the risk of cascading failures (Holmgren 2006). Both nodes and links in power transmission networks are vulnerable against a wide range of natural (seismic, hurricane) and man-made (terrorism, vandalism) hazards, which makes a comprehensive reliability and risk study challenging for real systems. To address this challenge, this section adopts a different approach to investigate the response of the case study power transmission networks, and a vulnerability study replaces scenario based or probabilistic reliability evaluation which was pursued for the other infrastructure systems. The vulnerability analysis systematically evaluates system weaknesses against all possible failure contingencies, from known or unknown hazards. In comparison, reliability studies assess the systemic performance under known hazards using specific or randomly generated hazard scenarios. The difficulty of collecting all significant hazard scenarios and the possibility of missing out on scenarios potentially capable of leading to disastrous outcomes make the vulnerability study well suited for power transmission systems, as it does not require prior knowledge on the nature of hazards. Instead, it investigates the negative consequences associated with all possible damaged states the system can suffer from.

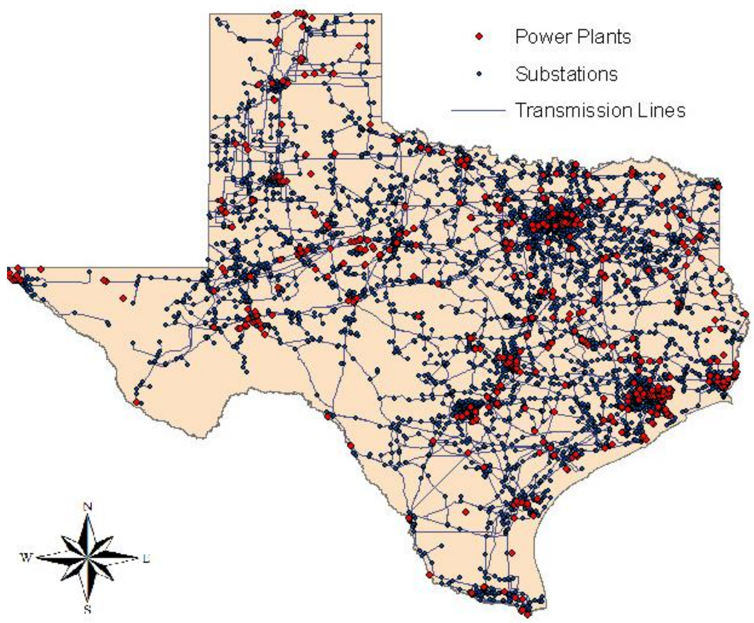


Figure 6.15. The layout of the power transmission grid in the state of Texas, US

Most power transmission planning and expansions follow the contingency enumeration approach, which studies the effects of all possible combinations of one component failure, i.e. the $N-1$ criterion (Billinton and Allan 1992). According to this criterion, power transmission networks must remain fully functional in case any one of its N system components fails. This criterion ensures a level of redundancy in the system to stay operational under small or frequent disruptions. However, this procedure does not fully capture the failure events and associated system performance of networks under severe natural hazards such as earthquakes and hurricanes, or targeted attacks such as vandalism and terrorism. The vulnerability analysis extends the $N - 1$ criterion to all possible contingency sets, i.e. $N - k$, with $k = 1, 2, \ldots, N$. However, this thesis only considers the failure of nodes (power plants and substations), since their removal will also put the power lines connected to them out of service. Load node failures are especially important in studying interdependent systems, as observed in the case study of the water distribution network. The adopted vulnerability approach which investigates the performance of networks under all node failure contingencies is also the subject of percolation studies in network theory literature (Newman 2010), where removing k nodes from the system is also interpreted as assigning a uniform probability of failure of $f = k / N$ to all nodes in the network and determining system level properties as a function of f.

Although vulnerability studies provide a viable solution to investigate the performance of power transmission systems, such studies may involve intractable number of simulations for large networks, due to the fact that they require permutations of all possible component failures. Therefore, this section also introduces performance bounds on the systemic performance. The performance bounds are developed using the results of the vulnerability analysis on synthetic networks with extreme topological formations. The application of the performance bounds provides reasonable estimates of systemic performance with manageable number of simulations for initial assessment and decision making. The adopted synthetic networks are referred to as ideal topological formations hereafter.

The methodology to implement the vulnerability analysis and the choice of system performance metrics are discussed in the next section. This thesis examines twenty five case study power transmission networks across the United States along with their ideal topological formations. The results of vulnerability analyses on the case study networks enable developing the performance bounds, which in turn enable fast systemic assessments with reasonable accuracy.

6.3.1. Vulnerability Analysis Methodology

The network performance metric may be defined by either topology, such as connectivity, or by current flow (Pagani and Aiello 2011). Pagani and Aiello (2011) have surveyed many studies on the performance of power networks under attack scenarios, and report that the majority of researches focusing on actual networks use topological metrics such as efficiency, size of the largest cluster, and the connectivity loss. This research adopts Connectivity Loss (C_L), proposed by Albert et al. (2004), as the metric for vulnerability analysis in order to investigate the performance of power transmission networks by topology. Connectivity Loss does not take into account the current redistribution process in the system after component failures that often results in the failure of additional power lines due to overload. Nevertheless, maintaining connectivity is an essential precondition for the network to function under severe conditions (Pagani and Aiello 2011). Equation 6.2 presents for formulation of C_L upon removing k components:

$$C_L(k) = 1 - \frac{1}{n_D} \sum_{i=1}^{n_D} \frac{n_G^i}{n_G} \qquad 6.2$$

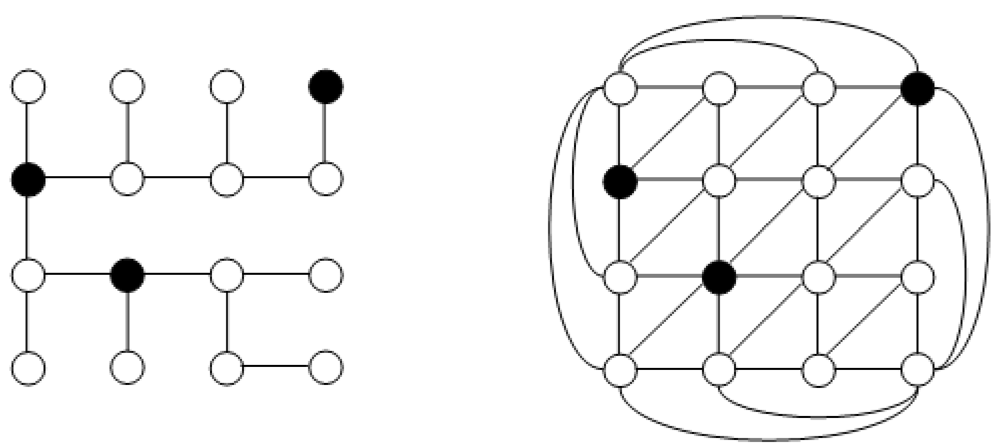
where $C_L(k)$ is the connectivity loss index for k removed nodes, n_G and n_D are the number of power plants (generators) and substations (distribution nodes), respectively, and n^i_G is the number of generator nodes still able to supply power to the i^{th} distribution node after removing k nodes. $C_L(k)$ varies in [0, 1], assuming the value of zero when the network is fully functional and one in case there are no generators connected to any substations.

