RESILIENCE OF URBAN INFRASTRUCTURE PRONE TO NATURAL HAZARDS

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FRANCESCO ROUHANA

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Notre Dame University – Louaize

Faculty of Engineering

Department of Civil and Environmental Engineering

We hereby approve the
thesis of

FRANCESCO ROUHANA

Candidate for the degree of
MASTER OF SCIENCE IN CIVIL ENGINEERING

Dima Jawad

Dr. DIMA JAWAD — Supervisor, Chair

Sophie Ghanimeh

Dr. SOPHIA GHANIMEH — Committee Member

Maya atieh

Dr. MAYA ATIEH — Committee Member

Dr. CHRISTINE MADY — Committee Member

ABSTRACT

Civil infrastructure systems such as transportation networks, power gridlines, water and wastewater networks, telecommunication services are vital modules creating the backbones of modern cities. Transportation networks are key components of civil infrastructure systems that can impede societal and commercial events, and impair post-disaster evacuation, response and recovery. Performance of transportation networks under natural hazards shed light on the necessity to assess their fundamental topological properties in order to provide and correlate appropriate resilience measurements to comprehend the preparedness and functionality level of such infrastructure system. Therefore, this thesis is devoted to providing network analysis functionalities for vulnerability assessment in transportation networks with respect to natural disruptive events. Through combining the Geographic Information System derived spatial data and network concepts, the vulnerability of transportation networks is evaluated and so the engineering resilience is defined along its aspects by a quantitative approach and statistical modeling of the topological graph properties. The various scenarios-based methodology is applied in the highly populated capital of Lebanon, Beirut. This topology was selected for analysis because of the susceptibility of its territory to natural events. In this context, transportation agencies, legislators, and decision-makers are better able to direct and optimize resources by prioritizing the critical network components, thus reducing the downtime in the functionality system.

DEDICATION

I would like to thank God Almighty for giving me the strength, knowledge, ability and opportunity to undertake this research study and to persevere and complete it satisfactorily. Without his blessings, this achievement would not have been possible.

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I. INTRODUCTION

1.1 Background

Civil infrastructure systems such as transportation networks, power gridlines, water and wastewater networks, telecommunication services are vital modules creating the backbones of modern cities. These critical systems are susceptible to natural hazards such as earthquakes, tsunamis, floods which can damage their performance and lead to substantial socio-economic losses especially in risk-prone urban areas where the rapid growth of urbanization increases the potential risk and vulnerability. Accordingly, it is crucial to analyze the current infrastructure state resilience for improvement, thereby lessening the vulnerability of civil infrastructure networks to extreme events and interruptions, allowing preparedness for possible damage scenarios, absorptiveness, adaptation after the probable disruptions, and recovery.

Earthquakes are among the most dangerous natural hazards that cannot be avoided nor predicted even in the susceptible areas where earthquakes are reliably recognized. Regardless of the very intense seismological researches, strong events time could not be exactly forecasted. If such events occurred in an urban setting, it may result in a massive number of fatalities within seconds, primarily due to collapsed buildings (Bouchon et al., 2011). In the last century, cities around the world are faced more than one thousand strong earthquakes triggering one and half million causalities where 90 percent of direct deaths were due to destroyed buildings (Lantada et al., 2009). The dominance of earthquake resistant construction controls the vulnerability of property to seismic risks. Structures built in compliance with the required codes and standards are safer than old structures that are not retrofitted. Accordingly, prepared communities to seismic hazards experience less disruptions (Jawad et al., 2019).

Transportation networks are key components of civil infrastructure systems that can impede societal and commercial events, and impair post-disaster evacuation, response and recovery (Basöz and Kiremidjian, 1996; Nojima, 1998; Chang and Nojima, 1998; Chang, 2012). For instance, collapsed bridges and damaged primary roads due to a disastrous earthquake or landslide could hamper emergency teams to rescue and evacuate the population at risk efficiently to safer zones. After a disaster, it is of paramount importance also to account for the operation of the transportation networks where the traffic flow under emergency situations may change significantly from pre-disaster normal conditions due to deteriorated network capacities and variations in travel demand as well (Shen et al., 2009). Connectivity is described as the availability of a serviceable path between an origin-destination (OD) and it is one of the core function of transportation networks. The functionality consequences of any extreme disruption result in longer paths; thus, it is essential to identify the main critical roads and have adequate knowledge about the most vulnerable networks through developing and evaluating criteria and performance metrics for an effective prioritization (Novak et al., 2012).

Performance of transportation networks under natural hazards shed light on the necessity to assess their fundamental topological properties in order to provide and correlate appropriate resilience measurements to comprehend the preparedness and functionality level of such infrastructure system. Resilience is the capability of a system to cope, absorb, and withstand the effect of a random attack, then survive and recover immediately afterwards (Jawad et al., 2019). Resilience can be described as the aggregate of its components which can be summarized as the estimated physical impairment after an extreme event, the consistency of the network topographical layout, the prioritization objectives and the recovery speed of the system to reach a suitable level (Furtado, 2015). Although the resilience concept is of high importance and has been introduced from decades, yet its implementation into complex networks in transportation sector is a novel subject. Therefore, this study will focus on applying the concepts of resilience to transportation networks in urban areas prone to natural hazards specifically seismic risks.

1.2 Scope and Objectives

Transportation networks offer daily accessibility and vital services to societies; thereby, they must also maintain an acceptable connectivity to critical infrastructure when exposed to natural hazards or manmade attacks. According to the chart of the Sendai Framework for Disaster Risk Reduction (2015-2030), future directions and principles are outlined for substantially cutting down the disaster risks, damage, and disruption of basic services by 2030. The framework is calling for methodologies and strategies to evaluate and bolster the resilience of new and present key infrastructure. It stresses that such structures and facilities must persist secure and effective during and after any calamity (United Nations, 2015). For these circumstances, this thesis is devoted to providing network analysis functionalities for vulnerability assessment in transportation networks with respect to natural disruptive events. Through combining the Geographic Information System (GIS) derived spatial data and network concepts, the vulnerability of transportation networks is evaluated and so the engineering resilience is defined along its aspects by a quantitative approach and statistical modeling of the topological graph properties. These properties of Graph Theory (i.e., the study of the relationships between the graph's components) were examined to illustrate the behavior and distribution of network graph of the urban area under study subject to random or/and targeted attacks. With this premise in mind, there are important questions which need to be answered before an actual disaster arises: How to develop a framework to quantify resilience of transportation networks to withstand failures in the case of data insufficiency? How can the developed framework be implemented to evaluate the road network of Beirut? What are the critical network locations where an interdiction would cause damages to the system?

It is a real challenge for researchers to study the resilience of infrastructure systems especially in developing countries. In fact, such contexts are more adversely affected by natural hazards and offer limited capacity to collect and process the necessary data. Even with the acceptance of the data scarcity in these contexts, this work provides a resilience assessment that has tangible benefits to society. The various scenarios-based methodology is applied in a developing country namely Lebanon (33.8547° N, 35.8623° E), specifically within its highly populated capital Beirut. This topology was selected for analysis because of the susceptibility of its territory to natural events. In fact, Lebanon is considered a moderate to high seismic hazard country. Natural hazards, mainly earthquakes (i.e., ground failure), that are most relevant to the study area were examined along some secondary hazards such as liquefaction, landslides, floods, and tsunamis. This region was chosen due to the study performed by Baytiyeh and Naja (2015) that showed a poor level of earthquake preparedness knowledge across college students in Lebanon. Accordingly, integrating such topics encourage future graduates to be actively engaged and have a proactive role in planning and preparing for future earthquakes tragedies. The purpose of this thesis is to understand the effects that transportation networks introduce in their response to disturbances. This cannot be achieved without assessing the efficiency of road networks based on connectivity analysis and topological measures which can reveal some relevant information pertaining to the functional classification of the roads. Thus, after investigating the statistical parameters for description of network topology and identifying the role that various network elements have in maintaining the connectivity and serviceability of the studied system, a research agenda should be established to address future research questions revealed by the results of the scenarios-based analysis.

In this context, transportation agencies, legislators, and decision-makers are better able to direct and optimize resources by prioritizing the specific network components which are most critical to maintaining the system functionalities. Therefore, this strategy allows for more reasonably budgeted allocation to natural crisis and prepares for possible consequences with the focus of reducing the downtime in the functionality system.

1.3 Organization of the thesis

The thesis will be divided into seven chapters. After this brief background, chapter 2 reviews the definitions and evolutions of the resilience concept in different fields with emphasis on the engineering context. Also, this chapter addresses the concept of risk and vulnerability along with the role of resilience properties and their quantification theories. Chapter 3 presents the resilience of transportation systems. It starts with the pre-event damage mitigations, then it reviews the seismic risk analysis and the network performance measures, and it finishes with the post-event performance assessment. Chapter 4 deals with the networks in transportation systems, the types of graphs, the fundamental concepts of Graph Theory, and the quantification methods using these networks. In addition, the evaluation of network response to failures is presented along the state of the art of the implementation of Graph Theory in transportation. Chapter 5 presents the proposed methodology for resilience evaluation of spatially distributed networks under seismic vulnerability in Beirut. Chapter 6 reveals the analysis and results of this thesis and the efficiency evaluation of the proposed methodology application. Conclusions, recommendations, and limitations for future researches will be given in Chapter 7.

II. RESILIENCE EPISTEMOLOGY

2.1 Introduction

A standard approach along a descriptive algorithm of the process will be formulated to quantify the resilience of critical infrastructure (e.g., transportation networks, buildings…) in order to bolster the system resilience in the most efficient method. But, before evaluating and measuring the resilience of critical infrastructure through a topological-based system, it is essential to conduct a comprehensive review and study the evolution of resilience concept in different fields and approaches along with its derivations and applications.

“Resilience” has turned out to be a vague buzzword that most of the time is used carelessly without an accurate recognition of its meaning. “Resilience” etymology originates from a Latin verb “resilio” denoting to rebound (Rose, 2009). For more than 40 years ago, ecologists were the earliest to embrace and document the concept of resilience where it is used to define the adaptive behavior of ecological systems by Holling (1973, p. 17) as “a measure of the ability of these systems to absorb changes of state variables, driving variables, and parameters, and still persist. In this definition resilience is the property of the system and persistence of probability of extinction is the result”. In that manner, ecologists through Holling were the pioneers to apply resilience definition in the survival of complex systems which served as a foundation for future ecologists and biologists. In fact, in addition to the use of the term in ecology, it is also used in biology where two aspects of resilience are outlined: the equilibrium and disequilibrium conditions; the former returning to the original state while the latter to an adapted new state.

In different fields, most of the researchers consider that the essence of resilience is derived from the flexibility and adaptability of the system (Levin et al., 1998). Timmerman (1981) linked resilience to vulnerability and defined it in the long-term scope (e.g., climate change) as a measurement of the system capacity to absorb and recover after a damaging scenario. Another definition of resilience was stated by Pimm (1991) stressed on the speediness of the system to return to equilibrium. As did Timmerman, Manyena (2006) agreed that resilience and vulnerability are interconnected. Pelling (2012) split the latter under natural hazards to three main measures (i.e., exposure, resistance, and resilience), and described resilience as the capability of an individual to cope with hazard stress. According to Rose (2009) vulnerability is related to the pre-disaster condition, then resilience comes up as the result of the post-disaster response. Numerous ecologists related resilience to the concept of sustainability which incorporates long term survivability without decreasing the quality of life (Common, 1995). In this context, the environment and natural resources dependability played a key feature in sustainability concept. Then, the ecological resilience was extended to human communities for the first time by measuring the social resilience through Adger (2000) who incorporated social capital, economic factors, institutions and demographics. Many researchers dealt with resilience concept from an economic perspective taking into consideration the financial consequences of a hazardous event where economic losses may outweigh the physical losses of the system. Short-term economic and physical losses seem more tangible for computation within the economic resilience in the post-disaster situation. Besides, according to financial operations, direct and indirect losses involved in the long-term hazard loss quantification (Rose, 2004). In studying the economic resilience, two types of resilience are distinguished, inherent and adaptive. The former occurs in normal circumstances whereas the latter occurs in crisis situations due to ingenuity or extra effort such as saving water after a disastrous earthquake (Rose, 2004; Rose and Wein, 2011). Economic resilience is necessary not only to avoid underestimation of losses incurred due to an extreme event, but it also helps decision-makers to assess recovery strategies to reduce the economic losses. While preparedness deals with actions done before the extreme event like building up inventories which enhance inherent resilience of the system, other actions such as creation of an advance communication network, improve the capacity of adaptive resilience. Resilience is separated by three levels: (1) the microeconomic level such as individual behavior of firms, households or organizations, (2) the mesoeconomic level such as economic sector, individual market, or cooperative group, and (3) the macroeconomic level where economic resilience is that of all individual unites and markets combined (Rose, 2004). Accordingly, dividing an infrastructure system into subsystems level, the previous resilience concept could be employed to study the infrastructure resilience.

2.2 Engineering Resilience

In the engineering context, resilience was also differentiated by the ecologist Holling (1996) where in contrast to the ecological resilience concept, which is designed to be dynamic and inherently adaptive, engineering resilience is not. While the ecological concept could return to an improved state after a damaging scenario, engineering system could ideally bounce back to its original state. Over diverse fields, the concept of resilience practically embraces the pre- and post-event actions. Bruneau et al. (2003) defined that a system resilience has three aspects through reducing (1) the probabilities of failure, (2) the results of failures, and (3) the recovery time. They contended that these aspects are secured if the system includes the four “R’s” for resilience: robustness, redundancy, resourcefulness, and rapidity. Robustness is the ability of the structures or system to bear stress with no degradation in their functionality; in other words, it is a measure of the insensitivity or system’s strength to resist the disruption forces. Redundancy is the ability to provide substitutions and options and to assume the failed components without adversely disturbing the quality performance of the network itself; in the transportation network, this may be defined as the arrangements of paths allowing commuters to move between two locations. Resourcefulness is the ability to direct resources, prioritize actions and repairs during the post-event to realize the system objectives. Finally, the speed at which these objectives are realized, and the recovery time describe the latest resilience “R” rapidity. These four important “abilities” (i.e., to anticipate, to absorb, to adapt, and to recover) ensure the speed and completeness of recovery (Carlson et al., 2012). Similarly, there are four dimensions of resilience: (1) the technical aspect deals with the physical performance of the system in the post-event, (2) the organizational aspect deals with the capability in reacting applicably to hazards by the organizations and make critical tasks, (3) the social aspect reflects the ability to reduce the societal damage, and (4) the economic aspect refers to the ability to lessen the financial losses caused by extreme events (Bruneau et al., 2003). According to the aspects and dimensions, critical infrastructure resilience in specific transportation networks resilience is a concept defined as the ability to withstand, adapt to, and rapidly recover from various disturbing events consequences (Turnquist and Vurgin, 2013). Similarly, Ortiz et al. (2009) defined the transportation network resilience as the ability to absorb slight disruptions and to make a quick return into normal service condition after additional extreme events. Resilience should be a process and outcome, including learning, adaptation, anticipation, and improvement in structures and functions (Jawad et al., 2019). Since it is acknowledged that cities are in dynamic change, then resilience is not static only but also dynamic. The static resilience is the ability of a system to maintain function after a hazardous event while the dynamic resilience refers to the speed at which this system returns to an efficient functionality condition (Rose, 2009). Consequently, some authors have defined resilience under short term disturbance (Bruneau et al., 2003; Rose, 2004), and others for long term (Dovers and Handmer, 1992) due to natural hazards. Seismic events affect greatly the transportation networks and induce considerable spatial damages to the system that has an interdependent nature. For instance, any damage in functionality within the system could harmfully impact other networks such as telecommunication networks. Many researchers emphasis on studying transportation networks resilience where some studies centered on the post-earthquake flow models to assess their functionality (Lee et al., 2011; Chang et al., 2012), others developed annual risk curves through probabilistic scenario-based model (Alipour, 2010), and used the regional economic models within transportation networks to approximate direct and indirect costs induced through bridges failure (Rose et al., 2011; Furtado and Alipour, 2014). In fact, bridges in transportation networks are a key component and turn to be a bottleneck in a failure circumstance due to a severe event. Thereby, some researchers applied retrofit studies to these critical components to improve their functionality by means of prioritization methods (e.g., post-earthquakes flow models, supply capacity for evacuation…) (Chang et al., 2012; Bocchini and Frangopol, 2012; Rokneddin et al., 2013; Venkittaraman and Banerjee, 2014).

2.3 Resilience, Risk, and Vulnerability

Time is a major factor in recovery phase within resilience concept that differentiates it from risk. Risk assessment is to quantify the expected damage while resilience focuses on the critical aspects of a network to recover. Both concepts are used interchangeably because of their interconnected properties. Yet, risk has inherent simpler concept characterized as the probability of loss or damage occurrence due to destructive events. For example, considering seismic risk assessment, some of the threats are classified as the likelihood and intensity of ground motion, liquefaction, landslides. Moreover, another term referred to resilience and risk simultaneously that cannot be simply evaluated in a single metric and is imperfectly interchanged to them, is called vulnerability. This latter is the proneness of a system or structure to experience adverse effects, and the expected level of loss or damage that will take place in the system components for certain types and magnitudes of extreme events. In other terms, resilience and vulnerability are the two side of the same coin, both express the system states, yet the latter focuses only on the security of the system while the former goes beyond by emphasizing its recovery after a disruptive scenario (Haimes, 2009). Sometimes resilience is seen as the measuring extent of vulnerability, where it is considered as the reaction to the threats that are vulnerable to the system components. For some authors, decreasing vulnerability is considered as the primary phase to enhance resilience (Gitz and Meybeck, 2012). All these concepts follow complex measurements, where resilience incorporates absorptive, adaptive, and restorative capacities, risk analysis paradigm consists of hazards or threats identification, exposure, and their vulnerability. In other words, risk is the product of the likelihood of occurrence of a hazard (e.g., seismic event), the sensitivity of the hazard level or vulnerability (i.e., likelihood of exceeding a certain damage as a function of ground motion), and all the system components exposed to this hazard (i.e., transportation networks, structures, residents, economic sectors…). Authors claimed that resilience analysis combined with risk analysis lead to improve the management plan of any catastrophe (Haimes, 2009; Park et al., 2013). To ensure communities' protection and adequate mitigation to failures and disasters, all these concepts must be put together into application (Park et al., 2013).

2.4 Resilience Quantification

The inherent complex nature and the ubiquity the resilience concept obstruct all efforts to have an accurate and acceptable method of quantification with respect to natural hazards. For some authors, no comparison could be done appropriately between the civil infrastructure and the diverse community's resilience (Simonovic, 2012). This is to mention that some authors postulate that quantifying resilience efficiently with single metric is not possible, due to the lack of a concise definition and complicated foundation with diverse uncertainties. This should be done through proposing multi-dimensional method with a set of contributing parameters and studying the range of diverse sectors under hazards (Haimes, 2009). Yet, the evaluation of quantifiable characteristics such as the system performance under spatio-temporal conditions can assist in quantifying resilience. There is widespread attention on including the probabilistic characteristics of adverse extreme events through the application of probabilistic methods that improve the validity of resilience study and lead to more effective strategies to decrease losses. A Probabilistic Hazard Assessment (PSHA) for seismic event effect on the network resilience was compared to a deterministic approach of a single seismic scenario by Adachi (2007), which showed different outcomes with more tendency using the probabilistic approach over the single scenario. For spatial adaptability, some researchers (Berche et al., 2009; Leu et al., 2010; Bono and Gutiérrez, 2011; Freiria et al., 2015) used more comprehensive methods by the application of Graph Theory in accordance to geographic positioning system (GPS) navigation data and GIS. Bruneau et al. (2003) acknowledged the necessity of having efficient measures for resilience quantification which are effective in comparing the system modules and determining its weaknesses. Hence, minimizing any decline in the quality of life through identifying the most critical organizations within the system that have the most impact on life quality such as the infrastructure networks, emergency centers and hospitals, utility businesses and others. By integrating resilience dimensions, some authors outlined and identified uncertainty sources during the quantification of this concept as intensity levels, response parameters, performance limits, performance measures, induced losses, and recovery time (Cimellaro et al., 2011). The quality of community infrastructure changing with time is defined as *Q(t)* and its quality and functionality reduction capacity over time is represented by the resilience (*R)* which is a modified integral of the former function (i.e., "resilience triangle"). As the area of this "resilience triangle" is smaller, the resilience of the system is greater. The normalized area below *Q(t)* is the resilience as described by Bruneau et al. (2003) and Cimellaro et al. (2010). The initial phase is called anticipation where the forecasting and plans for different severe events take place along with the estimation of the system components under probability of failure. The preparation of hazards in this stage is done under normal functionality state where the system is 100% functional before the event. Then, the second phase is the absorption where the system can absorb the shock of the event while decreasing its consequences harshness depending on both robustness and redundancy of the studied network. The initial system percentage drop in functionality at time t_0 is based on these two interlinked aspects without differentiation. Subsequently, the system uses the resources in order to enhance its functionality just after the shock and before the recovery stage. This phase is called adaptation and it may embrace temporal reparation, utilization of redundant modules, and prioritization of the utmost critical components (Najarian and Lim, 2019). Lastly, the recovery phase is when the system returns gradually to an acceptable performance level at time t_f based on standards set by decision-makers and managerial bodies. The final state of the system could return to its initial state before the shock, below or above the pre-event level depending on the repair and improvements extent (Ayyub, 2014). The aforementioned four phases are not mutually exclusive where the final phase may begin amid the preceding one. For that reason, network performance (i.e., infrastructure quality) versus time is drawn in Figure 2.1 showing the resilience properties. In this figure, the system resourcefulness is illustrated as the shaded area between the two curves: the top curve represents the recovery process with goals prioritization with adequate resources while the second did not account for that. Moreover, the time t_1 is linked to the rapidity performance criteria revealing the importance of prioritization in achieving an enhanced quality performance level in contrast with the non-prioritization recovery process.

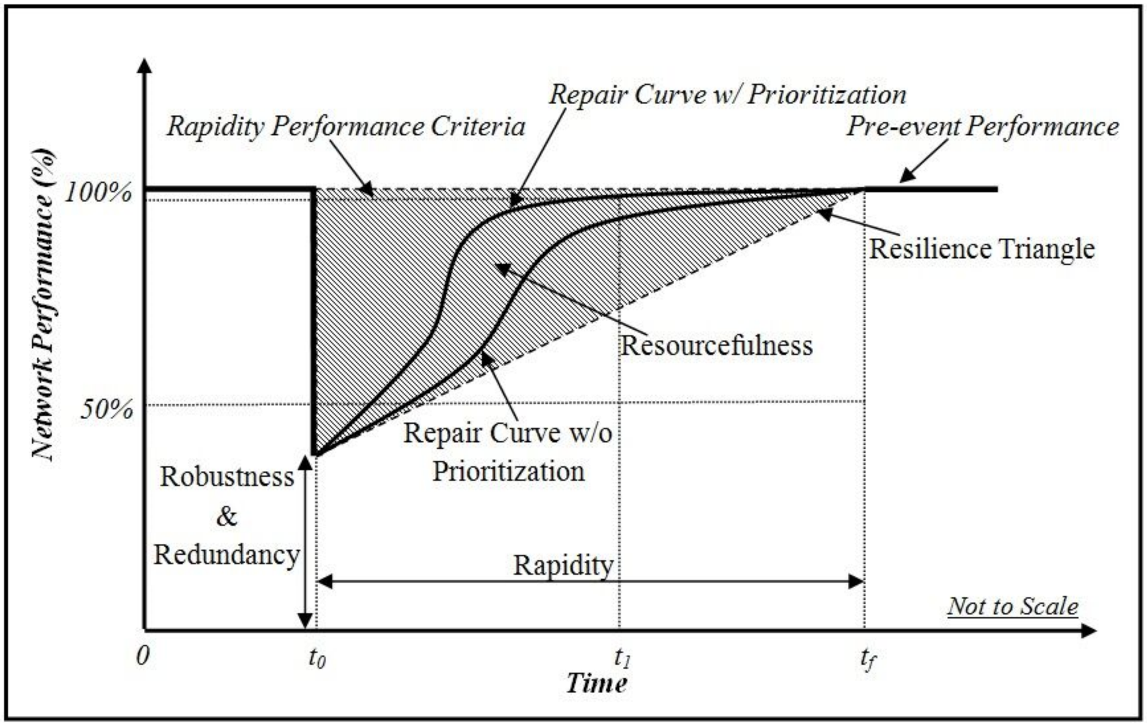


Figure 2.1: Role of resilience properties on network performance versus time

Measuring the resilience based on the size of the expected reduction in the quality of civil infrastructure system through the quantification of the four phases mentioned previously was discussed by Bruneau and Reinhorn (2007). Likewise, resilient systems observed by Tierney and Bruneau (2007), support in abating the likelihood of failure and provide recovery improvements in terms of resources and time required to return to its initial performance state. As noted, the four phases outlined built the concept of resilience having both inherent and adaptive capacities. It is generally quantified in Equation (2.1) which could be seen also in another form as a function of the vulnerability, exposure, and adaptive capacity.

$$R = \int_{t_0}^{t_f} [100 - Q(t)]dt \tag{2.1}$$

Simonovic and Peck (2013) quantified resilience in delineating the system performance in a specific space and time through space-time dynamic resilience measurement. In their study, all shocks are summed or incorporated in a definite integral to portray the influences of catastrophes on the community considering the following performance impacts indicator: physical (e.g., road length inundated by flood), health (e.g., hospital beds in emergency centers), economic (e.g., impact measures through the gross domestic product GDP aggregates), social (e.g., age, gender, social status, education…), and organizational (e.g., share of disaster management facilities to the inhabitants). In other network-based infrastructure researches, an approach is defined to quantify network resilience as the proportion of failed links and nodes separately in accordance with the system performance after an external shock (Garbin and Shortle, 2007). Resilience index of urban infrastructure through belief functions was formulated by Attoh-Okine et al. (2009) in which the concept of resilience (Figure 2.1) and various probable paths of system performance were used. This index (RI) defined in Equation (2.2) where t_0 and t_f represent the time of occurrence of an extreme event and the full recovery time respectively.

$$\mathrm{RI} = \frac{\int_{t_0}^{t_f} Q(t)dt}{100(t_0 - t_f)} \tag{2.2}$$

An extensive survey technique was adopted to quantify resilience as a combination of adaptive and coping capacity revealing that the lack of adaptive capacity makes the residents even with disaster experience less resilient relative to other residents. Over this quantification, the authors provided insight into the humanitarian effect in achieving enhancement to adapt and cope with climate-related disasters (Joerin et al., 2012).

