Predicting Accessibility in Highway Networks After an Earthquake by Path Reliability

by

İdil Arşık

A Thesis Submitted to the
Graduate School of Engineering
in Partial Fulfillment of the Requirements for
the Degree of

Master of Science

in

Industrial Engineering

Koç University

August 2013

Koç University

Graduate School of Sciences and Engineering

This is to certify that I have examined this copy of a master's thesis by

İdil Arşık

and have found that it is complete and satisfactory in all respects,

and that any and all revisions required by the final

examining committee have been made.

Committee Members:

Assoc. Prof. Fatma Sibel Salman (Advisor)

Assoc. Prof. Lerzan Örmeci

Assist. Prof. Dilek Günneç

Date:

ABSTRACT

In the event of an earthquake, highway network components such as bridges and viaducts may collapse, and the roads may be blocked by debris or landslides, impeding critical response activities. Experts state that both the radiation of seismic waves and the structural properties of highway components are likely to create correlated failures. We represent a risk-prone highway network by an undirected graph whose edges are subject to random failure/survival. With given the marginal survival probabilities, we propose a new link failure dependency model to predict the post-earthquake status of the network. We generate a family of joint probability distributions for the random surviving graph by means of a control parameter with varying level of dependency. We conduct sensitivity analysis on the parameter to understand how the likelihood of possible outcomes changes and compare the proposed dependency model to an existing model in the literature and the independent failure case. We also give a representation of the dependency model using belief networks and show that the probability of any network realization can be computed by the chain rule. Additionally, we examine the dissimilar path generation methods for the selection of the emergency routes between origin and destination points. Using the proposed dependency model and three path generation methods in sampling algorithms, we investigate accessibility and service levels of relief operations in a case study of the İstanbul highway network.

ÖZETÇE

Deprem sonrası, köprü, viyadük gibi karayolu ağı elemanları çökebilir; enkazları veya göçükleri yolları kapatabilir. Bu durum, acil müdahale faaliyetlerini engelleyebilir. Uzmanlar, sismik dalgaların yayılımının ve karayolu ağı elemanlarının yapısal özelliklerinin ağ elemanlarının ilişkili yıkımlarına sebep olabildiklerini belirtmektedirler. Bu çalışmada, deprem riski olan bir karayolu ağını, ayrıtları rassal yıkıma veya ayakta kalmaya tabi olan yönsüz bir ağ olarak tanımladık. Karayolu ağının deprem sonrası durumunu tahmin etmek için, ayrıtların marjinal ayakta kalma olasılıklarını kullanarak, yeni bir bağımlı ayrıt yıkım modeli önerdik. Tanımladığımız kontrol parametresi sayesinde, depremden sonra ayakta kalan rassal ağ için farklı bağımlılık düzeylerinde bileşik olasılık dağılımlar familyası ürettik. Olası dağılımların nasıl değiştiğini anlamak için, kontrol parametresi ile duyarlılık analizi yaptık. Önerdiğimiz bağımlı ayrıt modelini, bağımsız yıkım modeli ve literatürdeki bir yıkım modeli ile karşılaştırdık. İnanç ağlarını kullanarak önerdiğimiz bağımlılık modelinin grafiksel gösterimini yaptık; herhangi bir ağ gerçekleşme olasılığının zincir kuralı kullanılarak hesaplanabileceğini gösterdik. Bunlara ek olarak, ağ üzerinde belirlenmiş başlangıç ve varış noktaları arasında acil yardım güzergahlarını belirlemek için yol yaratma metodlarını inceledik. Önerdiğimiz bağımlı yıkım modelini ve literatürdeki üç yol yaratma methodunu örnekleme algoritmalarında kullanarak, kurtarma operasyonlarındaki erişilebilirlik ve servis düzeylerini İstanbul karayolu ağı için yaptığımız vaka çalışmasında inceledik.

ACKNOWLEDGMENTS

I would like to express my sincere gratitude to my advisor, F. Sibel Salman for her guidance during my graduate study. She generously shared her knowledge, time and experience with me to better my research.

I am very grateful to the rest of my thesis committee members: Lerzan Örmeci and Dilek Günneç for their insightful comments.

Along my graduate study, I had the chance to meet many great people whose friendship I greatly value. Many thanks go to my roommates Zeynep, İlknur, Müge, İrem and Aylin who made me feel like I am home and were there for me through the good times and bad. I would like to thank the members of ENG 231: Erdal, İsmail, Can, Ayşenur, Özge, Hassan, Burcu, Süha, and Salih for their friendship and for all the fun we had. I feel lucky to know Önay, Uğur, Can, Zehra and Gökhan and have them in my life. Above all, I sincerely thank Enis for his invaluable friendship and unfailing support. Without him, this graduate experience would not be the same.

Finally, I thank my family for supporting me throughout my studies and life in general. I especially thank my brother, Arda Arşık, for being a great friend and for putting up with his little sister's whims with great patience.

I dedicate this thesis to my parents, Hermine Arşık and Arsin Arşık, who are the greatest parents I know. I am indebted to them for their understanding and endless love.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Chapter 1

INTRODUCTION

Disasters fall into two categories, natural and man-made. While man-made disasters are caused by human actions, natural ones are inevitable events that result from natural hazards. Due to the randomness in occurrence, location and impact, natural disasters may result in great losses. Earthquakes are among the most destructive and deadly natural disasters. In the event of an earthquake, shock waves generated by seismic forces along the fault line cause ground shaking, surface ruptures, liquefaction, landslides, mudflows and earth cracking which create further damages [1]. The negligence of preparedness activities in pre-disaster stage and the inefficient emergency response activities in post-earthquake stage boost the negative effects of these earthquake damages.

Infrastructure systems such as public transportation, water, natural gas and electric power distribution provide critical services. In the aftermath of an earthquake, these systems can be damaged and lose their functionality, which may cripple response operations and paralyze daily life in the damaged areas. A vivid example for damages on infrastructure systems is the Kobe earthquake in 1995 [6]. Water to 1 million, natural gas to 857 thousand and electricity to 916 thousand households were cut. A total of 410 thousand subscribers could not use the telephone as a result of the damages on the telephone network. Finally, major highways were damaged at 1257 different points.

Highway systems constitute a significant part of the transportation systems through which the commodities such as food, shelter and medical supplies must be transferred from supply facilities to the affected areas as quickly as possible in order to support the rescue and relief operations [37]. Therefore, the assessment of the earthquake vulnerability of these systems and the selection of alternative emergency routes according to the vulnerability assessment is essential for pre-disaster preparedness. The information can also be used for capacity building and investment decisions for mitigation. For instance, highway administrators can prioritize structural strengthening of highway components with respect to a system-wide vulnerability and accessibility analysis. In this study, we investigate the vulnerability of a highway system in an earthquake and how its post-earthquake condition would effect the relief operations and casualty transportation. We represent the highway system by an undirected graph/network whose edges/links are subject to random failure/survival. The road segments correspond to network edges/links and the highly populated residential areas, emergency response facilities and junction points on the highway system are represented by network nodes. In this network, we assume that the nodes are reliable, and the edges/links can either be operational ($survive$) or nonoperational ($fail$). With the marginal survival probability of each link in an expected earthquake scenario given, we postulate that both the radiation of seismic waves and the structural properties of edge/link components such as bridges and viaducts create a dependency among the link failures in the event of an earthquake. In other words, links that carry the same seismic intensity are exposed to the similar amount of destruction and the link components with the same structural properties are typically equally vulnerable to the same amount of impact.

To represent this combined dependency structure, we suggest a practical approach. To begin with, we partition the links into mutually exclusive sets according to their seismic risk levels. Among each set, we divide links into subsets according to their structural properties related to earthquake vulnerability.

In a set, the level of spatial and structural dependency is controlled with a parameter. Given the marginal survival probability of each link and the value of this parameter, we generate a joint probability distribution of the network edges/links, which all together characterize a network realization/scenario. According to our dependency model, the failure of links in the same dependency set with low marginal survival probabilities (weak links) are affected from the failure of links with higher marginal survival probabilities (stronger links). As a result, the likelihood/probability of network realizations in which the failure of strong links is accompanied by the failure of weaker links increases with the value of the parameter. We investigate this dependency model with belief networks (Bayesian networks) which is a graphical modelling tool for specifying probability distributions and conditional dependencies between variables [19]. We represent our dependency relationship between a link and the links weaker and stronger than it with parent-child relationships in a Bayesian network. We show that the probability of a network realization can be computed with the chain rule applied in Bayesian networks. However, the calculation of the probability of each network realization requires extensive computation for large networks since even counting the possible network realizations is #P-complete [21]. Therefore, we rely on an external sampling algorithm to generate samples of network realizations and estimate their probabilities from their frequency in the generated sample. This approach enables us to estimate probabilistic measures of network performance.

The randomness in the survival/failure of network links engenders the selection of a set of reliable and alternative emergency routes between origin and destination (O - D) points in the pre-disaster stage. Although the selection of dissimilar paths increases the O - D reliability, longer paths are undesirable in the post-earthquake stage. To understand the trade off between reliability and path lengths, we implement dissimilar path generation methods and analyze their effects on network performance measures according to our proposed dependency model. We investigate three path generation methods (k - shortest path algorithm [36], iterative penalty method [20], p - dispersion method [4]) from literature. We also propose to generate another set of paths by extending p-dispersion method to include the shortest paths in the path sets.

Over the generated sample of network realization and set of dissimilar paths, we calculate a path-based accessibility measure, various service levels and fairness among demand points. Finally, we conduct a computational study on İstanbul highway network. We calculate the performance measures for İstanbul highway network, which is subject to earthquake hazard due to its vicinity to the seismically active North-Anatolian Fault to obtain insights for mitigation and preparedness.

The remainder of this thesis is organized as follows. In Chapter 2, we review the literature on disaster vulnerability of infrastructure networks, network reliability and performance measures, dissimilar path generation methods, link failure dependency and Bayesian networks in reliability assessment and in disaster vulnerability analysis. In Chapter 3, we propose the link failure dependency model and its Bayesian network representation. In Chapter 4, we describe the path-based performance measure with its properties as well as demand service levels and fairness among demand points. In Chapter 5, we present the computational study that we conducted on İstanbul highway network. We explain the data collection and generation, path generation, results and analysis of the results in this chapter. Finally, in Chapter 6, we provide our concluding remarks and possible extensions of the study.

Chapter 2

LITERATURE REVIEW

In this chapter, we present studies on disaster vulnerability of infrastructure systems, focusing on the network reliability and some of the recent measures presented for network performance. We also review the methods for dissimilar path generation and discuss the existing network link failure dependency models in the literature. We explain Bayesian networks and present the studies on the application of Bayesian networks in reliability analysis. Finally, we summarize our contributions to the literature.

2.1 Disaster Vulnerability of Infrastructure Networks

Infrastructure systems comprising transportation, water, energy and communication systems provide commodities and services that are essential to enable and sustain societal living conditions. The physical components of these interrelated systems can be crippled by natural or man-made disasters and thus paralyze the system functionality. To maintain societal welfare in general and to handle emergency response activities in post-disaster stage effectively, the vulnerability of the infrastructure systems should be investigated. Studies on the assessment of disaster vulnerability of the infrastructure systems are prevalent in network reliability literature since these systems can be characterized as networks.

Moghtaderi-Zadeh [27] introduces a systematic procedure for reliability upgrading of existing lifelines for the post-earthquake serviceability. In this method, he determines the critical network components whose strengthening improves the network reliability at most according to specified serviceability criteria. He introduces measures that assess the effectiveness of upgrading these components. The step-by-step upgrading procedure aims a specified target reliability level while reducing the costs for upgrading the component and also the losses due to the failure of the lifeline. Finally, he carries a case study on the water-distribution system in the San Francisco Bay Area.

Sohn [33] carries an analysis to evaluate the importance of the highway network links under flood damage. He introduces an accessibility index to embody the decreasing effect of distance and the volume of traffic influence on a highway network. He identifies the critical links to prioritize retrofiting based on either the distance-only or distance-traffic volume criteria and compares the percentage loss of accessibility due to the degradation of a link in two cases. Finally, he calculates the accessibility level of individual counties in Maryland and of the state as a whole before and after the hypothetical disruption of individual links caused by a flood.

Chang and Nojima [10] suggest new system performance measures for the post-disaster stage. They assess the network performance in terms of network coverage and transportation accessibility. They apply these measures to the urban railway and highway systems in Kobe, Japan that was affected by the destructive Hyogo-Ken Nanbu earthquake in 1995.

Selçuk and Yücemen [31] work on the quantification of the reliability of lifeline networks under a seismic hazard. They introduce a probabilistic model to evaluate the seismic reliability of network components, whose seismic capacities are random and spatially correlated. They implement their model to assess the seismic reliability of a water distribution system located in Bursa, Turkey.

2.2 Network Reliability and Performance Measures

The assessment of reliability can be seen as the complement of the assessment of vulnerability. Husdal [17] states that vulnerability is the *non-operability* of the network under certain circumstances while he describes the reliability as the *operability* of the network under varying strenuous conditions. In other words, network reliability indicates the ability of a network to perform and maintain its functions properly. Thus, the reliability analysis is engaged with the performance of a network in terms of its ability to withstand the failures of its components [31].

In the context of a highway transportation network, the evaluation of reliability mostly depends on the concerns of the decision maker. The decision maker can define reliability either from the point view of the individual traveller or from the point of view of all travellers with different reliability thresholds. Apart from these definitions, there are performance measures based on theoretical interpretation of reliability such as connectivity/terminal reliability, travel time reliability and capacity reliability [18].

Connectivity/terminal reliability is the probability that the nodes of a network stay connected. Special cases of connectivity measures are *two-terminal reliability*, *all-terminal reliability* and *K-terminal reliability* [21]. *Two-terminal reliability* refers to the probability that two specific nodes are connected. *All-terminal reliability* is the probability that every node is connected with every other node in the network. *K-terminal reliability* is the probability that every node in a node subset with cardinality K is connected with every other node in that subset. These measures are suitable for different network systems. For instance, two-terminal reliability is a proper measure for evaluating the connectivity of a specific O - D pair.

Travel time reliability is the probability that a trip between two specified nodes is completed within a specified time interval [35]. The capacity reliability, on the other hand, refers to the probability that a network serves a given level of travel demand successfully. Beside these reliability measures, there are various measures in the literature that assess the performance of a network. Two recent studies with flow networks are conducted by Nagurney and Qiang [28] and Gertsbakh and Shpungin [15].

Nagurney and Qiang [28] define a unified network performance measure which integrates the flow information and is applicable to different types of networks with either fixed or elastic demands on them. For a given network topology and the equilibrium or fixed demands for given O - D pairs, the network performance/efficiency measure is defined as the sum of the ratios of demands to disutility functions over all O - D pairs divided by the number of O - D pairs. With this measure, they can evaluate network efficiency in the case of disconnected O - D pairs. Additionally, they measure the importance of a network component by the relative drop in their proposed performance measure after the component is removed from the network. Thus, they identify the network components that are critical for the network reliability.

Gertsbakh and Shpungin [15] evaluate the network reliability in flow networks such as communication networks, transportation and supply networks whose capacitated edges are subject to failure. They assume that the flow network is reliable or *UP* if the maximal flow from a source node to sink node is not less than a given threshold. Accordingly, they estimate a topological characteristic of the network called destruction spectrum (D-spectrum). This network topological invariant depends on the network structure and the network *DOWN* state definition. They consider the permutations of the network edges which are initially *UP*. In each permutation array, starting from the beginning they change the state of the edges from *UP* to *DOWN* one by one and check whether the network state becomes *DOWN*. They identify the ordinal number of the first edge in the permutation that makes the network state *DOWN*. They call these ordinal numbers the anchor of the permutation. Considering a set of all permutations, they call the discrete density function of these anchors *the system destruction spectrum (D-Spectrum)*. For the case of network edges having equal *DOWN* probabilities, they express the probability that the network is in the *DOWN* state with the cumulative D-spectrum. Since the exact computation of D-Spectra is #P-complete, they estimate it using an efficient Monte Carlo simulation.