In computing $C_L(k)$, the k nodes to be removed may be selected from n possible nodes where n is the total number of generators and substations. Therefore, computing the connectivity loss for k failure contingencies requires $C(n, k)$ simulations, where $C(n, k)$ is the combination of k out of n. Consequently, exploring the performance of the network under all possible failure contingencies involves a total of 2^n failure realizations which results in a Non-Polynomial (NP) problem with intractable number of simulations for large transmission networks with hundreds to thousands of nodes. For this research, the vulnerability requires an estimate of the mean value of $C_L(k)$ with 95% confidence and an error of 0.005. To comply with the stated error and confidence bound, only 300 out of $C(n, k)$ scenarios need to be simulated per k value. Nonetheless, the vulnerability study on the twenty five case study networks still requires exploiting parallel computing on computer clusters due to the size of those systems. The twenty five networks are selected from the states of Texas, California, and southeast states of Florida, Tennessee, South Carolina, and North Carolina to represent different geographical regions, network designs, and growth rates. For each city, the largest connected cluster of the grid within the city boundaries is considered. In addition to the case study networks, the vulnerability analysis is also performed for ideal topological formations, which are described next.

6.3.2. Ideal Topological Formations

Ideal topological formations have extreme topological characteristics that can bound those of the real networks, and are formed by reorganizing, adding or subtracting the links connecting the same nodes in the real network. Many past studies compare the properties of real networks to those of the random graphs (Watts and Strogatz 1998) or the scale-free networks (Albert and Barabasi 2002); however, Minimum Spanning Trees (MST) and Greedy Triangulations (GT) are better suited for planar infrastructure networks (Buhl et al. 2006; Cardillo et al. 2006). A planar network can be represented in the two dimensional space with no link intersections. Planar networks are closest ideal representation to capture geographically distributed systems. This research also introduces Pseudo-Greedy Triangulation (PGT) for planar networks, as explained below.

Figure 6.16 depicts schematic representations of MST and PGT formations on a 16-node lattice network. A spanning tree barely includes the minimum number of links to connect all nodes in the network. The Minimum Spanning Tree is a spanning tree that has the minimum total edge weight (cost) among all possible spanning trees. If all links are assumed to be the same, any spanning tree is a MST. A spanning tree requires only $n-1$ links to connect a network of order *n*. Many real networks tend to be close to a spanning tree in structure because it is the most cost efficient topological formation. However, this formation compromises the reliability of the network for lack of redundancy as any component failure results in a disconnected residual network. A Greedy Triangulation, on the other hand, is the maximally connected network formation to comply with the planarity constraint, i.e., no edge can be added to a Greedy Triangulation without violating the graph planarity. A GT is shown to have $3n-6$ edges (Buhl et al. 2006), far less than $n(n-1)/2$ for complete graphs which are not planar, but are used as ideal networks as well. A GT formation has many redundant edges in addition to what is required for minimum network connectivity (i.e., $n-1$) and, therefore, is far more resilient to component failures than spanning trees. On the other hand, GT topologies may contain very long edges, for example, an edge connecting two nodes on the extreme ends of a network. Such long edges are unlikely to exist in real infrastructure networks due to their construction costs. Therefore, PGT, a topological formation close to GT, is introduced here which excludes long edges from GT and is more computationally efficient to generate as well. If power transmission networks can be morphed into a lattice, PGT drops connections between nodes that are farther away than the third neighbors. For large networks, the difference in the number of edges between PGT and GT is in the order of O($\sqrt{n}$).



(a) (b)

Figure 6.16. . a) Minimum Spanning Tree, and b) Pseudo-Greedy Triagulation formations on a 16-node network. The dark nodes represent generators.

6.3.3. Vulnerability Analysis by Node Removals

The vulnerability analysis results are presented in the form of mean connectivity loss estimates against the fraction of node removal ($f = k/n$). Figure 6.17 shows the performance of the 25 case study networks along with the performance of their ideal formations. Interestingly, the performance of ideal topological formations in terms of the connectivity loss bounds that of the real networks. The figure also reveals that the slope of the performance curves roughly remains the same until reaching a critical node removal ratio. For real networks, this critical point occurs at around $f = 0.4$ for all the networks under study. This value is in good compliance with a theoretical value that computes the fraction of component removals until a network is divided into smaller, separate networks. The theoretical value for the critical node removal ratio, which neglects node degree correlations, is given by (Rosas-Casals et al. 2007):

$$\varphi_c = \frac{\mathrm{E}[k]}{\mathrm{E}[k^2] - \mathrm{E}[k]} \qquad 6.3$$

where $\mathrm{E}[\cdot]$ denotes the expected value, and k is the node degree. Therefore, $\mathrm{E}[k]$ is equivalent to the average node degree. The value of φ_c is computed to be in [0.35, 0.43] for the twenty five case study networks. The conformity of the analytical estimate from Equation 6.3 to the observed values in Figure 6.17 in spite of neglecting degree correlations is due to the fact that high degree nodes tend to connect to low degree nodes in technological networks such as infrastructure systems (Boccaletti et al. 2006).

Figure 6.17 also reveals that the variability in the performance across the case study systems increases from MST to PGT networks. This observation can be explained by the density of the networks and the number of generator nodes selected to be removed for a given value of f. Since the curves show the mean CL values, the differences in the number of removed generator nodes across different networks results in more variability in the sparser MST networks. In far denser PGT networks, the difference in generator node removals is minimal, since there will be redundant links to connect the remaining substations to the remaining generators.

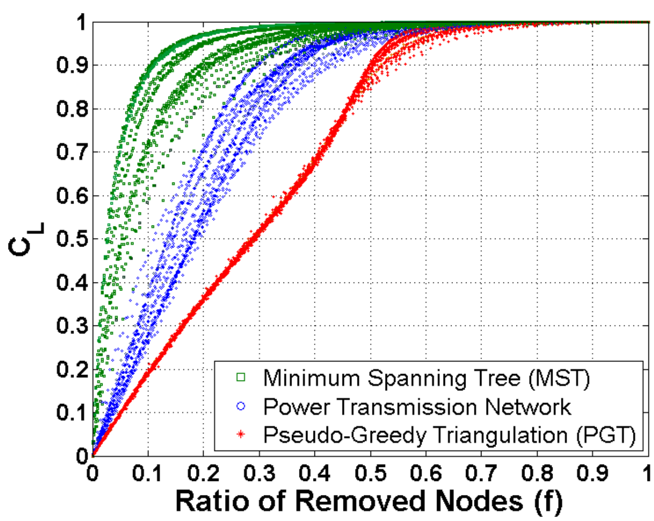


Figure 6.17. Performance assessment of case study power transmission networks against possible failure scenarios in a vulnerability analysis

The shape of the vulnerability curves may be represented by a bilinear form, both for the real networks and their ideal formations. Such bilinear functional forms can be exploited to reduce the computational complexity of the problem by implementing the vulnerability analysis for enough values of k in order to fit two lines. A sample bilinear model fitting is displayed for the transmission network of Los Angeles, CA in Figure 6.18. As the figure suggests, the actual transmission networks are a better fit to the bilinear model compared to their ideal formations. In fact, the error is minimal for the network of Los Angeles, except around the critical node removal fraction. Therefore, the application of the bilinear model can save computation time for the vulnerability analysis of power transmission networks, especially if the failure scenarios do not involve close to 40% node removals. The application of the bilinear form is especially useful since most practical $N - k$ assessments focus on only a few node removals (k = 1, 2, or 3). Based on the bilinear forms, the same assessments can be expanded for higher node removal ratios.