In this thesis, the resilience approach will include some of the definitions and criteria discussed in the earlier literature review that contained an account of different applications and descriptions of resilience concept. Precisely, Graph Theory characteristics will be executed into transportation networks and civil infrastructure engineering to efficiently quantify the four resilience aspects while selecting useful concepts in other fields application in real civil infrastructure networks. Such networks are commonly defined as the addition of many smaller local networks known as clusters. Evaluation of cluster features provide an understanding of network redundancy and resilience, permitting to effectively emphasize on improvements and prioritization of the most critical localities. Concerning the assessment of graph parameters contextualized by resilient factors (i.e., robustness, redundancy, resourcefulness, and rapidity) which can give insights on the system's state, decision-makers will be better conversant in directing the necessary resources to the most critical sites. By applying the concepts presented in Bruneau et al. (2003) especially in the context of infrastructure quality represented thru *Q(t)*, the serviceability, connectivity, and flow of road networks will be of paramount importance in this study in a way to holistically prepare for failure consequences of probable disasters which will prompt response, improve recovery and contain losses.

III. RESILIENCE OF TRANSPORTATION SYSTEMS

3.1 Pre-Event Damage Mitigation

Transportation infrastructure plays a major role in providing local communities with smooth access for their daily activities (e.g., business, emergency, freight …), so any disruption to their performance due to natural hazards will induce excessive losses that could propagate to communities and accumulate over time. Disruption in these systems is highly related to the functionality of its components, in particular seismic prone regions where bridges are susceptible to damage and can act as "bottlenecks" hindering the emergency services. In this chapter, the effects of pre-event retrofit activities and techniques to strengthen deteriorated bridges with low seismic response will be presented. It is especially for relatively underdeveloped networks to start planning and take actions to reap strength, thus bolster network robustness against seismic hazards. Nowadays, seismic design became a vital phase of the bridge design practice in order to increase its ductility and avoid sudden failure. Yet, even those designed with seismic concerns will weaken over time, thus retrofitting techniques are used to extend their lifespan. Costs of such techniques are usually lower than the repair or replacement of large-scale damaged bridges. Seismic risks vary considerably across regions where some areas are more affected than others especially those that are subject to liquefaction and landslides. Accordingly, seismic retrofit techniques are geographically specific, and these could comprise isolation bearings, seat extenders, catcher blocks, bar and cable restrainers, column jacketing, shear keys (Figure 3.1). From the various retrofit methods, bridges could benefit in many ways through enhancing flexural capacity to avoiding unseating failures.

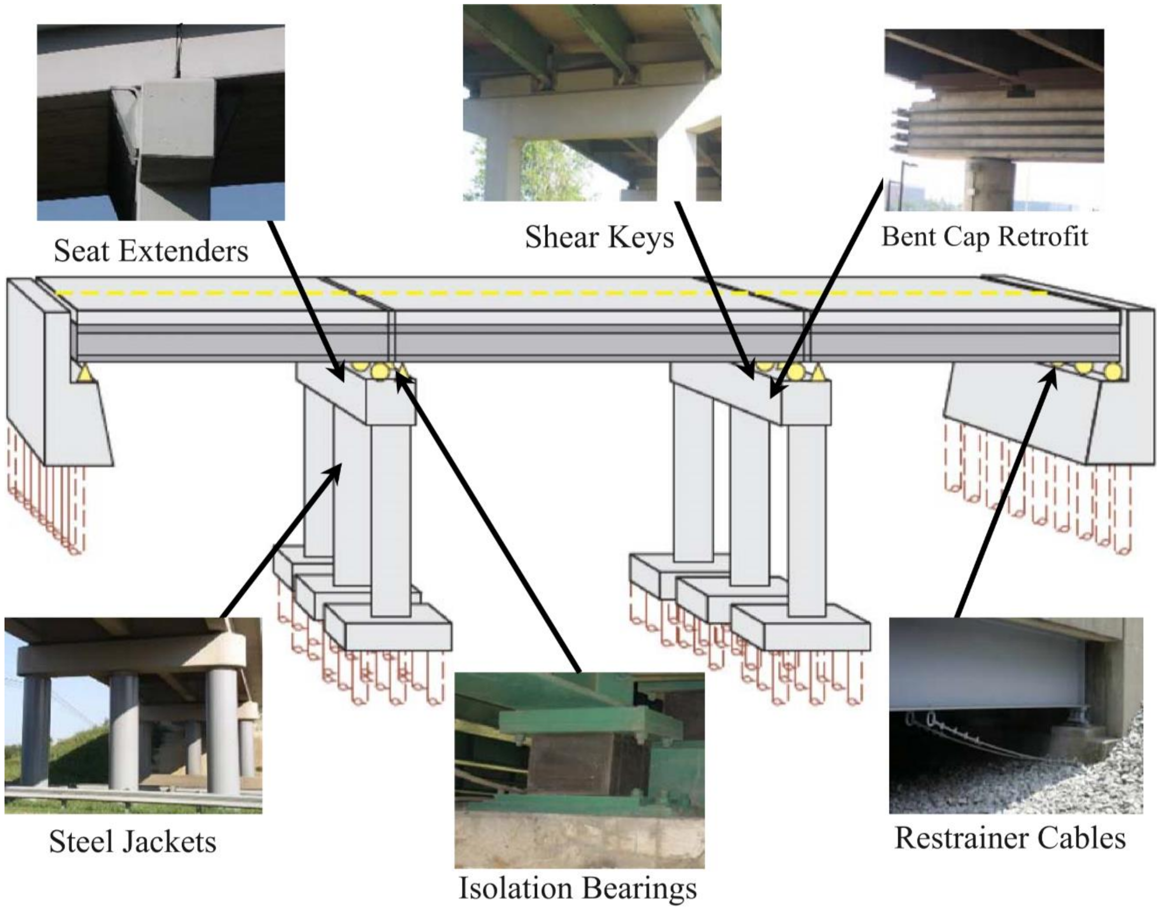


Figure 3.1: Example of some seismic bridge retrofit practices (Wright et al., 2011)

Installing isolation bearings such as elastomeric bearings help in dissipating energy under seismic scenario by augmenting the fundamental vibration period of the bridge, dropping the accelerations in the superstructure, thus declining the inertia forces transferred into the substructure (FHWA, 2006). Using bar and cable restrainers that usually carry tension forces only while staying in the elastic range under pressure, constitute a low-cost technique to avoid losing support in the bridge components. Yet, even though this technique is regarded as efficient, it has failed in large scale seismic events like in California 1989 (i.e., Loma Prieta earthquake) and Japan 1995 (i.e., Kobe earthquake). Therefore, it is recommended to be used in conjunction with other retrofitting techniques (Shafieezadeh et al., 2009). Among the most cost-effective techniques to prevent unseating are the seat extenders or catcher blocks which are steel or concrete additions to the sides of bent caps and abutments. The major role of bent caps is to transmit loads from the bearing to the column of the bridge, however under seismic hazards, the shear strength and flexural capacity of such caps are weakened; for this reason, they are considered for retrofit by adding steel rods to add compressive strength, steel plates from top and bottom of the caps for bracing purpose against shear forces, or concrete or steel to encase the entire bent cap surface (Wright et al., 2011). For column strengthening, it is common in reinforced concrete to apply column jacketing using steel, concrete or fiber-reinforced polymer which envelopes the column preventing it from bursting and bowing out of the vertical reinforcement, thus avoid the collapse of the bridge in extreme earthquakes (FHWA, 2006). Another useful retrofit technique consists of using shear keys or keeper brackets. The formers are reinforced concrete blocks placed between girder and attached to the top of bent caps with dowels to prevent excessive transverse movement during a swaying earthquake event while the latter are steel brackets with similar purpose serving as lateral restraint (Wight et al., 2011). According to roadways, some of the retrofit measures use easily repairable pavement sections (e.g., replacement of rigid pavement with flexible pavement, reduction of joint spacing), replace the inferior pavement structures (e.g., replace old and poor quality embankments with higher quality and well-compacted materials), strengthen the foundations beneath roadway grades (e.g., compact soft or loose soils, improve foundation drainage, add struts to embankments), and clear and strengthen the side and cut slopes (e.g., clearance of loose debris, placement of wire netting, flattening of grades, rock-bolting). To know more about retrofitting standards and practices the Federal Highway Administration (FHWA) *Seismic Retrofitting Manual for Highway*

Structures and its associated publications work as guidelines for many transportation agencies and help in retrofit prioritization for these critical infrastructure components (FHWA, 2006).

3.2 Seismic Risk Analysis

This section is centered on seismic risk analysis and its components It presents a review of different modeled methodologies for transportation systems. Earthquake is one of the major threats to transportation networks that can cause catastrophic disruptions to its components. Dealing with spatially distributed transportation networks within seismic risk analysis turns to be challenging especially that it necessitates performance modeling and assessment at both components and network levels. As defined, risk is the product of the likelihood of occurrence of a seismic event with its vulnerability, and all the system components exposed to this hazard. Risk analysis is to quantify the expected damage while resilience focuses on the critical aspects of a network to recover. Outlining hazards in earthquake events involve ground motion and failure levels estimated through attenuation relationships defined as peak ground motion parameters or peak structural responses (Elnashai et al., 2009). In addition, liquefaction, landslides, soil amplification and surface rupture factors can pose serious damage to the system under consideration. Vulnerability or the sensitivity of the hazard level, such as the likelihood of exceeding the conditional prescribed limit damage as a function of ground motion, is an essential factor for evaluating the seismic risk and assess damage probabilities of transportation networks; though, this is based upon the availability of the damage functions known as the fragility curves along with the necessary hazards data (Padgett and DesRoches, 2009). Rossetto and Elnashai (2003) divided the fragility curves into four types based on: expert judgments, observations of empirical-historical damage data (Basöz and Kiremidjian, 1996; Shinozuka et al., 2003), analytical assessment of the system response, and hybrid that embrace information from different references while taking into account the shortage of observational data, bias of judgmental documents, and modeling insufficiencies of the analytical approaches (Jeong and Elnashai, 2007). Network vulnerability could be evaluated through four methods according to Murray et al. (2008): the scenario-specific approach deals with small scale disturbing events, the strategy-specific approach deals with the probable structured loss of facilities, the simulation-based assessment is related to the assumption of working with an adequate number of simulation to have sufficient depiction of vulnerability, finally, the mathematical approach deals with extreme events seeking for the worst and best-case scenarios. The relationship between the damage state and the functionality of the system is described with the residual traffic capacity which is the ability for a link to carry a certain percentage of the normal system capacity even when subject to road closure or bridge collapse (Chang, 2010). Because seismic hazards analysis and vulnerability evaluation can deliver insightful outcomes for decision-makers and network owners, many researchers studied several geographical areas prone to seismic sources by applying various network performance criteria using general methodologies. Some of them created risk curves to predict the annual delay of the network under earthquakes (Shiraki et al., 2007), others established a seismic risk assessment to study the expected damage to the main trucking roads due to an earthquake scenario that will greatly harm the economic and social activities (Mehary and Dusicka, 2012). As well, Rossi et al. (2012) developed seismic risk analysis to evaluate multiple retrofitting cases for bridge prioritization, while Alipour et al. (2011) evaluated the performance of deteriorating highway bridges located in high seismic areas. Chang et al. (2012) dealt with the vulnerability of metropolitan road network areas to assess the ability to supply capacity for emergency services. Sarris et al. (2010) developed a GIS-based approach based on structural and geological data in a high seismic region in Chania city located in Greece. Specific weights were assigned to the attributes which were verified based on the recent seismic dataset in the region. The proposed risk map turns to be an important tool for management and control strategies in the future. HAZUS and RADIUS which stand for Hazards U.S. and Risk Assessment Tools for Diagnosis of Urban Areas against Seismic Disasters respectively are from the few GIS-tools that tackle the seismic risk assessment problem through either expert knowledge or local observations and measurements. According to Sarris et al. (2010), using the mentioned approaches in the Mediterranean region is often difficult due to the lack of the necessary information that must be provided sufficiently as inputs for the application. Similarly, RADIUS and GIS were used to apply a seismic damage assessment of Sylhet city in Bangladesh. Data such as building structures, infrastructure, and geological information were used from recent studies presented by the local government. This can be considered as a good starting point in seismic risk mitigation planning (Mazumder and Salman, 2019). The seismic risk evaluation in an urban context is challenging due to several difficulties that arise, not only from the data shortage but also from the budget and extensive time constraints. Another study applied in Blida city in Algeria in which the authors assessed the earthquake risk through GIS. The seismic hazard (i.e., surface peak ground acceleration) and the vulnerability (i.e., the building fragility) were determined in order to calculate the damages provoked by the seismic event of different scenarios (Tadjer and Bensaibi, 2017). Liu et al. (2011) established an earthquake disaster risk assessment model from a historical seismic dataset to determine quantitatively major factors such as population exposure, population damage coefficient, and the probability of earthquake occurrence. After that, GIS through spatial analyst is used to analyze the population risk-prone seismic events and to create the corresponding distribution map highlighting the dangerous parts of the Wenchuan region. Karimzadeh et al. (2014) presented an assessment of earthquake hazards, building vulnerability and human loss using a GIS-oriented procedure for the city of Tabriz in Iran. Akgun et al. (2012) presented a landslide risk assessment for Izmir city in west Turkey through remote sensing and GIS techniques. The risk map was obtained for the city by merging the hazard and vulnerability indexes which will help the local government authorities as preliminary planning for the future. In the same context, the resilience of road networks is also seen as a challenging topic of paramount importance towards holistic disaster risk planning, mitigation, and management. Therefore, Kilanitis and Sextos (2019) addressed the resilience aspects in the case of seismic events by establishing a comprehensive and multi-criterion framework for mitigating the overall expected losses, both direct (i.e., structural failures) and indirect (i.e., travel delays), as well as the global social and financial outcomes in the damaged region. Adding to that, both pre- and post-event were considered in the probabilistic risk management framework, in order to prioritize and strengthen the pre-event systems and boost the examination and recovery actions correspondingly.

This sub-section reports the perceived transformations in transportation systems after major past earthquakes in most developed countries (i.e., the United States and Japan) that have very high seismic risks and where the events data were recorded and collected. The 1989 Loma Prieta earthquake (Mw 6.9) induced great damages in San Francesco and

Oakland, especially in the bridge between the two cities where a segment of the Bay Bridge was collapsed which affected the Bay Area travel. This resulted in a significant rise in traffic volume on other main bridges after the disruptions, where the traffic on the San Rafael Bridge intensified by 79.9% in comparison with the pre-event volume. Also, about 300,000 commuters had to choose substitute roads for approximately 3 years after the earthquake (Chang et al., 2012). The 1994 Northridge earthquake (Mw 6.7) generated the highest ground acceleration in the urban region of North America and is considered as one of the detrimental earthquakes in terms of costs in U.S. history. Four motorways and interchanges were damaged by this quake, yet because of the $1.5 trillion retrofit plan in California, the damages to the transportation networks were not considered enormous (Chang, 2010).

The 1995 Kobe earthquake (Mw 6.8) impacted extensively the transportation systems in Japan more than the previously stated quakes that occurred in the United States. This natural hazard triggered a long-term shutting down of the main elevated Osaka-Kobe motorway which was collapsed. This affected greatly the travel demand in the whole region including the parallel routes (Kiremidjian et al., 2007). Another earthquake hit Japan in 2004 called Niigate-Chuetsu (Mw 6.9) affected the transportation networks specifically the Shinkansen and the expressways of the Chestsu area. Yet, the general system functionality after the quake was fair due to the detour paths. This catastrophic event led the freight transit and the business travel cost to increase considerably (Tatano and Tsuchiya, 2008).

In 2011, the East Japan Earthquake that struck the Pacific coast area of eastern Japan (Mw 9.0) is considered as the largest in Japan's history. In fact, after this disastrous event, several tsunami waves hit the North East of Japan leading to an inundation of an area of 507 km^2. This event damaged the Fukushima nuclear reactor and is described by the Japanese Prime Minister as the toughest crisis in Japan since World War II. The losses were estimated to be 3 to 5 % of Japan's GDP from which ¥7-9 trillion costs induced from the social infrastructure's damages (i.e., roads, bridges, ports, houses) (Chang et al., 2012).

3.3 Network Performance Measures

To assess the serviceability state of the transportation network in the pre- and post-scenario, it is indispensable to pinpoint the network performance measures through a holistic framework that compares its functionality effectiveness. These transportation network metrics can be summarized into three appropriate measures: (1) Connectivity (i.e., reachability), (2) Network flow capacity, and (3) Travel time (i.e., travel delay costs). The former two metrics are OD-independent (i.e., Origin-Destination) in contrast with the latter that is based on OD demands that mirror the sum of vehicle or person trips between sites and are directly related to the vehicle possession, households' number, employment rate, income share, zoning, and business activities. Such data can be accessed through surveys, mathematical simulations or direct vehicle identification reports.

3.3.1 Connectivity

Connectivity or reachability analysis is one of the most applied metrics for transportation networks and it is described as the ability to move from a given origin to a destination node or vertex via at least an operational path or link (Chang, 2010). This reliability of network connectivity is applied in Graph Theory which is extremely dependable on the post-event connectedness of the network especially considered in the post-event emergency services to mitigate probable isolation in the system. In connectivity analyses, the primary concern is to identify the reachable paths or the residual capacities after a disruptive event without incorporating the traffic capacities, duration or length of the trips (Rojahn et al., 1992). Simulation-based and analytical algorithms are two types that are mostly used in the field of network connectivity to evaluate network reliability (Chang, 2010).

The simulation-based algorithm is one of the most commonly used technique due to its ease of application that incorporates the component reliabilities and network structure as input. As an example, one of the known applied approaches in the engineering field, when analytical algorithms are not viable, is the Monte Carlo simulation (MCS) which produces acceptable but not exact outcomes. This straightforward approach generates random numbers under a uniform distribution for components damage simulation of the system; after that, the graph search algorithms are employed to identify the system node-pair connectivity. This procedure is reiterated several thousands of times, dependent on the network size, in order to have a steady convergence of network reliability known as the connectivity frequencies. While MCS is extensively used and easy to implement in any size of networks, it has many drawbacks such as the long time required for convergence which is not controllable, the sensitivity to component reliability, and the independence consideration of component failure. All these factors make this network reliability analysis algorithm category computationally inefficient without the ability to regulate the accuracy of the results. This issue could be fixed using the analytical approach especially for small-size networks (Chang, 2010).

The analytical algorithms approach such as the decomposition methods, evaluates the network connectivity by decomposing the complex system into several subsystems (i.e., parallel or series) in order to discover the relation between them. Computation of network connectivity reliability started employing the shortest track algorithm (Kroft, 1967), then some researchers transformed the large network into simpler series that work in parallel (Panoussis, 1974; Taleb-Agha, 1977) and others proposed a split of the shortest path-based algorithm (Aggarwal et al., 1975); yet all these methods and others (i.e., full-probability analytical algorithm, ordered binary decision diagram algorithm) are limited to the small network evaluation and cannot handle large systems (Wu and Sha, 1998; Kuo et al., 1999). Consequently, the disjoint of the shortest path proposal is improved later to provide accurate connectivity outcomes for complex networks (He and Li, 2001; Li and He, 2002); they implemented the recursive decomposition algorithm (RDA) that uses the De Morgan's rule and disjoint theorem to find the failure probability. Their method is based on decomposing the complex system into sub-systems until no route exists between node-pair (i.e., source-terminal) in these sub-systems; however, an estimate output with reliability bound having a satisfactory error should be predefined due to the inability to find all the disjoint paths in the system. To surpass the incomplete information problem and the estimation of the network reliability with bounds, Kang et al. (2008) implemented an easy and flexible method called matrix-based system reliability (MSR). In this matrix-based method, if the full information is accessible, the system reliability can be identified by constructing the event and probability vectors, and if not, the linear programming will provide insightful results within the closest reliability bounds.

To emergency and rescue teams, of a great concern are the knowledge of probable closure in the transportation systems and whether their reliability is interrupted. Thereby, the aforementioned performance measure will be used later in this study, to establish the holistic methodology that evaluate the resilience of transportation networks and their state in the pre- and post-event.

3.3.2 Network Flow Capacity

As an alternative to connectivity-based metrics, the network flow capacity can be employed to assess the performance of transportation networks and the post-event failure extent in the system. It is to some extent “in-between” the other two performance metrics. It reflects the maximum possible flow between source and terminal nodes without exceeding the capacity of the connecting links in the network (Ajuha et al., 1993). Some authors used this performance metric after a seismic event to study the functionality of transportation networks in which the maximum flow capacity was presented (Nojima, 1998; Lee et al., 2011). However, these studies are relatively minor in total comparing to the other two performance metrics and it did not incorporate the resources restrictions and the transportation components (Chang, 2010). However, as this thesis focuses mainly on topological measures and connectivity indices of road and highway networks, this performance measure is beyond the scope of this study.

3.3.3 Travel Time

Travel time or travel delay cost metric is broadly employed to estimate the performance level of transportation networks prone to seismic risks (Nojima and Sugito, 2000; Kiremidjian et al., 2007; Kim et al., 2008; Stergiou and Kiremidjian, 2010; Zhou et al., 2010). The stated travel costs can be estimated through the traffic assignment step used as the fourth step within the conventional four steps of the transportation demand estimation which involves trip generation (i.e., travel decision), trip distribution (i.e., destination choice) and mode choice (i.e., travel method) (Weiner 1987). Traffic assignment methods are widely employed in modeling the road networks flow based on a full OD demand and commuter movement data. Accordingly, two expansive classes come into place namely static and dynamic traffic assignment models.

The static traffic assignment model has a time-independent nature. For example, the travel time and traffic demand in the network are constant over time, and the model shows a steady traffic flow state in user equilibrium without the possibility of individual change in direction to enhance their travel time (Wardrop, 1952). Hence, in the case of seismic hazard, these parameters are considered similar to the pre-event situation. According to these assumptions, this model can be sorted in two further categories namely deterministic and stochastic user equilibrium model. The former model assumes that the traveler will always select the shortest path which is practical especially in urban networks to minimize the travel cost. However, the stochastic model is based on the driver preference where the road choice is determined stochastically; the model is suitable for traffic planning used most frequently in less congested areas (i.e., rural), where the shortest path could be not the first choice (Sheffi, 1985). Static traffic assignment models are acceptable and used in many transportation agencies for their estimation of the mean travel time in the networks (Kim et al., 2008). This model is employed to assess the performance and functionality of transportation networks after a seismic event based on the travel time (Nojima and Sugito, 2000; Kim et al., 2008). Although the stated static models are good in modeling the traffic flow with inelastic demand (Werner et al., 2006), it should be noted that this assumption does not reflect the real situation of the network especially after a disruptive event (Fan, 2006). Thus, it is necessary to account for the dynamic traffic assignment models that implement modification factors to the network demand and travel costs (Shinozuka et al., 2005; Kiremidjian et al., 2007; Shiraki et al., 2007).