2.3 Dissimilar Path Generation For Two Terminal Reliability Analysis

In the aftermath of a post-earthquake stage, the shortest path between any O - D pair may not always be reliable. The edges/links of the shortest path may be blocked and/or collapsed. However, another path with a slightly higher path length may survive. Thus, it is more realistic to take a set of paths instead of only the shortest path into consideration for two terminal reliability analysis in the post-earthquake stage. For instance, as part of pre-earthquake preparedness activities, municipalities identify alternative emergency routes for the selected O - D pairs.

In the literature, there are various methods to generate a set of dissimilar paths between an O - D pair. The most-known one is k-shortest path algorithm [36], which produces k loop-less shortest paths from one node to another node in a network. The output is an ordered list of k alternative paths connecting an O - D pair. The drawback of this method is that it generates similar paths with common links. If a common link of the two generated paths fails, then both of the paths fail.

Johnson et al. [20] propose an iterative penalty method (IPM) as an alternative way for dissimilar path generation. In this method, Dijkstra's algorithm is applied between a given O - D pair iteratively. After each iteration, a penalty is applied to all the links on the resulting shortest path, i.e., a chosen penalty magnitude is added to the link costs and Dijkstra's algorithm is repeated with the current link costs. The links on the previous path with updated higher link costs become undesirable for the paths to be generated. Hence, the dissimilarity between generated paths increases.

Beside its simplicity, the method has some drawbacks. There are several decisions to be made in the implementation that affect the generated paths and their costs. The decisions are on the components to which the penalty is applied, the penalty magnitude, the penalty structure (additive penalty or multiplicative penalty) and on the paths to be penalized (the most recent path or all paths).

Another dissimilar path generation procedure is suggested by Akgün et al. [4] who use the idea of the classic discrete p-dispersion problem. It is the selection of $p \in P$ points out of $m \in M$ points $(1 < p < m)$ in some space in order to maximize the minimum distance between any two selected points. The formulation of p-dispersion problem is given below, where w_{ij} is the dissimilarity between two points, $i, j \in P$.

$$\max_{P \subseteq M} \quad [\min_{i \neq j; i,j \in P} \{w_{ij}\}] \tag{2.1}$$

In their procedure, they adopt this problem formulation to generate dissimilar paths between a O - D pair. They select a set of p paths out of a set of m candidate paths between O - D pair with the objective of maximizing the minimum dissimilarity between any two selected paths. In the dissimilar path generation procedure, w_{ij} corresponds to the dissimilarity between any two paths between O - D pair. This dissimilarity is expressed in terms of the similarity index given below.

$$S(P_i, P_j) = \frac{\frac{L(P_i \cap P_j)}{L(P_i)} + \frac{L(P_i \cap P_j)}{L(P_j)}}{2} \tag{2.2}$$

where L(P_i) is the length of path P_i and $S(P_i, P_j)$ is the similarity index between path i and path j. Then, the dissimilarity is equal to

$$w_{ij} = D(P_i,P_j)\text{=1-S}(P_i,P_j) \tag{2.3}$$

They adopt a two-phase heuristic as the solution approach. Their heuristic requires a candidate set of paths as an input. Candidate set generation can be handled by various methods. *IPM* and k-shortest path algorithm are two alternatives for the generation of candidate sets.

2.4 Link Failure Dependency

Most studies on network reliability analysis have assumed independent link failures and reliable nodes. However, in the event of a disaster, some network components are exposed to the same amount of impact, which creates a dependency relationship among component failures. This phenomenon is taken into consideration in a limited number of studies in the literature.

Botev et al. [7] estimate the reliability of a network in terms of the probability that a given set of network nodes is connected. They assume that the network links can be either in operational or nonoperational states with given probabilities. They propose a novel simulation-based method adapting the generalized splitting algorithm, which defines a discrete-time Markov chain evolving to a state of rare event of interest. The complementary problem, unreliability, is often a rare event and cannot be sampled with crude Monte Carlo method. With variance reduction techniques, they change the sampling distribution and sample the rare events. They note that unlike other variance reduction methods their proposed method works with dependent link failure case. However, they do not conduct any study with dependent link failures.

Selçuk and Yücemen [32] assess the seismic reliability of lifelines. They focus on the connectivity of two specified points after a catastrophic event such as an earthquake. They conduct a seismic hazard, capacity determination and network reliability analysis to evaluate this performance measure. In their capacity determination analysis, they identify the seismic capacity (strength) of each network component. They suggest point-site and multi-site models in which they divide the links into smaller segments, and they determine the seismic capacity along the total length of the links. In multi-site model, the survival of the link depends on the survival of each and every segment on that link. They articulate that the segments of the same link are expected to be highly correlated due to spatial proximity and shared material properties. Although they suggest a dependency among segments of a link, they assume independent link failure in their network reliability analysis.

Sumalee and Watling [34] assume dependent link failures for transportation networks where only the drivers on directly degraded (damaged) link are adaptable. They articulate that the link independence assumption is not suitable in the study of transportation networks. They argue that the degradation of different links might have common underlying causes such as disasters. They assert that when a network link fails, the adjacent links or the links in the same area of that link can be degraded. They also suggest that the mode of the link does not have to be binary (operational/non-operational). Thus, they assume dependent multi-mode link failures where the links can be partially operational. Based on this dependency model, they introduce an algorithm for estimating the bounds on the probability of a path travel time exceeding a threshold value.

Günneç and Salman [16] define dependent link failures for highway networks under seismic hazard. Given the marginal link failure probabilities, they propose a link failure dependency model in which they define vulnerability-based (VB) and set-based (SB) dependencies. According to this model, the links are divided into vulnerability sets based on deterministic *peak ground acceleration* (PGA) values. Links within the sets depend on each other with *VB-dependency* while links in different sets fail independently with *SB - dependency.* In a vulnerability set, if a stronger (lower failure probability) link fails due to an earthquake, they assume that the weaker (higher failure probability) links fail with a probability equal to 1. For a network composed of one vulnerability class with m number of links and links having 2 states (*failure, survival*), *VB-dependency* yields $m+1$ surviving network realizations. This number is equal to 2^m if the links fail independently.

2.5 Bayesian Networks in Reliability and Disaster Vulnerability Assessment

Over the last decade, the Bayesian Network (BN) approach which originated in the field of artificial intelligence has attracted attention as a robust and efficient framework for reasoning with uncertainty [22]. Briefly, a BN is a directed acyclic graph (DAG) where the nodes represent random variables and the edges represent the causal relationship and conditional dependencies between those variables. This probabilistic graphical model is used as an inference engine for the calculation of beliefs or probability of events given the observation/evidence of other events in the same network [25]. Its applications exist in engineering decision strategy [19], in the software-based system assessments [11] and the risk assessment of water distribution systems [8] [9].

Recently, the use of BN to estimate and improve the reliability and safety of systems has also increased. In contrast to existing modelling frameworks like fault trees and reliability block diagrams, the BN framework models and analyses complex systems, makes predictions, as well as diagnostics, computes exactly occurrence probability of an event, updates the calculations according to evidence and represents multi-mode variables [29].

Mahadevan et al. [25] suggest a BN model to assess the system reliability of structural systems by applying their methodology to mechanical and civil systems.

They combine the BN method with the branch-and-bound method to improve the BN efficiency and facilitate its application to large structures. In their model, they incorporate the correlations among component failures and the existence of multiple failure sequences.

Langseth and Portinale [22] argue that the BN approach is suitable for reliability applications. In their study, they explain building BNs, their causal interpretation and their usage as inference engines. They also discuss the use of BNs for modelling systems, which are traditionally handled with the fault-tree analysis (FTA) technique. Finally, they give the dependability analysis on a real-life system using BNs.

The applications of BNs exist also in the disaster context. Li et al. [24] study the assessment of catastrophic risks. They discuss using the domain knowledge and spatial data for the construction of a BN. They integrate multiple factors associated with catastrophic risk and the quantification of uncertainties within a probabilistic graphical system. As a case study, they investigate the flood risk in northwest China. They use a flood disaster data set and the related factors to construct a BN learner, which is used to predict the flood's loss risk.

In another study, Li et al. [23] use spatial analysis and BN to model vulnerability of an individual subject to the damage arising from a catastrophic disaster and to estimate insurance pricing accordingly. Using spatial analysis, they pre-process the spatial attributes of geo-features to obtain the relevant indicators. Then, they integrate these indicators with other indicators such as hazard intensity, environment and individual characteristics within a BN model. Each node of the BN represents an indicator for vulnerability assessment and insurance pricing. They exemplify their model with an earthquake vulnerability analysis and insurance pricing of the residency buildings in the study region of interest, which is located in an earthquake prone province of China.

2.6 Our Contributions

We present a new dependency model for the failure of links on a transportation network. We define a control parameter α which determines the degree of dependency between link failures. Accordingly, we generate a family of joint probability distributions for the random network subject to link failures. The proposed model is more realistic compared to independent failure case in the sense that it incorporates the common causes of link failures such as seismic intensity and spatial proximity in the disaster context. Unlike the *VB-dependency* model [16], it also does not limit the number of network realizations. All possible network realizations may have a positive occurrence probability, but for many realizations this probability goes to a very small number. Hence, we use sampling based approaches for large networks.

In the literature, the studies on Bayesian networks either assess the reliability of a single network component or the disaster risk. Unlike these studies, we represent the relationship between network links with BN and calculate the probability of each realization. We believe that this is the first study that investigates BN for link failure dependency models.

We propose an accessibility measure which is an expected value over the generated network realizations. The measure is path-based, taking sets of paths between each O - D pair as inputs. We compare three dissimilar path generation methods in the literature and examine the network performance for each method.

We conduct a case study of the İstanbul highway network under a highly likely earthquake scenario. We compare the proposed dependency model to *VB-dependency* model in the literature and the independent failure case. We carry out a sensitivity analysis on the parameter α to understand how likelihood of possible outcomes changes. Finally, we compute the proposed accessibility measure, demand service level measures and fairness among demand points.

Chapter 3

THE PROPOSED DEPENDENCY MODEL

In the event of an earthquake, highway roads may become nonoperational. Earthquakes can cause cracks and deformations on the roads obstructing the transportation. The collapse of roadside buildings, viaducts, bridges and pedestrian overpasses on the highway may paralyze the transportation on a particular road. However, highway roads are not equally vulnerable to a possible earthquake. According to the proximity to the earthquake epicentre, each piece of road has different regional seismic risk. For instance, roads under the high regional seismic risk are more prone to earthquake related damages while roads under low regional seismic risk are more reliable. Moreover, the structural properties of the buildings, bridges and viaducts define the earthquake vulnerability of these structures and indirectly the earthquake vulnerability of roads carrying these structures.

While most of the studies in network reliability assume that links fail independently, this assumption is not valid in a disaster context. Experts state that the roads that are in the same seismic region and carry the structures with similar earthquake vulnerability are expected to behave similarly in the event of an earthquake. We introduce a practical approach that captures this dependency between the state of the roads. To begin with, we represent the highway system by an undirected graph/network whose edges/links are subject to random failure/survival and nodes are reliable. In this graph, edges/links correspond to road segments. It is assumed that the network edges/links can be either operational (*survive*) or nonoperational

($fail$) and their marginal survival probabilities are known. The links are divided into mutually exclusive and spatially separated sets according to their regional seismic risks. Within each set, links are divided further into structural dependency sets according to the earthquake vulnerability of structures on the links. For the structural dependency set partitioning, the structural qualifications such as length, width, construction year, supporting structure are relevant.

The link failure dependency model is based on the modification of link survival probabilities. The survival probabilities are modified so that the links in the same spatial and structural dependency sets behave similar to the failed stronger links. In other words, failure of a stronger link makes the failure of weaker links of the same kind more likely by decreasing the survival probabilities of weaker links by a factor of (1-α)%. This dependency model focuses on the decrease in survival probability of weaker links with respect to the failure of stronger links but not vice versa.

Definition 3.1. Given two links i and j in the same dependency set with survival probabilities p_i and p_j, if $p_i \leqslant p_j$, then P(i survives | j fails)=(1-α)p_i.

According to 3.1, links i and j within a dependency set do not fail independently. To confirm this dependency, we check the covariance of links i and j.

Lemma 3.1. The covariance between states of links i and j, $Cov(i, j)$, is greater than or equal to 0, and is positive when $0 < p_i \leqslant p_j < 1$.

Proof. The states of links i and j are represented by Bernoulli random variables and can be either 1 or 0. Hence, four possible cases exist. (Case 1: $i = 0, j = 0$, Case 2: $i = 1, j = 0$, Case 3: $i = 0, j = 1$ and Case 4: $i = 1, j = 1$)

The expected values of i and j are given in 3.1 and 3.2 respectively.

$$\begin{aligned} E[i] &= \sum_i iP(i) = 1 * P(i=1) + 0 * P(i=0) \\ &= P(i=1) = \sum_j P(I=i, J=j) \\ &= P(i=1, j=0) + P(i=1, j=1) \\ &= p_i(1-\alpha)(1-p_j) + p_i p_j \\ &= p_i - \alpha p_i + \alpha p_i p_j \end{aligned} \tag{3.1}$$

$$\begin{aligned} E[j] &= \sum_j jP(j) = 1 * P(j=1) + 0 * P(j=0) \\ &= P(j=1) = \sum_i P(I=i, J=j) \\ &= P(i=1, j=1) + P(i=0, j=1) \\ &= p_i p_j + (1-p_i)p_j \\ &= p_j \end{aligned} \tag{3.2}$$

$$\begin{aligned} Cov(i,j) &= E[(i - E[i])(j - E[j])] \\ &= (0 - (p_i - \alpha p_i + \alpha p_i p_j))(0 - p_j)(1 - p_i(1-\alpha))(1-p_j) \\ &+ (1 - (p_i - \alpha p_i + \alpha p_i p_j))(0 - p_j)(p_i(1-\alpha))(1-p_j) \\ &+ (0 - (p_i - \alpha p_i + \alpha p_i p_j))(1 - p_j)(1-p_i)p_j \\ &+ (1 - (p_i - \alpha p_i + \alpha p_i p_j))(1 - p_j)p_i p_j \\ &= \alpha p_i p_j (1-p_j) \end{aligned} \tag{3.3}$$

For two extreme cases $\alpha = 1$ and $\alpha = 0$, we investigate $Cov(i,j)$

Case 1 ($0 < \alpha \leq 1$): $Cov(i,j) = p_i p_j (1 - p_j) > 0$ for $0 < p_i \leqslant p_j < 1$.

Case 2 ($\alpha = 0$): $Cov(i,j) = 0$. In this case i and j are independent.

From case 1 and case 2, it follows that $Cov(i,j) \geq 0$ for $0 \leq \alpha \leq 1$. □

In the case of the failure of n links stronger than link i in the same dependency set, the survival probability of link i is equal to $(1-\alpha)^n p_i$.

We can argue that, as α increases, the likelihood of the failure of a link with respect to a stronger link in the dependency set also increases. For α=0, the problem turns into the independent link failure case. On the other hand, the case where α=1 is the totally dependent case.

3.0.1 Bayesian Network Representation

The hierarchical relationship between network links according to the proposed dependency model can be represented by a Bayesian network, also called a belief network. A Bayesian network is a graphical modelling tool for specifying probability distributions. It is a directed acyclic graph whose nodes represent propositional variables whereas edges are the direct causal influence among variables. For each variable, a conditional probability table (CPT) is defined which quantifies the relationship between the variable and each of its parents [12]. With its special structure, Bayesian network satisfies Markovian assumption, which dictates that every variable is conditionally independent of its non-descendants given its parents.