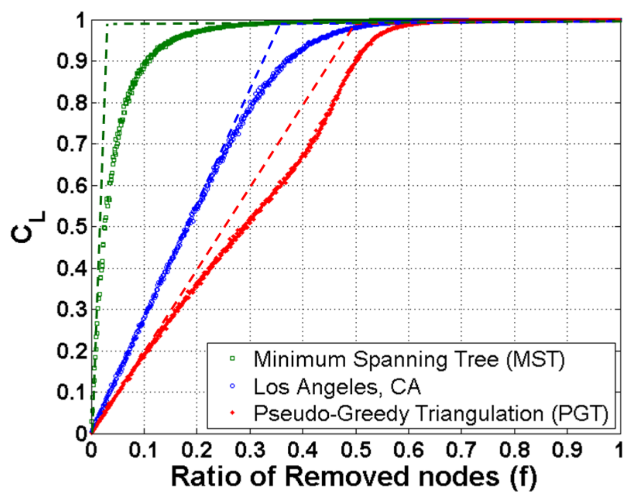


Figure 6.18. Vulnerability curves for the network of Los Angeles, CA. The gap between the curves and the tangent dashed lines show the error induced by bilinear model estimation

In summary, as the dynamics of power grid management gradually change in an energy market influenced by deregulation laws, traditional assumptions on contingencies such as $N - 1$ threatening power systems may not be accurate enough for reliability analysis. Moreover, the lack of dependable component reliability estimates, in contrast to bridge networks where advanced bridge fragility models have emerged, suggests that vulnerability analysis may provide adequate understanding of the systemic performance over reliability analysis for power transmission networks. As explained in the previous sections, vulnerability analysis does not require the nature of hazards be known; instead, it identifies system weaknesses against systematic component failures, and therefore, can complement the reliability analysis which studies the performance of the system against hazards.

The performance curves resulting from the vulnerability analysis on the twenty five case study networks can be represented by bilinear forms, which can be exploited to enhance the computational efficiency of vulnerability analyses for power transmission networks. The bilinear functions, which can be considered surrogate models for vulnerability analysis, closely match the performance of power transmission systems except close to the critical node removal value, which is close to 0.4.

Despite the limitations of reliability analysis for power transmission networks (mainly resulting from the lack of knowledge on all potential hazards), reliability evaluations are required for probabilistic risk assessments. The same methods for network reliability and risk assessment as well as the interdependency models are applicable to power transmission systems. Vulnerability analysis, meanwhile, contributes to the design of more resilient power transmission systems by realizing the systemic performance against contingencies which may not be included in reliability analysis.

6.4. Summary

This chapter illustrated network reliability assessments in three infrastructure systems with different performance metrics, reliability objectives, and hazard scenarios. For highway bridge networks, the BRAN methodology incorporates different sources of correlations among bridge failures, and evaluates the reliability of large and complex networks by a modified MCMC reliability approach. Sources of correlations such as the structural conditions of bridges, type of the roads they carry, traffic, and topological implications of the bridge network impose extra correlations among the failure probabilities that are often impractical to include in the analytical bridge modeling, particularly on a structure-by-structure basis. BRAN proposes the use of auxiliary data sources to quantify the extra correlations, and uses a practical approach based on the general Dichotomized Gaussian Method (DGM) to simulate correlated bridge failures.

Furthermore, BRAN makes use of data available from field instrumentation of bridges, and provides enhanced bridge fragility models to account for aging and deterioration. Application of BRAN to seismic reliability assessment of the case study bridge network in South Carolina reveals that neglecting the extra correlations among bridge failures may lead to over or underestimation of network reliability estimates, depending on the sign of correlations and network topology.

The BRAN methodology is also used to assess the probabilistic seismic risk of the South Carolina bridge network, by providing the annual probability of exceeding network reliability levels. For risk assessment, a data set of network reliability evaluations by BRAN is used to form a surrogate model by statistical learning methods, which then replaces network reliability algorithms such as MCMC for reliability assessments. The application to the South Carolina bridge network shows surrogate models formed by random forests are well suited for reliability and risk assessment in networks. Two approaches are used to generate the input data for model selection: 1) independent uniform sampling of bridge failure probabilities, and 2) simulating bridge failure probabilities according to network consistent seismic scenarios. Both approaches are shown to provide surrogate models which estimate the outcome of the case study seismic scenario with high accuracy. Nevertheless, the second approach provides further improvements as it builds upon hazard scenario reduction methods such as importance sampling.

The case study of South Carolina bridge network also applies the importance measures developed in Chapter 5 to assess the criticality of bridges for seismic retrofitting. Both developed methods, the Bridge Rank (*BR*) and Random Forest Importance Measure (*RFIM*) account for the role of bridges within the network in addition to bridge vulnerabilities. *BR* is shown to be a fast, all-to-all implementation providing a balance between those two criteria for a given hazard scenario. *RFIM*, on the other hand, provides a probabilistic ranking which is not dependent on a single hazard scenario, but customized towards network reliability objectives. Nonetheless, both methods offer bridge rankings that are significantly different from the practical approaches in the seismic retrofit manual of highway bridges or other approaches not considering both ranking criteria (bridge vulnerabilities and their role in the network). Moreover, since the developed methods rely on dependable estimates of bridge vulnerabilities, they benefit from the BRAN methodology, in which enhanced fragility models account for bridge deterioration mechanisms to provide present day bridge failure probabilities.

While the same methodologies are transferrable across different infrastructure systems, the case studies on water distribution networks and the power transmission grid emphasize different aspects of reliability and risk analysis. For the case study water distribution network under the hurricane hazard, the adopted network reliability objective is to provide a minimum water pressure at the consumption nodes, presenting a reliability objective different from connectivity reliability. As the result, hydraulic simulations by EPANET replace the connectivity reliability analysis used for the highway bridge networks. The components of the water distribution network are assumed to be invulnerable to direct hit from the hurricane; although small vulnerability levels are assumed for sensitivity analyses. Nevertheless, the interdependency with the power grid causes failures in power load nodes to propagate to pump stations in the water system. A two stage reliability analysis is adopted for the performed reliability evaluations, which decouples the failure propagation in the power and water systems. The results show that interdependency-induced failures account for most of the water pressure shortage in the reliability analysis against simulated hurricanes of Category 1 to 5. The methodology presented to study the interdependence between power and water networks is transferable to other infrastructure systems as well, especially since most infrastructure systems show interdependent response against natural hazards.

The reliability of power transmission networks may be analyzed using similar reliability methods as BRAN; however, because the hazard scenarios influencing the performance of the power grid are very diverse, and all significant scenarios may not be accounted for in a reliability study. Therefore, the performance of twenty five case study power distribution networks is evaluated using vulnerability analysis, which investigates the performance of the system against a wide range of failure contingencies without associating them with specific hazard scenarios. Vulnerability analysis provides insights to identify systemic weaknesses of the systems under study, and can complement the reliability analysis. The performance metric for vulnerability analysis is selected to be the Connectivity Loss, which is widely used in the study of electric power systems and is different from the metrics used in this thesis for water and bridge networks. The vulnerability study is performed on the ideal topological formations (networks set up based on the case study networks with extreme topological characteristics) in addition to the twenty five case study networks. Ideal formations Minimum Spanning Tree (MST) and Pseudo-Greedy Triangulation (PGT) are shown to provide bounds on the performance of their corresponding case study networks in the vulnerability analysis. Moreover, the functional form of the resulting vulnerability curves allows for a surrogate bilinear function to be fitted to those curves. The use of bilinear models can significantly reduce the computational complexity of vulnerability analysis, especially for large power transmission networks, and provide approximations with minimal error except for node removal ratios close to the critical value, which is around 0.4 for the case study networks.

The vulnerability study is not a direct replacement for the reliability evaluations, especially since the latter are needed for risk assessments. However, urban infrastructure systems can benefit from joint reliability and vulnerability analysis to study their systemic behavior which can result in the emergence of more resilient systems.

The next chapter provides a summary of the contributions that the developed methods in this thesis have made to the reliability and risk evaluations of critical urban infrastructure systems. Additionally, it identifies areas for improvement and lists opportunities for future research, which concludes this thesis.