Dynamic traffic assignment models address the variation in road traffic parameters that were presented in the literature through Yagar (1971). Like the static models, dynamic ones can also be sorted in two main vast categories which are the analytical and simulation-based models. The analytical dynamic traffic assignment models have three methodological classifications: mathematical programming, optimal control and variational inequality (Boyce et al., 2001). The mathematical programming stemming from the earliest formulation of the static models (Beckmann et al., 1956), yet it has shown intrinsic technical issues in describing the traffic dynamics factors (i.e., asymmetry of travel cost functions and time-dependent relations of travel flow and travel time) (Boyce et al., 2001). The optimal control model was first introduced by Merchant and Nemhauser (1978a and 1978b) and refined later by other researchers such as Carey (1986, 1987 and 1992) and Friesz et al. (1989). This dynamic-based model employs inflow as control variable and shows clear correlation between the exit flow and the link flow; yet it has some requirements in order to perform multiple OD sets and give realistic flow circulation (i.e., the exit flow function and rate must be convex and positive respectively). Adding to that, this model remains problematic due to the concavity problems that could arise from the first-in-first-out condition of traffic circulation and the holding-back of vehicles on links that impact the traffic realism (Peeta and Ziliaskopoulos, 2001). The last category namely variational inequality is more general than the first two formulations within the analytical dynamic models; it has some flexibility in dealing with several dynamic traffic assignment problems but still computationally intensive, bringing up difficulties of computational controllability for real-time deployment. Such difficulties are further magnified especially for path-based variational inequality formulations that need a full path enumeration (Peeta and Ziliaskopoulos, 2001). Regardless of their abilities in representing link interactions and traffic flow circulation, traffic realism and the intractable computational cost within the analytical dynamic traffic assignment models in the context of complex transportation networks persist (Boyce et al., 2001). In the real-world deployment context, complex dynamics of traffic flow in transportation networks are evaluated through traffic simulators within the simulation-based dynamic traffic assignment models. Such models have progressed quickly and been accepted greatly. For instance, it is used to assess the evacuation approaches during an emergency event (Tuydes and Ziliaskopoulos, 2006) and to ascertain the most vulnerable road sections (Murray-Tuite and Mahmassani, 2004). After a disruptive event, travel demand could change considerably due to the driver's response to congestion or road closure, therefore many of them could forego their trips. These forgone trips induce costs relative to the lost opportunities (Werner et al., 2006). While direct costs represent the actual repair costs in the network, indirect costs are associated with delays (e.g., detours, congestion) which can be defined as the product of the delay in time, average vehicle occupancy and the value of time in monetary value (i.e., average hourly wage). The product factors are relative to geographic, demographic and preferences conditions. Unlike repair costs that can be assessed directly after a seismic event in accordance with the network damage state, indirect costs are more complex to estimate which keep piling up in the post-event until the recovery process is finished and the network is totally functional. The fact that it is very challenging to have an accurate and realistic driver road choice behavior especially in a short term emergency response period in complex networks, makes the estimation work through traffic simulations very difficult, thereby travel delay costs turn to be unrealistic in the network behavior models. As a final point, the main restrictions of simulation-based dynamic traffic assignment models in the context of real-world deployment are summarized by the incapability to derive the related mathematical properties and the computational burden linked to the traffic simulator application that can be operationally limited (Peeta and Ziliaskopoulos, 2001).

3.4 Post-Event Performance Assessment

The potential network segments closure due to a seismic event would disturb the integrity of transportation networks and delay the evacuation teams and relief resources. A primary concern is to identify the emergency paths and study the reliability of network reachability that is extremely dependable on the completeness of such transportation networks. As described, the level of performance of these networks directly after an earthquake is related to robustness property while the ability to provide alternate paths is linked to the redundancy property. However, main property in the post-event relies on resourcefulness aspect which is the capacity to deliver extra resources in order to prioritize goals. These goals should contain accelerated repair that defines the rapidity aspect of resilience leading to an overall improvement in the network performance. Consequently, when considering the repair costs in the network, it is vital to describe the repair strategies employed. In the case of (A+B) bidding, bids are awarded to the contractor who can cut the repair costs of the network damages (A) and reduce the repair time (B). So, the total cost of the repair phase will be the total product of the bidding and daily closure cost. Also, to ensure that the damage network will be repaired on time, incentives are rewarded, or disincentives are fined to the contractors if they finished ahead or behind schedule respectively (Furtado, 2015). Another strategy used is the accelerated construction (ABC) (e.g., bridges, tunnels) where for instance, bridge sections are constructed and assembled off-site and after that placed on site. In fact, notable outcomes have been demonstrated when combining incentivizes with accelerated techniques under emergency construction and replacement (California Department of Transportation, 2008). Also, modular temporary segments could be used until the main parts in the network is functional again. Studies show that accelerated repair strategies help in reducing the indirect costs for the users more than those with incentivized only (Furtado, 2015). In other words, to have a valuable investment through acceleration techniques means to have the reduction of indirect costs should be greater than the added repair costs. Through the repair phase, as the physical state of the network components is enriched, the associated indirect costs declined considerably. After an earthquake, the indirect costs will be the dominant accumulated costs in comparison to all the additional repair costs and incentives. Hence, this enlightens the importance of being sufficiently resourceful to at least accelerate the reparation on the most critical links in the network and avoid in that way the burden of large costs.

This chapter provides a review of the major pre-event retrofit activities and techniques to strengthen the network components. Disruptions in these networks are directly related to the functionality of their structures especially in risk prone regions. Seismic risk analysis and decision-making in disaster management of transportation systems are particularly challenging because it requires the assessment of system performance of transportation networks and their components. This entails the characterization of physical damage of network components and system response to any given events. Relevant literature review for three major categories of performance metric is presented to highlight their computational methodologies, applications and limitations. Yet, due to data insufficiencies of travel demand in normal condition and the lack of information of such data on previous post-events records, OD demand-dependent metric is not used in this research. Instead, the reliability of network connectivity is applied reflecting the post-event connectedness of the network to mitigate probable isolation. Post-event performance assessment highlights the importance of being resourceful enough and focuses on prioritization of the utmost critical network components to reduce the recovery time of the system.

IV. NETWORKS IN TRANSPORTATION SYSTEMS

4.1 Introduction

Transportation networks entail fundamentally nodes and links. Their properties can be effectively assessed through Graph Theory which is employed by many researchers who applied its principles to study networks (Buhl et al., 2004; Adachi, 2007; Hu et al., 2011). The topological characteristics applied are used clearly from the fundamental principles of Graph Theory in order to realize consistency and reliability in quantifying the network resilience which reflects the degree of preparedness of the system to extreme hazards. Resilience and real networks are best described through topological properties included in Graph Theory due to its ability to define the whole network characteristics along with the contribution of each of its components. Resilience is reliant on the network configuration, vulnerability, and adaptive capacity. The latter parameter is close to the concept of system flexibility that is the ability to simply adapt and adjust during and after a disruptive event while preserving the network functionality. Civil infrastructure systems are not all flexible. For instance, while road networks and highways can have alternative routes, railway systems are less likely to have it after a disturbing event. This raises the question of how the resilience of infrastructure can be evaluated and enhanced by the decision-makers and public authorities. The utmost phase is to recognize the most critical network constituents by ranking them by their level of importance. Some researchers suggested a ranking robustness index for the most critical network components (Scott et al., 2006; Cimellaro et al., 2011). In order to study the properties behavior of network topology, Cimellaro et al. (2011) employed a cluster coefficient and betweenness centrality as a means to quantify the local connectivity and nodal centrality respectively. Network topological properties should be further investigated to find their behavior against network attacks. Thus, a comprehensive literature review of the principals and practices of Graph Theory was executed.

4.2 Historical Review

Historically, network studies were launched by Leonhard Euler in 1736 when he published the solution to the Königsberg bridge problem that consists in finding a round trip to cross the seven bridges of the Prussian city exactly once (Barabási, 2003; Boccaletti et al., 2006). Vertices were assigned to land and edges are considered to replace the bridges (Figure 4.1). He proved that there is no way to cross all bridges at once. Other studies in the field appear in 1959 with Erdős and Rényi who established random networks theory and presented probabilistic approaches to validate the presence of graph properties (i.e., connectivity) (Dueñas-Osorio, 2005). Later, the birth of a new movement of interest has been witnessed during the 1990s tackling the study of complex networks (Boccaletti et al., 2006).

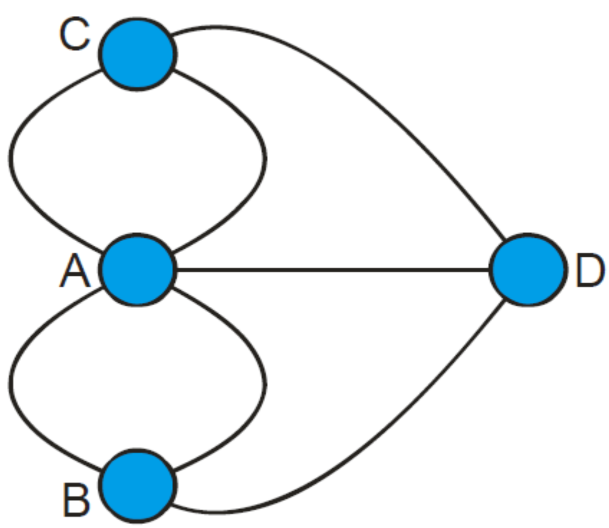


Figure 4.1: The illustration of Königsberg bridges problem

4.2.1 Random Graphs

The elaboration of the random graph constituted a major improvement in Graph Theory (Figure 4.2) where it is one of the important evaluated graphs for simulations. The presence of a certain vertex is based on a probability *p*. The degree distribution is based on the number of vertices in the graph where it usually follows a binomial distribution (i.e., the probability that certain link exists is the same for all other edges) unless the presence of a large number of vertices, then a Poisson distribution takes place. The study of such graphs includes generating a graph in various phases in an increasing *p* order. In addition, a certain graph characteristic is followed, and the associated transitioned probability *p* becomes the focus of the study. In random graphs, there are numerous modified clustering coefficients that reflect the likelihood *p* that two vertices are adjacent. This likelihood is greater in real networks than in random graphs (Testa, 2015).

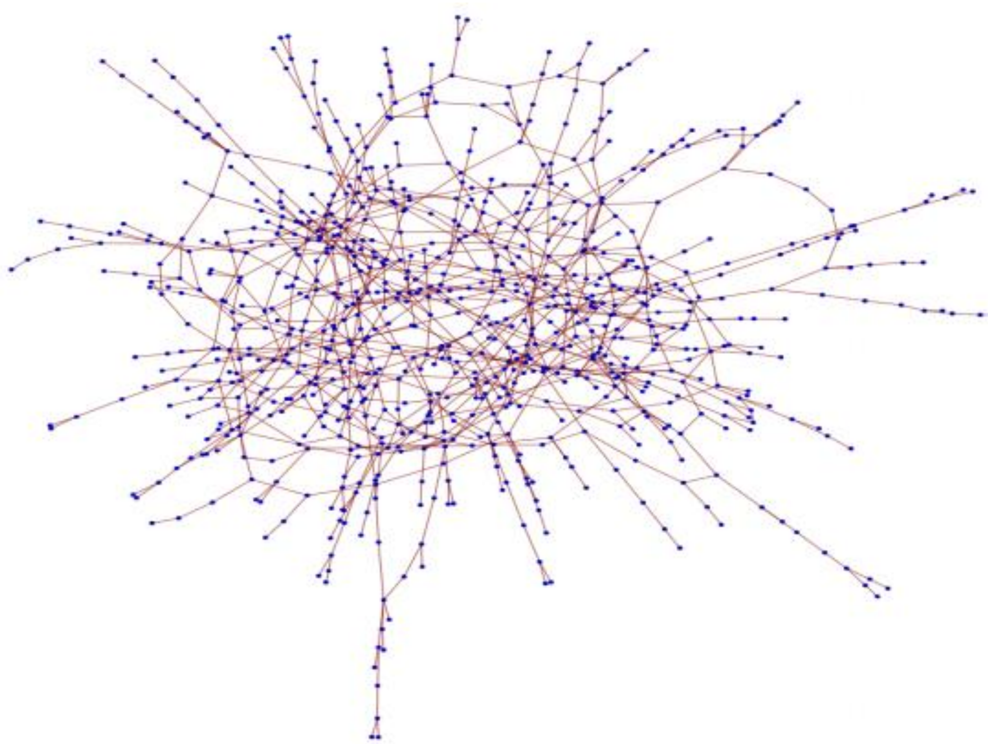


Figure 4.2: Erdős-Rényi random graph (Narayan et al., 2012)

Random graphs can be changed into generalized forms to be more realistic, but such forms lack the transitivity feature which is very problematic to be introduced within the random networks due to the existence of loops. In the beginning, due to the ambiguity in complex networks properties, random networks were employed to analyze it. Although random graphs and their properties are not like the complex networks, one of the few things that is shared is called the small-world effect (Albert and Barabási, 2002). The small-world model is applied to study different path methods (i.e., percolation). According to Newman (2002), the network exhibits small-world effects when the average shortest path is in a logarithmic scale or slower with network size for a fixed mean degree. Understanding the basis of many graph properties is a challenging task especially in the complex graphs that need distinct analysis.

4.2.2 Complex Networks

The significant growth in network complexity and dimensions like the Internet example (Figure 4.3), imposed a modification in the conventional analytical approaches using a different set of properties. This divergence can be recognized in the degree distributions where real networks act as heterogeneous graphs with power degree distribution, whereas homogeneous graphs possess a uniform degree distribution. Due to the importance of dynamic characteristics that network topology holds (e.g., response to failure), it becomes crucial to use complex networks (Boccaletti et al., 2006). These complex networks are usually designated as sparse for their sizeable scope. Scale-free networks were the primary models to imitate power-law distribution. These models are applied to define graphs with matching functional arrangement at all scales. While sociological, technological, and biological studies are most of the time described as heterogeneous with short paths and high local clustering, civil infrastructure studies (e.g., roads, telecommunication, power networks) are more effectively modeled through small-world and scale-free networks (Cimellaro et al. 2006). The topological aspects of three complex networks (i.e., highway, Internet, and flight networks) were examined by Gastner and Newman (2006). They found that all studied networks show preference to short edges over long ones. In specific, highway networks possessed much shorter edges, lower degrees and larger diameter than the other networks and this is explained by the planar nature of highway networks.

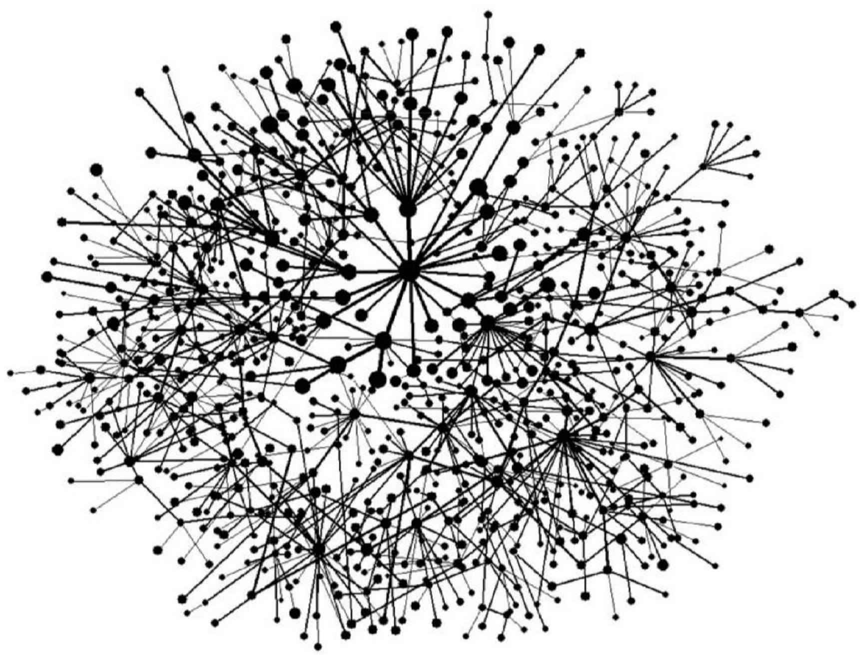


Figure 4.3: Complex network example of the Internet (Dezsö et al., 2006)

4.3 Fundamental Concepts of Graph Theory

4.3.1 Definitions and Terminology

Understanding of topological perspectives on Graph Theory is of utmost concern, thereby an outline of the core meanings and keywords are presented. A Graph consists of two fundamental components called edges or links and vertices or nodes. Graphs and networks are two diverse terminologies that denote the same concept, yet the latter is usually used as real examples of the former. The main graph properties can be found out through the associations and localities of vertices and edges. A network is described as a broad inclusive term that can encompass various types of edges and vertices, loads and directions. Graphs can be categorized into several types from which: directed graphs (i.e., digraphs) can be cyclic or acyclic (i.e., with or without closed loops), hypergraphs are those graphs with hyperlinks (i.e., links attached to more than two edges), and bipartite graphs (i.e., two-mode graph) enclose two dissimilar sorts of vertices where edges commonly cannot join two vertices from the same set. Vertices and edges collections can be described as the subsets of the central graph namely subgraphs. In road networks analysis, the characteristics of a path between two vertices are of distinct significance where it is defined as the orderly arrangement of edges required to move from the origin to the destination vertices; the cumulative edges included will constitute the path length (i.e., distance) which is always described as the shortest path. In case no route joining is two vertices, the length is considered as infinite.

4.3.2 Graph Theory properties

Graph theory topology is extremely dependent on numerous measures of connectivity which is tied to the physical and structural properties of the graph. The network topological properties can be used to quantify the efficiency of network functionality (Cimellaro et al., 2011). If these measures are linked with the network flow properties, then it will be described as topology-flow effects. Connectivity is strictly correlated to the intra-dependencies of the network which is defined as the adjacency and smooth flow between vertices through edges. Connectivity holds many levels, yet a complete graph possesses the uppermost one in which there is an edge between every couple of vertices. Accordingly, retaining a specific level of connectivity is compulsory to sustain the functionality or serviceability of the network. The network nodal degree measurement determines the sum of vertices to the sum of edges per vertex $|E(v)|$. The average network nodal degree is a computation of the system connectivity by considering the mean of the number of edges connected to every vertex. The degree $d(v)$ for one vertex is described through equation (4.1). In addition, the network average degree is defined in equation (4.2) where it is equal to the sum of all nodal degrees divided by the total number of vertices in the network (Dueñas-Osorio, 2005).

$$d(v) = |E(v)| \tag{4.1}$$

$$d(G) = \frac{1}{|V|} \sum_{v \in V} d(v) \tag{4.2}$$

The features of graph topology are usually counting on the law followed by the degree distribution. These features depend on p_k, the ratio of vertices that possess a degree k and the probability that a random vertex has the degree k. An illustration of the degree distribution can be generated simply through collecting all the vertex degrees into a histogram; yet the analytical value of this representation can be low for complex networks, therefore it is essential during the generation of such histograms to consider modifications by augmenting exponentially the bin sizes to lessen the noise dominant in large networks or plotting the cumulative distribution function that reveals the probability of having the degree greater or equal to k. The illustration of cumulative distribution via a log or semi-log scales eases the determination of the power-law and exponential distribution; yet in some cases like in the directed graphs, networks have two sets of degrees (i.e., the in-and-out degrees) which must both be carefully included in discovering the degree of the system. Similarly, in bipartite graphs in which two different sets of vertices exist and edges are connected only vertices of different set category, a degree of distribution is held for every vertex category (Newman, 2003). In general, the supreme degree value is contingent upon the network scope and can be created by various operations of the cumulative degree distribution.

Clusters are described as subgraphs of vertices that are strongly attached where its existence reflects how perfectly the network behaves as a system. When all the vertices designate a complete adjacency, the cluster is namely a clique and it is considered as the most powerful cluster category. The computation of the local connectivity along with the transitivity property of the considered graph is achieved through the clustering coefficients which are appropriate means to calculate the local clustering of graph components into neighborhoods. The network transitivity indicates that if a vertex v_1 is joined with a vertex v_2 which is adjacent to a third vertex v_3, it says that there is a high probability of adjacency between v_1 and v_3. This likelihood is denoted as the clustering coefficient and rates the concentration of transitive triangles in the network. A neighborhood of vertex *v* is referred to as *Γ(v)* and is principally a subgraph contained the vertices adjacent to *v* but excluding it. The clustering coefficient rate ranging between null and unity reveals the linked share of *v* neighbors (Equation 4.3). |*E(Γv)*| represents the number of edges in the neighborhood of *v* whereas the number of possible edges in *Γ(v)* is denoted in the denominator in the following equation (Dueñas-Osorio, 2005).

$$\gamma_v = \frac{|E(\Gamma v)|}{0.5\, d(v)(d(v)-1)} \tag{4.3}$$

The combination of graph components into more isolated neighborhoods is described as the creation of clusters that can take place in various network simulations. Figure 4.4 illustrates two clustering cases of central vertex *v* where the left-side network shows a null clustering coefficient in contrast with the right-side one where it is highly clustered; this is based on the degree of connection of the neighboring vertices to the considered vertex. Based on specific network components properties, clusters are expected rather than being arbitrary collections of vertices. For instance, in social networks, homophilic nature is defined as the tendency of people to be attracted to others with similar race, gender, age or income, thereby the vertices and edges are divided into communities (Testa, 2015).

One of the significant concepts used in transportation networks is the shortest path. The traffic moving through edges based on the vehicle trips constitutes the flow of the road network which is reliant on the OD pairs data along with the shortest path between them. In order to compute the shortest path between vertices, many approaches come into place, yet all revolve around the same fundamental practice.

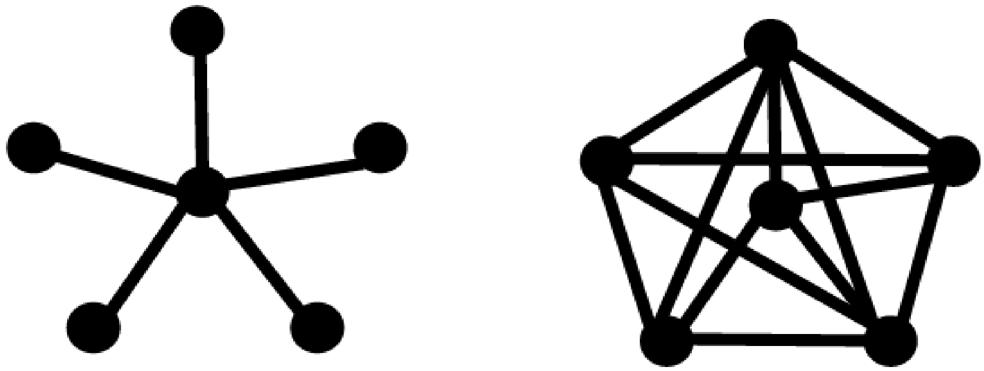


Figure 4.4: High clustering (right) versus zero clustering (left)

In equation 4.4, *n* signifies the network vertices number. Beginning with vertex *i* while all the remaining is set unused, the distances to each vertex neighbor by an edge is detected. More distances are considered as the algorithm moves further to other neighborhoods. When shortest paths are determined, all other detected distances are substituted and therefore, all vertices in the network are valued to check the shortest way to get from vertex *i* to another j.

$$l_G = \frac{1}{n(n-1)} \sum_{i \neq j} d(i, j) \tag{4.4}$$

The most significant critical vertices can be identified through measuring their centrality with the betweenness centrality described in equation 4.5.

$$b_v = \sum_{i \neq v \neq j} \frac{g(i,v,j)}{n(i,j)} \tag{4.5}$$

The numerator in this equation defines the number of shortest paths from vertex *i* to *j* passing by *v* whereas the denominator designates the total number of shortest paths between *i* and *j*. The value of betweenness centrality can be assessed through all vertices in the system in order to choose the adequate directions for resources and take resourcefulness actions accordingly. Using this measure, edges and vertices can be classified corresponding to their functions in topology. Therefore, the likelihood of overlooking imperative vertices that may be critical bridges between regions is prevented. In this context, ranking network components forms the former pace in expecting response to the exclusion or breakdown of components.

4.4 Resilience Quantification via Network Properties

Resilience is described by various aspects which can be measured by different elements defined in the previous section of this chapter. Through nodal and average degrees, the degree distribution is formed which is vital to the vulnerability assessment of network failure (i.e., vertex and edge failures). The robustness of the network is bonded to the degree distribution of all vertices in the system. The classification of this distribution (i.e., homogeneous or heterogeneous) can reveal the damage level of the network after a disastrous event. Noticeably, the nodal degree process is usually the former phase in determining further factors (e.g., betweenness). The significance of vertex relative to edges in a system is highlighted by the analysis of betweenness centrality. Vertex elimination potentially disturbs numerous edges specifically those attached to it. Yet, edge elimination impacts mainly the serviceability of one edge. Thus, network performance is highly dependent on the network vertices stability. Ranking vertices based on betweenness centrality makes the quantification of resilience after a disruptive event possible. Incidents that lead to high-ranked vertices failure are evidently more detrimental than those of lower importance. Real networks combine generally other smaller networks namely clusters which can offer evidence about the local redundancy of the network. In other terms, clusters assessment via clustering coefficient can aid in resources prioritization and enhancement of the most critical zones in transportation networks. The clustering coefficient represents the network connectivity status which is described sometimes as the regularity or locality of the system. With such graph properties circumstanced by measures appropriate to resilience aspects, the network resilience is well comprehended.