To clarify the concepts, we illustrate the proposed dependency model on a network with four nodes and four undirected edges. Let the four edges/links of this network belong to the same dependency set and let e_1 represent the edge/link between nodes 1 and 2, e_2 between nodes 2 and 3, e_3 between nodes 3 and 4, and finally e_4 between nodes 1 and 4. Let the individual survival probabilities of e_1,e_2,e_3 and e_4 be 0.85, 0.75, 0.7 and 0.55, respectively. The joint probability distribution of network realizations

ξ=$e_1e_2e_3e_4$	$\alpha = 1$	$\alpha = 0.75$	$\alpha = 0.50$	$\alpha = 0.25$	$\alpha = 0$
0 0 0 0	15%	11.55%	7.2%	3.06%	0.51%
0 0 0 1	0%	0.1%	0.53%	0.92%	0.62%
0 0 1 0	0%	0.51%	1.42%	1.78%	1.18%
0 0 1 1	0%	0.02%	0.23%	0.8%	1.44%
0 1 0 0	0%	2.24%	3.15%	2.77%	1.52%
0 1 0 1	0%	0.08%	0.5%	1.24%	1.86%
0 1 1 0	0%	0.42%	1.43%	2.6%	3.54%
0 1 1 1	0%	0.07%	0.54%	1.83%	4.33%
1 0 0 0	21.25%	16.93%	11.91%	6.97%	2.87%
1 0 0 1	0%	0.6%	1.9%	3.12%	3.51%
1 0 1 0	0%	3.21%	5.39%	6.55%	6.69%
1 0 1 1	0%	0.51%	2.05%	4.6%	8.18%
1 1 0 0	19.13%	16.5%	13.87%	11.24%	8.61%
1 1 0 1	0%	2.63%	5.26%	7.89%	10.52%
1 1 1 0	20.08%	20.08%	20.08%	20.08%	20.08%
1 1 1 1	24.54%	24.54%	24.54%	24.54%	24.54%

Table 3.1: Joint Probability Distribution For Five α Values

for different α values is given in Table 3.1.

The results in Table 3.1 show that the increase in α increases the likelihood of certain realizations while the likelihood of other realizations either decreases or does not change for a given network topology and marginal link survival probabilities. We can interpret this effect of α as follows: Our dependency model favours the network realizations in which weaker links are nonoperational if stronger links in the same dependency set are nonoperational. The value of α corresponds to the degree of this dependency between link failures. As α increases from 0 to 1, the probabilities of some realizations add up to the probabilities of other realizations. In the case of α=1, the probabilities of certain realizations become zero. For instance, the independent failure case-probabilities of network realizations [0 1 1 1], [0 0 1 1], [0 1 0 1], [0 0 0 1], [0 1 1 0], [0 0 1 0] and [0 1 0 0] add up to the probability of [0 0 0 0] in the case of α=1. Likewise the probabilities of network realizations [1 0 0 1] and [1 0 1 0] add up to the probability of [1 0 0 0] and the probability of [1 1 0 1] add up to [1 1 0 0].

The probabilities of [1 1 1 0] and [1 1 1 1] for α=1 remain almost the same as the probabilities for α=0. The reason is that we do not manipulate the marginal survival probability of a link as long as the stronger links survive according to the proposed dependency model.

The Bayesian network representation of the network is given in Figure 3.1 and the *CPT* tables of Bayesian nodes according to our dependency model are given in Tables 3.2, 3.3, 3.4 and 3.5.

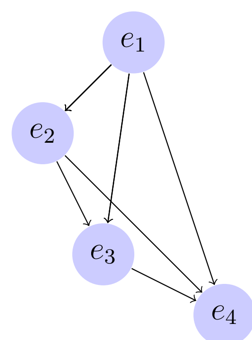

Figure 3.1: Bayesian Network Representation

e_1	P(e_1)
0	0.15
1	0.85

Table 3.2: CPT for e_1

e_1	e_2	P(e_2 | e_1)
0	0	1-0.75(1-α)
0	1	0.75(1-α)
1	0	0.25
1	1	0.75

Table 3.3: CPT for e_2

e_1	e_2	e_3	P(e_3 | e_1,e_2)
0	0	0	1-0.7(1-α)^2
0	0	1	0.7(1-α)^2
0	1	0	1-0.7(1-α)
0	1	1	0.7(1-α)
1	0	0	1-0.7(1-α)
1	0	1	0.7(1-α)
1	1	1	0.7
1	1	0	0.3

Table 3.4: CPT for e_3

e_1	e_2	e_3	e_4	P(e_4 | e_1,e_2,e_3)
0	0	0	0	1-0.55(1-α)^3
0	0	0	1	0.55(1-α)^3
0	1	0	0	1-0.55(1-α)^2
0	1	0	1	0.55(1-α)^2
0	1	1	0	1-0.55(1-α)
0	1	1	1	0.55(1-α)
0	0	1	0	1-0.55(1-α)^2
0	0	1	1	0.55(1-α)^2
1	0	0	0	1-0.55(1-α)^2
1	0	0	1	0.55(1-α)^2
1	1	0	0	1-0.55(1-α)
1	1	0	1	0.55(1-α)
1	0	1	0	1-0.55(1-α)
1	0	1	1	0.55(1-α)
1	1	1	0	0.45
1	1	1	1	0.55

Table 3.5: CPT for e_4

Given the CPT for each Bayesian node, the probability of any network realization can be computed as a chain rule in 3.4.

$$\text{P}([e_1\ e_2\ e_3\ e_4])=\text{P}(e_1) * P(e_2|e_1) * P(e_3|e_1, e_2) * P(e_4|e_1, e_2, e_3) \tag{3.4}$$

For instance, the probability of network realization [1 0 0 1] with α=0.25 is given by P([1 0 0 1])=0.85*0.25*(1-0.7(1-0.25))*0.55$(1-0.25)^2$=0.0312.

In our study, the random variables associated with the state of each link after the earthquake correspond to the Bayesian network nodes. The parents of a Bayesian network node are the nodes representing the state of links with higher survival probabilities in the same dependency set, whereas its children are the nodes representing the state of links with lower survival probabilities in the same dependency set. Hence, given the available data on marginal survival probabilities, using belief networks we can make inferences about the state of network links according to our link failure dependency model. The chain rule allows us to calculate the probability of a possible network instantiation/realization/scenario in our study.

To sum up, Bayesian network provides a graphical representation of the dependency relationship between the highway network links and the exact calculation of the joint probability distribution of highway network links. However, the computation increases with the number of CPT tables, in other words the number of the highway network links. Since counting the number of reliable network realizations is a #P-complete problem [7], the calculation of the probability of each and every network realization is impractical. Therefore, we apply the external sampling method for large networks to generate a sample from the population of network realizations and estimate their probabilities.

3.0.2 External Sampling

Notation

Let $s = (s_1, s_2, ..., s_m)$ be a network realization vector representing the state of the network edges/links and S be the set of all possible network realizations (outcomes) defined by s. $s_i = 1$, if link i is operational, and $s_i = 0$, if link i is nonoperational. The probability of network realization $s \in S$ is defined as $P(s)$. For each link $i \in E$, its marginal survival probability p_i is given. Let parameter for link i, $n_{ij} = 1$, if link j is in the dependency set of link i and $p_j \geq p_i$, and $n_{ij} = 0$, otherwise. In other words, n_{ij} denotes whether j is a parent of i in BN or not.

Unlike the *VB-dependency* [16], our model does not limit the number of realizations. Thus, it becomes computationally intractable to generate the joint probability distribution as the number of network links increases. Therefore, we propose an external sampling algorithm to generate a sample of network realizations and then utilize sample average approximation to estimate any probabilistic measure. We give the pseudo-code of the external sampling in Algorithm 3.1, where the number of replications is specified as R.

Algorithm 3.1 External Sampling of Network Realizations

Input: α, p_i and n_{ij} $\forall i, j \in E$
Step 1: Order network links such that $p_i \geq p_{i+1}$.
for $r = 1$ to R **do**
  for $i = 1$ to m **do**
    Step 2: Generate a network realization array s with size m.
    Step 3: Set $s_i \leftarrow 0$, $\xi_i \leftarrow 1$ $p'_\alpha(i) \leftarrow 0$, $\forall i = 1, .., m$.
    Step 4: Update the survival probability of link i as
    $$p'_\alpha(i) = p_i(1-\alpha)^{\sum\limits_{j=1}^{i-1} \xi_j n_{ij}}.$$
    Step 5: Generate a random number φ between 0 and 1.
    if $p'_\alpha(i) \geq \varphi$ **then**
      $s_i \leftarrow 1$ and $\xi_i \leftarrow 0$.
    end if
  end for
end for
Let S be the set of unique realizations in sampling
Calculate the occurrence frequency, $p(s)$, $\forall s \in S$
Output: $s, p(s)$ $\forall s \in S$

In Algorithm 3.1, we use the marginal survival probability of each edge/link i, p_i, n_{ij} for every pair of edges i and j, and the control parameter α as inputs. In Step 1, we sort the links with respect to their marginal survival probabilities in non-increasing order. In Step 2, in each replication, we generate an array of all zeros with length m representing an empty network realization array. In Step 4, we update the marginal survival probabilities of each link according to the state of the stronger links in its dependency set. In Step 5, we update the state of each link in the network realization. Finally, we select the unique realizations from the set of generated network realizations with size R, and output, we obtain a set of unique network realizations and their frequencies as the estimate for the probabilities.

3.0.3 Average Hamming Distance

Algorithm 3.1 would yield similar number of realizations in each generated sample. We expect that these equally crowded samples generated by Algorithm 3.1 according to the proposed dependency model differentiate with respect to the control parameter. We know that as α increases, the edges depend more heavily on the edges stronger than them in their dependency set. For instance, in the extreme case, $\alpha = 1$, the generated realizations depend on the state of stronger edges in the dependency set. On the other hand, in the case of $\alpha = 0$, realizations are generated independent from the state of stronger links.

We investigate the Hamming distance between each pair of network realizations in a given sample in order to assess the effect of the dependency model and α on the composition of generated samples. Briefly, the Hamming distance is the number of positions at which the characters are different between two equal strings. In our case, the Hamming distance corresponds to the number of edges that are in different states between a pair of network realizations.

For each sample, we calculate the average of Hamming distances over all pairs of unique network realizations. The average Hamming distance serves to measure the differentiation of the samples according to the choice of the control parameter α.

As the sample size increases, calculating the average Hamming distance takes too much time.

Chapter 4

PERFORMANCE MEASURES

In this chapter, we present performance measures and service levels to assess the effectiveness of relief operations on a highway network in the aftermath of an earthquake according to the proposed dependency model.

Notation

Given an undirected graph $G = (N, E)$, where E is the set of edges/links and $N = \{N_1 \cup N_2 \cup N_3\}$ is the set of nodes consisting of three disjoint sets. N_1 represents the set of demand points, N_2 the set of supply points, and N_3 the set of transmission points. Let $|E|= m$ and $|N|= n$. Additionally, the casualty demand at node $v \in N_1$ is denoted by w_v. Π^{vw} is the set of paths, π_l^{vw} represents l^{th} path of Π^{vw} and finally c_l^{vw} is the length of the l^{th} path between node $v \in N_1$ and node $w \in N_2$. Finally, $a_{sl}^{vw} = 1$, if the l^{th} path between nodes v and w survives in network realization s and 0, otherwise.

4.1 Accessibility Measure: Expected Weighted Average Distance (EWAD)

The accessibility measure that we introduce in this section incorporates the disaster risk in terms of demand figures as well as the condition of the highway network according to the proposed dependency model. The measure evaluates the expected weighted average distance to fulfill unit relief aid demand on a random network with given demand (casualty locations) and uncapacitated supply points (emergency response facility locations) and sets of paths between them.

For each network realization $s \in S$ and for each demand point $v \in N_1$, the length of the surviving shortest path from demand point v to the closest supply point $w \in N_2$, d_{sv}, is given by:

$$d_{sv} = \min_{w,l}(\pi_l^{vw} a_{sl}^{vw}) \tag{4.1}$$

In a network realization s, when there exists no path from a demand point $v \in N_1$ to any supply point $w \in N_2$, d_{sv} is set to $PenaltyCost$ which can be interpreted as the relative distance corresponding to an alternative and reliable mode of transportation.

The expected shortest path length to serve a demand point $v \in N_1$ over all network realizations is given by:

$$EWAD(\mathrm{v}) = \sum_{s \in S} P(s) d_{sv} \tag{4.2}$$

The weighted average distance (WAD) to serve one unit of demand in scenario s is given by:

$$WAD(s) = \frac{\sum\limits_{v \in N_1} d_{sv} w_v}{\sum\limits_{v \in N_1} w_v} \tag{4.3}$$

Finally, the average expected shortest path length to serve a unit demand is given by the following equation:

$$EWAD = \frac{\sum\limits_{s \in S} \sum\limits_{v \in N_1} P(s) d_{sv} w_v}{\sum\limits_{v \in N_1} w_v} \tag{4.4}$$

4.1.1 Solution Approach

Exact calculation of the accessibility measure grows as the number of network realizations, demand points, emergency facility locations and number of paths increase. Even checking the operational paths in path sets between each demand and supply point in each network realization requires extensive computation as the size of the network and path sets grows. Since our objective is to assess the accessibility level of the highway network in the aftermath of an earthquake, we assume that the supply points are uncapacitated. Hence, we only consider the paths with path length under a threshold value for each demand point without keeping track of the supply point from which the demand point is served.

Therefore, along with the sampling method explained in Chapter 3, we suggest an approximation of the measure with the pre-processing of paths and the introduction of a penalty mechanism in Algorithm 4.1. We select a subset of paths for each demand point $v \in N_1$, including the paths to any supply point $w \in N_2$ less than a given threshold for path lengths, $PenaltyCost$. Paths having path length greater than $PenaltyCost$ are excluded from the calculation. $PenaltyCost$ represents a threshold distance for effective casualty transportation.

Algorithm 4.1 Path Reduction as Pre-Processing

Input: Π^{vw}, $PenaltyCost$
List all generated shortest paths from each demand node $v \in N_1$ to all supply nodes in N_2.
Let the set of shortest paths to/from each demand node be Π^v
For each demand node $v \in N_1$, select a subset, Π^v, that includes each and every path with path length, $c_l^{vw} \leqslant PenaltyCost$. Name the subset Π'^v
Let π_a^v be a^{th} shortest path and c_a^v be the length of a^{th} shortest path to/from demand node v, where a=1,2,..,$|\Pi'^v|$.

Using network realization samples generated by Algorithm 3.1 and the path sets generated by Algorithm 4.1, we calculate the accessibility measure $EWAD$ for various values of the control parameter and for three dissimilar path generation methods. In Algorithm 4.2, we provide the psuedo-code of the calculation.

Algorithm 4.2 *EWAD*

Input: S, $P(s)$ $s \in S$, w_v, Π^v, c_a^v, $v \in N_1$, $PenaltyCost$
Initialize $d_{sv} \leftarrow 0$ and $EWAD \leftarrow 0$
for $s = 1$ to S **do**
  for $v = 1$ to N_1 **do**
    for $a = 1$ to $|\Pi'^v|$ **do**
      if Any link on the shortest path π_a^v is nonoperational in scenario s **then**
        $a = a + 1$
        Check the next shortest path
      end if
      if All links on the shortest path π_a^v are operational **then**
        Select the shortest path π_a^v as the shortest surviving path
        in scenario s
        $d_{sv} = c_a^v$
        $v = v + 1$
        Go to the next demand point v
      end if
      if No path is operational from/to demand point v in scenario s **then**
        $d_{sv} = PenaltyCost$
        $v = v + 1$
        Go to the next demand node v
      end if
    end for
    $EWAD = EWAD + (d_{sv} * w_v)$
  end for
  $EWAD = EWAD * P(s)$
end for
$EWAD = EWAD / \sum_{v \in N_1} w_v$
Output : $EWAD$

The accessibility measure that we propose in this chapter satisfies three properties [13] such as scale invariance, monotonicity and membership in an interval. In Lemma 4.1, we explain these properties.

Lemma 4.1. Let $G = (N, E)$ be a random undirected graph with link failures according to the proposed dependency model. The following properties hold.

(1) Scale Invariance: The measure, *EWAD* is invariant with respect to scale changes in demand values, w_v, at demand points.

(2) Monotonicity: Let $E^* = E \cup \{e^*\}$. Then, $EWAD(N, E^*) \leq EWAD(N, E)$.

(3) Membership in [*Deterministic Upper Bound (DUB)*, *Deterministic Lower Bound (DLB)*]: $DLB \leq EWAD(N, E) \leq DUB$.