Chapter 7

Conclusions and Future Research

With the urban population around the globe on a sharp and steady rise, maintaining and expanding urban infrastructure systems has become critically important at both the local and the national levels, where lifeline systems are the subject of a wide range of studies from engineering to public safety and homeland security. Reliability and risk evaluations of infrastructure systems under natural hazards are part of this awareness movement that supports the development of informed operation, management and renewal plans by system stakeholders; however the size and complexity of infrastructure systems are often limiting for realistic modeling and analysis. Hence, this thesis develops new frameworks which enable practical modeling of networked infrastructure systems by providing more efficient computational methods for reliability and risk assessment using a variety of contemporary metrics and objectives. A literature review of the existing studies on reliability and risk assessment of infrastructure systems has revealed three areas for improvement, which became the three major research questions of this thesis, including:

1. The need for an enhanced network reliability assessment framework which is applicable to large, complex infrastructure systems and can account for multiple sources of correlations among component failures as well as their deteriorating condition over time,

2. The need for highly efficient risk assessment frameworks which enable incorporating a large number of hazard scenarios without requiring an otherwise intractable number of simulations for large systems,

3. The need for improved component prioritization methods that account for the components' role inside the network in addition to the component vulnerabilities.

The contributions of the developed methods in this thesis with regard to the above research questions are summarized in Section 7.1, while Section 7.2 identifies areas for further improvement, and elaborates on opportunities for future research.

7.1. Summary and Concluding Remarks

The Bridge Reliability Assessment in Networks (BRAN) methodology for bridge reliability assessments in networks quantifies and incorporates the effects of extra correlations for the first time. While bridge failure correlations induced by seismic intensity at bridge locations have been the subject of extensive reliability and risk studies, the extra correlation have not received the same amount of attention despite being a known need (Lee and Kiremidjian 2007). BRAN uses auxiliary data sources in bridge condition ratings, functional road classes, and network topological similarities in order to quantify these extra correlations. In addition, it provides a methodology to simulate samples from multi-dimensional Bernoulli random variables with a correlation matrix by the tractable Dichotomized Gaussian Method (DGM). DGM simulates correlated bridge failures to be used in a Markov Chain Monte Carlo simulations reliability method (MCMC), which is modified for incorporating correlated component failures. The seismic reliability assessment of the bridge network in South Carolina, US (509 bridges) against a defined seismic scenario shows the potential impact of extra correlations on reliability estimates. A sensitivity analysis with varying correlation levels also confirms that ignoring the extra correlations can lead to over or underestimation of network probability of failure. The estimates of the network failure probability are varying by 20% when different correlation levels are considered.

BRAN has focused on highway bridge networks, as one of the most critical infrastructure systems in urban societies along with power and telecommunication. The BRAN framework takes advantage of the availability of advances bridge fragility models which account for deteriorating bridge conditions. However, the same methodology can apply to evaluate the reliability of other infrastructure systems, such as water distribution systems and the power transmission grid, once component failure probabilities are identified using a physics-based model similar to bridge fragility models.

The BRAN methodology is also applied to probabilistic risk assessment, where network connectivity reliability is adopted as the network performance metric. Although BRAN is efficient for single scenario reliability evaluation, the number of required hazard scenarios which need to be analyzed in a probabilistic risk study (i.e. 1,000 in the presented case study) can be prohibitive. Accordingly, this thesis develops surrogate models which are trained based on a limited number of hazard scenario evaluations by

BRAN. The development of the surrogate models applies emerging methods from statistical learning such as random forests, which efficiently establish a predictive network reliability model with minimal errors. The use of surrogate models in network reliability and risk assessment studies has not been explored before, and is introduced in this thesis for the first time. Random forests are found to be well suited for network reliability applications due to their ability to de-emphasize the contributions of insignificant bridges in the network. The abundance of irrelevant features introduced in the statistical learning model by such bridges can deteriorate the performance of other methods, for example the Support Vector Machines.

In addition to developing frameworks to assess the reliability and risk in networked systems, this research has developed novel methods to prioritize the criticality of network components for retrofit actions. The application has been shown for highway bridge networks and seismic hazard, but the methods are transferrable to other systems (water, power, telecommunication, etc.) under different types of hazards as well. Two new importance measures are developed in this thesis. They enhance upon the current practical or state-of-the-art methods on the bridge seismic retrofit prioritization in terms of scope, computational complexity, and applicability. Bridge Rank (*BR*) builds upon the PageRank algorithm, and provides a method to balance the contributions from network topology and bridge vulnerabilities due to a hazard scenario to its rankings. The advantage of *BR* to other importance measures is in its fast implementation, and the flexibility to give more importance to the contribution of either aspects (bridge vulnerability or role in network). The Random Forests Importance Measure (*RFIM*), on the other hand, does not depend on a particular hazard scenario, which makes it especially desirable for probabilistic risk assessment studies, where the network stakeholders want to evaluate the overall significance of bridges within a highway transportation system with no regard to a certain hazard scenario.

Contributions to study the performance of water distribution and power transmission networks build upon the methods presented for highway bridge networks, but focus on different and also important aspects of interdependency and vulnerability analysis. The two-stage interdependency method to evaluate the reliability of water distribution networks under hurricane hazard is introduced for the first time, which enables hydraulic system reliability evaluations of large water networks. Although the literature offers an established record of interdependence studies between the power and water networks, such interdependencies have not been the subject of reliability studies with hydraulic analysis in the past. The computational intensity of Monte Carlo simulations with the adopted flow based metric requires efficient treatment of the interdependence links between power and water systems, which is incorporated in the presented two-stage framework. The developed methodology may help the system stakeholders with planning, particularly against hurricanes in the coastal communities, and be better prepared in devising restoration plans by identifying the troubled areas in the network. For power transmission networks, a vulnerability study, which explores failure contingencies $N - k$, is proposed to complement reliability studies, since the major threatening hazards and component fragilities are not as easily identifiable for such systems as for other networks. However, comprehensive vulnerability analyses are computationally intensive, and require cloud computing to implement. Therefore, this thesis proposes topological bounds on systemic performances in vulnerability analysis for rapid assessments. Moreover, a new ideal topological formation, Pseudo-Greedy Triangulation (PGT) is proposed for planar infrastructure networks. Together with the Minimum Spanning Tree (MST), the ideal formations provide bounds on the performance of power transmission networks in vulnerability studies. The evaluated performance curves are also found to follow a bilinear form, which can replace the curves with minimal error except around the node removal ratio of 0.4. Using the bilinear functions as surrogates to the performance curves enables expedited vulnerability evaluations with reduced simulations.

7.2. Future Research Opportunities

The presented BRAN methodology is generally applicable to reliability and risk evaluation of infrastructure networks with a range of reliability objectives. In bridge network studies, specifically, travel time and network traffic capacity have been extensively used in the literature as performance metrics for reliability and risk evaluations. To incorporate those performance metrics in the seismic reliability studies of transportation systems, specific models are available to relate the structural damage to the bridge structures to the traffic flow capacity reductions, e.g. in HAZUS (FEMA 2008) among others. Moreover, a range of traffic assignment models with varying complexity are available to predict the traffic demand in the aftermath of natural disasters. Integrating either of those approaches enhances the presented BRAN methodology. Furthermore, network surrogate models can be formed for the new reliability objectives as well in order to perform risk assessments that require a multiplicity of scenarios for convolving hazard with fragility.

While the application of BRAN is shown to seismic reliability and risk assessment of bridge networks, the hurricane hazard can readily be incorporated within the same procedure. Similar to bridge seismic fragility models, fragility models for hurricane hazard are also emerging in the literature. Those models evaluate the bridge failure probabilities in a hurricane scenario, after which BRAN can be applied to perform reliability and risk assessments. The same network surrogate models are still applicable to any other hazard as well, since they only depend on learning the functional form of the limit state function, not the input bridge failure probabilities.

With regard to the importance measures, a framework may be devised for Bridge Rank to provide a probabilistic ranking similar to the one offered by random forests importance measure. Since the hazard event contribution only appears in the matrix of bridge vulnerabilities in the formulation of the Bridge Rank, providing a probabilistic ranking simply requires a modified definition for the bridge vulnerability matrix. A probabilistic Bridge Rank can be employed where specific origin and destination nodes are not considered for bridge prioritization, and can complement the (O, D) dependent rankings by random forests.