A challenging argument concerning network topology specifically the importance of nodal degree in quantifying network resilience, is pinpointed by Holme et al. (2002). This implies that not only high-ranked vertices are important but also low-ranked ones which can act as a major bridge in joining critical clusters. Accordingly, this issue should not be ignored during network resilience assessment in order to avoid unsteadiness in the average shortest paths due to nodal elimination. Goh et al. (2002) consented that high-degree vertices are expected to possess greater betweenness and revealed that the power-law distribution of betweenness centrality is prevalent in scale-free networks. Generally, it is supportive to illustrate and compare the correlation between vertex degree and betweenness through some types of network models. A similar measure with an equal pattern called network robustness index was employed by Scott et al. (2006); the utmost variance between the used index and capacity is within networks that hold low connectivity. They discovered that attacks that are local and global based on vertex degree and betweenness respectively, are leading to a more ineffective process. Dueñas-Osorio (2005) focused on the redundancy as a crucial measure of the network resilience and determined the vertex redundancy ratio R_{Rv} (Equation 4.6) through the number of routes between each vertex and the neighborhood of its neighborhood. Consequently, the capacity to control and reshare the local disruptions will influence the global stability of the system.

Otherwise, imminent cascading failures, traffic congestion, and extensive economic losses will arise to the networks.

$$R_{Rv} = \frac{1}{(|S|-1)^2} \sum_{J \in V(\Gamma_v^2)} I(v,j) \tag{4.6}$$

This complex ratio designating the redundancy ratio is specific for one vertex. *I(v,j)* defines the number of vertex-independent paths between *v* and j. Γ_v^2 is the neighborhood of all the edges in the neighborhood of *v*; in other words, this describes the sum of vertex-independent paths going through the stated vertices and every vertex in the neighborhood of neighbors. The denominator represents the independent paths between v and the complete graph S joining *v*, Γ_v, Γ_v^2 . Finally, to get one representative ratio of the whole system, all vertices ratios are ordered, and the median is chosen as the redundancy ratio of the network.

Connectivity of the network is measured also by three indices that follow the network theory and define the number of vertices, edges, and cycles. The indices called alpha, beta, and gamma can provide information about the redundancy of graph connectivity (Testa, 2015; Furtado, 2015).

$$\alpha = \frac{u}{2n-5} \qquad , \alpha \in (0,1] \tag{4.7}$$

$$\beta = \frac{l}{n} \tag{4.8}$$

$$\gamma = \frac{l}{3(n-2)} \qquad , \gamma \in (0,1] \tag{4.9}$$

Equation 4.7 shows the alpha index which describes the ratio of the number of cycles over the maximum number of cycles in the network. A cycle is defined as the succession of edges that start and finish at the same vertex without reusing edges. Generally, higher values of alpha indicate more probable routes to take between vertices in the network. Equation 4.8 expresses the beta index which describes the number of edges over the number of vertices in the network. While simple networks show results less than one, complex systems have typically values exceeding one. Networks in which each vertex is joined but only have one cycle have unity value. Equation 4.9 shows the gamma index that considers the fraction between the number of edges and the ultimate probable number of edges. When each vertex is directly joined with each other vertex without transitory one, the gamma rate will be equal to unity. Even if it would be unlikely, this evaluation provides a fair insight for comparing the connectivity level in the network with the ultimate theoretical one. Through these indices, u, l, and n are the number of independent cycles, edges, and vertices respectively. The straightforwardness of these algorithms turns them to be convenient to determine many trials by comparing the level of connectivity of several networks and evaluate the consequences of adding extra edges or vertices for network enhancement.

Networks exhibit a distinct topology which depends on the structural configuration and the type of flow transported. In the case of transportation networks, their topology is more like a mesh structure. These networks are spatially restricted to planar models which limit the potential of connecting some adjacent pairs of edges. This is mainly due to the constraints of the costs associated with connecting them. Accordingly, to consider the planar nature of the networks, a new coefficient is offered namely the meshed coefficient

(Equation 4.10) entailing a fraction that describes the number of faces to the extreme possible number of them. Through it, m and n designate the number of edges and vertices respectively.

$$M = \frac{f}{f_{max}} \qquad , f = m - n + 1 \;\; and \; f_{max} = 2n - 5 \tag{4.10}$$

It is essential when measuring the network efficiency, on the macro, micro or average levels, to study the geometric properties (i.e., path lengths) along with the topological ones (i.e., paths number). Adding to that, the network size is directly related to the overall efficiency and meshedness; as the former goes up, the latter aspects increase. Accordingly, evaluating the main network components for various vertex removal after a disruptive event reflects the fragility degree of the network (Testa, 2015). Buhl et al. (2004) considered the cost of enhancing the resilience of the network through the geometric path length defined in equation 4.11. Where the numerator indicates the subtraction of the length of the minimum spanning tree from the total network length, and the denominator describes the subtraction of the formerly stated length from the length of the greedy triangulation. To end with, slight growth in the mentioned cost can radically boost the efficiency and robustness of the network paths.

$$c = \frac{L_{EXP} - L_{MST}}{L_{GT} - L_{MST}} \tag{4.11}$$

4.5 Evaluating Network Response to Failures

4.5.1 Networks Failure Modes

The main failure modes that impact the interdependent networks can be classified into three classes: parallel failures, escalating failures, and cascading failures (Rinaldi et al., 2001). Escalating failures arise when an existing failure or interruption in one system can adversely impact or intensifies the disruption of the functionality of an independent second system. Parallel failures or common cause failures occur when two or more systems are disrupted or failed at the same time due to the same triggering hazards. Cascading failures occur when certain network element is failed, and it is essential to reallocate the load that was supported by the failed element to other elements in order to maintain the functionality; yet, this distributed load can induce more disruptions to other elements due to overload and in that way, the damage still propagate until the load cannot be reallocated anymore (i.e., blackouts). Many researchers have focused on studying the impacts of cascading failures on the system especially in telecommunication and water distribution networks (Dueñas-Osorio, 2005; Blume et al., 2011; Zio and Sansavini, 2011; Shuang et al., 2014). Power networks are an example of heterogeneous networks that possess a quite uniform distribution flow and are considered vulnerable to cascading failures particularly if the damaged element was transmitting a high flow. According to Jiang et al. (2005), cascading failures should be assessed in transportation systems which are well-acknowledged as heterogeneous networks. Similar to Dueñas-Osorio (2005) study in which Monte Carlo simulations were applied to discover the probability of power system component failures, Blume et al. (2011) used a probabilistic approach to assess the resilience of networks under cascading failure event focusing on the network topology characteristics. It is explained that every vertex *v* has a limit *l(v)* where the failure mode exists if there are minimum failing *l(v)* neighbors which are based on probabilistic distribution. As revealed in the previous studies, cascading failures and other categories of propagating failures, are not only dependent on network topological measures (e.g., connectivity, centrality) but also it combines network flow features (i.e., demand) (Shuang et al., 2014). Yet, as this thesis focuses mainly on topological measures of road and highway networks, cascading network flow is beyond the scope of this study.

4.5.2 Removal Methods in Graph Theory

A crucial question arises when considering network elements under disruptive hazards: what would occur to the system in the absence or damage of a specific component? To answer this question, one should first identify the system components and its importance relative to system performance and functionality. This shed the light on the policy applied for the systematic removal of network components known as the method of removal of vertices. After each vertex deletion, variations in topology and performance conditions should be taken into consideration through the vertex rank-ordering update process. Four major removal methods are defined showing the importance of vertices under various types of disruptions (e.g., random or targeted attacks, overload): vertex degree rank-ordering, vertex betweenness rank-ordering, transshipment flow rank-ordering, and random removal (Dueñas-Osorio, 2005). While the first method involves topological knowledge of the networks centered on the connectivity, the second method deals with position and function that every vertex has in the produced, transmitted and distributed flows. The third method is the most comprehensive between the four methods, and it requires information about the flow capacities of all network components along the costs associated with these flows grounded on Euclidean distances. The fourth and final method works as a complement to the previous removal processes.

The fact that real networks expand and operate under less ideal conditions and atmospheres, let the researchers be interested to examine the resilience of such networks under removal policies. This resiliency is assigned to the inherent redundancy within such complex systems and it is described as error tolerance which is specifically vulnerable to targeted attacks (Albert et al., 2000; Barabási et al., 1999). Barabási and Albert (1999) applied vertex removal (i.e., targeted and random) over two real-world networks (i.e., Internet topology, World Wide Web WWW) which possess both nearly power-law degree distributions; they deduced that the mean vertex to vertex distance was noticeably impacted by targeted removal only. Similarly, Albert et al. (2000), concluded that the connectivity of heterogeneous network (i.e., scale-free network) is extensively reliant on few numbers of high-connected vertices that any damage to them can considerably alter the topological nature of the network; in contrast to homogeneous networks (i.e., Erdős–Rényi networks) where random and targeted attacks show comparable response in terms of the average shortest path changes. Barrat et al. (2008) concluded that heterogeneous networks are very robust to random attacks in distinction with targeted attacks that hit the most critical vertices and edges in the network; they applied the initial degree distribution removal and the recalculated degree removal techniques through the targeted attack process. Holme et al. (2002) revealed that even if scale-free graphs are well resilient to random attacks, though are extremely vulnerable to targeted failures, differently from random and small-world graphs that have a similar likelihood to failure for random or targeted attacks.

The Percolation Theory is a method in which vertex and edges are described as randomly functional occupied or unfunctional (Newman, 2002). This theory has turned to be a central part of Graph Theory due to the linkage with the resilience concept and the ability in simulating network disruptions. It consists of two forms: site percolation (i.e., vertices) and bond percolation (i.e., edges). Considering random network, the likelihood of functional vertices where edges are joined only to them is denoted by p. Thereby, the likelihood of an edge to be functional has similar p. Generally, grid network is used in the analysis of Percolation Theory. In addition, as this likelihood goes up, the clusters in the network rise. Another bound at which infinite clusters appear for various sizes are denoted by p_c. If this latter probability is larger than p, there is no presence of global connectivity and an infinite cluster takes place; yet if the bound is smaller, then the inverse is true. Percolation theory is extremely related to the fragility concept. As defined by Dueñas-Osorio (2005), the concept of fragility represents the vulnerability of a system to failure given particular degree of disturbance. This theory has opened the door to foster easy but effective dynamic models to predict cascades on networks. This is accomplished by using simple limits within random graphs to recognize the interaction of network components based on their neighbors' state (Watts, 2002).

4.6 Graph Theory Implementation in Transportation

The planning developments for urban transport have concentrated on the formation of urban networks categorized by high connectivity and interrelation between their constituents which can balance the supply and demand for mobility. Yet, this dependence can cause significant vulnerability and damages in terms of components disconnection, thus lower the efficiency level. Candelieri et al. (2019) concentrated on public transportation networks to analyze and assess vulnerability and resilience in terms of flexibility and the ability of the key functions to persist in the presence of disruptive events, targeted attacks, and cascading failures. Their study is based on a topological approach through using Graph Theory in order to measure the vulnerability after the loss in connectivity and efficiency of the urban networks. Due to the variations in the transportation networks, another study is done through focusing on the changes in traffic flows by implementing a novel approach called Networks in Networks (NiN) which helps in encoding multiple data from topology, paths, and OD information, all within one steady graph system (Hackl and Adey, 2019). A recent study approximated the betweenness centrality to determine the key nodes in a weighted urban complex transportation network (Liu et al., 2019). The results of the simulations presented a high accuracy and efficiency in computation in a relatively short amount of time, and it can be used to support decision-makers for planning, managing and optimizing urban road networks and traffic. De Montis et al. (2010) used complex networks analysis based on Graph Theory to compare between commuting systems. By a limited number of variables and without modeling the properties of every element within the system, Graph Theory provides a global characterization of the studied features of the system at a given degree of accuracy. Other researchers focused on transportation networks resilience through identifying the most crucial links in the system for which resistance should be amplified to mitigate disaster risk. However, such reliability estimation on resiliency is conducted under sensitivity and uncertainty analyses (Soltani-Sobh et al., 2015). An application of the Graph Theory to determine the structure of a metro system was conducted where new indicators are implemented such as routing degree, route connectivity, average link per link, intensity, and density of the route. This study could be applied to assess other metro networks as well as for preliminary design analysis (Stoilova and Stoev, 2015). Mussone and Notari (2017) depicted the transportation infrastructure by a planar connected simple graph and analyzed the graph properties through structural indicators to study the features of the system. Aydin et al. (2018) integrated stress testing with the aid of Graph Theory to evaluate the resilience of urban networks under seismic events. Their research involves five steps starting with establishing a scenario set of potential seismic damage range in the network, then assessing the resilience through graph-based metrics and topology-based simulations in order to determine the corresponding variations, finally, the resilience of these networks is examined based on the spatial distribution of their critical components as well as the overall network topology. Shanmukhappa et al. (2018) studied the topological behavior of the bus transport network in Hong Kong, London, and Bengaluru. Also, Guze (2015) applied Graph Theory parameters and algorithms as a means to assess and optimize transportation systems. Demšar et al. (2008) implemented a mathematical method that combines a dual graph modeling with connectivity analysis and topological measures to model the vulnerability risk of the network components, and thus, the spatially distributed critical locations were determined. Zhang (2017) evaluated the performance of bus networks in a structural analysis through the use of Graph Theory and complex network theory indicators. Tran et al. (2019) studied the robustness of the Vietnam bus network through a complex network analysis where they surveyed some robustness measures such as the average path length, the average clustering coefficient, the global efficiency and the size of the largest cluster. In their research, five critical nodes were identified, and the system was found to be robust against random failure but vulnerable to targeted attack which is following its scale-free nature. Other researchers concentrated on the changes in both single and integrated systems to determine and compare the topological characteristics of complex transportation networks, and therefore they drew insights for enhancing their performance (Hong et al., 2019). Ahmadzai et al. (2019) evaluated and patterned urban road networks highlighting the significance of nodes and road segments in a GIS-based approach. By using GIS, the authors have prepared the data, modeled and generated the integrated graph of the natural road network, and measured the centrality parameters. Their method showed accurate and helpful findings. Another graph-based model study was applied using GIS to provide insights into geographic network analysis. The mathematical model which is based on empirical study addressed subjects such as geo-computation, geographic networks, and graph-theoretic measures (Morgado and Costa, 2014).

Transportation networks consist fundamentally of nodes and links. Their properties can thus be effectively measured with Graph Theory: the study of networks and the relationships between their components. Consistency and reliability are achieved through directly deriving the topological properties from the fundamental theories of graph. These topology measures defined earlier in this chapter, translate best to networks and their resilience. In fact, this makes them convenient for their flexibility in defining the overall network properties and the contribution of each network component. After reviewing the vertex removal techniques, those related to degree and betweenness rank-ordering along the random removal will be applied to study the network response to targeted and non-targeted attacks. Most of the reviewed topological measures will be determined across simulated network scenarios. Thus, a concrete resilience quantification is achieved reflecting the preparedness level of the transportation network to extreme natural events.

V. METHODOLOGY for RESILIENCE EVALUATION of SPATIALLY DISTRIBUTED NETWORKS under SEISMIC VULNERABILITY: Case Study of BEIRUT

5.1 Resilience Assessment Methodology

After the extensive literature review presented in the previous chapters, the topological approach turns out to be a suitable method for analyzing the resilience of transport networks, specifically those networks in developing countries that possess a limited capacity in case of data availability and records. Graph-based techniques through Graph Theory are quantitatively evaluated and analyzed to investigate the robustness, redundancy, vulnerability and thus the resilience of the system. The examination of the resilience concept in terms of the spatial distribution of critical network components is applied through GIS-based approach where the road networks are evaluated via spatial and statistical configurations. GIS is a suitable software that provides a tool for integrating and managing spatially distributed information. Accordingly, it is imperative to collect and prepare the necessary data and maps. The first and vital dataset needed should be in the form of shapefiles of natural road networks. The ESRI Open Street Map (OSM) and Google Earth visualization are used in combination with the main road networks. Adding to these data, building inventories (e.g., localities, area, density, emergency centers), generalized geological map, seismic map, topographic map, and traffic network data need to be compiled. The shapefiles of the area of interest must be updated and corrected along with the required georeferenced features, attributes, and projection system.

As stated in Chapter 4, topology is defined as the connectivity and arrangement of the network. Road transport networks possess several definite topologies describing their assemblies in terms of nodes or vertices, links or edges, paths, and cycles. Accordingly, a real transport system is represented in the form of a network or an abstract graph, which are denoted by G=(V,E) comprising a set of vertices V= (v_1, $v_2 \ldots v_n$) and a set of edges E= (e_1, $e_2 \ldots . e_m$). Roads can be characterized as motorways, primary roads, secondary roads, tertiary roads, unclassified, bridges, and tunnels. This characterization is based on the road width and speed limit. GIS applications including ArcGIS Network Analyst Extensions are employed to import the shapefile that has a line feature into the feature dataset of geodatabase for the aim of generating network datasets. The centrality toolbox called the Urban Network Analysis toolbox (UNA) is utilized to compute certain important network analysis properties from betweenness and straightness (Sevtsuk and Mekonnen, 2012). Betweenness centrality represents the number of times that a node lies on the shortest routes between pairs of other accessible nodes in the graph. Straightness is defined as the closeness degree of the shortest path between certain node and all other nodes that are within the chosen radius and how it resembles the Euclidean distances (Vragović et al., 2005; Porta et al., 2005). This toolbox incorporates significant features related to spatial network analysis that account for geometry, topology, network elements (e.g., nodes and links), and spatial units (e.g., buildings). It is used by planners, geographers, analysts and others who are working on the spatial structures of urban areas and its associated social, economic and environmental developments. UNA toolbox requires an ArcGIS 10 software along with the network analyst extension. The calculation steps that are followed through UNA application are shown in Figure 5.1. The creation of all network dataset files, and the needed conversions forms the structures needed for the assessment. These structures comprise all the junctions that represent the nodes and the links that represent the roads.

Before considering any scenario analysis, the planar, connected, undirected, and unweighted original network graph is assessed, and the general graph properties are determined. At this point in the approach development, the interest is in undirected and unweighted graph even though the weighted graph will be considered in the upcoming scenarios. The directed networks are out of the scope of this work considering that people tend to disrespect traffic directions, especially in developing countries, in case of emergency scenarios after an extreme event. The process of assigning weights to nodes (i.e., junctions, crossroads) or links (i.e., road segments) is directly related to the points of interest (e.g., key locations, roads characterization) in the simple connected graph considered.

The degree distribution of the original network is evaluated to reveal significant properties related to the network nature. This is a significant property to estimate the vulnerability of a graph network. As discussed in previous chapters, the aforementioned degree is dependent on the probability $p(k)$ that a randomly selected node has a degree k. Both the degree distributions of a random graph and a scale-free graph are studied. Then, a goodness of fit test is applied to verify which distribution the network was fit in accordance with the normalized mean square error. Also, the trend of the degree correlation of the network is determined. It is similar to the degree of distribution where the probability that the nodes connect to other ones with comparable degrees is measured. The general graph properties that are first applied to measure the redundancy of the original graph are the connectivity indices which are defined by the alpha, beta and gamma index, and other classical and descriptive parameters. These indices are dependent on the number of nodes, links, and cycles existing in a network. In addition, the average nodal degree is one of the central properties to trace that represents the connectivity of the network and aids in comparing the ease of commuting between different distribution network types. As the average nodal degree defines global connectivity, local connectivity should be also measured. This is performed through the clustering coefficient which translates the degree of local redundancy and connectivity of the network. The clustering mirrors the existence of nodes assembled in delineated neighborhoods that are unreachable from the core network. For relatively local routes, clustering reflects the availability of substitute routes. Another parameter is considered which is called the average betweenness centrality that can reveal the level of relationship to the significance of a node to the network. This parameter is independent of the number of links associated with a node, yet it focuses on the number of shortest paths that are connected to the node. In transportation networks, the determination of the shortest paths is very important and critical for users to direct resources from certain origin to a specific destination. Hence, the average shortest paths are assessed which reflects the network property gauging the redundancy of the system. The smallest combination of links from an origin node to the desired destination node designates the shortest path in the graph network. Through Graph Theory, all the components of the graph network are reviewed in order to measure all the possible paths combinations and ascertain the shortest paths.

The graph-based model is subject to manipulation by random node removal and adjacent links removal separately. These fractions of nodes or links are simulated in random events that would lead to failure in different structures of the network. Subsequently, the stated topological properties are evaluated as the removal fraction escalates in order to examine the system properties trends. Through this evaluation method, the effects of various random failure scenarios can be illustrated and analyzed. Likewise, the degree distribution changes are inspected during each scenario at every removal fraction. The analysis described above is repeated to analyze vulnerabilities of transportation networks with respect to the removal of some of their components according to the ranking of their average degrees and centrality measures.

Vulnerability measures are determined as the reduction of connectivity and efficiency relating to several natural disruption events while considering the seismic features, geological and topographical characteristics, environmental sources and impacts, traffic networks data, buildings areas and neighborhoods, and population distribution and density. Thereby, vulnerability measures are determined from topology-based simulations that are applied to the case of weighted structures of the network by deleting randomly a portion of the nodes and links. Similarly, the removal process is repeated under the condition of targeted failure mode based on each considered scenario where the effects of both modes of removal are compared and interpreted. After considering each scenario according to the available features, illustrations are merged to highlight the hotspots and most critical network structures. Such structures are examined by their specific topological magnitudes according to their relative importance within the system performance.

The elaborated methodology that relies greatly on mathematical theory is combined within a spatially distributed assessment of the transport networks. Depending on this application in mind, the topological approach is best applied due to its limited data hungriness. The straightforwardness of this procedure makes it computational realistic to assess the performance of such systems under successive random or targeted attack strategies of nodes or links. As mentioned, by pinpointing the key components of the studied system that are considered potential sources of loss due to natural hazards, decision-makers can accordingly prioritize the riskiest parts of the network and optimize the use of the existing resources.