Proof. (1) Assume that the amount of demand at node $v \in N_1$ varies by a factor β, where $\beta \geq 0$ so that the new demand is $w_v^* = \beta w_v$, $\forall v \in N_1$. Denote by $EWAD^*$, the measure with the new demand vector $w*$ is equal to $EWAD^*(N, E) = \beta EWAD(N, E)$.

(2) Clearly, adding a new link to the network may decrease d_{sv} $\forall$ $s \in S$ and $\forall$ $v \in N_1$, but will not increase it.

(3) In the network realization s, where all links are operational, $a_{sl}^{vw} = 1$ $\forall$ $v \in N_1$, $\forall$ $w \in N_2$ and $\forall$ $k \in \Pi^{vw}$. Then, d_{sv} $\forall v \in N_1$ is equal to the shortest path to the closest emergency response facility $w \in N_2$ and *EWAD* is equal to *DLB*. In the network realization s, where all links fail, d_{sv} $\forall v \in N_1$ is equal to *PenaltyCost* which is also equal to DUB. Thus, *EWAD* can take values between *DLB* and *DUB*. □

4.1.2 Alternatives for Path-Based Approach

In this study, our objective with the path-based approach is to investigate and compare the dissimilar path generation methods in the disaster context. The selection of emergency routes is essential in pre-disaster planning activities. However, alternatively, this measure can also be computed by finding the shortest path from each demand point v to each supply w and selecting the shortest one among the generated shortest paths in each network realization. This method would require to call Dijkstra's algorithm for each demand point v in each network realization.

The performance of the path-based approach depends on the number of paths generated for each demand point. Since we use a penalty mechanism, we limit the number of paths in the path set of each demand point v. On the other hand, the performance of the alternative approach depends on the number of nodes. As the network size increases, the path-based approach will perform better compared to the alternative approach.

4.2 Demand Service Level Measures

In Section 4.1, we propose a weighted measure of demand points to assess the network performance. The measure incorporates the demand value of each demand point and gives an expectation on the average network performance. In this section, we investigate the reliability of each demand point v in terms of connectivity and service level criteria as well as fairness among demand points.

In a network realization s, when there exists no path from any supply point w to demand point v, then the demand point v will not receive any service in that realization, otherwise, it is counted as served. Accordingly, we study the network performance for each demand point v by the following three service levels.

4.2.1 Service Level I

This service level indicates the probability that demand point v is served from a supply point within a distance threshold, γ.

Let d_v be the shortest distance for demand point v to be served.

$$P(d_v \leq \gamma) \cong \frac{\#\ \textit{of realizations demand point } v \textit{ is served within } \gamma}{\#\ \textit{of realizations}} \tag{4.5}$$

4.2.2 Service Level II

Service Level II is the probability that demand point v is serviced from its closest facility.

$$P(v \text{ is served from its closest } w) \cong \frac{\# \text{ of realizations } v \text{ is serviced from its closest } w}{\# \text{ of realizations}} \tag{4.6}$$

It should be noted that this service level is independent of path selection. With this service level, we investigate whether a demand point is served from its closest supply point or not. Thus, it calculates the probability of the best case for each demand point v according to a given α value.

4.2.3 Service Level III

The third service level is the probability that demand point v is connected to any supply point v. In this service level, we evaluate the connectivity over a set of paths as opposed to only the shortest path in service level II.

$$P(v \text{ is served}) \cong 1 - \frac{\# \text{ of realizations with } d_{sv}{=}PenaltyCost}{\# \text{ of realizations}} \tag{4.7}$$

The comparison of service levels II and III shows the effectiveness of alternative path selection in terms of pre-disaster planning compared designating of a single path for emergency access to each demand point.

4.2.4 Fairness

One of the objectives in humanitarian logistics is fairness. While it is of high priority to serve a maximum level of demand in a short time, it is also important not to create big imbalances among the service levels of demand points. To pinpoint any imbalances, we evaluate the variability of the service levels among the demand points. We use *Pearson Variation Index* (standard deviation/mean) to measure the variability.

Chapter 5

COMPUTATIONAL STUDY ON İSTANBUL HIGHWAY NETWORK

The city of İstanbul with its 15 million inhabitants, spreads over two continents which are connected with two long span suspension bridges. The city on both European Side and Asian Side is located on a high seismic zone. According to stress transfer theory, the city is faced with having a destructive earthquake in the next 30 years with 60% probability [5] [30] [26]. Experts state that, in the event of a possible earthquake, the failure of structures on the highway may totally paralyze the whole transportation system in the city and the earthquake related problems such as the disruption of emergency response activities may increase due to failure of the highway network. We conduct a computational study to assess the earthquake vulnerability of İstanbul highway network and how it would affect emergency response operations. We test the proposed dependency model, conduct sensitivity analysis on the control parameter α and report the results of accessibility, service and fairness measures.

5.1 Data Generation

In this section, we explain the generation of the representative network, the selection of casualty demand and emergency facility locations, path generation methods and edge survival/failure probability generation.

5.1.1 Network Generation

The İstanbul highway network is composed of mainly two motorways, O1 and O2, which run in the east-west direction of the city. In the north-south direction, the secondary roads that are connected to O1 and O2 motorways expand the highway network throughout the city (see Figure 5.1). In this study, we create a simplified graph representation of this highway network using two geographical information systems (GIS) software programs, ArcGIS and GoogleMaps.

Figure 5.1: Highway Network of İstanbul

İstanbul consists of 38 districts excluding the islands, shown in Figure 5.2. In our network, except for the four districts, Beykoz, Sile, Çatalca and Silivri which have low population and low earthquake risk [3], each district is represented by a node. We also include 26 junction points where the secondary roads meet with O1 and O2 motorways into the node set. To simplify the reference, we number the nodes from 1 to 60 (see Table A.1). We calculate the path distances between each network node pair with GIS programs. Due to the topology of highway networks, the path length of going from node v to node w may differ from the path length of going from node w to node v. Therefore, we calculate and include path lengths for both directions between node pairs. Overall, the network consists of 60 nodes and 83 undirected edges with asymmetric edge lengths. We assume that the nodes are reliable while the edges are subject to failure.

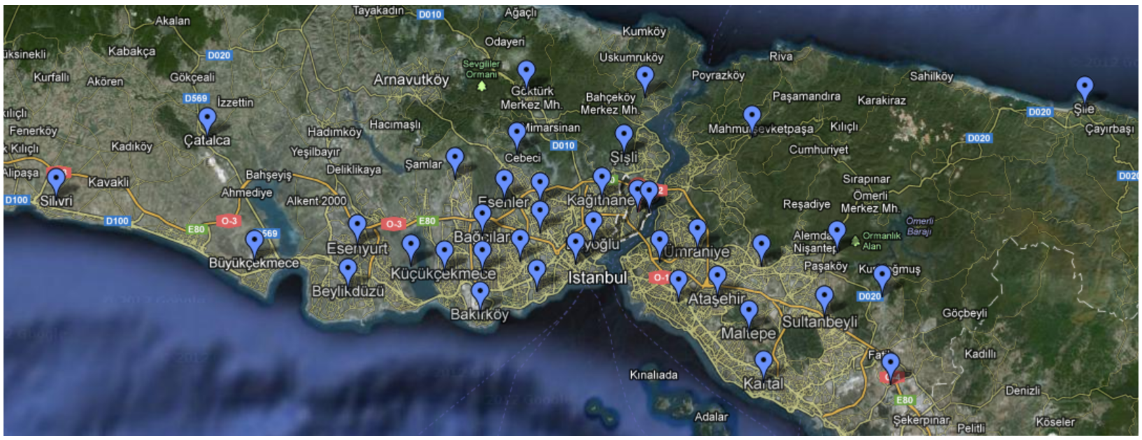

Figure 5.2: 38 Districts of İstanbul

5.1.2 Casualty Demand and Emergency Facility Locations

In the event of a disaster, according to Federal Emergency Agency (FEMA), extricating people and providing access to health care facilities are the top priorities followed by access to emergency operations infrastructures such as the emergency operations centres and supply distribution centres [1]. Thus, we believe that it is appropriate to select health care facilities as emergency facility locations in our study. We investigate the number of hospitals, policlinics and number of beds in each district given in Table A.3 [3]. We select the districts Bakırköy, Üsküdar, Şişli, Fatih, Kadıköy, Bahçelievler, Zeytinburnu and Beyoğlu in which the health care facilities are highly populated as emergency facility locations. We assume the emergency facilities are uncapacitated and therefore they will completely cover the casualty demand in their districts. We identify the remaining district as casualty demand locations where the number of health care facilities is not enough to serve the casualties in post-disaster stage. Therefore, these casualties are transported to the pre-identified emergency facility locations. We calculate the number of estimated casualties in each demand district by the casualty rates given in [3] (see Table A.2).

5.1.3 Edge Survival/Failure Probability Generation

For a vulnerability assessment of the highway network, we need to estimate the individual survival probabilities, i.e., reliability of individual edges. As explained in Chapter 3, there are various reasons which cause edges to become nonoperational. In this study, we take into account the seismic intensity of the earthquake and the collapse of structures on the highway for the estimation of edge survival probabilities. The incidents obtained from Kobe earthquake show that the probability of the total width of the collapsed buildings being more than the total width of the road is 98.7%, 11% and 0.3% for roads with width between 2 and 6 metres, 15 meters and 16 meters respectively [3]. Since we only consider the motorway roads and arterial roads with the width more than 15 meters, we exclude the possibility of road blockage due to collapse of roadside buildings.

We define the seismic intensity in terms of *peak ground acceleration (PGA)* level which measures how intensive the ground shakes in a given geographic area. In the previous studies such as JICA report [3], the earthquake risk assessment of İstanbul for the determination of earthquake ground motion is carried according to the deterministic methodology based on a selected earthquake scenario. Erdik et al. [26] propose a probabilistic methodology which is the combination of infinitely many earthquake scenarios for the relative comparison of ground motions in different sites in İstanbul. They choose to use a time dependent method because the earthquakes occurring along the North Anatolian Fault show characteristic earthquake property, i.e., the earthquakes are major and repeating earthquakes. Accordingly, they calculate site dependent PGA distributions corresponding to different exceedance probabilities for given time intervals. In this study, we use the one with 50% probability of exceedance in 50 years shown in Figure 5.3.

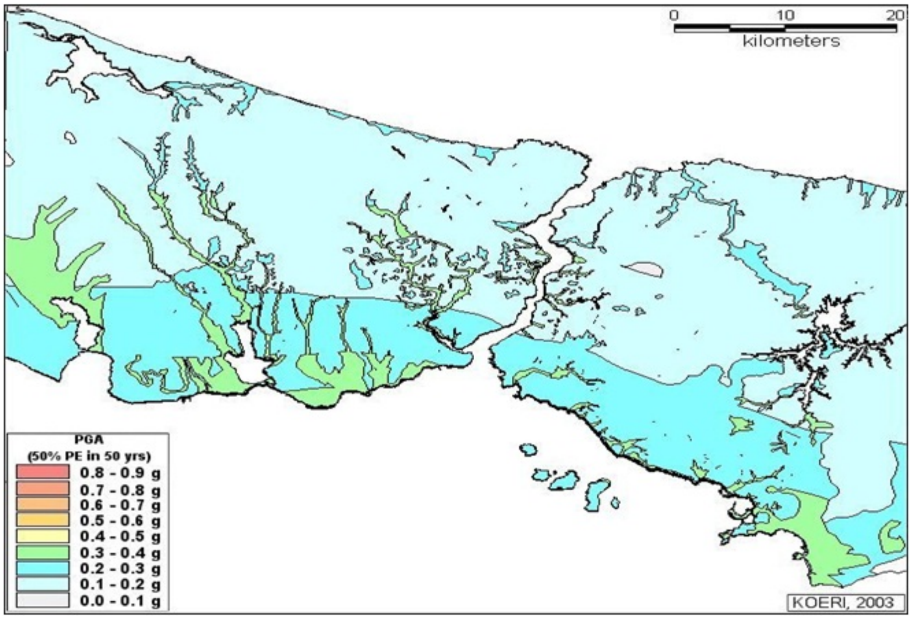

Figure 5.3: Site Dependent PGA Distribution With 50% Probability of Exceedance in 50 Years

According to this model, three PGA intervals exist in İstanbul. We represent these intervals as risk levels, where risk level 1 shows the region with high seismic risk, risk level 2 is the region with average seismic risk and risk level 3 is the region with low seismic risk given in Table 5.1. We identify the regions in which the nodes fall. An edge can be located in more than a single region, and it will be nonoperational if one of its adjacent nodes fails. Therefore, we take the seismic risk level of an edge as the maximum seismic risk level of its adjacent nodes. Then, we estimate the survival probability to each edge according to its risk level. We assign random survival probabilities with uniform distribution between 95-100 %, 90-94 % and 85-89% for risk level 1, 2 and 3, respectively. These survival probabilities represent the strength of links against the earthquake deformations.

We further partition edges in each region according to the earthquake vulnerability of structures on them. Within the boundaries of the 17^{th} Division of Highway

PGA (50% in 50 Years)	Risk Level
0.3-0.4 g	1
0.2-0.3 g	2
0.1-0.2 g	3

Table 5.1: Risk Levels

of State Highways of Turkey, 123 bridges/viaducts exist, 45 of them being on the Motorway O1, 51 on the Motorway O2 and 27 on the secondary roads [26]. In 2011, the 17^{th} Division was merged with the 1^{st} Division of State Highways [2] which is responsible for the roads and the bridges of the national motorways and intercity road network in the Marmara Region. Accordingly, the number of bridges in the city centre adds up to 165 bridges [5]. Among these bridges and viaducts, the coordinates of 104 structures are available in [26]. With GoogleMaps and ArcGIS, we identify network edges on which these structures are located. To partition these structures and indirectly the edges into structural sets, we use the preliminary earthquake risk assessment of bridges and viaducts on Motorways O1, O2 and secondary roads [14] and [38]. This preliminary assessment was conducted with the scoring method of ATC 6-2, one of the three widely used methods for preliminary assessment and priority listing of structures.

In this method, the vulnerability, seismicity and structure importance are equally important factors for the preliminary assessment. Vulnerability is about the structural properties such as type of bearing, skew angle of the superstructure, minimum support length, height of the middle bents, height of the abutments, seating at the abutments due to landfill. Seismicity represents the earthquake intensity, geology and geotechnical surrounding of the structure. Finally, importance of the structure is related to the daily average traffic, the physical size of the structure, population around the area of structure, usage, the role of the structure for transportation to the important facilities such as hospitals and fire departments. Each one of these factors is evaluated for each bridge/viaduct and given a score between 1 and 10. Then, the scores multiplied by 3.33 are added up to find the total score. Accordingly, a bridge/viaduct with a total score of 100 is the riskiest structure in an earthquake while a bridge/viaduct with a total score of 0 is risk free.

In our study, we exclude the importance of the structure factor in the structural property-based partitioning of bridges/viaducts since we are interested in the earthquake vulnerability of the structures. Hence, we modify the ATC 6-2 total scores as in 5.1.

$$\frac{\textit{Total Score-(3.33*Importance of Structure)}}{5 * 3.33} \tag{5.1}$$

The factors with their scores, total scores and modified total scores for bridges and viaducts of İstanbul evaluated with ATC 6-2 are shown in Figure A.1. Using the histogram in Figure 5.4, we analyse the distribution of the modified total scores and divide the structures based on their modified total scores into three sets. Between 100-70, the structures are at high risk, between 70-55 the structures are at medium risk and below 55 they are at low risk. According to the risks levels, the survival probabilities of edges carrying these structures are modified. For an edge having more than one structure on it, the riskiest structure determines its earthquake vulnerability. We decrease the survival probabilities of edges having a structure with a total score between 100-70 by 0.3, 70-55 by 0.2 and below 55 by 0.1.

Overall, we divide edges into 9 dependency sets and estimate the reliability of individual edges accordingly. The sets and the edges in each dependency set are given in Table 5.2.