In addition to the proposed expansion opportunities, there are prospective areas to further improve this research. The extra correlations have been estimated using auxiliary data sources in this thesis. However, those estimates may be improved in future when the data from detailed post-hazard reconnaissance reports is mined to associate extra correlations with specific structural details, material, deterioration, and live load. The framework to account for extra correlations in BRAN can accommodate such enhanced correlation estimates for an added accuracy in network reliability and risk assessments.

Finally, reliability and risk evaluations can be part of a resilience study, where they are considered along with system recovery and restoration process after a natural disaster. Resilience studies are receiving increasing attention in recent years, as they discuss the intervention actions in addition to probabilistic prediction of hazard outcomes. Accordingly, intervention scenarios may be devised using component prioritization schemes in order to evaluate their influence on system restoration to pre-hazard conditions.

The computational frameworks developed in this research, such as BRAN, surrogate models by statistical learning methods, and importance measures, provide unprecedented opportunities to explore various what-if questions. Consequently, system stakeholders can make more informed decisions on reliable maintenance and expansion of infrastructure networks against natural hazards.

References

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

Adeli, H. (2002). "Neural networks in civil engineering: 1989–2000." *Computer-Aided Civil and Infrastructure Engineering*, 16(2), 126–142.

"Advanced Sensing Technologies and Advanced Repair Materials for the Infrastructure: Water Systems, Dams, Levees, Bridges, Roads, and Highways." (2009). National Institute of Standards and Technology.

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

Albert, R., and Barabasi, A. L. (2002). "Statistical mechanics of complex networks. Review of Modern Physics." *vol*, 74, 47–97.

Allan, R., and Billinton, R. (2000). "Probabilistic assessment of power systems." *Proceedings of the IEEE*, 88(2), 140–162.

Amin, M. (2003). "North America's electricity infrastructure: are we ready for more perfect storms?" *Security Privacy, IEEE*, 1(5), 19 – 25.

Andersson, G., Donalek, P., Farmer, R., Hatziargyriou, N., Kamwa, I., Kundur, P., Martins, N., Paserba, J., Pourbeik, P., Sanchez-Gasca, J., and others. (2005). "Causes of the 2003 major grid blackouts in North America and Europe, and recommended means to improve system dynamic performance." *Power Systems, IEEE Transactions on*, 20(4), 1922–1928.

Archer, K. J., and Kimes, R. V. (2008). "Empirical characterization of random forest variable importance measures." *Computational Statistics & Data Analysis*, 52(4), 2249–2260.

ASCE. (2009). *ASCE: Infrastructure Fact Sheet. Available at: http://www.infrastructurereportcard.org/sites/default/files/RC2009_bridges.pdf*.

ASCE. (2013). "2013 ReportCard on America's Infrastructure."

Ataei, N., and Padgett, J. (2013). "Probabilistic Modeling of Bridge Deck Unseating during Hurricane Events." *Journal of Bridge Engineering*, 18(4), 275–286.

Atkinson, G. M., and Boore, D. M. (1995). "Ground-motion relations for eastern North America." *Bulletin of the Seismological Society of America*, 85(1), 17–30.

Au, S.-K., and Beck, J. L. (2001). "Estimation of small failure probabilities in high dimensions by subset simulation." *Probabilistic Engineering Mechanics*, 16(4), 263–277.

Aven, T. (2008). "A semi-quantitative approach to risk analysis, as an alternative to QRAs." *Reliability Engineering & System Safety*, 93(6), 790–797.

Bao, Y. (1990). "Model for water distribution system reliability." *Journal of Hydraulic Engineering*, 116, 1119.

Billinton, R., and Allan, R. N. (1992). *Reliability evaluation of engineering systems: concepts and techniques*. Springer.

Boccaletti, S., Latora, V., Moreno, Y., Chavez, M., and Hwang, D.-U. (2006). "Complex networks: Structure and dynamics." *Physics Reports*, 424(4–5), 175–308.

Bocchini, P., and Frangopol, D. M. (2011a). “A stochastic computational framework for the joint transportation network fragility analysis and traffic flow distribution under extreme events.” *Probabilistic Engineering Mechanics*, 26(2), 182–193.

Bocchini, P., and Frangopol, D. M. (2011b). “Generalized bridge network performance analysis with correlation and time-variant reliability.” *Structural Safety*, 33(2), 155–164.

Bommer, J., and Crowley, Helen. (2006). “The Influence of Ground-Motion Variability in Earthquake Loss Modelling.” *Bulletin of Earthquake Engineering*, 4(3), 231–248.

Breiman, L. (2001). “Random forests.” *Machine learning*, 45(1), 5–32.

Brin, S., and Page, L. (1998). “The anatomy of a large-scale hypertextual Web search engine.” *Computer Networks and ISDN Systems*, 30(1–7), 107–117.

Bucher, C. G., and Bourgund, U. (1990). “A fast and efficient response surface approach for structural reliability problems.” *Structural safety*, 7(1), 57–66.

Buckle, I., Friedland, I., Mander, J., Martin, G., Nutt, R., and Power, M. (2006). *Seismic retrofitting manual for highway structures: Part 1-bridges*.

Buhl, J., Gautrais, J., Reeves, N., Solé, R. V., Valverde, S., Kuntz, P., and Theraulaz, G. (2006). “Topological patterns in street networks of self-organized urban settlements.” *The European Physical Journal B-Condensed Matter and Complex Systems*, 49(4), 513–522.

Campbell, K. W. (2003). “Prediction of strong ground motion using the hybrid empirical method and its use in the development of ground-motion (attenuation) relations in eastern North America.” *Bulletin of the Seismological Society of America*, 93(3), 1012–1033.

Cardillo, A., Scellato, S., Latora, V., and Porta, S. (2006). “Structural properties of planar graphs of urban street patterns.” *Physical Review E*, 73(6), 066107.

Cardoso, J. B., de Almeida, J. R., Dias, J. M., and Coelho, P. G. (2008). “Structural reliability analysis using Monte Carlo simulation and neural networks.” *Advances in Engineering Software*, 39(6), 505–513.

Chang, L., Peng, F., Ouyang, Y., Elnashai, A., and Spencer, B. (2012). “Bridge Seismic Retrofit Program Planning to Maximize Postearthquake Transportation Network Capacity.” *Journal of Infrastructure Systems*, 18(2), 75–88.

Chang, S. E., Shinozuka, M., and Moore, J. E. (2000). “Probabilistic earthquake scenarios: Extending risk analysis methodologies to spatially distributed systems.” *Earthquake Spectra*, 16(3), 557–572.

Chen, A., Yang, H., Lo, H. K., and Tang, W. H. (2002). “Capacity reliability of a road network: an assessment methodology and numerical results.” *Transportation Research Part B: Methodological*, 36(3), 225–252.

Ching, J., and Hsu, W. C. (2007). “An Efficient Method for Evaluating Origin-Destination Connectivity Reliability of Real-World Lifeline Networks.” *Computer-Aided Civil and Infrastructure Engineering*, 22(8), 584–596.

Comfort, L. K. (2006). “Cities at Risk Hurricane Katrina and the Drowning of New Orleans.” *Urban Affairs Review*, 41(4), 501–516.

Cornell, C. A. (1967). “Bounds on the reliability of structural systems.” *Journal of Structural Division, ASCE*, 93(1), 171–200.

Crowley, H., and Bommer, J. J. (2006). "Modelling seismic hazard in earthquake loss models with spatially distributed exposure." *Bulletin of Earthquake Engineering*, 4(3), 249–273.

Crucitti, P., Latora, Vito, Marchiori, M., and Rapisarda, A. (2004). "Error and attack tolerance of complex networks." *Physica A: Statistical Mechanics and its Applications*, 340(1–3), 388–394.

Dai, H., Zhang, H., Wang, W., and Xue, G. (2012). "Structural Reliability Assessment by Local Approximation of Limit State Functions Using Adaptive Markov Chain Simulation and Support Vector Regression." *Computer-Aided Civil and Infrastructure Engineering*, 27(9), 676–686.