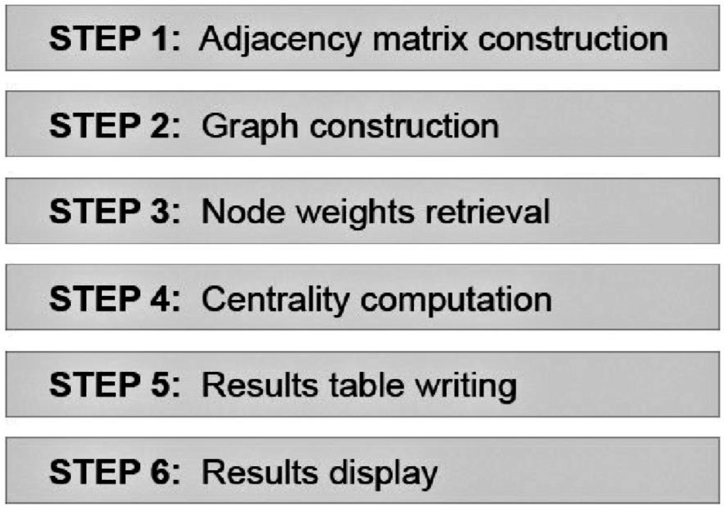


Figure 5.1: Calculation steps of UNA toolbox

5.1.1 Methodology Phases of Resilience Quantification

- ***Phase 1 A:*** Data Collection, Preparation and Correction

1) Data Collection: Shapefiles and Maps: Administrative (border, governorates, caza), Streets, Building Inventories, Geology, Seismic, Traffic Network
2) Preparation and Correction: Review Network Polylines (convert features to lines, overlays, missed and false connections), ESRI OSM, Google Maps
3) Framing the Study Area (boundary buffering)
4) Geoprocessing, Georeferencing (projection system)

- ***Phase 1 B:*** Primal Graph Modeling and Generation

1) Graph Generation (create file geodatabase, feature class, feature datasets)

2) Modeling Network Datasets (nodes and links)

- ***Phase 1 C:*** Abstract Graph Analysis

1) Original Graph Analysis (undirected, unweighted): generate the degree distribution
2) Study the Network Type and Characteristics

- ***Phase 2 A:*** Topological Evaluation of the Original Graph (random removal)

1) Network Random Removal (10%interval)
2) Calculate Redundancy Measures and Descriptive Indices (alpha, beta, gamma, GTP, eta, network related densities…)
3) Determine Network Topological Properties using UNA toolbox (avg. betweenness centrality, straightness, closeness), and using GIS tools (avg. lengths and shortest paths, mean avg. degree, avg. clustering)
4) Network Inspection after each Removal Interval (degree distribution, overall connectivity…)
5) Efficiency Loss Calculation

- ***Phase 2 B:*** Topological Re-Evaluation of the Original Graph (Network element rank-ordering)

1) Determine Nodal Betweenness and Degrees
2) Network Removal based on Vertex Degree Rank-Ordering and Vertex Betweenness Rank-Ordering (10%interval)
3) Calculate Redundancy Measures and Descriptive Indices (alpha, beta, gamma, GTP, eta, network related densities…)

4) Determine Network Topological properties using UNA toolbox (avg. betweenness centrality, straightness, closeness), and using GIS tools (avg. lengths and shortest paths, mean avg. degree, avg. clustering)
5) Network Inspection after each Removal Interval (degree distribution, overall connectivity…)
6) Compare Random Removal to Network Element Rank-Ordering

- ***Phase 3 A:*** Topological Evaluation of the Weighted Graph (random removal)

1) Identify Scenarios and Apply Weights (typical weekday traffic, roads classification, buildings location and height, natural hazards, soil damage increment, hospitals)
2) Generate Statistics of each Scenario (nodes and links vulnerability percentages, effects of weights between the total network and the susceptible components)
3) Network Random Removal (10%interval)
4) Calculate Redundancy Measures and Descriptive Indices (alpha, beta, gamma, GTP, eta, network related densities…)
5) Determine Network Topological Properties using UNA toolbox (avg. betweenness centrality, straightness, closeness), and using GIS tools (avg lengths and shortest paths, mean avg. degree, avg. clustering)
6) Network Inspection after each Removal Interval (degree distribution, overall connectivity…)

- ***Phase 3 B:*** Topological Evaluation of the Weighted Graph (Targeted removal)

1) Integrate Scenarios and Identify the Vulnerable Network Structures
2) Network Targeted Removal (10%interval)

3) Calculate Redundancy Measures and Descriptive Indices (alpha, beta, gamma, GTP, eta, network related densities…)
4) Determine Network Topological Properties using UNA toolbox (avg. betweenness centrality, straightness, closeness), and using GIS tools (avg. lengths and shortest path, mean avg. degree, avg. clustering)
5) Network Inspection after each Removal Interval (degree distribution, overall connectivity…)

- ***Phase 4:*** System Performance Interpretation and Resilience Quantification

1) Compare Both Modes in the Weighted Network
2) Determine the Global Connectivity of Hospitals in the Network (GIS)
3) Generate Redundancy Computation (Origins: all nodes, Destinations: hospitals)
4) Apply Targeted Removal (10%interval): based on the most vulnerable network components (i.e., weighted) which possess also the higher ranked degrees and centralities outputs.
5) Calculate the Avg. Redundancy after each Removal (i.e., Resilience Index)
6) Determine the Percentage Reach after each Removal
7) Mapping the Avg. Betweenness Centrality and Redundancy of the Weighted Network
8) Compute the Redundancy Loss due to Removal Process

5.2 Case Study of Beirut

Lebanon is a small developing country in the eastern Mediterranean region with a total area of 10,452 Km^2 and an estimated population of 6.8 million in 2018 (World Bank, 2019). Lebanon is divided into eight governorates: Akkar, North, Mount Lebanon, Beirut, Beqaa, Baalbeck-Hermel, South, and Nabatiyeh. The capital is around 20 Km^2 and it is the smallest, busiest and most expensive governorate in Lebanon. Beirut is inhabited more than 5000 years ago. It is positioned on a peninsula at the midpoint of Lebanon's Mediterranean coast, and it has the country's largest and principal seaport. Almost half of the Lebanese population resides in two governorates, the capital Beirut and its surrounding governorate Mount Lebanon. The number of commuters to the capital each day is equivalent to the number residing there (Central Administration of Statistics, 2009). Thus, it turned to be a densely populated capital where a rapid urbanization growth rate takes place and it is expected to reach 86% in 2020 (United Nations Population estimates and projections, 2017). Actually, in the absence of efficient public transport system at the moment, congestion becomes a major hurdle to development in Lebanon with another alarming rate of car ownership stands at one private passenger car per three persons making it one of the highest rates in the world (WHO, 2015). According to the classification of Beirut network, only around 2% of the roads are marked as motorway or trunk, 22% are primary, 12% are secondary, and the rest are tertiary, residential, or unclassified. A total of 23 major hospitals and emergency centers are available in this context. Also, this network entails a large number of bridges and tunnels in comparison to its small size. It is counted and approximated at 43% and 10% of Lebanon's tunnels and bridges respectively (Rouhana et al., 2019).

5.2.1 Tectonic Setting and Seismic History

Lebanon has rigorously suffered from many devastating earthquakes since 2150 BC, resulting in large-scale destruction and severe death tolls (Huijer et al., 2011). The seismic history of Lebanon is not surprising, due to its geographic position between the Arabian, African and Eurasia Plates and given that it is crossed by 1200 Km long Levant

Fault System (LFS): extending from the Gulf of Aqaba with the Dead Sea Fault (DSF) to Lebanon, then reaching Syria with the Ghab Fault (GhF) and ending in southern Turkey at the Eastern Anatolian Fault system (EAFS). When entering Lebanon, the LFS splits into three major branches called: Yammouneh Fault (YF), Mount Lebanon Thrust (MLT), and Rachaya-Sarghaya Fault (RSF) (Figure 5.2). These branches extend on land as well as offshore specifically MLT which is cutting the seabed from Tripoli in the north to Saida in the south with no more than 8 Km from the coast of central Lebanon between Beirut and Anfeh (Elias et al. 2007). Three major events traced the seismic history in Lebanon. In year 551, Lebanon was hit by an earthquake (Mw 7.5) generated by MLT and accompanied by a tsunami that struck the whole country coast destroying several cities (i.e., Beirut, Tripoli, Saida, Tyre) (Khair et al. 2000; Elias et al., 2007; Huijer et al., 2011; Salameh et al., 2016). Another earthquake in year 1202 (Mw 7.5) caused by YF resulted in disastrous damages. In year 1759, two significant earthquakes occurred (Mw 6,7 and Mw7.4) caused by RSF (Daëron et al., 2005). In the past century, numerous large earthquakes hit the country namely in year 1918 (Mw 6.8) (Harajli et al., 1994), in year 1956 (double shock, Mw 6.3 and Mw 6.1)(Khair et al., 2000), in year 1997 (two strikes Mw 5.6 and Mw 5). The double shock that occurred in year 1956, killed 136, destroyed 6000 houses, and damaged another 17,000 (Khair, 2000). The return of such events is about 1100 years along the YF (Daëron et al., 2007), 1300 years along the RSF (Gomez et al., 2003), and 1500 to 1750 years along the MLT (Elias et al., 2007). Taking into consideration the previous reoccurrence dates, a strong earthquake (Mw 7+) could occur at any time from the MLT and YF and it should not be a surprise as these faults are sufficiently mature enough. Accordingly, a possible earthquake can be considered as equally probable over the whole country because of its small size with respect to the important size of its active faults (Elias, 2012) (Figure 5.3). Figure 5.4 shows the local seismicity map of Lebanon between years 2006 and 2017 provided by the National Center for Geophysics (CNG)- one of the four centers of the Lebanese National Council for Scientific Research (CNRS). Note to mention that in year 2005, Lebanon was considered as one single seismic zone according to the Lebanese decree LD 14293 with a minimum horizontal peak ground acceleration (PGA) on the rock to be taken 0.2g. Yet, this decree was revised in 2012 (LD 7964 Article 3) by increasing the PGA from 0.2g to 0.25g which describes the seismic risk in the country as moderate. According to Huijer et al. (2016), Lebanon is considered a moderate to high seismic hazard country with an expected PGA varying between 0.2g and 0.3g with a 10% probability of exceedance in 50 years. Nevertheless, they proposed to intensify the PGA to 0.3g on the coastal zone ranging from Tripoli to Saida while keeping all other parts of the country with a value of 0.25g.

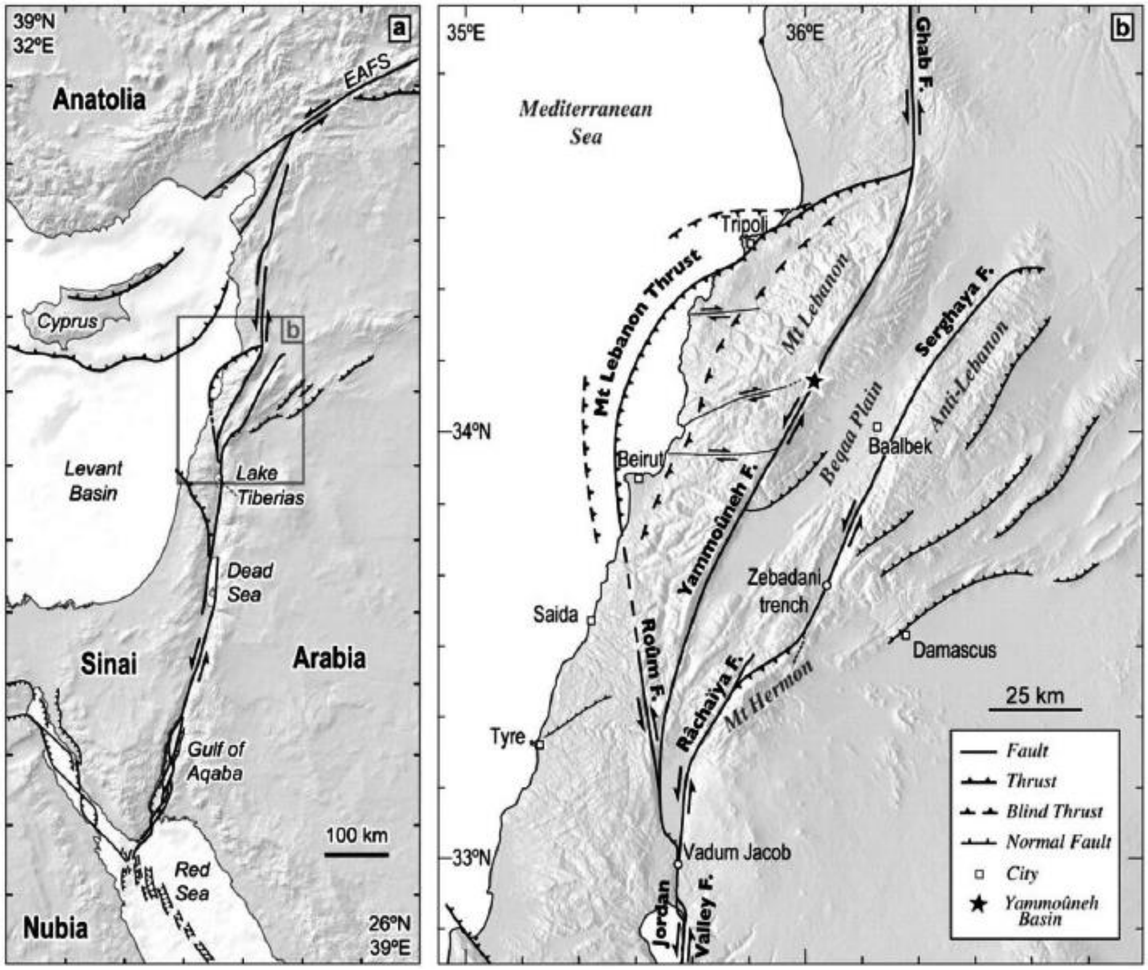
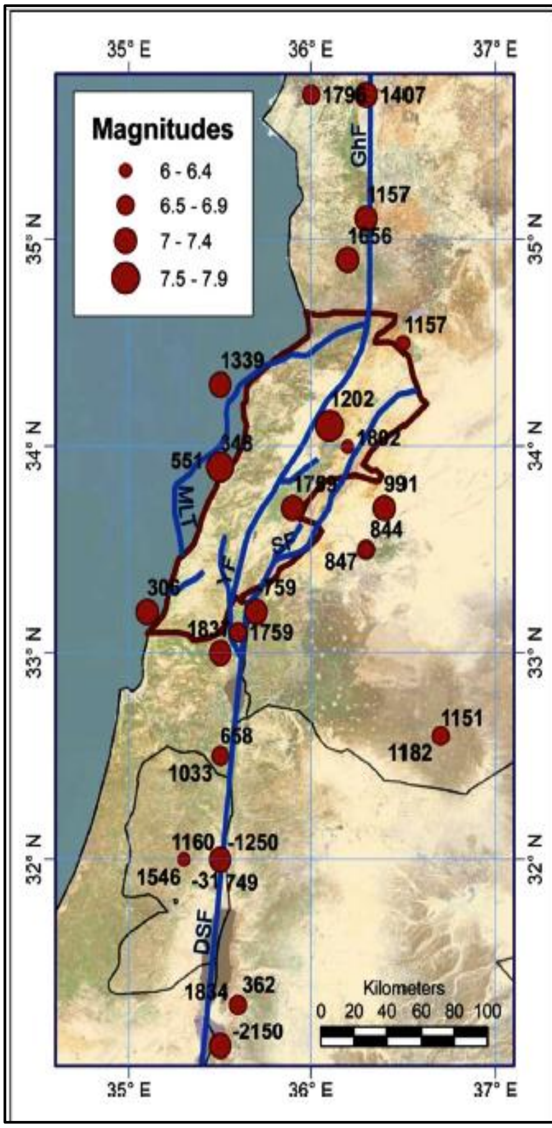


Figure 5.2: Study area tectonic setting: **a.** LFS regional map **b.** Map of the main faults within Lebanon (Daëron et al., 2007)



Year	Month	Day	Lat.	Long.	M_w	Zone
-2150	-	-	31.1	35.5	7.3	Jordan
-1250	-	-	32.0	35.5	6.8	Jordan
-854	-	-	-	-	6.9	Jordan
-759	10	11	33.2	35.7	7.3	Jordan
-590	-	-	-	-	6.8	Lebanon
-140	-	-	-	-	7.0	Lebanon
-31	9	2	32.0	35.5	7.0	Jordan
19	-	-	-	-	6.8	Lebanon
130	-	-	-	-	6.3	Lebanon
306	-	-	33.2	35.1	7.1	Lebanon
348	-	-	33.9	35.5	7.0	Lebanon
362	5	24	31.3	35.6	6.7	Jordan
525	-	-	-	-	6.7	Lebanon
551	7	6	33.9	35.5	7.5	Lebanon
658	6	15	32.5	35.5	6.9	Jordan
749	1	18	32.0	35.5	7.3	Jordan
844	9	18	33.5	36.3	6.8	Lebanon
847	4	-	33.5	36.3	6.4	Lebanon
991	4	5	33.7	36.4	7.2	Lebanon
1033	12	5	32.5	35.5	6.7	Jordan
1063	4	20	-	-	7.1	Lebanon
1151	9	28	32.6	36.7	6.4	Jordan
1157	7	15	34.5	36.5	6.3	Lebanon
1157	8	15	35.1	36.3	7.3	Ghab
1160	-	-	32.0	35.3	6.3	Jordan
1170	-	-	-	-	7.5	Ghab
1182	-	-	32.6	36.7	6.7	Jordan
1202	5	20	34.1	36.1	7.5	Lebanon
1339	-	-	34.3	35.5	7.1	Lebanon
1407	4	29	35.7	36.3	7.1	Ghab
1546	1	14	32.0	35.3	7.0	Jordan
1656	2	-	34.9	36.2	7.0	Ghab
1759	10	30	33.1	35.6	6.7	Jordan
1759	11	25	33.7	35.9	7.4	Lebanon
1796	4	26	35.7	36.0	6.7	Ghab
1802	-	-	34.0	36.2	6.4	Lebanon
1834	5	23	31.3	35.6	6.5	Jordan
1837	1	1	33.0	35.5	7.1	Jordan

Figure 5.3: Historical earthquakes along LFS with Mw greater than 6 (Huijer et al., 2011)

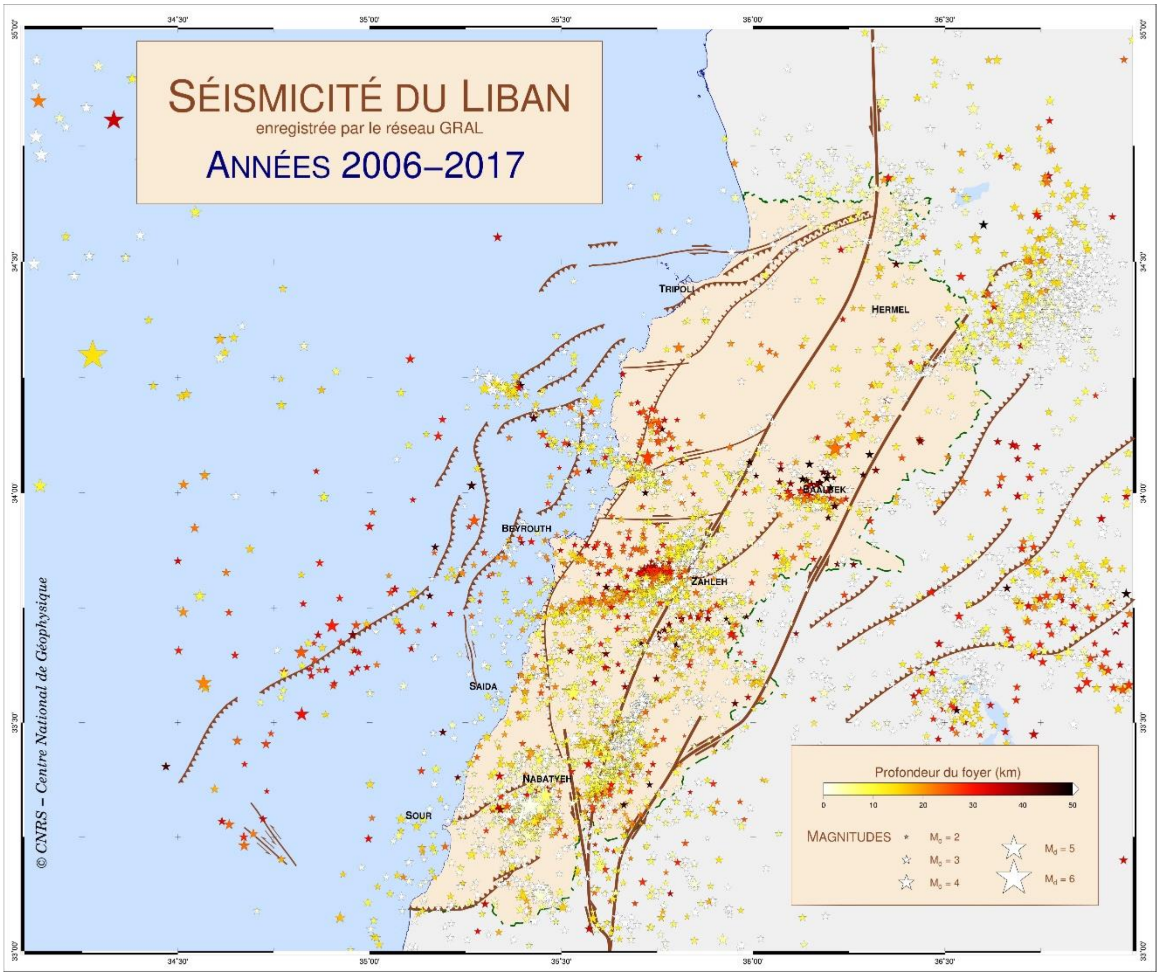


Figure 5.4: Local seismicity map of Lebanon between 2006 and 2017 (CNRS)

5.2.2 Beirut Geology

The city of Beirut extends over 19.8 Km^2 through 12 quarters and is built on 9 by 12 Km rocky cape extending into the Mediterranean Sea. Two hills, one in Achrafieh (East Beirut) and the other in Tallet el Khayat (West Beirut), reveal that the geological basement is dated from the Cretaceous and formed mainly from marly limestones coupled to conglomeratic beds in some locations. Yet, as seen in Figure 5.5, the main feature of Beirut geology is formed by a sandy cover especially in the southwest of the capital. This cover is overlaid by recent alluvium material in some areas like in Beirut downtown and along the River of Beirut (Salameh et al., 2016). Other geological details of Beirut city and its major parts along the faults are shown in Figure 5.6. According to Brax (2013), spatial geological variability will result in significant seismic amplification. Even if the Lebanese hard rocky geology will attenuate the seismic accelerations, the mountainous morphology over the whole country along some weak layer types will raise the probability of secondary hazards (i.e., slope instabilities, rockfalls, landslides) which will greatly damage the infrastructure system. Also, the water table elevation and the small number of fines in sandy areas, especially in coastal zones where constructions are taking place, can lead to soil liquefaction (Harb, 2003) or floods (e.g., River of Beirut). Such hazard can result in severe destructions in lifelines and put Lebanon in a direct risk especially that the country lacks any appropriate building seismic code measurements or disaster management plans (Elias, 2012).

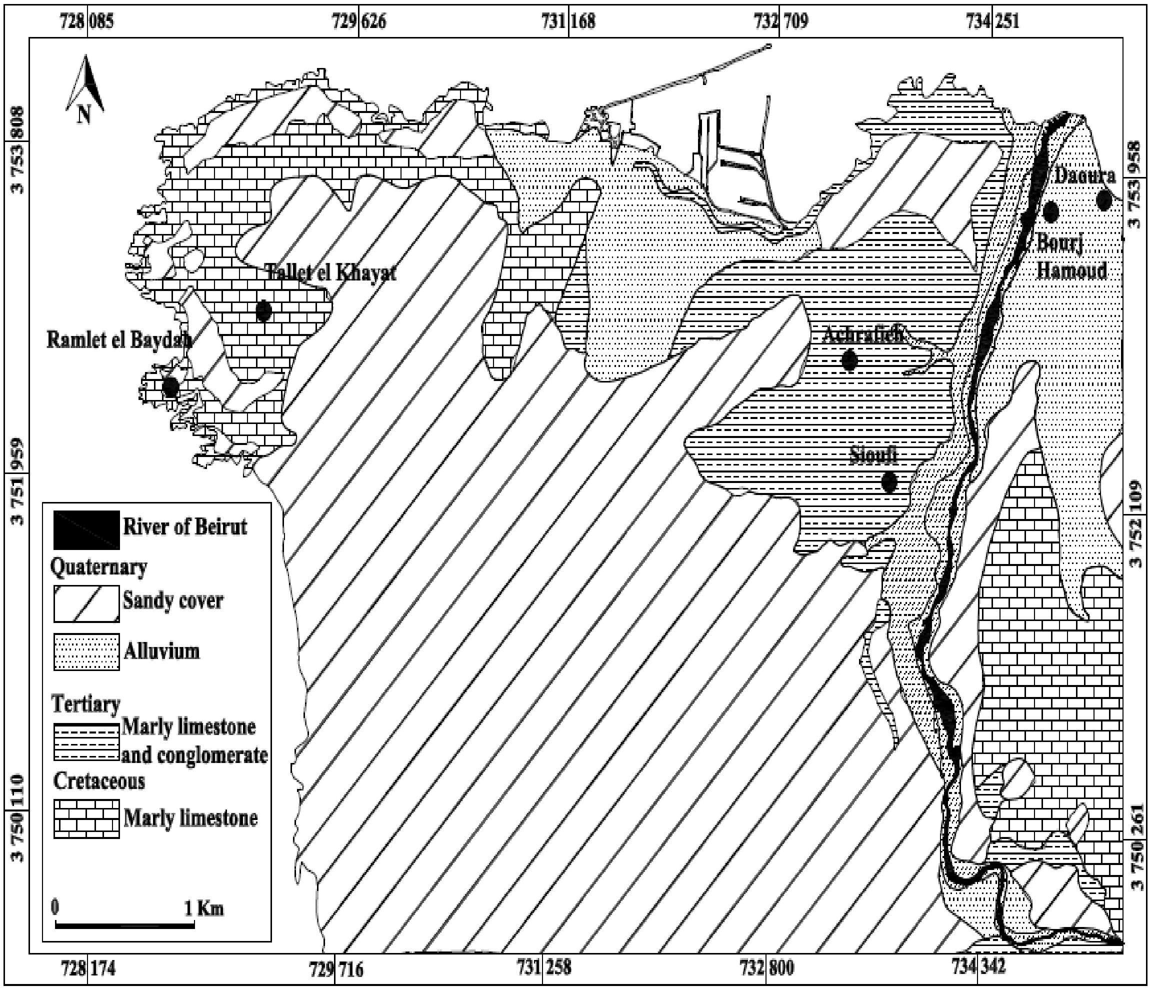


Figure 5.5: Beirut geological map simplified from Dubertret (1945) (Salloum et al., 2014)