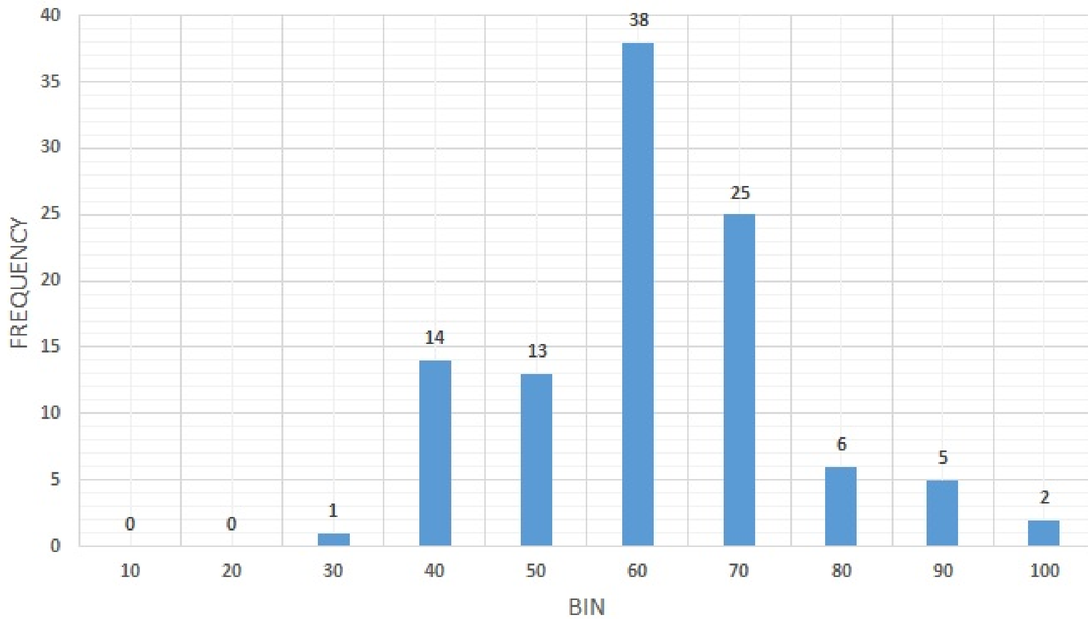

Figure 5.4: Histogram for Modified ATC 6-2 Scores

Sets	Edges
Set 1	81 1 6 4 19 52 22 21 13 2 23 10 11 12 50 53
Set 2	51 80 25 83 70 72 7 16 27 37 5 15 69 43 29 39 78 45 79 9 20 24 54 82 14 44 8 65
Set 3	67 66 71 68 35
Set 4	26 31 55
Set 5	49 77 48 56
Set 6	33 18 17 57 63 75 38 58 32 47 41 34 30 46 42 61
Set 7	36 40 62
Set 8	60 74 3 59
Set 9	28 64 76 73

Table 5.2: Dependency Sets

5.2 Results

We coded Algorithm 3.1 in C++ and conducted all other calculations in Matlab. We used a computer with a Intel(R) Xeon(R) CPU E5-2643 3.30 GHz processor and 32 GB RAM.

5.2.1 Sample Size Analysis

To decide on the replication number to be used in Algorithm 3.1, we tested different replication numbers for $\alpha = 0.20$ and calculated the accessibility measure with the set of paths generated with k-shortest path algorithm for each replication number. We report the number of replication (R), estimated $EWAD$ in kilometres, the variation(VAR), *Pearson Variation Index* (PVI), the lower bound ($LB_{95\%}$) and upper bound ($UB_{95\%}$) of 95% confidence interval on $EWAD$ given in Table 5.3.

R	250,000	500,000	750,000	1,000,000
$EWAD$	35.04	35.03	35.05	35.03
VAR	60.53	60.61	60.45	60.31
PVI	0.22	0.22	0.22	0.22
$LB_{95\%}$	35.01	35.01	35.03	35.02
$UB_{95\%}$	35.07	35.06	35.07	35.05

Table 5.3: Sample Size Analysis

In Table 5.3, $EWAD$ changes slightly as the replication number increases and the PVI remains almost unchanged. Hence, we choose R to be 1,000,000. However, the replication number is not equal to the number of unique realizations in the sample. In Table 5.4, we report the number of distinct realizations with different values of α for $R = 1,000,000$.

For $\alpha = 0$, the number of unique realizations is almost the same as the replication number whereas the number of unique realizations is lower for $\alpha = 1$. Between two extreme cases $\alpha = 0$ and $\alpha = 1$, the number of unique realizations oscillate. To track the differentiation with respect to the control parameter α, we investigated the average Hamming distance explained in Section 3.0.3. However, it takes too much time with a sample of 1,000,000 realizations. Thus, we generated samples with $R = 10,000$ and calculate the average Hamming distances for each control parameter values. In Table 5.5, we report the number of unique realizations and the average Hamming distance

α	# of Unique Realizations
0	998,056
0.02	998,426
0.05	998,663
0.1	998,922
0.15	999,103
0.2	999,086
0.25	999,023
0.5	995,829
0.75	966,034
1	829,829

Table 5.4: Size of Distinct Realizations Set with R=1,00,000

for each control parameter α. The results show that the average Hamming distance increases as the control parameter increases from 0 to 1. For $\alpha = 0.5$ and higher, the average Hamming distance changes slightly. This means that the generated samples for $\alpha = 0.5$ and higher have very similar composition of unique network realizations. Therefore, we investigate α values for $\alpha = 0.2$ and less and *VB-dependency* case ($\alpha = 1$).

In this study, a network realization represents the binary states of 83 edges. Therefore, the average Hamming distance can also be interpreted as the average number of edges that are different between network realizations in a given sample of unique realizations. For instance on the average, each network realization differentiates from the rest of the network realizations with 16 edges in a sample of 10,000 unique realizations for $\alpha = 0$. On the other hand, the number of edges that cause differentiation is 27 in a sample of 10,000 unique realizations for $\alpha = 0.2$. It is 29 edges for $\alpha = 1$ and 9957 unique realizations. This indicates that, as edges more strongly depend on each other, the realizations in the sample differentiate.

α	Number of Unique Realizations	Average Hamming Distance
0	10,000	16.12
0.02	10,000	17.52
0.05	10,000	19.69
0.1	9,999	23.48
0.15	10,000	25.74
0.2	10,000	27.12
0.25	10,000	27.69
0.5	9,999	28.61
0.75	9,993	28.63
1	9,957	28.85

Table 5.5: Average Hamming Distance with R=10,000

5.2.2 Path Generation

In this section, we explain the generation of alternative emergency path sets between each demand and each emergency facility location point by three methods explained in Chapter 2. With the pre-processing explained in Section 4.1.1, we select a subset of these paths for each demand point among the generated paths. For each demand point, we select all generated paths with path length less than the $PenaltyCost$ of 60 km.

Firstly, we generated dissimilar paths with k-shortest path algorithm between each demand point and each emergency facility location. We generated 80 paths for each O - D pair ($k = 80$). For each demand point, we selected all paths with path length less than 60 km.

Secondly, we coded *IPM* [20] and generated dissimilar paths accordingly. We used additive penalty structure penalizing the links on the most recent path. We tried out the several penalty amounts proportional to the edge lengths. We applied the same pre-processing procedure that we use in k-shortest path algorithm in this method. We observed that the number of paths and the composition of path sets are similar for different penalty amounts due to the pre-processing procedure. Thus, we only report the results of path set with penalty of 40 km as a representative path set.

Thirdly, we coded the method based on p-dispersion problem by Akgün et al. [4] in Matlab. For the candidate path set generation, we used the k-shortest path algorithm. We took $k = 10$ and $k = 30$. In the method, we set $p = 3$. Since, p-dispersion method selects the most dissimilar p paths among a candidate set, the final set of paths may not contain the shortest path. However, excluding the shortest path in emergency response planning is not realistic. Therefore, we suggest to generate a set of paths by merging the set of paths generated by p-dispersion method and set of shortest paths from a demand point to each supply point. We generate and report the results of paths for the candidate sets with $k = 10$ and $k = 30$.

Although *IPM* generates better candidate paths set in terms of dissimilarity compared to the one generated by k-shortest path algorithm, the average path length in the candidate set generated by *IPM* is higher than the average path length in the set generated by the k-shortest path algorithm. Since the average path length is one of the key measures in emergency response activities, *IPM* is disadvantageous compared to k-shortest path algorithm. Thus, we chose to apply k-shortest path algorithm to obtain a candidate set.

The number of paths (#), the minimum (Min) and maximum (Max) path lengths for each demand point in each method is given in Table 5.6 and Table 5.7. The last rows of the tables give the averages of these quantities.

- A stands for k-shortest path algorithm
- B for *IPM* with penalty of 40
- C for p-dispersion method with $p = 3$,$k = 10$
- D for p-dispersion method with $p = 3$, $k = 30$

- E for the modified p-dispersion method with $p = 3$, $k = 10$
- F for modified p-dispersion method with $p = 3$, $k = 30$.

In terms of the average number of paths with less length than *PenaltyCost* the methods generate, p-dispersion method yields less number of paths and higher Min and Max values compared to other methods. The modified p-dispersion method for both $k = 10$ and $k = 30$ yields more number of paths and lower Min and Max values compared to p-dispersion method. The properties of paths generated by k-shortest path algorithm and *IPM* are almost the same in both methods for each demand point.

5.2.3 EWAD

Initially, we determine the range of possible values that the performance measure can take. We calculate *EWAD* for the case in which all edges survive. This case represents the pre-disaster condition of the highway network and gives the deterministic lower bound on *EWAD* that is equal to 20.47 km. Similarly, the case when all edges fail gives the deterministic upper bound that is equal to *PenaltyCost*, 60 km.

For each dissimilar path generation method with its parameters in Section 5.2.2, we estimate *EWAD* for chosen α values (0.02, 0.05, 0.10, 0.15, 0.20), the independent link failure case (*Indep.*) and the *VB-dependency* (*VB*). We report the elapsed time (*ET*) in seconds, estimated *EWAD* in kilometres, the variation(*VAR*), *Pearson Variation Index* (*PVI*), the lower bound ($LB_{95\%}$) and upper bound ($UB_{95\%}$) of 95% confidence interval on *EWAD*. The results are given in Tables 5.8, 5.9, 5.10, 5.11, 5.12, and 5.13.

The execution time of calculation for each control parameter and set of paths is below an hour. For each dissimilar paths set, the calculation of *EWAD* in *VB-dependency* case takes the longest execution time for Algorithm 4.2 compared with other α values because Algorithm 4.2 checks the paths in the path set in non-increasing

	A			*B*			*C*		
Demand No	#	Min	Max	#	Min	Max	#	Min	Max
1	64	14.04	59.89	51	14.04	59.75	17	28.35	59.62
2	55	8.60	59.99	40	8.60	59.42	10	45.96	59.10
3	38	22.40	59.64	34	22.40	59.87	14	22.40	59.64
4	70	8.77	56.91	51	8.77	60.00	19	8.77	59.58
7	63	21.16	59.86	48	21.16	58.84	15	46.76	59.86
8	70	7.18	45.42	84	7.18	59.35	24	11.79	46.75
9	70	12.12	59.76	52	12.12	59.77	20	17.66	59.77
10	37	31.66	59.25	29	31.66	58.66	14	31.66	57.56
12	29	41.62	59.88	27	41.62	59.88	11	41.62	59.88
13	37	18.53	59.85	32	18.53	59.85	10	24.57	58.33
14	70	26.98	52.05	60	26.98	59.97	23	29.07	59.97
15	47	30.01	59.46	41	30.01	59.46	14	30.01	59.46
16	70	22.30	55.00	70	22.30	59.56	22	22.30	59.49
18	70	12.93	46.33	84	12.93	59.91	24	17.54	49.97
19	70	4.76	59.23	51	4.76	59.27	17	4.76	59.27
21	70	11.15	49.97	73	11.15	59.04	24	11.15	52.04
22	23	25.73	59.95	17	25.73	59.95	7	32.34	59.84
23	70	8.79	59.69	51	8.79	59.51	21	8.79	59.91
24	37	12.67	59.99	27	12.67	59.99	12	12.67	59.99
25	13	39.43	59.58	12	39.43	59.58	5	45.46	56.11
26	16	30.50	59.58	15	30.50	59.58	2	36.54	42.04
27	70	15.98	59.78	49	15.98	59.39	15	15.98	56.50
29	28	20.60	59.95	18	20.60	58.99	6	26.64	59.95
30	70	19.78	51.08	80	19.78	59.64	24	30.64	55.35
31	11	41.40	59.97	11	41.40	59.97	2	47.44	52.94
32	70	5.57	58.42	52	5.57	60.00	13	5.57	58.42
Average	51.46	19.79	57.33	44.58	19.79	59.58	14.81	25.25	56.97

Table 5.6: Properties of Path Sets

order with respect to path length until it finds an operational path. In *VB-dependency* case, more paths are checked compared to other α values.

As expected, the increase in α increases $EWAD$ for all three path-generation methods. As α increases, the failure of edges becomes more dependent to the failure of stronger edges in the same dependency set.

The variation (VAR) is the highest for *VB-dependency* case which can be justified with the average Hamming distance. We observe the maximum average Hamming

		D			*E*			*F*	
Demand No	#	Min	Max	#	Min	Max	#	Min	Max
1	0	0.00	0.00	25	14.04	59.62	8	14.04	45.4
2	0	0.00	0.00	18	8.6	59.42	8	8.6	59.42
3	13	22.40	59.64	14	22.4	59.64	13	22.4	59.64
4	15	8.77	58.36	23	8.77	59.58	18	8.77	58.36
7	2	57.98	58.84	23	21.16	59.86	10	21.16	58.84
8	22	7.18	55.89	28	7.18	46.75	24	7.18	55.89
9	1	58.53	58.53	27	12.12	59.77	9	12.12	58.53
10	12	31.66	57.56	15	31.66	57.56	12	31.66	57.56
12	10	41.62	59.88	13	41.62	59.88	11	41.62	59.88
13	1	19.30	19.30	16	18.53	58.33	6	18.53	56.23
14	5	48.73	59.41	31	26.98	59.97	13	26.98	59.41
15	13	30.01	59.46	17	30.01	59.46	14	30.01	59.46
16	17	22.30	58.49	27	22.3	59.49	20	22.3	58.49
18	22	12.93	58.10	31	12.93	49.97	27	12.93	58.1
19	9	4.76	58.36	22	4.76	59.27	13	4.76	58.36
21	19	11.15	58.09	29	11.15	52.04	21	11.15	58.09
22	5	32.34	58.09	11	25.73	59.84	8	25.73	58.09
23	15	8.79	43.96	24	8.79	59.91	18	8.79	57.38
24	6	12.67	59.99	16	12.67	59.99	9	12.67	59.99
25	4	45.46	59.58	8	39.43	59.58	6	39.43	59.58
26	2	31.27	50.65	7	30.5	58.54	5	30.5	58.54
27	11	15.98	54.78	19	15.98	56.5	13	15.98	54.78
29	4	26.64	58.98	10	20.6	59.95	9	20.6	60.42
30	4	52.51	59.97	32	19.78	55.35	12	19.78	59.97
31	2	47.44	52.94	3	41.4	52.94	3	41.4	52.94
32	9	5.57	59.50	20	5.57	58.42	13	5.57	59.5
Average	8.58	25.23	51.48	19.58	19.79	57.76	12.42	19.79	57.80

Table 5.7: Properties of Path Sets

	Indep.	$\alpha = 0.02$	$\alpha = 0.05$	$\alpha = 0.10$	$\alpha = 0.15$	$\alpha = 0.20$	*VB*
ET	562	605	677	885	1094	1189	1706
$EWAD$	24.81	25.41	26.63	29.39	32.43	35.03	45.11
VAR	7.24	9.45	15.06	31.03	48.22	60.31	74.75
PVI	0.11	0.12	0.15	0.19	0.21	0.22	0.19
$LB_{95\%}$	24.81	25.41	26.62	29.38	32.42	35.02	45.09
$UB_{95\%}$	24.82	25.42	26.63	29.40	32.44	35.05	45.13