DHS, H.-M. (2009). "MR4 earthquake model user manual." *Whashington (DC): Department of Homeland Security, Federal Emergency Management Agency, Mitigation Division*.

Dijkstra, E. W. (1959). "A note on two problems in connexion with graphs." *Numerische mathematik*, 1(1), 269–271.

Ditlevsen, O. (1979). "Narrow reliability bounds for structural systems." *Journal of structural mechanics*, 7(4), 453–472.

Ditlevsen, O., and Madsen, H. O. (1996). *Structural reliability methods*. Wiley New York.

Dobson, I., Carreras, B. A., Lynch, V. E., and Newman, D. E. (2007). "Complex systems analysis of series of blackouts: Cascading failure, critical points, and self-organization." *Chaos: An Interdisciplinary Journal of Nonlinear Science*, 17(2), 026103–026103–13.

Dubourg, V., Sudret, B., and Bourinet, J. M. (2011). "Reliability-based design optimization using kriging surrogates and subset simulation." *Structural and Multidisciplinary Optimization*, 44(5), 673–690.

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

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

Dueñas-Osorio, L., and Rojo, J. (2011). "Reliability assessment of lifeline systems with radial topology." *Computer-Aided Civil and Infrastructure Engineering*, 26(2), 111–128.

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

Echard, B., Gayton, N., and Lemaire, M. (2011). "AK-MCS: An active learning reliability method combining Kriging and Monte Carlo Simulation." *Structural Safety*, 33(2), 145–154.

Emrich, L. J., and Piedmonte, M. R. (1991). "A Method for Generating High-Dimensional Multivariate Binary Variates." *The American Statistician*, 45(4), 302–304.

Enke, D. L., Tirasirichai, C., and Luna, R. (2008). "Estimation of earthquake loss due to bridge damage in the St. Louis metropolitan area. II: Indirect losses." *Natural Hazards Review*, 9(1), 12–19.

EU Commission. (2006). *Green Paper: A European Strategy for Sustainable, Competitive and Secure Energy*. Brussels: The European Commission.

Faravelli, L. (1989). "Response-Surface Approach for Reliability Analysis." *Journal of Engineering Mechanics*, 115, 2763.

Federal Emergency Management Agency (FEMA). (2008). "Hazards U.S. Multi-Hazard (HAZUS-MH) Assessment Tool v1.3."

Federal Highway Administration. (2013). "National Bridge Inventory."

Frangopol, D. M., and Bocchini, P. (2012). "Bridge network performance, maintenance and optimisation under uncertainty: accomplishments and challenges." *Structure and Infrastructure Engineering*, 8(4), 341–356.

Frankel, A. D., Petersen, M. D., Mueller, C. S., Haller, K. M., Wheeler, R. L., Leyendecker, E. V., Wesson, Robert L., Harmsen, S. C., Cramer, C. H., and Perkins, David M. (2002). *Documentation for the 2002 update of the national seismic hazard maps*. US Department of the Interior, US Geological Survey.

Freeman, L. C. (1977). "A set of measures of centrality based on betweenness." *Sociometry*, 35–41.

Fujiwara, O., and Li, Jun. (1998). "Reliability analysis of water distribution networks in consideration of equity, redistribution, and pressure-dependent demand." *Water resources research*, 34(7), 1843–1850.

Fussell, J. B. (1975). "How to hand-calculate system reliability and safety characteristics." *Reliability, IEEE Transactions on*, 24(3), 169–174.

Ghosh, J., Rokneddin, K., Padgett, Jamie, and Dueñas-Osorio, Leonardo. (2013). "Seismic Reliability Assessment of Aging Highway Bridge Networks with Field Instrumentation Data and Correlated Failures; Part I: Methodology." *Earthquake Spectra*, (In press).

Grubesic, T. H., Matisziw, T. C., Murray, A. T., and Snediker, D. (2008). "Comparative Approaches for Assessing Network Vulnerability." *International Regional Science Review*, 31(1), 88–112.

Guan, and Melchers, R. E. (2001). "Effect of response surface parameter variation on structural reliability estimates." *Structural Safety*, 23(4), 429–444.

Hall, J. W., Henriques, J. J., Hickford, A. J., and Nicholls, R. J. (2012). *A Fast Track Analysis of strategies for infrastructure provision in Great Britain*. Environmental Change Institute, University of Oxford.

Halton, J. H. (1960). "On the efficiency of certain quasi-random sequences of points in evaluating multi-dimensional integrals." *Numerische Mathematik*, 2(1), 84–90.

Hasofer, A. M., and Lind, N. C. (1974). "Exact and invariant second-moment code format." *Journal of the Engineering Mechanics Division*, 100(1), 111–121.

Hastie, T., Tibshirani, R., and Friedman, J. (2009). *The Elements of Statistical Learning: Data Mining, Inference, and Prediction, Second Edition*. Springer.

Hernandez-Fajardo, I., and Dueñas-Osorio, L. (2011). "Sequential Propagation of Seismic Fragility across Interdependent Lifeline Systems." *Earthquake Spectra*, 27, 23.

Hernandez-Fajardo, I., and Dueñas-Osorio, L. (2011). "Probabilistic Study of Cascading Failures in Complex Interdependent Lifeline Systems." *ASCE Conference Proceedings*, 400(41170), 25–25.

Hines, P., Cotilla-Sanchez, E., and Blumsack, S. (2010). "Do topological models provide good information about vulnerability in electric power networks?" *Arxiv preprint arXiv:1002.2268*.

Hlavácek, I., Chleboun, J., and Babuska, I. (2004). *Uncertain input data problems and the worst scenario method*. Elsevier.

Hohenbichler, M., and Rackwitz, R. (1983). "First-order concepts in system reliability." *Structural Safety*, 1(3), 177–188.

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

Homenda, W., and Lesinski, W. (2011). "Features selection in character recognition with random forest classifier." *3rd International Conference on Computational Collective Intelligence, ICCCI 2011, September 21, 2011 - September 23, 2011*, Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), Springer Verlag, 93–102.

Hosni Elhewy, A., Mesbahi, E., and Pu, Y. (2006). "Reliability analysis of structures using neural network method." *Probabilistic Engineering Mechanics*, 21(1), 44–53.

Hurtado, J. E. (2004). "An examination of methods for approximating implicit limit state functions from the viewpoint of statistical learning theory." *Structural Safety*, 26(3), 271–293.

Hurtado, J. E. (2011). "Dimensionality reduction and visualization of structural reliability problems using polar features." *Probabilistic Engineering Mechanics*.

Jayaram, N., and Baker, J. W. (2009). "Correlation model for spatially distributed ground-motion intensities." *Earthquake Engineering & Structural Dynamics*, 38(15), 1687–1708.

Jayaram, N., and Baker, J. W. (2010). "Efficient sampling and data reduction techniques for probabilistic seismic lifeline risk assessment." *Earthquake Engineering & Structural Dynamics*, 39(10), 1109–1131.

Kang, W. H., Song, J., and Gardoni, P. (2008). "Matrix-based system reliability method and applications to bridge networks." *Reliability Engineering & System Safety*, 93(11), 1584–1593.

Kim, S. H., and Na, S. W. (1997). "Response surface method using vector projected sampling points." *Structural Safety*, 19(1), 3–19.

Kim, Y., and Kang, W.-H. (2013). "Network reliability analysis of complex systems using a non-simulation-based method." *Reliability Engineering & System Safety*, 110, 80–88.

Kinney, R., Crucitti, P., Albert, Reka, and Latora, Vito. (2005). "Modeling cascading failures in the North American power grid." *The European Physical Journal B-Condensed Matter and Complex Systems*, 46(1), 101–107.