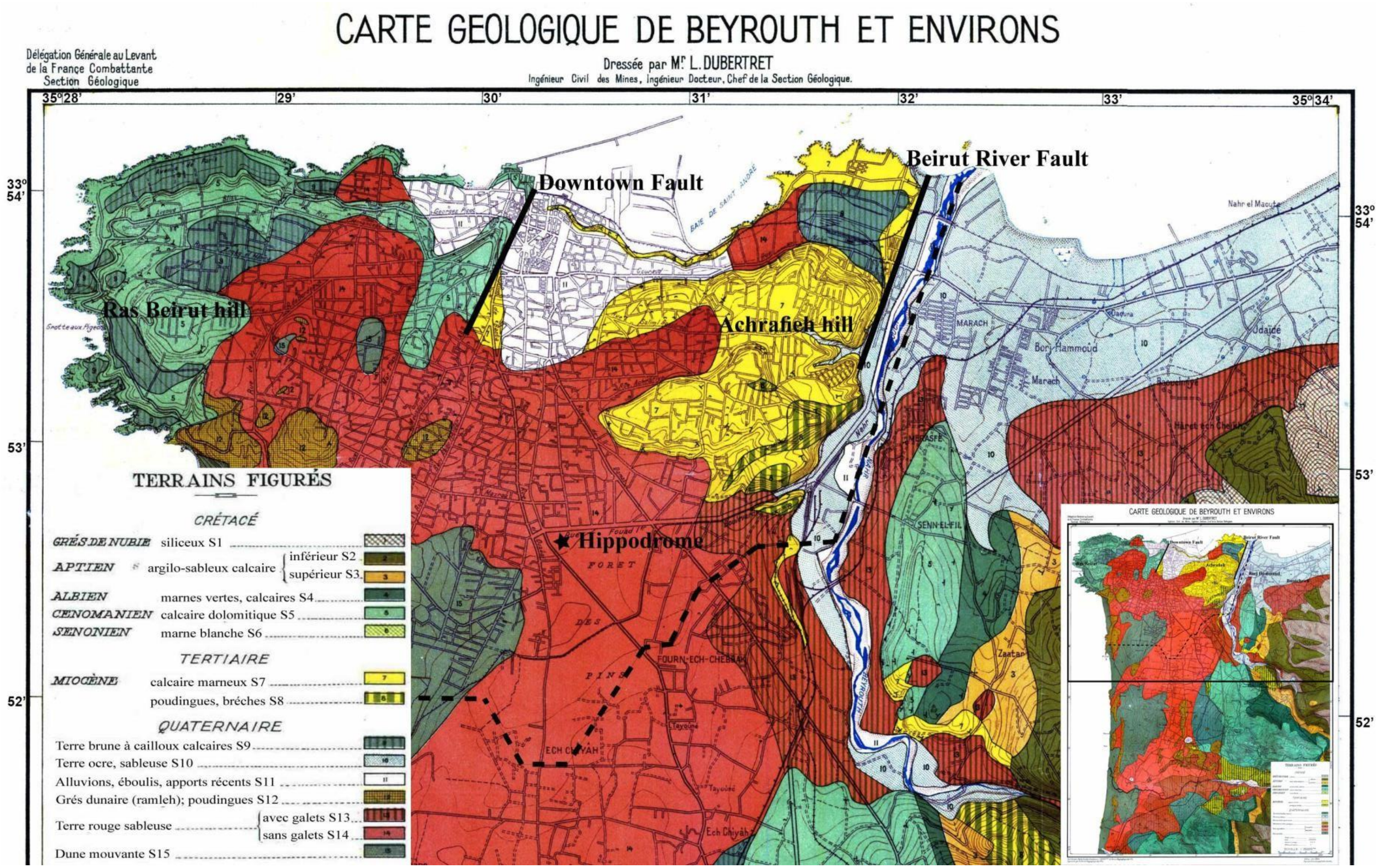


Figure 5.6: Beirut geological map with its faults and border limit (Dubertret, 1945)

VI. ANALYSIS and RESULTS

6.1 Graph Analysis

After creating a file geodatabase, feature dataset, and feature class, the necessary transportation shapefiles were imported into the feature dataset in ArcCatalog via GIS. These shapefiles were reviewed and corrected such as preparing the network polylines in an appropriate form to be integrated into Graph Theory analysis, fixing the missed segments and nodes, buffering the study area by 150 meters to frame and reach the important links of the neighboring governorate, correcting the overlays and false junctions especially in the case of tunnels and bridges, and removing footways and service roads in order to focus on the major links, avoid misleading outcomes, and reduce the computation burden. The road network of Beirut was condensed to a combination of 3,159 vertices connected by 4,694 unique edges (Figure 6.1). This model was running by randomly deleting a certain percentage of nodes to produce random cases that would cause the failure of diverse edges or vertices. Figures 6.2 compare an intact network diagram to other disturbed networks with 10, 20, 30, 40 and 50% node removals correspondingly. As the fraction of nodes removed was progressively increased, all topological properties of the system were computed to inspect the trends of the network properties. In other words, through this application, the impacts of various random or targeted failure events are assessed using the topological characteristics of the model. The outcomes are often shown as a declining trend of such characteristics that reflect the degradation of multiple features of system resilience.

Figure 6.1: The road network of Beirut (Base map: CNRS-NDU)

Figure 6.2: Nodal random removal of Beirut original graph with 10% interval

The degree distribution that can show several network properties was determined for the intact network of Beirut roads and is charted in Figure 6.3. It displays that the highest probability is "3" which means that the majority of the nodes in the system have a degree "3". Two types were studied: 1) the degree distribution of a random graph that follows a Poisson degree distribution, and 2) a scale-free graph that follows a power-law distribution. Figure 6.4 shows the difference between both types and are plotted in histogram form. After conducting a fitness degree computation, it was shown that the Poisson degree distribution related to the random nature of a graph indicates a better match than the scale-free power-law trend. Yet, one should not be confused with the high number of nodes having low degree. In fact, those nodes which possess a degree of one to signify the end of the network edges that are not of high interest in the previous description. This is mainly due to the deletion of some segment's types in the system and the clip feature of the study area. This explanation is logical since most of the graph nodes have quite comparable degrees and are average linked rather than having hubs of highly connected nodes. This turns to be a characteristic of a random graph. The uppermost degrees found in Beirut turned to be "6" and "7" with a very slight probability of being randomly chosen.

Therefore, the network of Beirut may act more similarly to a random graph when exposed to failure. The degree distribution was tested after each random removal scenario to check for any variation in the graph nature where the results revealed no trend. As mentioned, due to the absence of hubs in the random graph model, the networks possess some kind of robustness to targeted disruptions comparable in a way to random attacks. Furthermore, the hierarchy of the graph is tested through the exponent of the slope for the power-law drawn in a bi-log chart of node frequency over degree distribution (Figure 6.5).

Networks characterized by strong hierarchical configurations, often have values above “1”. So, the hierarchy figure indicates a fairly good hierarchy with an appropriate exponent of the slope but with a very low R-squared value signifying distant data points from the fitted regression line. Another factor associated with degree distribution is the degree correlation of the network. It determines the probability that nodes connected to other nodes with similar degrees. As nodes are removed from the network under study, the network tends to move from disassortative (i.e., high degree nodes link to low degree nodes) to random. This could be explained as a loss of efficiency of transportation networks due to the isolation caused by the random removal process. This is outlined by the variations of the degree correlation, where a randomly correlated network designates inferior ease of transportation flow.

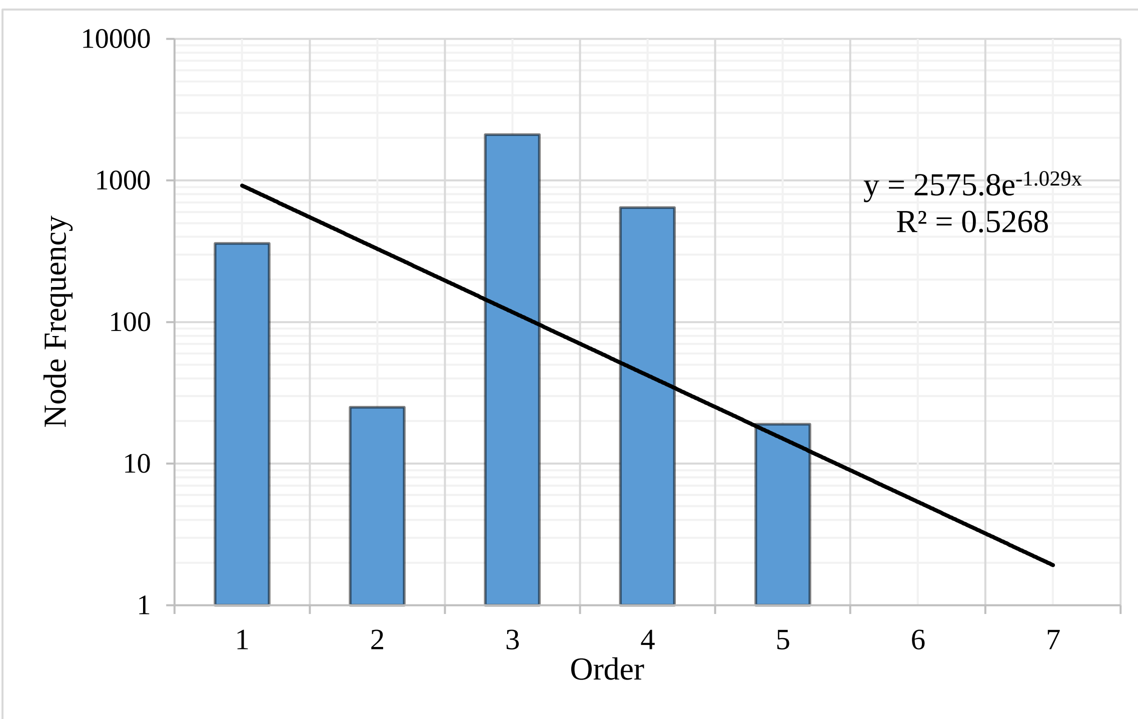


Figure 6.3: Degree distribution of Beirut Network

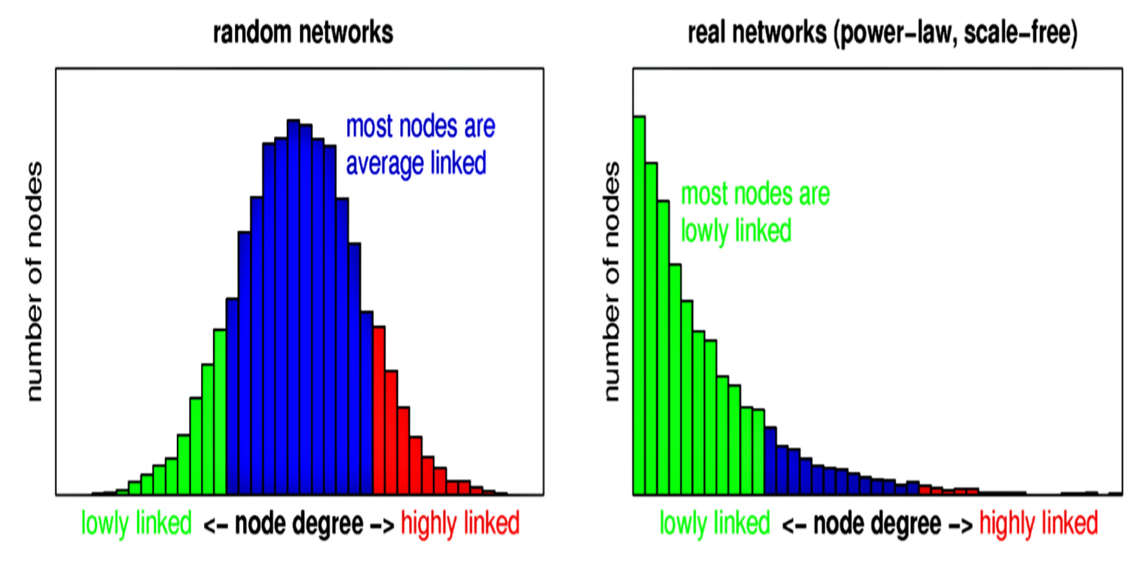


Figure 6.4: Degree distribution histograms of a random and a scale-free graph

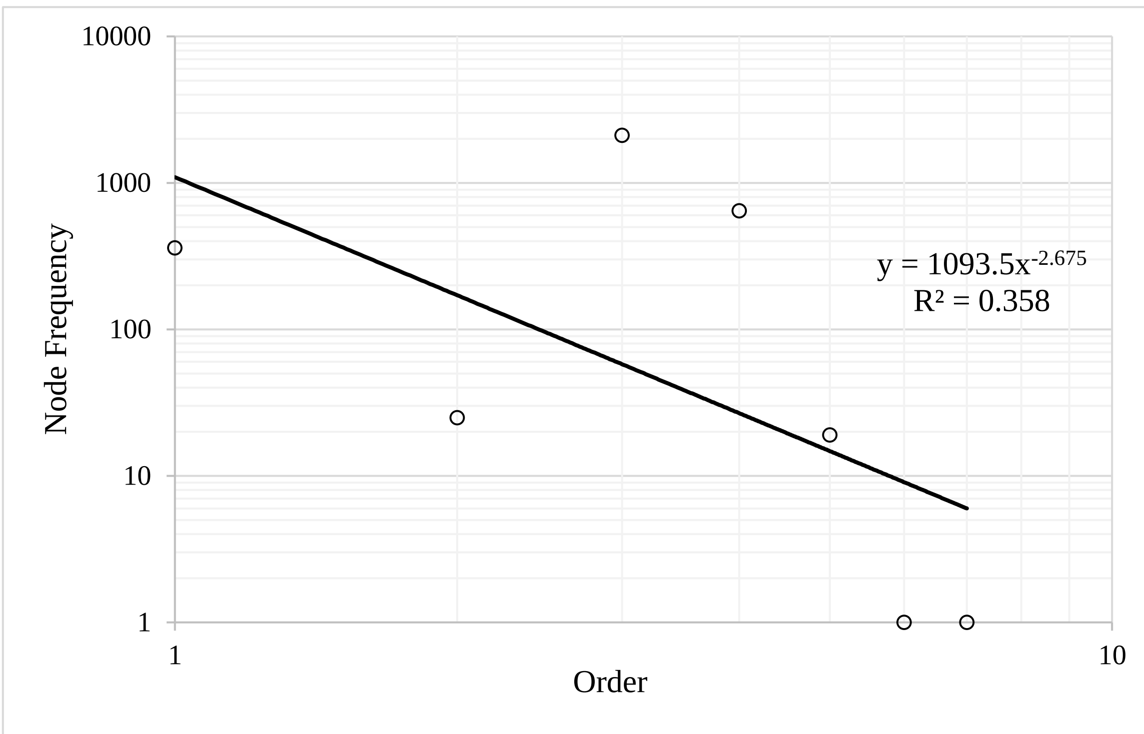


Figure 6.5: Hierarchy of Beirut graph

6.2 Topological Evaluation of the Original Graph

6.2.1 Network Random Removal

Many essential topological parameters are evaluated through a random removal technique of the original network. The average nodal degree is one of the most fundamental properties illustrated in Figure 6.6. This property reflects the network connectivity where the difference between the initial average degree of the intact graph and the disturbed network represents the variation in the ease of commuting. The trend of the average nodal degree is shown to decline exponentially starting from an initial value of the undisturbed network equal to 2.98 with a standard deviation of 0.84. As nodes are randomly removed in a constant fraction across trials, the average nodal degree decreases among simulation confirming that this topological property is entirely dependent on the state of nodes in the network. This latter property deals with global connectivity.

Another property that determines the local connectivity and is related to network local redundancy is called local clustering. The local clustering is all about the existence and accessibility of clusters and alternative routes. The original network of Beirut has an average clustering coefficient of 0.000041 that staggers vaguely downward to lose more than half of its value as 10% of nodes are randomly removed from the undisturbed graph (Figure 6.7). After this fast drop, the local clustering is shown to increase gradually as more fractions are removed from the network. This is mainly dependent on the importance of the removed nodes, where those with low connectivity significance will not affect the clustering results whereas those with high connectivity will lead to the isolation of some of the affected clusters of nodes. The isolated groups will generate more clusters and thus the clustering coefficient is going to rise. Generally, as nodes are removed from the graph the clustering results will decline.

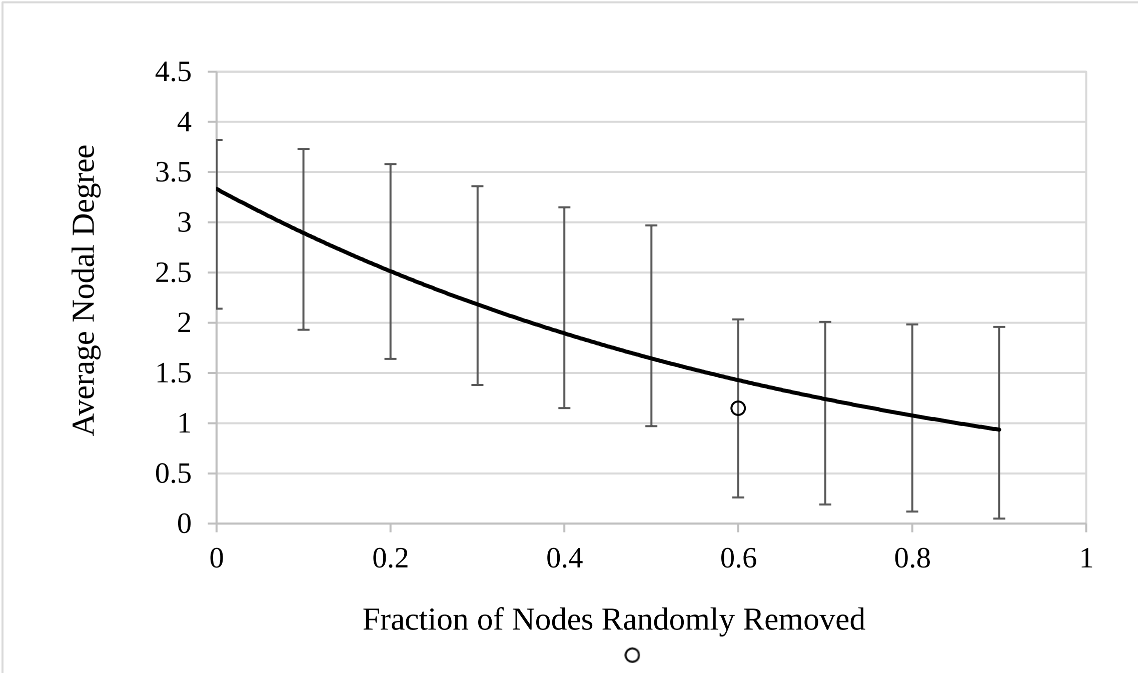


Figure 6.6: Effect of random node removal on average nodal degree

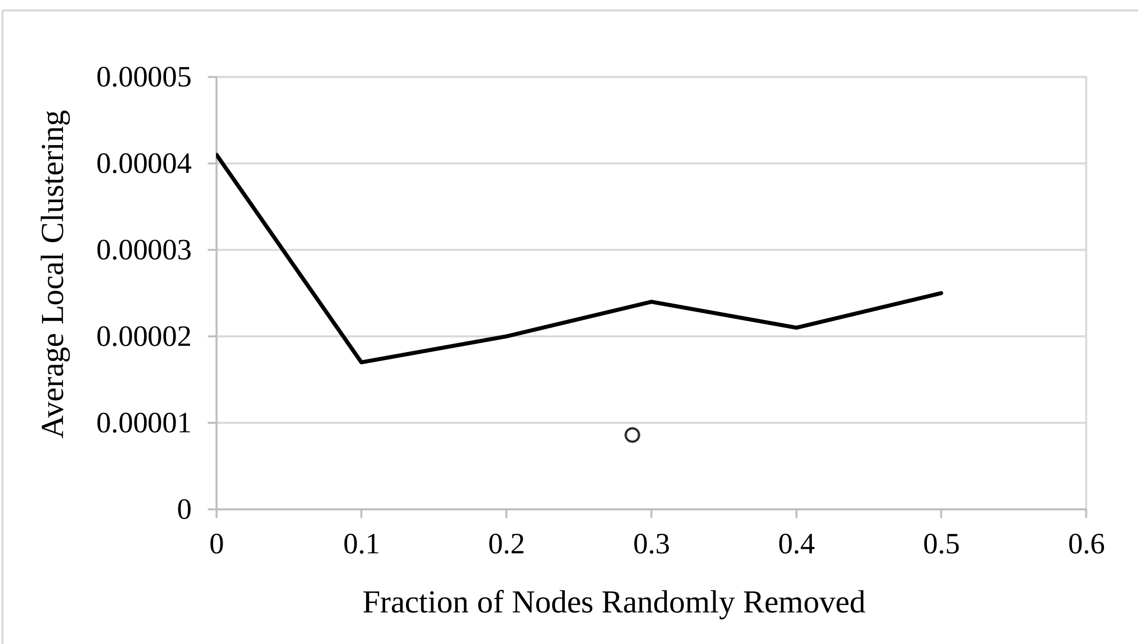


Figure 6.7: Effect of random node removal on average local clustering

The UNA centrality toolbox is applied to compute some important network analysis properties: betweenness and straightness. The graph centralities measurements calculated through mathematical procedures that reveal the importance of the network's structure. It focuses mainly on the centrality power of each of the network elements in accordance with the neighboring elements. The infinite radius is used to reach all the structures of the Beirut network. Accordingly, the betweenness centrality of each node in the graph is calculated. Such centrality measure is not reliant on the number of links connected to a certain node but instead on the sum of shortest routes that encompass the node. This turns the betweenness centrality to hold a robust connection to the significance of a node to the graph performance. In fact, the average shortest route is related to the system redundancy where it plays a critical role in directing resources in transportation networks. Commonly, the distance trend of such shortest paths is going to increase dramatically as more pairs are disconnected in the system. In other words, the average betweenness centrality and the average shortest path are inversely correlated.

Figure 6.8 shows the effect of random node removal on the average betweenness centrality. Accordingly, the stated centrality property drops rapidly and loses more than 50% of its efficiency after the random removal of only 30% of the network's nodes. This remarkable trend explains the likely damaging effects of the used strategy which is disturbing apparently the small fraction of nodes that have influences on the network performance. The results observed will lead to serious delays, detours and cancelations of trips in any real transportation system with a relatively small fraction of nodes disturbed.

According to the straightness centrality, Figure 6.9 illustrates the variation of the stated network property as nodes are randomly damaged. The straightness centrality trend of the Beirut network decreases dramatically which means that the mean distance to neighboring destinations corresponding to straight paths is not increasing as nodes are randomly deleted. This property can be helpful as a measure for detecting the areas that are most linked to their surrounding spots with different applications which help in economizing the urban network and sensing the chief attractions that are perceptible from remote distances. In this manner, every attribute in the network is determined separately and intuitively under the limits of the city geometry. Consequently, utilizing the spatial configuration of the analyzed environment, the described approaches from the graph analysis and land-use are joined into a unique framework.

Figure 6.8: Effect of random node removal on average betweenness centrality

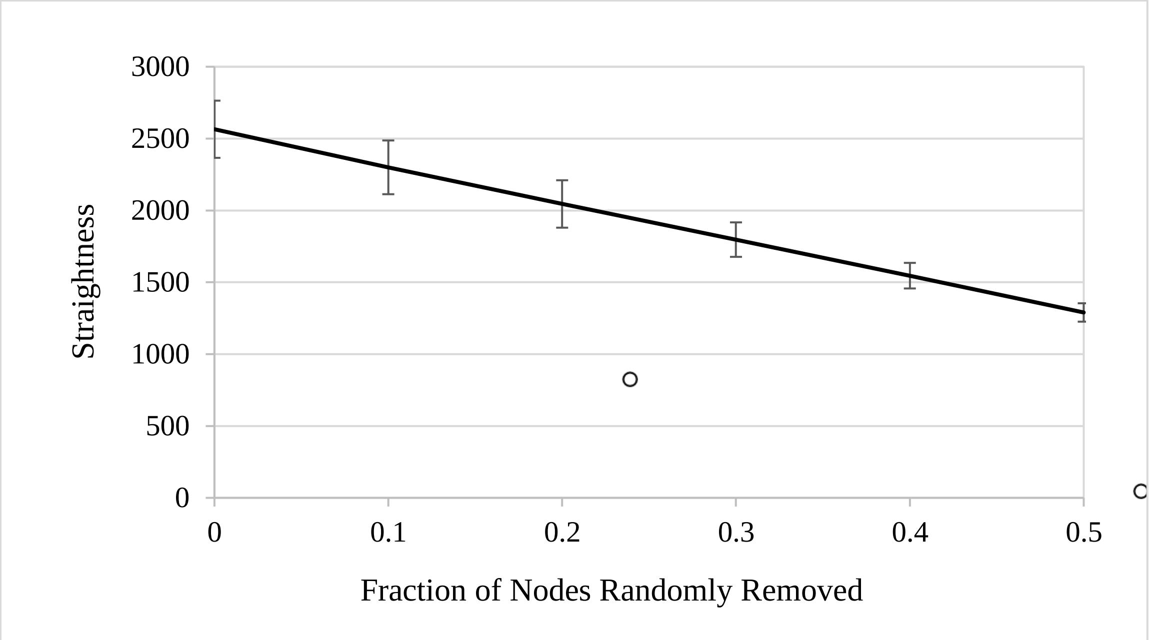


Figure 6.9: Effect of random node removal on straightness centrality

Alternative efficient indicators that can be examined to study the network redundancy are the connectivity indices and the density measures. These connectivity indices depend on the number of links and nodes as well as the number of cycles that form the network. From Figure 6.10, the plots exhibit a declining trend, indicating the disintegration of the system redundancy. Alpha index that represents the ratio of the existing circuits to the maximum possible circuits portrays the steepest downgrading slope through all the connectivity indices. It loses more than half of its value during the random removal of 30% of the network nodes. Beta index which represents the average number of links per nodes and gamma index that reflects the percentage of the existing routes to potential routes shows a gradually declining values and loses both almost 34% of their initial values after randomly removing half of the network nodes. The Grid Tree Pattern (GTP) describes the pattern of the graph that has values ranging between null and unity for a tree pattern and grid pattern respectively. Starting with an initial value of 0.5, GTP goes down by more than 60% after the random deletion of 30% of the nodes which outlines a tree pattern of the graph.