Table 5.8: $EWAD$ with k-shortest Path Algorithm

	Indep.	$\alpha = 0.02$	$\alpha = 0.05$	$\alpha = 0.10$	$\alpha = 0.15$	$\alpha = 0.20$	*VB*
ET	533	537	626	793	998	1132	1456
$EWAD$	24.83	25.43	26.65	29.43	32.48	35.08	45.13
VAR	7.33	9.57	15.25	31.38	48.60	60.65	74.78
PVI	0.11	0.12	0.15	0.19	0.21	0.22	0.19
$LB_{95\%}$	24.82	25.42	26.65	29.41	32.46	35.07	45.11
$UB_{95\%}$	24.83	25.44	26.66	29.44	32.49	35.10	45.15

Table 5.9: $EWAD$ with IPM $(Penalty = 40)$

	Indep.	$\alpha = 0.02$	$\alpha = 0.05$	$\alpha = 0.10$	$\alpha = 0.15$	$\alpha = 0.20$	*VB*
ET	380	393	432	500	572	638	740
$EWAD$	29.77	30.39	31.58	34.19	36.93	39.24	47.82
VAR	8.47	10.60	15.62	28.55	41.44	50.01	58.34
PVI	0.10	0.11	0.13	0.16	0.17	0.18	0.16
$LB_{95\%}$	29.77	30.38	31.58	34.18	36.92	39.23	47.80
$UB_{95\%}$	29.78	30.39	31.59	34.20	36.94	39.25	47.84

Table 5.10: $EWAD$ with p-dispersion Method $(p = 3, k = 10)$

	Indep.	$\alpha = 0.02$	$\alpha = 0.05$	$\alpha = 0.10$	$\alpha = 0.15$	$\alpha = 0.20$	*VB*
ET	629	842	843	841	965	1047	1179
$EWAD$	32.25	32.81	33.91	36.22	38.64	40.70	48.48
VAR	6.53	8.48	12.92	23.69	34.33	41.77	52.92
PVI	0.08	0.09	0.11	0.13	0.15	0.16	0.15
$LB_{95\%}$	32.24	32.81	33.90	36.21	38.63	40.68	48.47
$UB_{95\%}$	32.25	32.82	33.91	36.23	38.65	40.71	48.50

Table 5.11: $EWAD$ with p-dispersion Method $(p = 3, k = 30)$

	Indep.	$\alpha = 0.02$	$\alpha = 0.05$	$\alpha = 0.10$	$\alpha = 0.15$	$\alpha = 0.20$	*VB*
ET	382	403	441	527	624	706	854
$EWAD$	25.58	26.25	27.59	30.55	33.72	36.38	46.38
VAR	8.93	11.53	17.87	34.99	52.30	63.68	72.35
PVI	0.12	0.13	0.15	0.19	0.21	0.22	0.18
$LB_{95\%}$	25.57	26.25	27.58	30.54	33.71	36.37	46.36
$UB_{95\%}$	25.59	26.26	27.60	30.56	33.73	36.40	46.39

Table 5.12: $EWAD$ with p-dispersion Method Modified $(p = 3, k = 10)$

	Indep.	$\alpha = 0.02$	$\alpha = 0.05$	$\alpha = 0.10$	$\alpha = 0.15$	$\alpha = 0.20$	*VB*
ET	305	325	351	408	467	536	602
$EWAD$	25.87	26.59	28.01	31.10	34.34	37.01	46.81
VAR	9.75	12.56	19.38	37.22	54.31	64.92	70.77
PVI	0.12	0.13	0.16	0.20	0.21	0.22	0.18
$LB_{95\%}$	25.87	26.58	28.00	31.09	34.33	37.00	46.79
$UB_{95\%}$	25.88	26.60	28.01	31.11	34.36	37.03	46.83

Table 5.13: $EWAD$ with p-dispersion Method Modified ($p = 3, k = 30$)

distance in *VB-dependency* case. As the number of edges that are different in each realization increases, the variation among the generated paths increases. Hence, the accessibility measure can take dissimilar values between the deterministic lower and upper bounds in each realization.

Although the variance increases drastically, PVI, the ratio of standard deviation to the mean, remains lower than 0.25 in all cases. Additionally, the length of 95% confidence interval confirms that we are able to accurately estimate $EWAD$ for the sample of realizations for each α in all methods.

Among all three path generation methods, p-dispersion method yields the largest $EWAD$ for each α value. The first reason is that the set of paths generated by p-dispersion method do not necessarily contain the shortest path from demand point to the closest emergency facility location. Secondly, the number of paths generated by p-dispersion method which are less than $PenaltyCost$ is also smaller than the number of paths generated by other methods. Thus, this method does not suggest as many alternative paths as the other two methods do.

The size of the candidate set affects the accessibility measure in p-dispersion method. The paths generated by p-dispersion method vary in length. Selecting a subset from a larger candidate set may result in paths with larger path lengths compared to selecting from a smaller candidate set. Since the candidate sets are generated by k-shortest path algorithm, the larger set includes all paths in the smaller set. Thus, a candidate set with 30 paths yields larger *EWAD* compared to a candidate set with 10 paths. Relatively, the difference between $k = 10$ and k=30 is larger for α values less than 0.25.

The result for k-shortest path algorithm and *IPM* are almost equal for each α value. As a result of pre-processing, the set of paths generated by each method are quite similar since generated paths for each demand point to every emergency facility are sorted and the paths with lengths less than *PenaltyCost* are taken into consideration. However, as we increase the penalty amount, *IPM* yields slightly better *EWAD* for each α compared to k-shortest path algorithm. As penalty increases, generated paths become more dissimilar and thus they may remain operational in given scenarios.

The suggested modified p-dispersion method yields better results in terms of accessibility than the results with p-dispersion method, however still worse than the ones with k-shortest path algorithm and *IPM*. For small values of the control parameter, *EWAD* with path sets of modified p-dispersion method is 5-6 km less than the results with the path sets of original p-dispersion method. In *VB-dependency* case, the both methods produce accessibility measures close to each other. The reason is that the shortest paths do not survive in *VB-dependency* case and the modification of p-dispersion method becomes irrelevant.

5.2.4 Demand Service Levels

We calculated each type of service level for each demand point with each path generation method. To exemplify this analysis, we present the results for Beylikdüzü district. *Service Level I* with $\gamma = 25$, *Service Level I* with $\gamma = 50$, *Service Level II* and *Service Level III* of Beylikdüzü for different α values are given in Figure 5.6, Figure 5.5, Table 5.14, and Figure 5.7, respectively. In the figures, A represents the results for k-shortest path algorithm, B for *IPM* with penalty of 40, C for p-dispersion method with $p = 3$, $k = 10$, D for p-dispersion method with $p = 3$, $k = 30$, E for the modified p-dispersion method with $p = 3$, $k = 10$ and F for modified p-dispersion method with $p = 3$, $k = 30$.

Among α values, each service level performs at its best with $\alpha = 0$ for each path generation method. As the results for $EWAD$ have shown, p-dispersion method produces low service levels. However, the path set with modified p-dispersion method increases the demand service levels in both candidate sets.

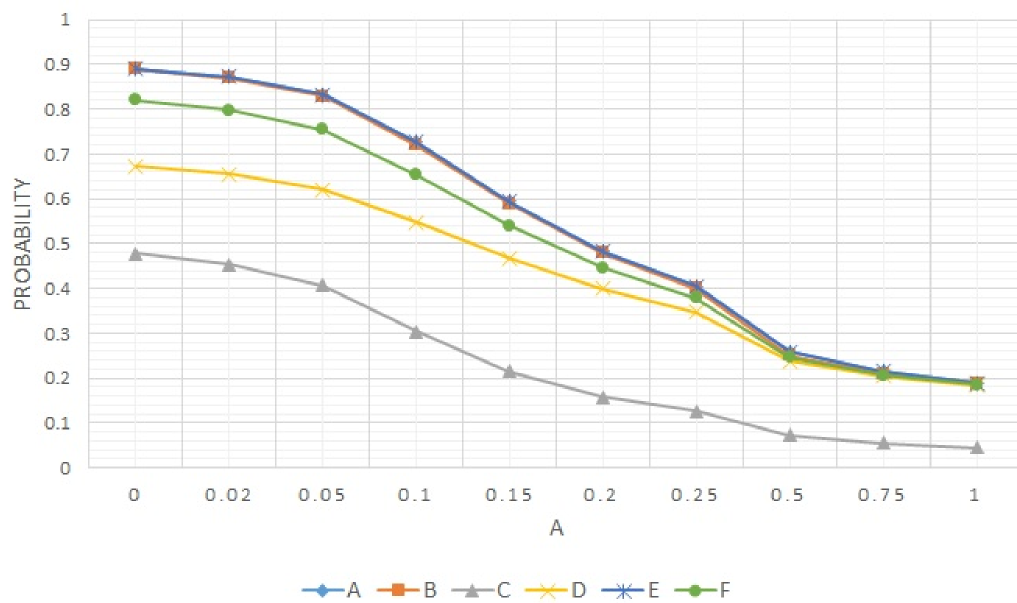

Figure 5.5: Beylikdüzü - *Service Level I* ($\gamma = 25$)

We calculate *Service Level I* of Beylikdüzü with two distance threshold values. For $\gamma = 25$, *Service Level I* converges to 0.2 as α increases from 0 to 1 for each path generation method except for p-dispersion method with $p = 3$, $k = 10$ which performs worse than any other methods. Although p-dispersion method with $p = 3$, $k = 10$ outperforms p-dispersion method with $p = 3$, $k = 30$ in accessibility measure, investigating a single district shows that selecting more dissimilar paths from a larger candidate set can improve the probability of coverage.

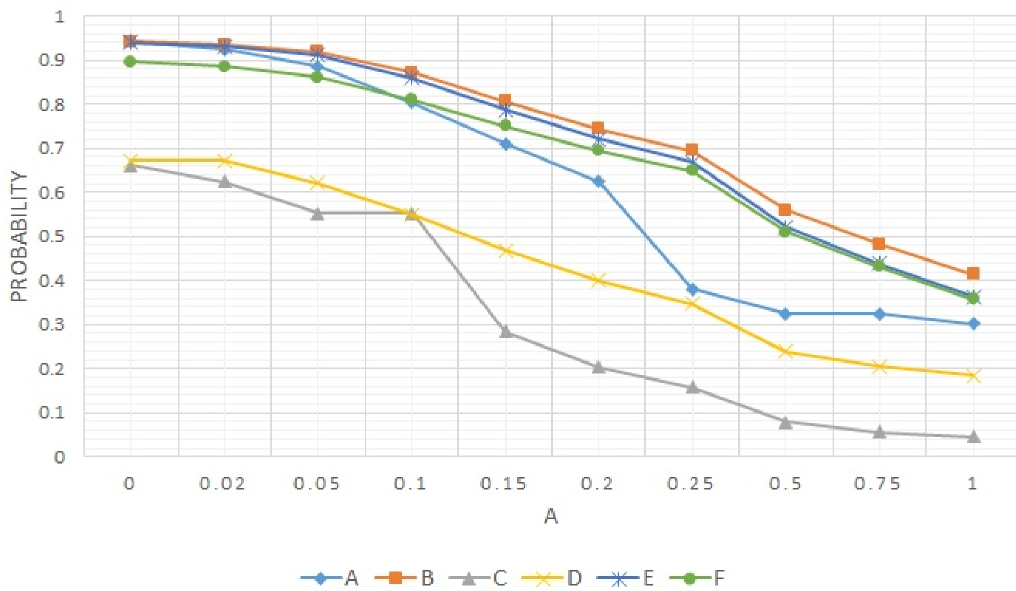

Figure 5.6: Beylikdüzü - *Service Level I* ($\gamma = 50$)

The service levels with k-shortest path algorithm and *IPM* do not suggest any differentiation for $\gamma = 25$. With the threshold increase from 25 to 50, *IPM* outperforms k-shortest path algorithm. Additionally, for $\gamma = 50$, the service level for p-dispersion methods increase compared to the service levels for $\gamma = 25$, since longer paths become acceptable with larger threshold value.

We observe that *Service Level II* values of Beylikdüzü are below 50% for each α value. This means that Beylikdüzü has low probability of getting service from its closest facility. Although the probability of best-case service level is low, Beylikdüzü has high connectivity level (*Service Level III*) for small values of α shown in Figure 5.7. The connectivity is above 50% for each path generation method.

α	0	0.02	0.05	0.1	0.15	0.2	0.25	0.5	0.75	1
Service Level II	0.45	0.42	0.36	0.27	0.18	0.13	0.09	0.03	0.02	0.010

Table 5.14: Beylikdüzü - *Service Level II*

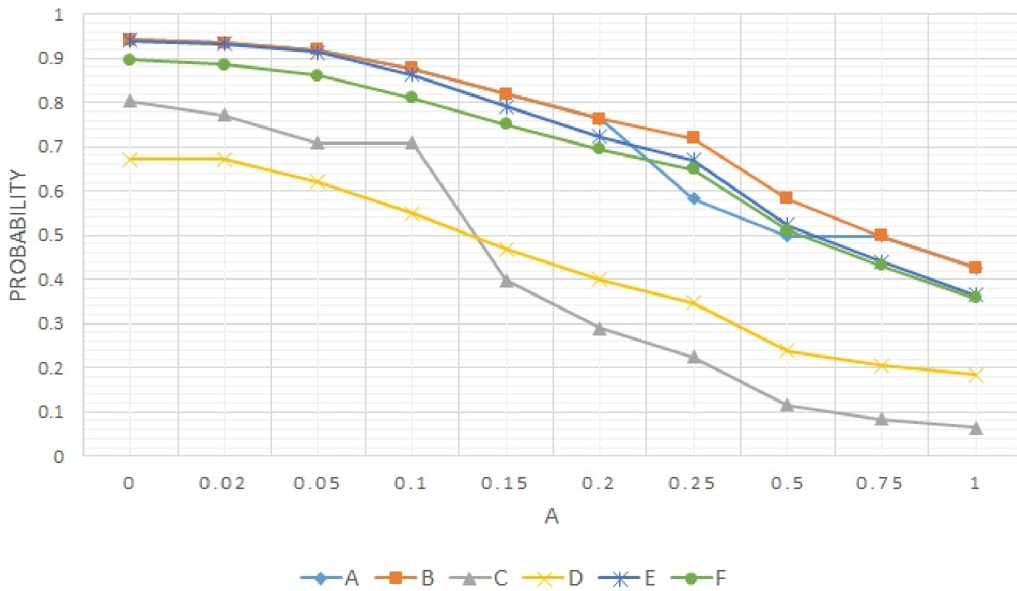

Figure 5.7: Beylikdüzü - *Service Level III*

5.2.5 *Fairness*

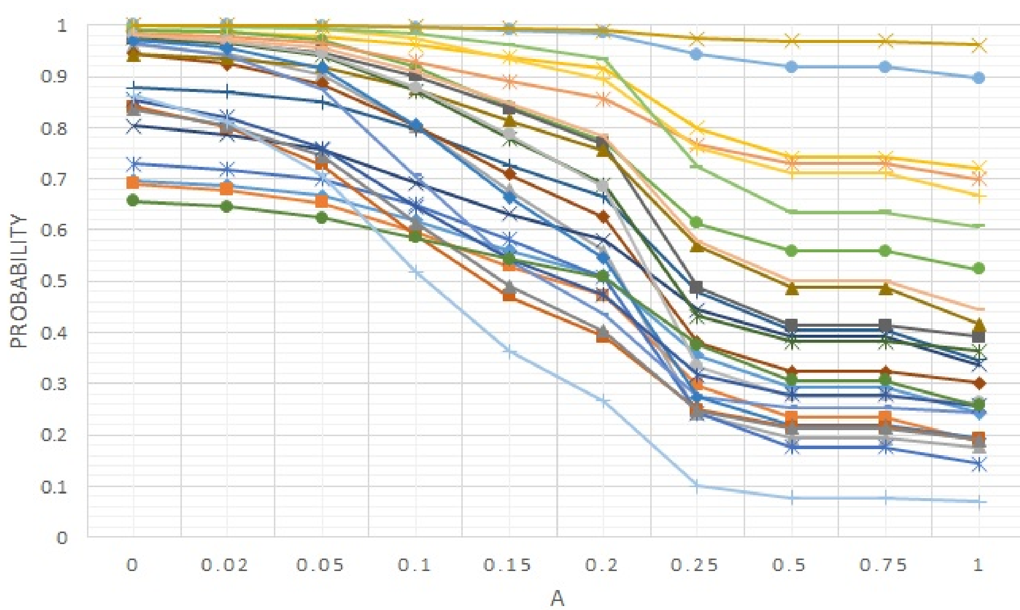

Figure 5.8: Variability Among Demand Points For *Service Level I* ($\gamma = 50$)

Figure 5.8 shows the variability of *Service Level I with γ=50* among 26 demand points with path set generated by k-shortest path algorithm. This service level takes diverse values for different demand points. In order to quantify this variability, we calculate PVI as explained in Section 4.2 for each service level given in Tables 5.15, 5.16, 5.17, and 5.18.