Kiremidjian, A., Stergiou, E., and Lee, R. (2007). "Issues in seismic risk assessment of transportation networks." *Earthquake geotechnical engineering*, 461–480.

Der Kiureghian, A., and Song, J. (2008). "Multi-scale reliability analysis and updating of complex systems by use of linear programming." *Reliability Engineering & System Safety*, 93(2), 288–297.

Korobov, N. (1957). “The approximate calculation of multiple integrals using number theoretic methods Dokl.” *Acad. Nauk SSSR*, 115, 1062–1065.

Kropp, T. (2006). “System threats and vulnerabilities [power system protection].” *Power and Energy Magazine, IEEE*, 4(2), 46 – 50.

Latifi, H., and Koch, B. (2012). “Evaluation of most similar neighbour and random forest methods for imputing forest inventory variables using data from target and auxiliary stands.” *International Journal of Remote Sensing*, 33(21), 6668–6694.

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

Lee, R., and Kiremidjian, A. S. (2007). “Uncertainty and correlation for loss assessment of spatially distributed systems.” *Earthquake Spectra*, 23, 753.

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

Leisch, F., Weingessel, A., and Hornik, K. (1998). “On the generation of correlated artificial binary data.” Working Paper, <http://epub.wu.ac.at/286/> (Jul. 29, 2011).

Lemieux, C. (2009). *Monte Carlo and Quasi-Monte Carlo Sampling*. Springer Verlag.

Li, J., and He, J. (2002). “A recursive decomposition algorithm for network seismic reliability evaluation.” *Earthquake engineering & structural dynamics*, 31(8), 1525–1539.

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

Lim, H. W., and Song, J. (2012). “Efficient risk assessment of lifeline networks under spatially correlated ground motions using selective recursive decomposition algorithm.” *Earthquake Engineering & Structural Dynamics*.

Liu, M., Frangopol, D. M., and others. (2006). “Probability-based bridge network performance evaluation.” *Journal of Bridge Engineering*, 11, 633.

Liu, W., and Li, J. (2009). “An improved recursive decomposition algorithm for reliability evaluation of lifeline networks.” *Earthquake Engineering and Engineering Vibration*, 8(3), 409–419.

Liu, Wei, and Li, Jie. (2012). “An improved cut-based recursive decomposition algorithm for reliability analysis of networks.” *Earthquake Engineering and Engineering Vibration*, 11(1), 1–10.

Luna, R., Hoffman, D., and Lawrence, W. T. (2008). “Estimation of earthquake loss due to bridge damage in the St. Louis metropolitan area. I: Direct losses.” *Natural Hazards Review*, 9(1), 1–11.

Lunn, A. D., and Davies, S. J. (1998). “A note on generating correlated binary variables.” *Biometrika*, 85(2), 487–490.

Mao, W., and Kelly, S. (2007). “An optimum random forest model for prediction of genetic susceptibility to complex diseases.” *Advances in Knowledge Discovery and Data Mining. 11th Pacific-Asia Conference, PAKDD 2007. Proceedings, 22-25 May 2007*, Advances in Knowledge Discovery and Data Mining. 11th Pacific-

Asia Conference, PAKDD 2007. Proceedings (Lecture Notes in Artificial Intelligence Vol. 4426), Springer, 193–204.

Melchers, Robert E. (1999). *Structural Reliability Analysis and Prediction*. Wiley.

Miller, L. M., Antonio, R. J., and Bonanno, A. (2011). "Hazards of neoliberalism: delayed electric power restoration after Hurricane Ike1." *The British journal of sociology*, 62(3), 504–522.

National Hurricane Center. (n.d.). "Saffir-Simpson Hurricane Wind Scale." <http://www.nhc.noaa.gov/aboutsshws.php> (Mar. 27, 2013).

Nelsen, R. B. (1999). *An introduction to copulas*. Springer Verlag.

Newman. (2003). "The structure and function of complex networks." *SIAM review*, 167–256.

Newman. (2010). *Networks: an introduction*. Oxford University Press, Inc.

Niederreiter, H. (1992). "Random number generation and quasi-Monte Carlo methods. 1992." *SIAM, Philadelphia*.

Nielson, B. G., and DesRoches, R. (2007). "Analytical seismic fragility curves for typical bridges in the central and southeastern United States." *Earthquake Spectra*, 23, 615.

Ouyang, M., and Dueñas-Osorio, L. (2011). "Efficient Approach to Compute Generalized Interdependent Effects between Infrastructure Systems." *Journal of Computing in Civil Engineering*, 25, 394.

Padgett, J. E., DesRoches, Reginald, and Nilsson, E. (2010). "Regional seismic risk assessment of bridge network in Charleston, South Carolina." *Journal of Earthquake Engineering*, 14(6), 918–933.

Padgett, J. E., Spiller, A., and Arnold, C. (2012). "Statistical analysis of coastal bridge vulnerability based on empirical evidence from Hurricane Katrina." *Structure and Infrastructure Engineering*, 8(6), 595–605.

Pagani, G. A., and Aiello, M. (2011). "The Power Grid as a Complex Network: a Survey." *arXiv:1105.3338*.

Papadrakakis, M., and Lagaros, N. D. (2002). "Reliability-based structural optimization using neural networks and Monte Carlo simulation." *Computer Methods in Applied Mechanics and Engineering*, 191(32), 3491–3507.

Park, C. G., Park, T., and Shin, D. W. (1996). "A Simple Method for Generating Correlated Binary Variates." *The American Statistician*, 50(4), 306–310.

Pipattanasomporn, M., Willingham, M., and Rahman, S. (2005). "Implications of on-site distributed generation for commercial/industrial facilities." *IEEE Transactions on Power Systems*, 20(1), 206–212.

Poljanšek, K., Bono, F., and Gutiérrez, E. (2012). "Seismic risk assessment of interdependent critical infrastructure systems: The case of European gas and electricity networks." *Earthquake Engineering & Structural Dynamics*.

R Core Team. (2012). "R: A Language and Environment for Statistical Computing."

Raad, D. N., Sinske, A. N., and Van Vuuren, J. H. (2010). "Comparison of four reliability surrogate measures for water distribution systems design." *Water Resources Research*, 46(5).

Rajashekhar, M. R., and Ellingwood, B. R. (1993). "A new look at the response surface approach for reliability analysis." *Structural Safety*, 12(3), 205–220.

Ramirez-Marquez, J. E., and Coit, D. W. (2005). "Composite importance measures for multi-state systems with multi-state components." *Reliability, IEEE Transactions on*, 54(3), 517–529.

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

Rojo, Javier, and Duenas-Osorio, L. (2011). "Probability Models for the Reliability Metrics of Practical Power Distribution Networks." *Safety, Reliability, and Risk of Structures, Infrastructurs, and Engineering Systems*, Teylor and Francis group, Zurich, Switzerland.

Rokneddin, K., Ghosh, J., Dueñas-Osorio, L., and Padgett, Jamie. (2013). "Seismic Reliability Assessment of Aging Highway Bridge Networks with Field Instrumentation Data and Correlated Failures; Part II: Applications." *Earthquake Spectra*, (In press).

Rokneddin, K., Ghosh, J., Dueñas-Osorio, Leonardo, and Padgett, Jamie. (2012). "Bridge retrofit prioritization for aging transportation networks subject to seismic hazards." *Structure and Infrastructure Engineering*.

Rosas-Casals, Marti, Valverde, Sergi, and Solé, Ricard V. (2007). "Topological vulnerability of the European power grid under errors and attacks." *International Journal of Bifurcation and Chaos*, 17(07), 2465–2475.

Shinozuka, M. (1983). "Basic analysis of structural safety." *Journal of Structural Engineering*, 109(3), 721–740.

Solé, Ricard V., Rosas-Casals, Martí, Corominas-Murtra, B., and Valverde, Sergi. (2008). "Robustness of the European power grids under intentional attack." *Physical Review E*, 77(2), 026102.