According to density measures, Figure 6.11 illustrates four of them which are the eta index (i.e., average length per link), the network density, the node density, and the edge density. The network density measures the territorial occupation of the transportation network in terms of length of links per area of the surface; the higher the value, the more the network is developed. The node density and edge density correspond to the number of nodes per area and the number of edges per area respectively. As nodes are randomly removed from the network, all of the four measures decrease dramatically revealing the effect of nodes on the whole graph where edges seem more affected since each node can impair one or more edges. Finally, at the end of the random removal process, all the centralities and indices are normalized in order to approximate the efficiency loss of the system. This increase in the loss of network's efficiency is drawn in Figure 6.12 which shows a loss of half of the system's efficiency before the fourth randomly removed a fraction of nodes.

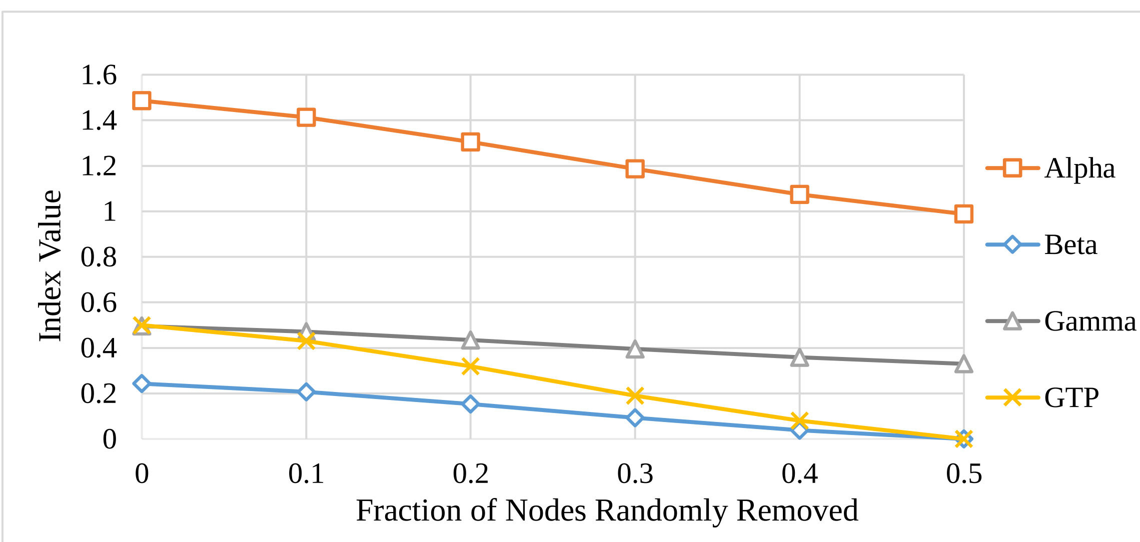


Figure 6.10: Effect of random node removal on connectivity indices

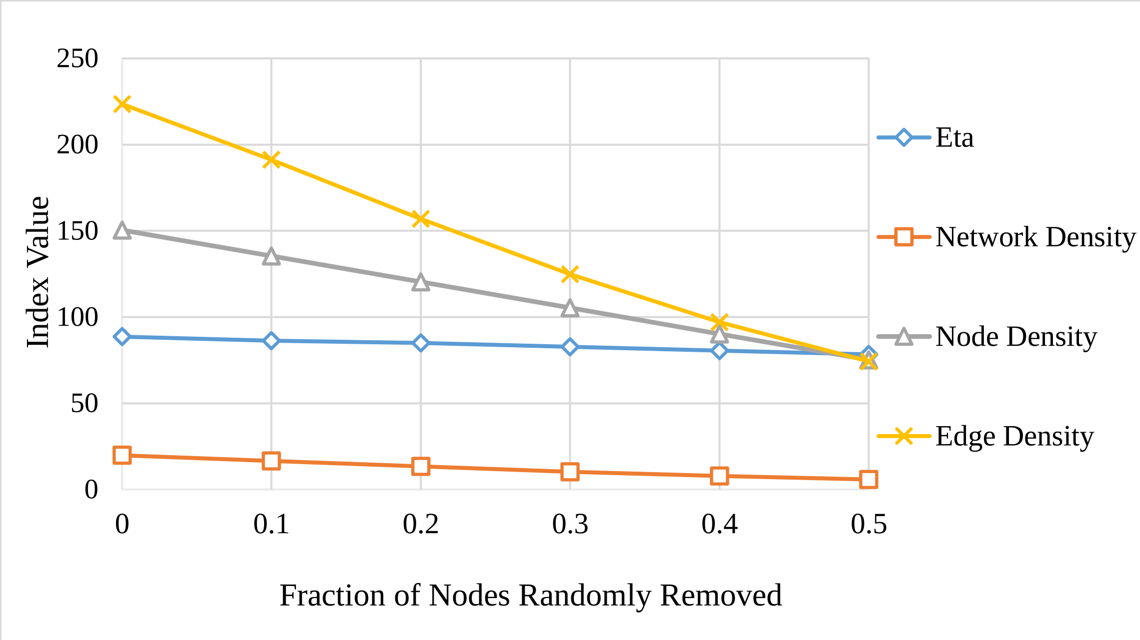


Figure 6.11: Effect of random node removal on density indices

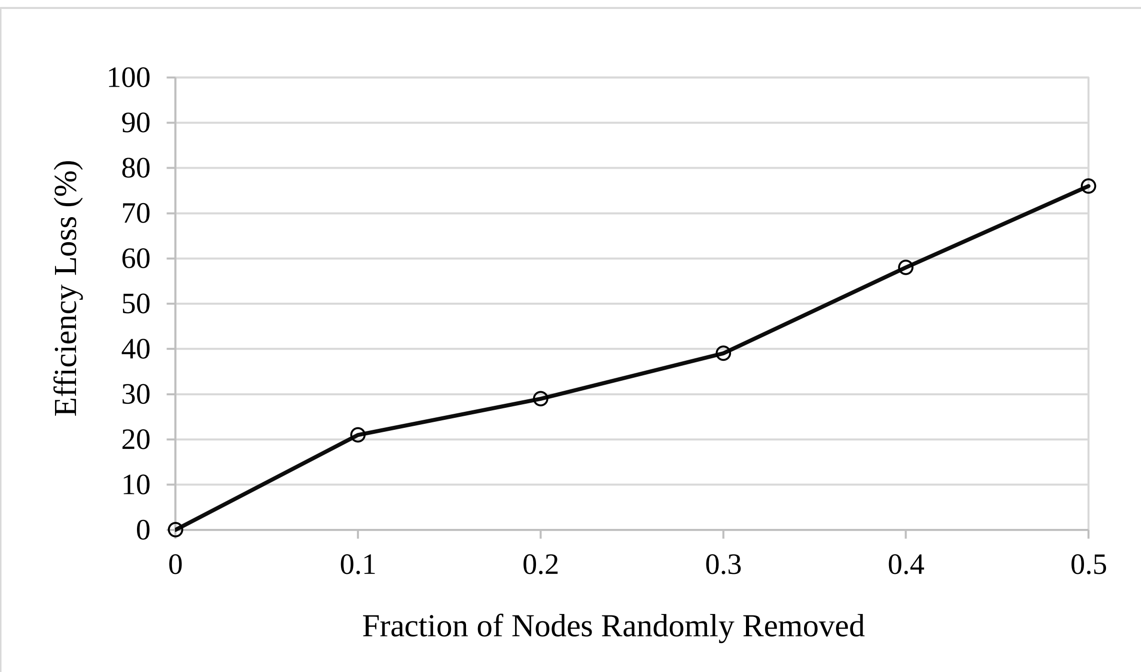


Figure 6.12: Efficiency loss of Beirut Network during the random removal process

6.2.2 Network Element Rank-Ordering Removal

Another removal technique is related to the removal of specific elements from the network based on certain centrality's measures in descending order. This choice was made because nodes that are connected to a large number of links are the most critical to the network performance. As node removal is more effective at being harmful to the network performance, the node degree rank-ordering and the node betweenness rank-ordering are employed for this removal scenario. Yet, in some cases, low-ranked network elements with a minimal nodal degree could play an important role in joining two vital or isolated areas. Thus, the average betweenness centrality which is not dependent on the number of nodes connected to a node was considered along the average nodal degree through the network elements rank-ordering removal technique. The main cause of applying such technique is due to the propagation mechanism that generally occurs in the networks. These networks tend to exhibit avalanches after the damage of high importance nodes. After each removal, the high-ranked sets of the new redistributed centralities are used for the next removal fraction. All of the computation results are illustrated in the form of the difference in the percentage of the removal modes between the random removal (i.e., arbitrary selection) over the rank-ordering removal (i.e., directed selection).

The variation in percentages of centralities and topological measurements of random and rank-ordering removal is shown in Figure 6.13. In this figure, there is no significant variation between the two modes, except for the difference in average betweenness centrality which is expected to be much less in the direct selection process in comparison to the random removal mode. According to the percentage difference of the connectivity indices of the random removal over the rank-ordering removal shown in

Figure 6.14, a positive change of the first technique over the latter means that the targeted nodes in the rank-ordering removal have disturbed more links and thus, the indices values have declined. The major change was seen only through alpha and GTP results, mainly because of the cyclomatic number which is a measure of route redundancy. As high importance nodes are removed, the network shifts faster toward the tree pattern and the number of links gets more closer to the number of nodes. Then, for the final fraction removed (i.e., 50%), these two indices turn to zero in both modes. Yet, for the average change for beta and gamma indices, the change is not meaningful (i.e., 5% and 3% respectively) in comparison to the extent of the removal of the top high-ranked node sets. Lastly, the density measures of the graph for both removal modes are displayed in Figure 6.15 where a better organization is revealed through the network development in the targeted removal process.

In light of the above, the outcomes comply with the affirmation which outlines that the random networks (e.g., small-world graph) respond similarly to random and targeted attacks. This is shown in Figure 6.16 where the efficiency loss of both modes applied on the Beirut original network are illustrated and compared.

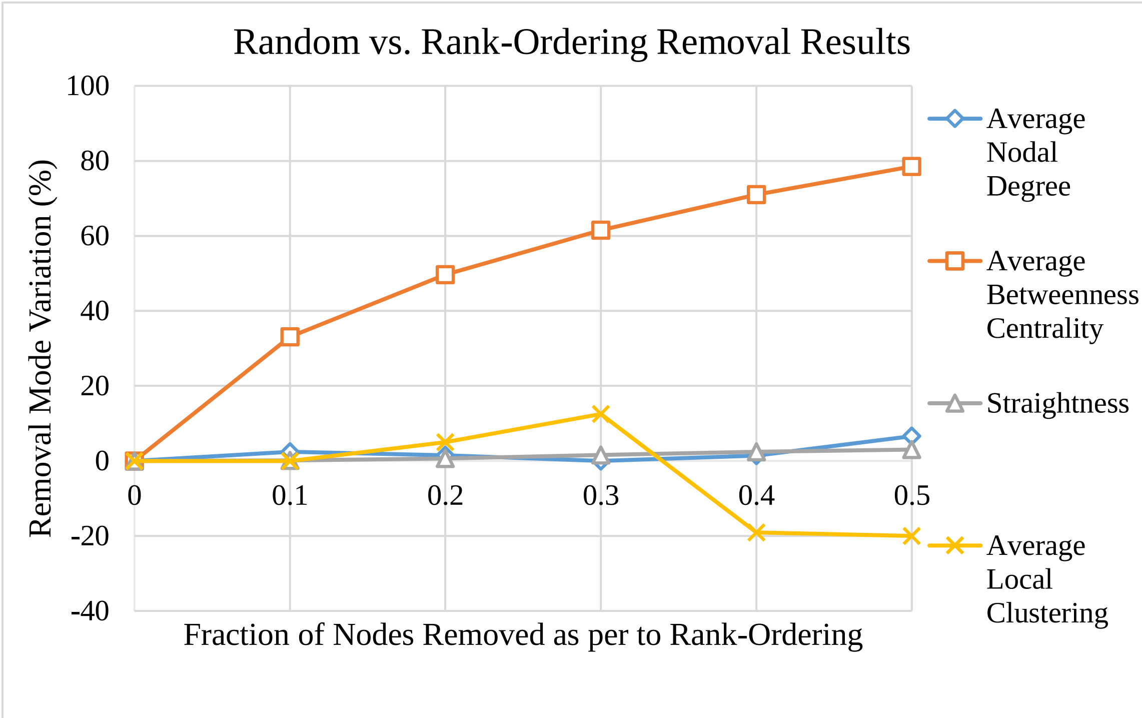


Figure 6.13: Topological properties variation of random over rank-ordering removal

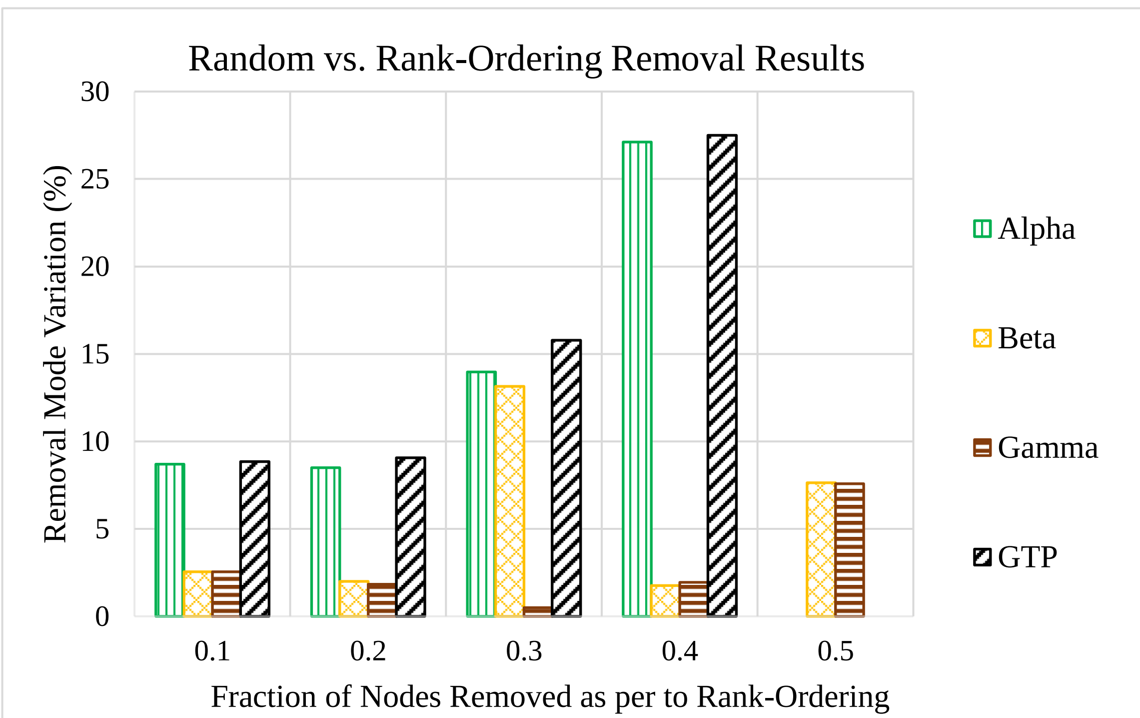


Figure 6.14: Connectivity indices variation of random over rank-ordering removal

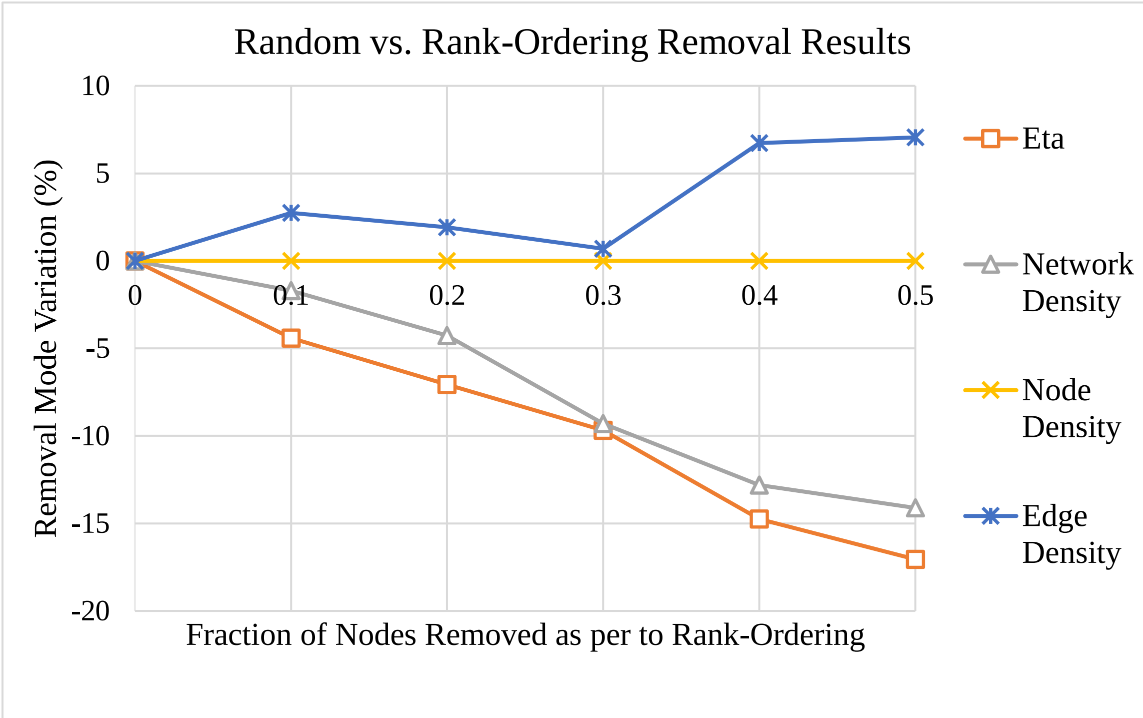


Figure 6.15: Density indices variation of random over rank-ordering removal

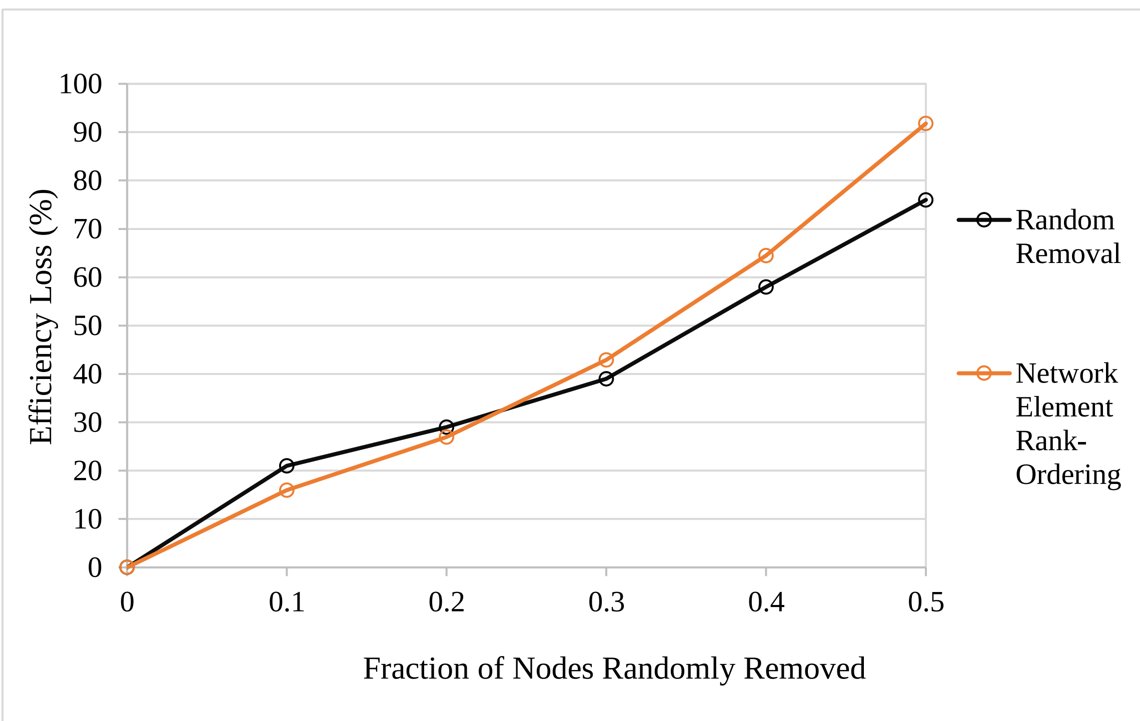


Figure 6.16: Efficiency loss comparison between random and rank-ordering removal modes of Beirut original network

6.3 Topological Evaluation of the Integrated Weighted Graph

6.3.1 Analysis and Classification of the Weighted Scenarios

The integrated weighted graph evaluation of different scenarios is presented in this section. The vulnerability measures and network effectiveness are determined with respect to the seismic features, geological and topographical features, environmental sources, traffic networks data, buildings areas and neighborhoods. These scenarios are weighted according to their specific characteristics, and impact on the network. The scenarios are as follow: the traffic data of a typical peak weekday (i.e., typical Monday traffic in Beirut governorate) (Figure 6.17), the roads' classification of Beirut transportation network along with the location of major hospitals (i.e., a total of 29 hospitals and Red Cross centers found in Beirut governorate and in the surrounding governorate that is the closest to the capital) (Figure 6.18), the natural vulnerabilities (i.e., sea-level rise, tsunamis, river floods) (Figure 6.19), geological characteristics (i.e., damage increment of soil and rock) (Figure 6.20), and buildings (i.e., height, area, location, density…) (Figure 6.21). In this part of the research, it is imperative to consider the geometric weights of links and nodes in the simulations. For example, the considered attributes for the classification of the roads are the speed limit, the width of the road (i.e., number of lanes), and the critical destination led by this road (e.g., hospitals). For the current network, only around 2% of the roads are marked as motorway or trunk, 22% are primary, 12% are secondary, and the rest are tertiary, residential, or unclassified. According to the noon peak traffic period on Monday, only about 16% of the classified links are noticeable as fast roads,74% have moderate speed, and 10% show very high traffic or slow flow. Besides, 12% of the links, based on their locations (i.e., buffer zones), have a higher probability of being disturbed in case of natural hazards such as tsunamis or floods. Concerning the soil and structures data, a damage increment map that was computed by Salameh et al. (2016) is used. This latter was based on Neural Network approach with respect to three typology classes: (1) frequency ratio between soil and structure, (2) PGA for various seismic scenarios, and (3) an interpolated H/V amplitude which is horizontal to vertical spectral ratio used in seismic vulnerability and risk assessment. As seen in Figure 6.20, the high seismic risk is shown in red areas (i.e., Badaro, Borj Hamoud, and the River of Beirut zones). As well, the damage increment is very minor in the two hills of Beirut that are created of rock formations, thus there are no aggravating effects on the structures. Recalling that usually the damage on rock foundations is less than on soft soil due to the absence of soil amplification. Correspondingly, maps created through Neural Network approach for PGA equal 0.25, display an apparent damage increment for low-rise buildings (i.e., one to three floors with an average height of 3 meters each) that are surveyed on the stated research study. The results of Figure 6.20 could be improved by increasing the number of measurements on the soil and buildings especially in the center and the south of the capital; yet, due to some political and security obstacles, these areas are left without data (Salameh et al., 2016). Alternatively, the damage increment map is combined with the transportation network of Beirut. Also, about 18,400 buildings are added and represented with their necessary data specifically the height of the structures (e.g., floors numbers). Around 25% of network links are counted as high risk due to the locations of buildings combined with the soil category of the concerned zones. Buildings are divided into three categories where 27% of total buildings in Beirut are low-rise (i.e., 1-3 floors), 31% are medium-rise (i.e., 4-7 floors), and 42% are high-rise (i.e., >7 floors). It was considered that the low-rise buildings are the most vulnerable to seismic events as the majority of these structures were built before 1950 (i.e., masonry class) or between 1975 and 1990 during the civil war period where the lack of quality control, construction, and reconstruction of structures were prevalent (Salameh et al., 2016).