α	0	0.02	0.05	0.1	0.15	0.2	1
A	84.22%	84.71%	85.59%	87.54%	90.38%	93.80%	118.30%
B	84.22%	84.71%	85.59%	87.54%	90.38%	93.80%	118.30%
C	105.01%	105.37%	106.21%	108.84%	113.20%	118.41%	146.94%
D	111.29%	111.44%	111.83%	113.16%	115.71%	118.99%	140.48%
E	84.21%	84.71%	85.62%	87.62%	90.48%	93.94%	122.78%
F	84.23%	84.75%	85.68%	87.73%	90.66%	94.16%	122.97%

Table 5.15: PVI (*Service Level I* (γ=25))

α	0	0.02	0.05	0.1	0.15	0.2	1
A	12.07%	12.78%	14.46%	19.20%	25.25%	30.78%	61.18%
B	12.21%	12.94%	14.64%	19.35%	25.31%	30.75%	60.70%
C	30.21%	32.19%	35.68%	35.68%	49.31%	55.22%	89.31%
D	58.51%	58.51%	62.25%	67.06%	71.97%	76.76%	106.00%
E	84.21%	84.71%	85.62%	87.62%	90.48%	93.94%	122.78%
F	84.23%	84.75%	85.68%	87.73%	90.66%	94.16%	122.97%

Table 5.16: PVI (*Service Level I* (γ=50))

α	0	0.02	0.05	0.1	0.15	0.2	1
PVI	45.83%	47.18%	49.65%	55.35%	62.69%	70.09%	115.63%

Table 5.17: PVI(*Service Level II*)

PVI for *Service Level III* is low for small values of α which indicates that the level of connectivity is similar among demand points. PVI for *Service Level I*, the supplementary indicator of connectivity, points out that the distances to be covered are diverse among demand points.

α	0	0.02	0.05	0.1	0.15	0.2	1
A	11.60%	12.09%	13.29%	17.11%	22.44%	27.47%	56.45%
B	11.56%	12.04%	13.17%	16.92%	22.32%	27.46%	56.89%
C	22.72%	24.55%	27.80%	27.80%	41.02%	47.08%	82.68%
D	43.17%	43.17%	46.50%	50.59%	55.10%	59.75%	92.85%
E	14.22%	15.29%	17.22%	21.40%	26.67%	32.06%	67.98%
F	14.93%	16.13%	18.30%	22.92%	28.60%	34.26%	71.58%

Table 5.18: PVI (*Service Level III*)

PVI for *Service Level I* depends heavily on the threshold value γ. The increase in γ from 25 to 50 decreases the variability of the service level among demand points, hence it increases the fairness significantly. A vivid example is the change in service level with k-shortest path algorithm (A) for $\gamma = 25$ and $\gamma = 50$. With $\gamma = 50$, the variability among demand points is around 20% for $\alpha = 0.1$ while it is around 90% with $\gamma = 25$. This means that, most of the demand points cannot be served within short distances.

Finally, the PVI for *Service Level II* indicates that there is high variability between demand points in terms of getting service from their closest facilities. While some demand points can get service from their closest facility, others are directed to farther emergency facilities.

Chapter 6

CONCLUSION

Predicting the post-earthquake status of highway networks is important for the decision-making process in the planning stage. In this study, we concentrated on modelling the post-earthquake status of highway networks subject to an earthquake risk realistically. We assumed that the radiation of seismic waves and structural properties of network components on the network links create dependent link failures. Thus, we proposed a practical dependency model in which we defined a control parameter that represents spatial and structural dependency between link failures in mutually exclusive dependency sets. While the independent link failure model suggests an optimistic view of the surviving network and the *VB-dependency* model gives more probability to the worst-case scenarios, the control parameter allows us to investigate more realistic dependency levels for link failures. Although, different control parameters in different dependency sets can be used, we chose to use the same control parameter in each dependency set to simplify the computation.

According to this model, it is possible to generate a family of joint probability distributions for the survival of network edges/the network realizations with varying levels of dependency. We gave the representation of the dependency model using belief networks and showed that the probability of any network realization can be computed by the chain rule. However, as the network size gets larger, the computational time makes this method intractable. For large networks, network realizations from the generated distribution according to the chosen dependency level can be sampled using an external sampling algorithm.

The transportation of casualties to health care facilities and the distribution of relief aid supplies are two essential response activities in the aftermath of an earthquake. These activities are carried out between various origin and destination (O - D) points that are identified in the pre-disaster planning stage. It is advantageous to identify a number of alternative paths between these O - D pairs by which the post-earthquake network performance and reliability can be predicted. In the event of a disaster, response activities can be initiated according to the condition of these alternative paths. Moreover, in the case of disconnectivity between an O - D pair, the retrofitting the connectivity can start with these paths. For these reasons, we studied path generation methods in the literature and generated set of dissimilar paths between O - D pairs. Using a pre-processing approach we identified a set of alternative paths for each demand point.

We proposed a path-based accessibility measure and tested the network performance of İstanbul highway network according to the sampled network realizations and generated set of alternative paths between O - D pairs. We investigated the dissimilarity of the selected paths and its effects on the accessibility. In addition to that, we assessed three demand service levels and fairness among demand points with respect to these service levels.

We used the length of paths instead of travel times since it is hard to predict travel times in the disaster context. Additionally, we used uncapacitated supply points since the capacities change after a disaster with the incoming relief items and establishment of temporary facilities. However, a study with current facility capacities can be conducted to determine the congestion points and solve facility locations problems for the additional temporary facility locations to be built in the aftermath of an earthquake. Finally, the failure of supply points and junction points can be taken into consideration to study the node failures.

BIBLIOGRAPHY

[1] Debris Management Guide. http://www.fema.gov/public-assistance-local-state-tribal-and-non-profit/debris-management-guide#4. Accessed: 02/08/2013.

[2] http://www.kgm.gov.tr/Sayfalar/KGM/SiteTr/Bolgeler/1Bolge/Bolge1.aspx. Accessed: 07/11/2012.

[3] The study on a disaster prevention-mitigation basic plan in İstanbul including micro-zonation in the republic of Turkey. Final report volume V. Technical report, Japanese International Cooperation Agency and Local Municipality of İstanbul, September 2002.

[4] V. Akgün, E. Erkut, and R. Batta. On finding dissimilar paths. *European Journal of Operational Research*, 121:232 – 246, 2000.

[5] N. Apaydın. Earthquake retrofit campaign for large scale bridges in İstanbul. Stresa,Lake Maggiore,Italy, July 8 - 12 2012. IABMAS 2012 6th International Conference on Bridge Maintenance, Safety and Management, Taylor and Francis.

[6] M. N. Aydınoğlu and M. Erdik. 17 January 1995 Hyogo-Ken Nanbu (Kobe) earthquake reconnaissance and assessment report. Technical report, Boğaziçi University Kandilli Observatory and Earthquake Research Institute, 1995.

[7] Z. I. Botev, P. L'Ecuyer, G. Rubino, R. Simard, and B. Tuffin. Static network reliability estimation via generalized splitting. *INFORMS Journal on Computing*, 2012.

[8] E. Castillo, C. Solares, and P. Gómez. Estimating extreme probabilities using tail simulated data. *International Journal of Approximate Reasoning*, 17:163 – 189, 1997.

[9] E. Castillo, J. M. Sarabia, C. Solares, and P. Gómez. Uncertainty analysis in fault trees and bayesian networks using Form/Sorm method. *Reliability Engineering and System Safety*, 65:29 – 40, 1999.

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

[11] G. Dahll. Combining disparate sources of information in the safety assessment of software-based systems. *Nuclear Engineering and Design*, 195:307 – 319, 2000.

[12] A. Darwiche. *Modeling and Reasoning with Bayesian Networks*. Cambridge University Press, 2009.

[13] A. De-Los-Santos, G. Laporte, J. A. Mesa, and F. Perea. Evaluating passenger robustness in a rail transit network. *Transportation Research Part C: Emerging Technologies*, 20:34 – 46, 2000.

[14] G. Duman. Seismic vulnerability of highway bridges in İstanbul. Master's thesis, Boğaziçi University, Kandilli Observatory and Earthquake Research Institute (KOERI), Department of Earthquake Engineering, 1997.

[15] I. Gertsbakh and Y. Shpungin. Spectral approach to reliability evaluation of flow networks. In *Proceedings of the European Modeling and Simulation Symposium*, 2012.

[16] D. Günneç and F. S. Salman. Assessing the reliability and the expected performance of a network under disaster risk. *OR Spectrum*, 33:499 – 523, 2011.

[17] J. Husdal. Reliability and vulnerability versus cost and benefits. pages 182 – 188, Christchurch, New Zealand, 2004. Proceedings of the Second International Symposium on Transportation Network Reliability(INSTR).

[18] E. Jenelius, T. Petersen, and L. G. Mattsson. Importance and exposure in road network vulnerability analysis. *Transportation Research Part A: Policy and Practice*, 40:537 – 560, 2006.

[19] F. V. Jensen. *An Introduction to Bayesian Networks*. Springer, New York, 1996.

[20] P. E. Johnson, D. S. Joy, D. B. Clarke, and J. M. Jacobi. Highway 3. 1: An enhanced highway routing model: Program description, methodology, and revised user's manual. Technical Report ORNL/TM-12124, Oak Ridge National Lab., TN, 1993.

[21] A. Konak and A. E. Smith. Network Reliability Optimization. In *Handbook of Optimization in Telecommunications*, pages 735 – 760. Springer US, 2006.

[22] H. Langseth and L. Portinale. Bayesian networks in reliability. *Reliability Engineering and System Safety*, 92:92 – 108, 2007.

[23] L. F. Li, J. F Wang, and H. Leung. Using spatial analysis and bayesian network to model the vulnerability and make insurance pricing of catastrophic risk. *International Journal of Geographical Information Science*, 24:1759 – 1784, 2010.

[24] L. F. Li, J. F. Wang, H. Leung, and C. Jiang. Assessment of catastrophic risk using Bayesian network constructed from domain knowledge and spatial data. *Risk Analysis*, 30:1157 – 1175, 2010.

[25] S. Mahadevan, R. X. Zhang, and N. Smith. Bayesian networks for system reliability reassessment. *Structural Safety*, 23:231 – 251, 2001.

[26] M.Erdik, B. Siyahi, K. Sesetyan, M. Demircioğlu, and H. Akman. Earthquake masterplan for İstanbul. Technical report, Boğazici University, İstanbul Technical University, Middle East Technical University. Yıldız Technical University, 2004.

[27] M. Moghtaderi-Zadeh. Reliability upgrading of lifeline networks for post-earthquake serviceability. *Earthquake Engineering And Structural Dynamics*, 11: 557 – 566, 1983.

[28] A. Nagurney and Q. Qiang. Fragile networks: Identifying vulnerabilities and synergies in an uncertain age. *International Transactions in Operational Research*, 19:123 – 160, 2012.

[29] G. M. Oliva, P. Weber, C. Simon, and B. Iung. Bayesian networks applications on dependability, risk analysis and maintenance. pages 245 – 250, Bari Italy, 2009. 2nd IFAC Workshop on Dependable Control of Discrete Systems.

[30] T. Parsons, S. Toda, R. S. Stein, A. Barka, and J. H. Dieterich. Heightened odds of large earthquakes near İstanbul: An interaction-based probability calculation. *Science*, 288:661 – 665, 2000.

[31] A. S. Selçuk and M. S. Yüceman. Reliability of lifeline networks under seismic hazard. *Reliability Engineering and System Safety*, 65:213 – 227, 1999.

[32] A. S. Selçuk and M. S. Yücemen. Reliability of lifeline networks with multiple sources under seismic hazard. *Natural Hazards*, 21:1 – 18, 2000.

[33] J. Sohn. Evaluating the significance of highway network links under the flood damage: An accessibility approach. *Transportation Research Part A: Policy and Practice*, 40:491 – 506, 2006.

[34] A. Sumalee and D. Watling. Travel time reliability in a network with dependent

link modes and partial driver response. *Journal of the Eastern Asia Society for Transportation Studies*, 5:1686 – 1701, 2003.

[35] M. A. P. Taylor, S. V. C. Sekhar, and M. D'Este. Application of accessibility based methods for vulnerability analysis of strategic road networks. *Networks and Spatial Economics*, 6:267 – 291, 2006.

[36] J. Y. Yen. Finding the k shortest loopless paths in a network. *Management Science*, 17:712 – 716, 1971.

[37] Y. Yuan and D. Wang. Path selection model and algorithm for emergency logistics management. *Computers & Industrial Engineering*, 56:1081 – 1094, 2009.

[38] C. Zülfikar. Preliminary seismic evaluation of highway bridges in İstanbul. Master's thesis, Boğaziçi University, 1995.

Appendix A

District Name	Node No	District Name	Node No
Arnavutköy	1	Tuzla	31
Ataşehir	2	Ümraniye	32
Avcılar	3	Üsküdar	33
Bağcılar	4	Zeytinburnu	34
Bahçelievler	5	J1	35
Bakırköy	6	J2	36
Başakşehir	7	J3	37
Bayrampaşa	8	J4	38
Beşiktaş	9	J5	39
Beylikdüzü	10	J6	40
Beyoğlu	11	J7	41
Büyükçekmece	12	J8	42
Çekmeköy	13	J9	43
Esenler	14	J10	44
Esenyurt	15	J11	45
Eyüp	16	J12	46
Fatih	17	J13	47
Gaziosmanpaşa	18	J14	48
Güngören	19	J15	49
Kadıköy	20	J16	50
Kağıthane	21	J17	51
Kartal	22	J18	52
Küçükçekmece	23	J19	53
Maltepe	24	J20	54
Pendik	25	J21	55
Sancaktepe	26	J22	56
Sarıyer	27	J23	57
Şişli	28	J24	58
Sultanbeyli	29	J25	59
Sultangazi	30	J26	60

Table A.1: Node Numbers

District No	District	Population	Casualty Rate (%)	w_i
1	Arnavutköy	197,271	1.30	2565
2	Ataşehir	290,818	1.10	3199
3	Avcılar	490,630	2.70	13247
4	Bağcılar	741,909	1.10	8161
7	Başakşehir	206,846	1.30	2689
8	Bayrampaşa	294,292	2.40	7063
9	Beşiktaş	365,083	1.20	4381
10	Beylikdüzü	222,357	2.80	6226
12	Büyükçekmece	183,208	4.80	8794
13	Çekmeköy	141,400	0.50	707
14	Esenler	541,250	1.20	6495
15	Esenyurt	102,692	1.30	1335
16	Eyüp	302,214	1.40	4231
18	Gaziosmanpaşa	434,167	0.60	2605
19	Güngören	212,016	1.80	3816
21	Kağıthane	395,000	0.80	3160
22	Kartal	429,615	1.30	5585
23	Küçükçekmece	647,077	1.30	8412
24	Maltepe	438,727	1.10	4826
25	Pendik	516,667	1.20	6200
26	Sancaktepe	148,200	0.50	741
27	Sarıyer	222,333	0.30	667
29	Sultanbeyli	256,545	1.10	2822
30	Sultangazi	434,500	0.60	2607
31	Tuzla	143,185	2.70	3866
32	Ümraniye	664,800	0.50	3324