Song, J., and Kang, W. H. (2009). "System reliability and sensitivity under statistical dependence by matrix-based system reliability method." *Structural Safety*, 31(2), 148–156.

Song, J., and Der Kiureghian, A. (2003). "Bounds on system reliability by linear programming." *Journal of Engineering Mechanics*, 129, 627.

Song, J., and Der Kiureghian, A. (2005). "Component importance measures by linear programming bounds on system reliability." *Proceedings of the ninth international conference on structural safety and reliability (ICOSSAR9)*, 20–23.

Stergiou, E. C., and Kiremidjian, A. S. (2010). "Risk assessment of transportation systems with network functionality losses." *Structure and Infrastructure Engineering*, 6(1-2), 111–125.

Strobl, C., Boulesteix, A.-L., Zeileis, A., and Hothorn, T. (2007). "Bias in random forest variable importance measures: Illustrations, sources and a solution." *BMC Bioinformatics*, 8(1), 25.

Takewaki, I. (2007). *Critical excitation methods in earthquake engineering*. Elsevier Science Limited.

TELEATLAS. (2010). "Digital Mapping and Navigation Solutions." <http://www.tomtom.com/en_gb/licensing/?IdcService=SS_GET_PAGE&siteId=TeleAtlasCW1&siteRelativeUrl=%252Findex.htm&ssUrlPrefix=/> (Mar. 26, 2013).

Texas Administrative Code (TAC). (n.d.). “Title 30, Part 1, Chapter 290, Subchapter D, “Rules and Regulations for Public Water Systems.” <http://www.sos.state.tx.us/tac/index.shtml> (Mar. 27, 2013).

Thornton, A., and Monroy, C. R. (2011). “Distributed power generation in the United States.” *Renewable and Sustainable Energy Reviews*, 15(9), 4809–4817.

Todinov, M. T. (2007). *Risk-based reliability analysis and generic principles for risk reduction*. Elsevier Science.

Toro, G. R., Abrahamson, N. A., and Schneider, J. F. (1997). “Model of strong ground motions from earthquakes in central and eastern North America: best estimates and uncertainties.” *Seismological Research Letters*, 68(1), 41–57.

Tvedt, L. (1990). “Distribution of quadratic forms in normal space-application to structural reliability.” *Journal of Engineering Mechanics*, 116(6), 1183–1197.

U.S. Environmental Protection Agency (USEPA). (2000). “EPANET 2 Users Manual v2.0.”

US–Canada Power System Outage Task Force. (2004). *Final Report on August 14, 2003 Blackout in the United States and Canada: Causes and Recommendations*.

USGS. (2010). “USGS Interactive Deaggregations Maps. Available at: http://eqint.cr.usgs.gov/deaggint/2008/index.php.”

Vaziri, P., Davidson, R., Apivatanagul, P., and Nozick, L. (2012). “Identification of optimization-based probabilistic earthquake scenarios for regional loss estimation.” *Journal of Earthquake Engineering*, 16(2), 296–315.

Vibrans, A. C., McRoberts, R. E., Moser, P., and Nicoletti, A. L. (2013). “Using satellite image-based maps and ground inventory data to estimate the area of the remaining Atlantic forest in the Brazilian state of Santa Catarina.” *Remote Sensing of Environment*, 130, 87–95.

Volkanovski, A., Cepin, M., and Mavko, B. (2009). “Application of the fault tree analysis for assessment of power system reliability.” *Reliability Engineering & System Safety*, 94(6), 1116–1127.

Wagner, J. M., Shamir, U., and Marks, D. H. (1988). “Water distribution reliability: simulation methods.” *Journal of Water Resources Planning and Management*, 114(03).

Wang, J. W., and Rong, L. L. (2009). “Cascade-based attack vulnerability on the US power grid.” *Safety Science*, 47(10), 1332–1336.

Watts, D. J., and Strogatz, S. H. (1998). “Collective dynamics of ‘small-world’ networks.” *Nature*, 393(6684), 440–442.

Wesson, R. L, and Perkins, D. M. (2001). “Spatial correlation of probabilistic earthquake ground motion and loss.” *Bulletin of the Seismological Society of America*, 91(6), 1498–1515.

Wesson, Robert L., Perkins, David M., Luco, N., and Karaca, E. (2009). “Direct calculation of the probability distribution for earthquake losses to a portfolio.” *Earthquake Spectra*, 25, 687.

Winkler, J., Dueñas-Osorio, L., Stein, R., and Subramanian, D. (2010). “Performance assessment of topologically diverse power systems subjected to hurricane events.” *Reliability Engineering & System Safety*, 95(4), 323–336.

Wong, I., Bouabid, J., Graf, W., Huyck, C., Porush, A., Silva, W., Siegel, T., Bureau, G., Eguchi, R., and Knight, J. (2005). "Potential losses in a repeat of the 1886 Charleston, South Carolina, Earthquake." *Earthquake spectra*, 21, 1157.

Wu, S.-J., Yoon, J.-H., and Quimpo, R. G. (1993). "Capacity-weighted water distribution system reliability." *Reliability Engineering & System Safety*, 42(1), 39–46.

Yazdani, A., and Jeffrey, P. (2010). "A complex network approach to robustness and vulnerability of spatially organized water distribution networks." *Arxiv preprint arXiv:1008.1770*.

Ziming Zhao, Cuihua Li, Hua Shi, and Quan Zou. (2011). "Material Classification Using Random Forest." *Advanced Materials Research*, 301-303, 73–9.

Appendix A

This section provides a proof to support the independence assumption among bridges with very large or very small failure probabilities. The level of dependencies is evaluated by the difference between the joint failure probability P_{ij} and the product of marginal probabilities P_iP_j. The three possible combinations with extreme failure probabilities among bridges are examined:

Case 1) $P_i \rightarrow 0$ and $P_j \rightarrow 0$

Assume $P_\mathrm{i} = P_j = \varepsilon$ as $\varepsilon \rightarrow 0$. From Equation 3.9:

$$P_{ij} - P_iP_j = R_{ij}\sqrt{P_i\left(1-P_i\right)P_j\left(1-P_j\right)} = R_{ij}\sqrt{\left(\varepsilon\left(1-\varepsilon\right)\right)^2} = R_{ij}\varepsilon\left(1-\varepsilon\right) \rightarrow 0 \quad as\,\varepsilon \rightarrow 0$$

Case 2) $P_i \rightarrow 1$ and $P_j \rightarrow 0$

Assume $P_\mathrm{i} = 1 - \varepsilon$ and $P_j = \varepsilon$ where $\varepsilon \rightarrow 0$. Similar to Case 1:

$$P_{ij} - P_iP_j = R_{ij}\sqrt{P_i\left(1-P_i\right)P_j\left(1-P_j\right)} = R_{ij}\sqrt{\left(\varepsilon\left(1-\varepsilon\right)\right)^2} = R_{ij}\varepsilon\left(1-\varepsilon\right) \rightarrow 0 \quad as\,\varepsilon \rightarrow 0$$

Case 3) $P_i \rightarrow 1$ and $P_j \rightarrow 1$

Assume $P_\mathrm{i} = P_\mathrm{j} = 1 - \varepsilon$ where $\varepsilon \rightarrow 0$. Similarly:

$$P_{ij} - P_iP_j = R_{ij}\sqrt{P_i\left(1-P_i\right)P_j\left(1-P_j\right)} = R_{ij}\sqrt{\left(\varepsilon\left(1-\varepsilon\right)\right)^2} = R_{ij}\varepsilon\left(1-\varepsilon\right) \rightarrow 0 \quad as\,\varepsilon \rightarrow 0$$

Q.E.D.

In application of the Dichotomized Gaussian Method (DGM) to simulate realizations of the n-dimensional Bernoulli random variable (Section 3.4), ε is selected to be 0.05. Smaller values have found to induce numerical instabilities in the DGM process, and should be avoided.