Table A.2: Number of Casualties in Demand Nodes

District Name	Number of Hospitals	Number of Policlinics	Number of Beds
Şişli	21	0	1,597
Kadıkoy	20	42	1,127
Üsküdar	17	16	2,036
Fatih	16	16	1,081
Bahçelievler	12	0	1,126
Gaziosmanpaşa	11	0	491
Bakırkoy	10	10	4,229
Beyoğlu	8	15	861
Güngören	6	1	207
Bayrampaşa	6	12	259
Kartal	6	9	918
Zeytinburnu	6	10	1,325
Maltepe	5	2	85
Pendik	5	11	244
Avcılar	5	6	323
Eyüp	4	10	75
Ümraniye	4	24	87
Buyukçekmece	4	0	134
Beşiktaş	4	0	173
Bagcılar	4	23	177
Kucukçekmece	4	23	177
Esenler	3	11	147
Silivri	3	0	147
Kagıthane	3	0	285
Beykoz	3	6	300
Sarıyer	3	15	510
Çatalca	1	0	50
Tuzla	0	0	0

Table A.3: Number of Medical Facilities by District

Node 1	Node 2	Edge No
Bağcılar	Bahçelievler	1
Bahçelievler	Bakırköy	2
Arnavutköy	Beşiktaş	3
Avcılar	Beylikdüzü	4
Beylikdüzü	Büyükçekmece	5
Avcılar	Esenyurt	6
Beylikdüzü	Esenyurt	7
Beyoğlu	Fatih	8
Bayrampaşa	Gaziosmanpaşa	9
Bahelievler	Güngören	10
Avcılar	Küçükçekmece	11
Bahçelievler	Küçükçekmece	12
Bakırköy	Küçükçekmece	13
Kartal	Maltepe	14
Çekmeköy	Sancaktepe	15
Pendik	Sancaktepe	16
Eyüp	Saryer	17
Sarıyer	Şişli	18
Kartal	Tuzla	19
Ümraniye	Üsküdar	20
Bakırköy	Zeytinburnu	21
Fatih	Zeytinburnu	22
Güngören	Zeytinburnu	23
Esenyurt	J1	24
Bağcılar	J2	25
Başakşehir	J2	26
J1	J2	27
Esenler	J3	28
Beyoğlu	J4	29
Beşiktaş	J5	30
J4	J6	31
Eyüp	J7	32
Eyüp	J8	33
Kağıthane	J8	34
J4	J8	35
J7	J8	36
Beyoğlu	J9	37
Kağıthane	J9	38
J4	J9	39
J5	J9	40
Sarıyer	J10	41

Node 1	Node 2	Edge No
Şişli	J10	42
Bayrampaşa	J11	43
Fatih	J11	44
J6	J11	45
Gaziosmanpaşa	J12	46
J3	J12	47
Ümraniye	J13	48
Ataşehir	J14	49
Sultanbeyli	J15	50
Sultanbeyli	J16	51
Tuzla	J17	52
J15	J17	53
Bayrampaşa	J18	54
J2	J18	55
J3	J18	56
Kağıthane	J19	57
Şişli	J19	58
J8	J19	59
J10	J19	60
Gaziosmanpaşa	J20	61
Sultangazi	J20	62
J7	J20	63
J12	J20	64
Üsküdar	J22	65
J5	J22	66
J14	J22	67
J21	J22	68
Kadıköy	J23	69
Maltepe	J23	70
J14	J23	71
J21	J23	72
J10	J24	73
J13	J24	74
Çekmeköy	J25	75
J13	J25	76
J14	J25	77
Kartal	J26	78
J14	J26	79
J16	J26	80
J15	Pendik	81
J2	Küçükçekmece	82
J1	Büyükçekmece	83

Table A.4: Edge Numbers

Name	Longitude	Latitude	Type	Support	Abutment	Pier	Liquefaction	Seismicity	Importance of Structure	Total Score	Modified Total Score
V6	28.92	41.1	Viaduct	10	0	2	0	6	10	87	80.5
V5	28.93	41.1	Viaduct	10	0	2	0	6	10	87	80.5
V7	28.85	41.07	Viaduct	10	0	2	0	6	10	87	80.5
V3	28.96	41.07	Viaduct	10	0	1	5	8	8	87	90.5
V302	29	41.07	Viaduct	10	2	2	0	6	10	87	80.5
V408	29.03	41.05	Viaduct	8	0	2	0	6	10	80	70
V409	29.03	41.05	Viaduct	7	0	2	0	6	10	77	65.5
V1	28.98	41.1	Viaduct	5	0	0	5	8	9	73	64.5
V411	29.02	41.06	Viaduct	6	0	2	0	6	10	73	59.5
B1	28.84	41.06	Viaduct	5	3	5	7	7	8	72	68
LMV1	29.03	41.09	Viaduct	5	0	2	0	6	10	70	55
KMU3	29.1	40.98	Viaduct	5	3	5	3	8	8	69	63.5
VMO1	29.09	41.09	Viaduct	5	0	0	3	7	8	68	62
V2A	28.96	41.09	Viaduct	5	0	0	0	6	9	65	52.5
V2	28.96	41.08	Viaduct	5	0	0	0	6	9	65	52.5
V7A	28.9	41.09	Viaduct	3	0	0	0	6	10	63	44.5
K1	29.08	41.02	Viaduct	5	0	0	0	6	8	63	54.5
NMU4	29.12	41	Viaduct	5	0	0	5	6	8	63	54.5
RMO1	29.12	41.03	Viaduct	5	0	0	5	6	8	63	54.5
RMO2	29.12	41.03	Viaduct	5	0	0	5	6	8	63	54.5
BLU1	29.01	41.08	Viaduct	5	0	0	0	6	10	63	44.5
B16	28.97	41.1	Viaduct	5	0	0	0	6	8	62	53
K521	29.03	40.99	Underpass	2	5	5	10	10	7	90	100
K407	29.02	41.06	Underpass	0	0	5	5	10	8	77	75.5
M5U1	29.1	40.99	Underpass	5	3	5	5	8	8.33	71	64.85
K205	28.98	41.07	Underpass	2	2	5	5	7	9	70	60
K104	28.92	41.03	Underpass	3	0	0	5	7	8.67	69	60.15
K300	28.99	41.07	Underpass	0	2	5	5	7	8.33	68	60.35
B15	28.97	41.1	Underpass	0	4	2	4	8	8	67	60.5
K511	29.06	41	Underpass	0	0	3	2	10	7	67	65.5
UMU5	29.1	41.03	Underpass	0	0	2	5	8	7	67	65.5
K412	29.01	41.05	Underpass	0	1	5	0	6	8	63	54.5
K513	29.05	40.99	Underpass	0	1	2	2	10	7	63	59.5
K518	29.03	40.99	Underpass	0	2	0	2	10	7	63	59.5
M2U2	29.05	41.09	Underpass	5	0	0	0	6	8	63	54.5
M302	29.08	41.09	Underpass	5	0	0	3	6	8	63	54.5
B5	28.88	41.09	Underpass	5	0	0	0	6	7.67	62	54.65
B3B	28.87	41.08	Underpass	5	0	0	0	6	7.33	61	54.85
B3C	28.87	41.08	Underpass	5	0	0	0	6	7	60	55
K201	28.95	41.05	Underpass	0	0	5	0	6	7	60	55
K208	28.97	41.06	Underpass	0	0	2	2	8	8	60	50
K211	28.97	41.06	Underpass	0	0	2	2	8	8	60	50
K502	29.05	41.03	Underpass	0	1	5	0	6	7	60	55
K504	29.05	41.02	Underpass	0	0	5	0	6	7	60	55
K501	29.04	41.04	Underpass	3	0	0	3	6	8.33	58	45.35
K203	28.96	41.06	Underpass	4	0	0	0	6	7	57	50.5
K210	28.97	41.06	Underpass	0	0	2	0	7	8	57	45.5
NMU1	29.12	41	Underpass	0	3	2	0	7	7	57	50.5
RMU1	29.12	41.03	Underpass	0	3	2	0	7	7	57	50.5
U208A	29.13	41	Underpass	0	4	2	0	7	6	57	55.5
UMU8	29.11	41.03	Underpass	0	0	3	0	7	7	57	50.5
K509	29.06	41	Underpass	2	0	0	0	6	9	55	37.5
K301	28.99	41.07	Underpass	0	0	2	0	6	8	53	39.5
UMU7	29.11	41.03	Underpass	0	0	2	0	7	7	53	44.5
K304	29.02	41.08	Underpass	0	0	2	0	6	7	50	40
K401	29.01	41.07	Underpass	0	0	2	0	6	7	50	40
K405	29.01	41.07	Underpass	0	0	2	0	6	7	50	40
UMU3A	29.08	41.03	Underpass	0	0	2	0	6	7	50	40
B9	28.95	41.1	Underpass	0	0	0	0	6	7	43	29.5

Name	Longitude	Latitude	Type	Support	Abutment	Pier	Liquefaction	Seismicity	Importance of Structure	Total Score	Modified Total Score
KMV1	29.1	40.98	Overpass	10	2	0	0	8	7	83	89.5
K510	29.06	41	Overpass	0	0	0	0	6	8.67	79	75.15
K515	29.04	40.99	Overpass	0	2	0	5	10	8.67	79	75.15
K517	29.04	40.99	Overpass	0	2	5	5	10	8.67	79	75.15
K512	29.05	40.99	Overpass	2	2	5	5	10	8.33	78	75.35
NMO1	29.11	41	Overpass	5	3	5	7	8	8	76	74
B11	28.96	41.1	Overpass	5	3	5	7	7	8.33	74	69.35
B12	28.97	41.1	Overpass	5	3	5	7	7	8.33	74	69.35
B13	28.99	41.1	Overpass	5	3	5	5	8	8.88	73	65.1
K101	28.91	41.02	Overpass	2	0	0	5	8	8.67	72	64.65
K102	28.92	41.03	Overpass	2	0	0	5	8	8.33	71	64.85
KMO1	29.09	40.98	Overpass	5	3	5	5	8	8.33	71	64.85
BF2	29.01	41.1	Overpass	5	0	0	0	8	8	70	65
BRO	29.01	41.1	Overpass	5	3	5	5	7	8.33	68	60.35
K103	28.92	41.03	Overpass	0	0	0	5	7	8.33	68	60.35
K106	28.93	41.03	Overpass	2	0	0	5	7	8.33	68	60.35
K204	28.97	41.06	Overpass	0	2	5	0	7	8.33	68	60.35
BF1	29.01	41.08	Overpass	6	2	0	0	6	8	67	60.5
M301	29.08	41.09	Overpass	5	0	0	3	6	8.67	65	54.15
M101	29.03	41.09	Overpass	5	0	0	0	6	8.33	64	54.35
M401	29.11	41.07	Overpass	5	0	0	5	6	8.33	64	54.35
M501	29.12	41.02	Overpass	5	0	0	5	6	8.33	64	54.35
K4A	28.81	41.07	Overpass	5	4	5	5	8	6	63	64.5
M102	29.02	41.1	Overpass	5	0	0	0	6	8	63	54.5
M402	29.12	41.05	Overpass	5	0	0	5	6	8	63	54.5
B10	28.96	41.1	Overpass	5	0	0	0	6	8.33	62	51.35
B3	28.87	41.08	Overpass	5	0	0	0	6	7.67	62	54.65
B6	28.89	41.09	Overpass	5	0	0	0	6	7.67	62	54.65
B2	28.86	41.07	Overpass	5	0	0	0	6	7	60	55
K2	29.09	41.03	Overpass	5	3	2	0	7	6	60	60
UMO5	29.08	41.03	Overpass	2	4	5	0	7	6	60	60
K503	29.05	41.02	Overpass	2	0	0	3	6	8.67	59	45.15
K202	28.95	41.05	Overpass	3	0	0	0	6	8.33	58	45.35
K206	28.98	41.07	Overpass	2	2	0	0	7	8.33	58	45.35
K505	29.06	41.02	Overpass	2	0	0	3	6	8.33	58	45.35
K212	28.96	41.06	Overpass	2	0	0	0	6	8.67	55	39.15
K402	29.01	41.07	Overpass	2	0	0	0	6	8.67	55	39.15
K404	29.01	41.07	Overpass	2	0	0	0	6	8.67	55	39.15
K207	28.96	41.06	Overpass	2	0	0	0	6	8.33	54	39.35
K410	29.02	41.06	Overpass	2	0	0	0	6	8.33	54	39.35
UMO7	29.1	41.03	Overpass	2	0	4	0	6	6	53	49.5
UMO6	29.09	41.03	Overpass	2	0	3	0	6	6	50	45
K303	29	41.07	Overpass	0	0	0	0	6	8.67	49	30.15
K305	29.02	41.07	Overpass	0	0	0	0	6	8.67	49	30.15
K414	29.01	41.06	Overpass	0	0	0	0	6	8.67	49	30.15

Figure A.1: ATC 6-2 Scores

Edge No	Edge Risks	Max ATC Score	Probabilities	Modified Probabilities
1	1	0	0.89	0.89
2	1	0	0.85	0.85
3	3	65.5	0.99	0.79
4	1	0	0.90	0.90
5	2	0	0.94	0.94
6	1	0	0.86	0.86
7	2	0	0.94	0.94
8	2	0	0.94	0.94
9	2	0	0.92	0.92
10	1	0	0.85	0.85
11	1	0	0.85	0.85
12	1	0	0.88	0.88
13	1	0	0.89	0.89
14	2	0	0.92	0.92
15	2	0	0.93	0.93
16	2	0	0.94	0.94
17	3	0	0.96	0.96
18	3	0	0.98	0.98
19	3	0	0.85	0.85
20	2	0	0.93	0.93
21	1	0	0.90	0.90
22	1	0	0.89	0.89
23	1	0	0.86	0.86
24	2	0	0.92	0.92
25	2	0	0.93	0.93
26	2	64.5	0.93	0.73
27	2	0	0.95	0.95
28	3	55	0.98	0.88
29	2	0	0.94	0.94
30	3	0	0.99	0.99
31	2	60.35	0.93	0.73
32	3	0	0.97	0.97
33	3	0	0.98	0.98
34	3	0	0.96	0.96
35	2	90.5	0.93	0.63
36	3	80.5	0.9955	0.69
37	2	0	0.91	0.91
38	3	0	0.99	0.99
39	2	0	0.90	0.90
40	3	80.5	0.98	0.68
41	3	0	0.95	0.95
42	3	0	0.96	0.96

Edge No	Edge Risks	Max ATC Score	Probabilities	Modified Probabilities
43	2	0	0.94	0.94
44	2	0	0.92	0.92
45	2	0	0.95	0.95
46	3	0	0.99	0.99
47	3	0	0.95	0.95
48	2	50.5	0.92	0.82
49	2	55.5	0.93	0.73
50	1	0	0.89	0.89
51	2	0	0.94	0.94
52	1	0	0.89	0.89
53	1	0	0.86	0.86
54	2	0	0.92	0.92
55	2	68	0.94	0.74
56	2	44.5	0.93	0.83
57	3	0	0.97	0.97
58	3	0	0.99	0.99
59	3	69.35	0.99	0.79
60	3	65.1	0.98	0.78
61	3	0	0.98	0.98
62	3	75.15	0.97	0.67
63	3	0	0.98	0.98
64	3	55	0.95	0.85
65	2	0	0.90	0.90
66	2	75.5	0.93	0.63
67	2	74	0.95	0.65
68	2	75.15	0.93	0.63
69	2	0	0.91	0.91
70	2	0	0.95	0.95
71	2	89.5	0.90	0.60
72	2	0	0.90	0.90
73	3	55	0.96	0.86
74	3	62	0.98	0.78
75	3	0	0.99	0.99
76	3	54.5	0.98	0.88
77	2	54.5	0.92	0.82
78	2	0	0.93	0.93
79	2	0	0.93	0.93
80	2	0	0.94	0.94
81	1	0	0.87	0.87
82	2	0	0.93	0.93
83	2	0	0.94	0.94

Table A.5: Survival Probabilities of Edges

VITA

İdil ARŞIK was born in İstanbul, Turkey, on February 26 1986. She graduated from German School of İstanbul in 2006. She received her B.S. degree in Industrial Engineering from Koç University, İstanbul, in 2010. In September 2010, she joined the Industrial Engineering Department of Koç University, İstanbul, as a teaching and research assistant.