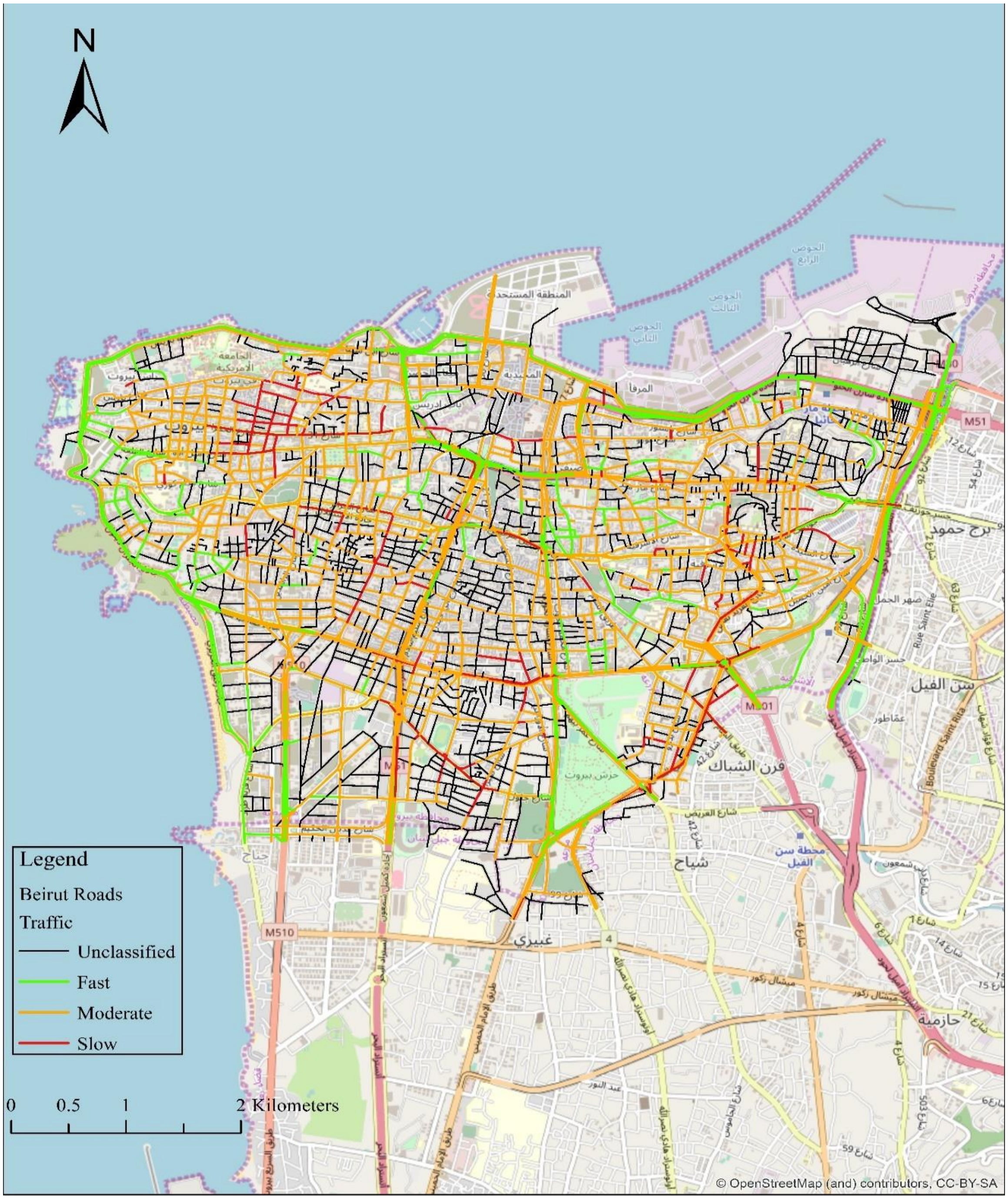


Figure 6.17: Typical Monday peak traffic (12:00pm) of Beirut transportation network

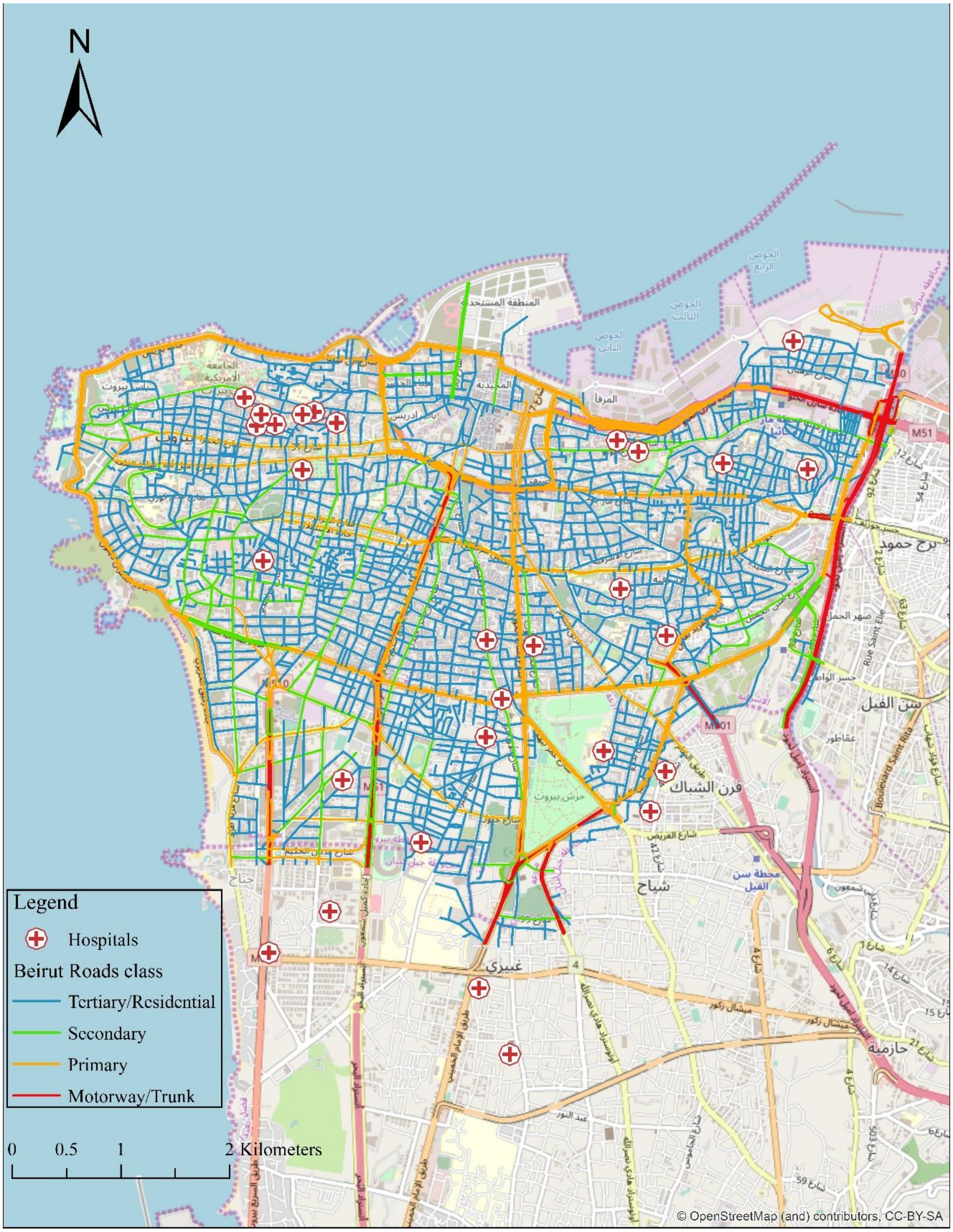


Figure 6.18: Beirut roads classification and major hospitals

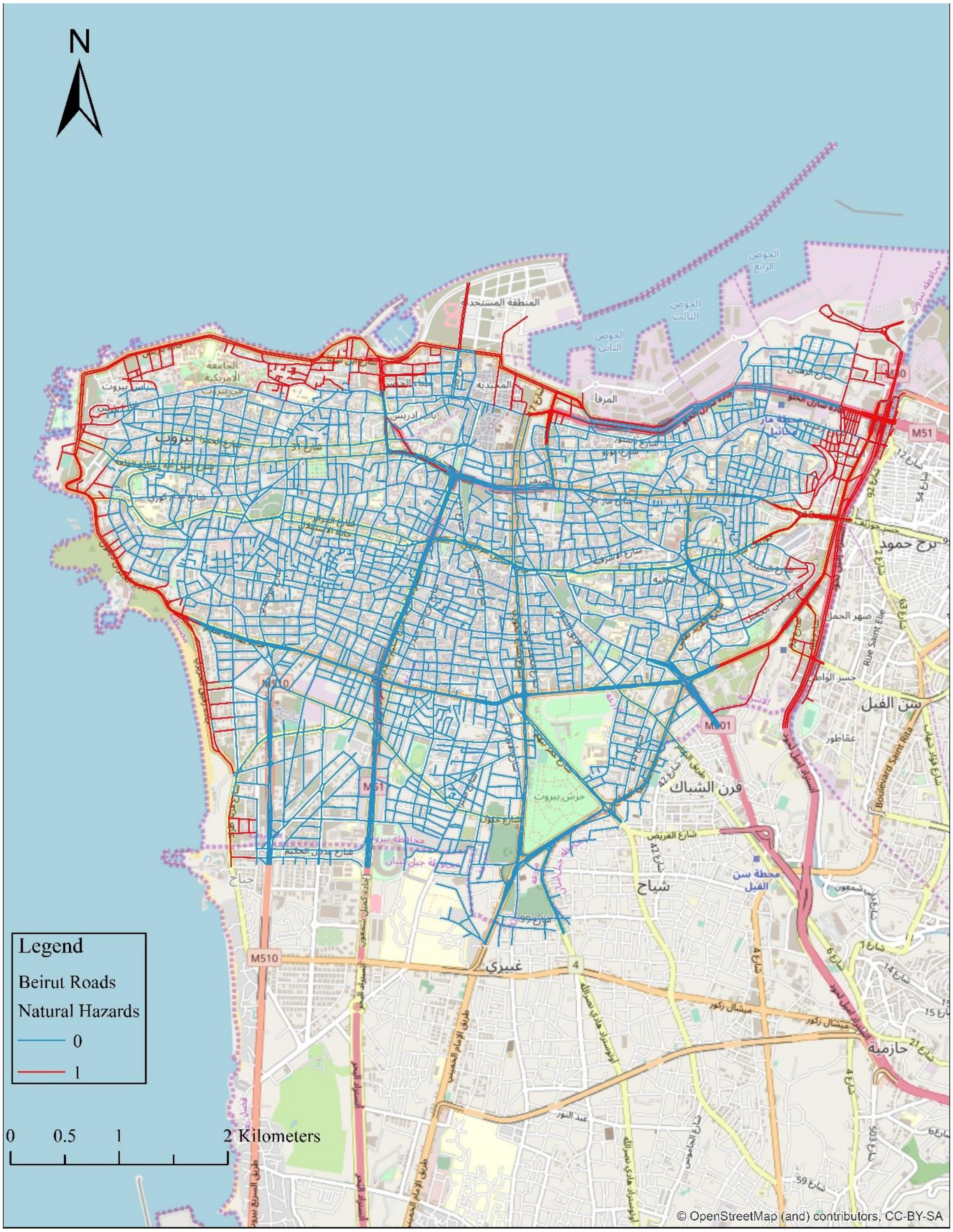


Figure 6.19: Beirut vulnerable network links to environmental hazards

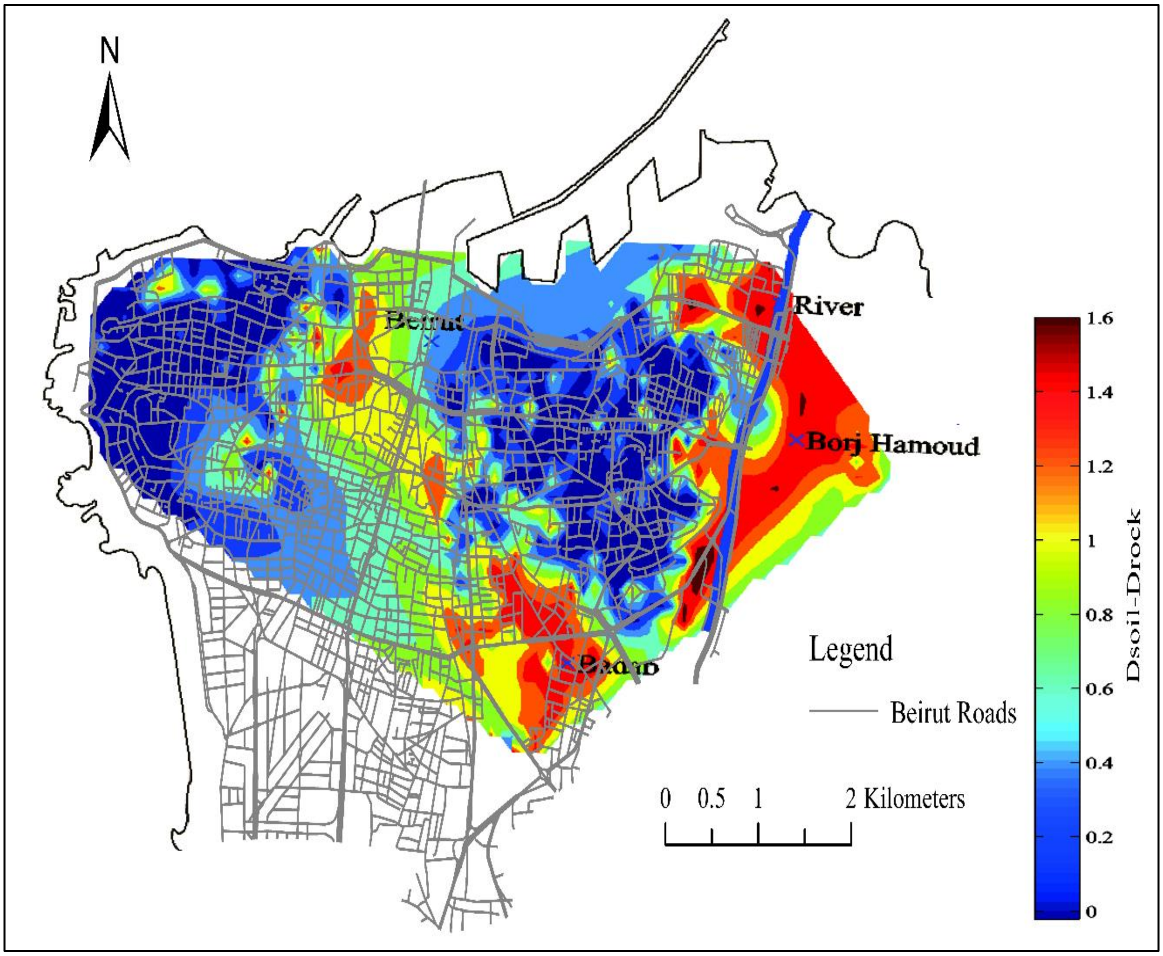


Figure 6.20: Interpolated map of the damage increment computed based on the Neural Network Approach for PGA=0.25 g, modified from (Salameh et al., 2016)

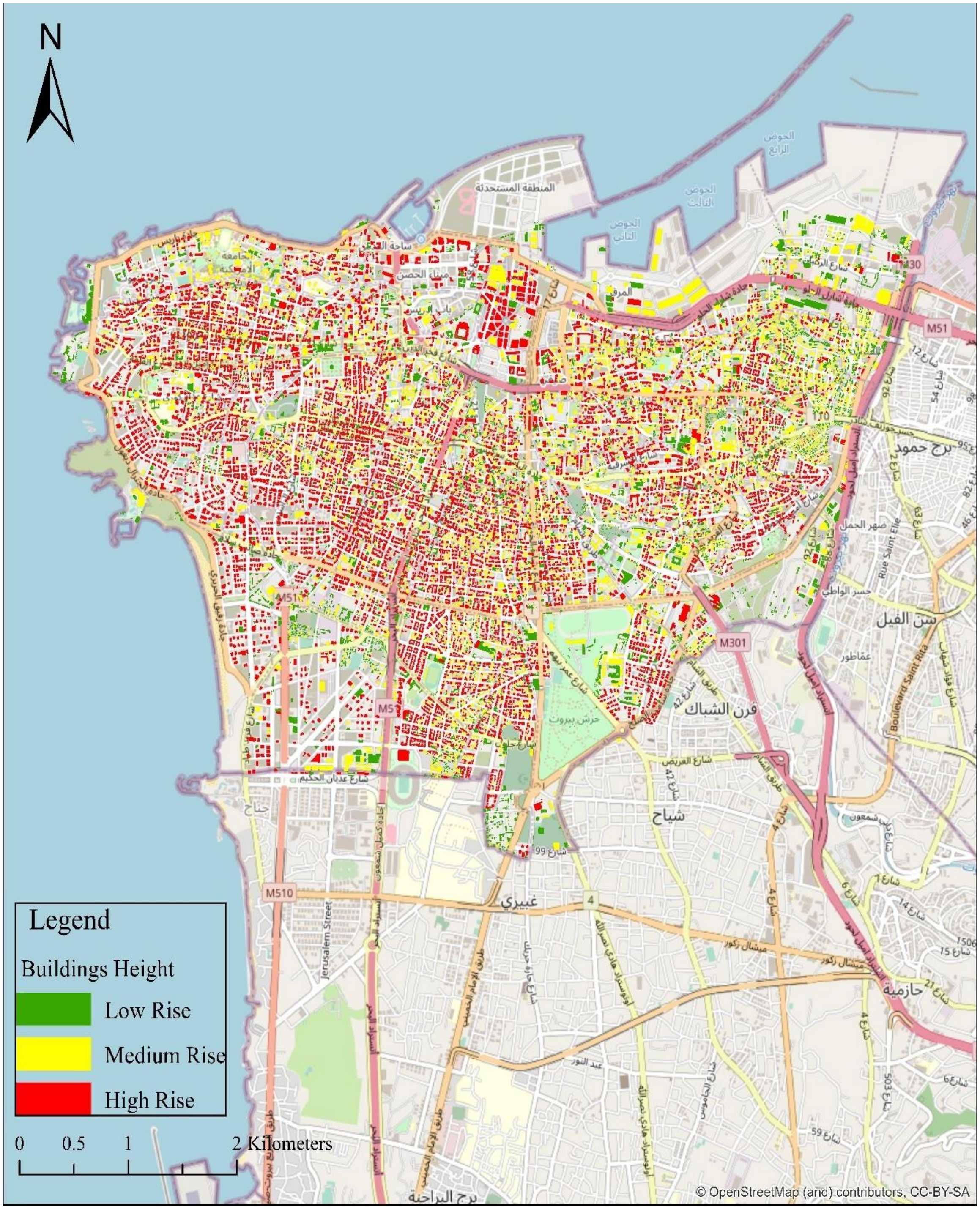


Figure 6.21: Beirut buildings height distribution

6.3.2 Random Failure Removal

The topological parameters of the weighted graph are interpreted through a random node removal. Each scenario is tested after every fraction of nodes randomly removed. The most significant properties that show a remarkable trend are illustrated in Figures 6.22 and 6.23. The first one shows the average betweenness centrality and the latter depicts the straightness property of the weighted network. After the second random removal, the average betweenness centrality expresses an intense decrease in its value for all the studied cases. Yet, nodes in the degraded network are rearranged to form some newly separated clusters which are appeared in the slight increase in the bar chart after the third removal. After that, a huge decrease in this topological characteristic indicates a failure of network's structure. According to straightness, the trend is dramatically declining for all the weighted cases. A low average path length is recognized in the network where few edges are involved between the pair of nodes. This random network property is often related to the small-world network which holds a relatively high clustering level. Also, the connectivity indices in Figure 6.24 reveal a very slight degradation of the network property. This is due to the new used random removal strategy in which nodes are deleted in a consecutive way leading to many small isolated clusters. In this way, the changed strategy reduces the disruption effects on the number of links. However, in real-world networks, such isolation could lead to serious scarcity in resources and hinder the transportation of emergency supplies. The sensitivity of random networks to attacks relies basically on the choice of nodes of high probabilities (i.e., possessing high degrees). Yet, this is not the case in this random network that shares comparable properties with the small-world network type. In fact, most of the node degrees are focused close to the average degree of the system which makes the overall network structure reasonable. These results complete the previous unweighted cases by proving that the network is vulnerable to random attacks. In this regard, the key nodes of the network along its robustness and redundancy will be meticulously discussed in the next section, tackling the overall performance of the system under targeted attack.

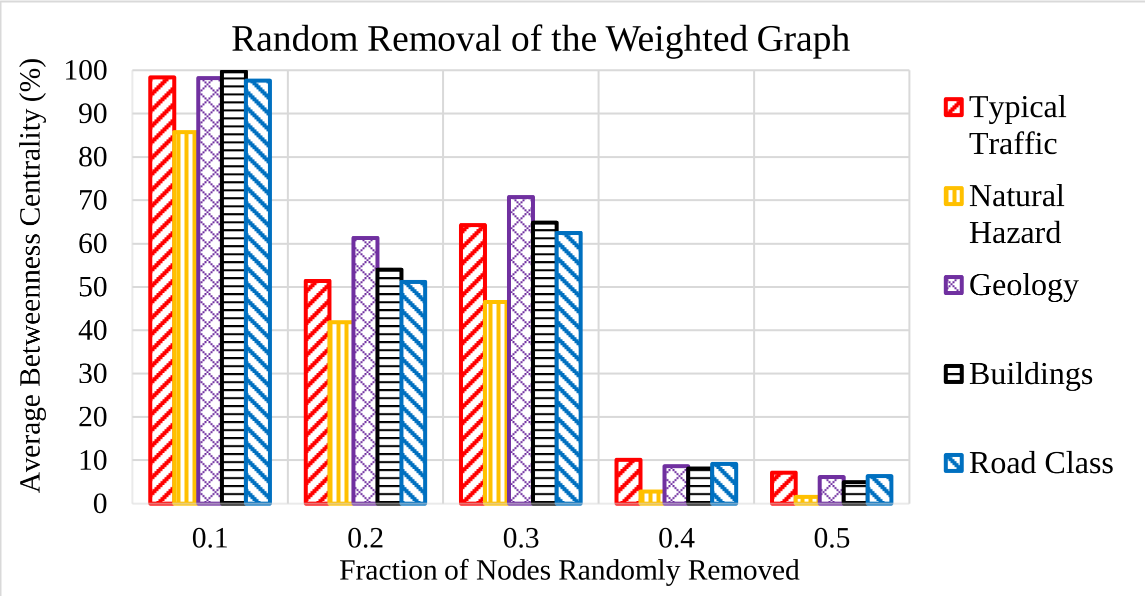


Figure 6.22: Effect of random node removal on average betweenness centrality of different weighted graph scenarios

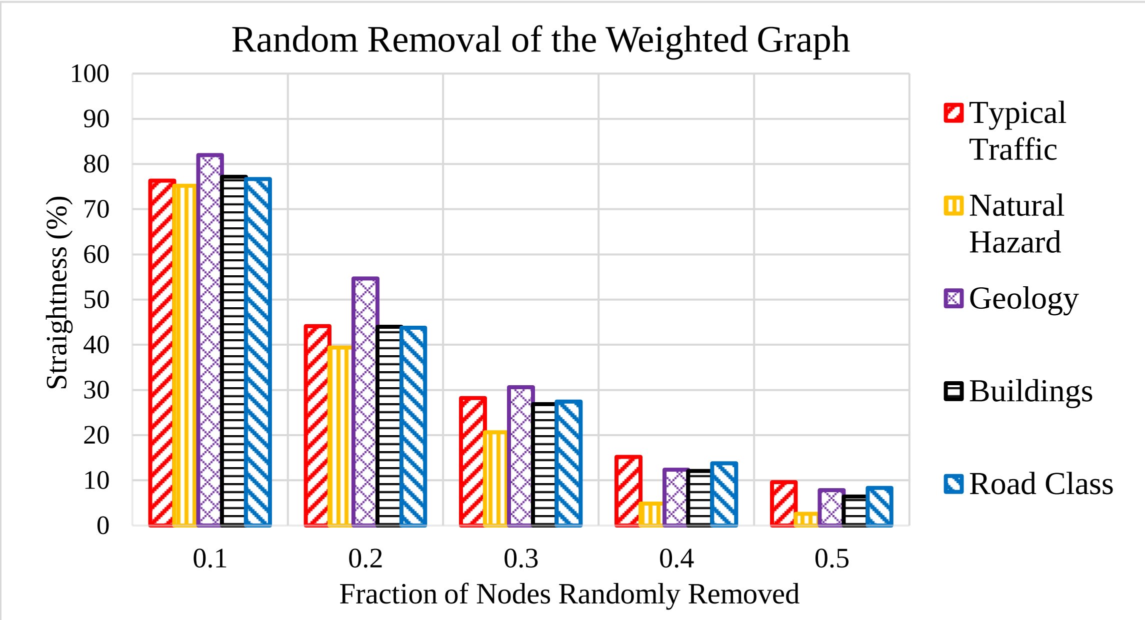


Figure 6.23: Effect of random node removal on straightness of different weighted graph scenarios

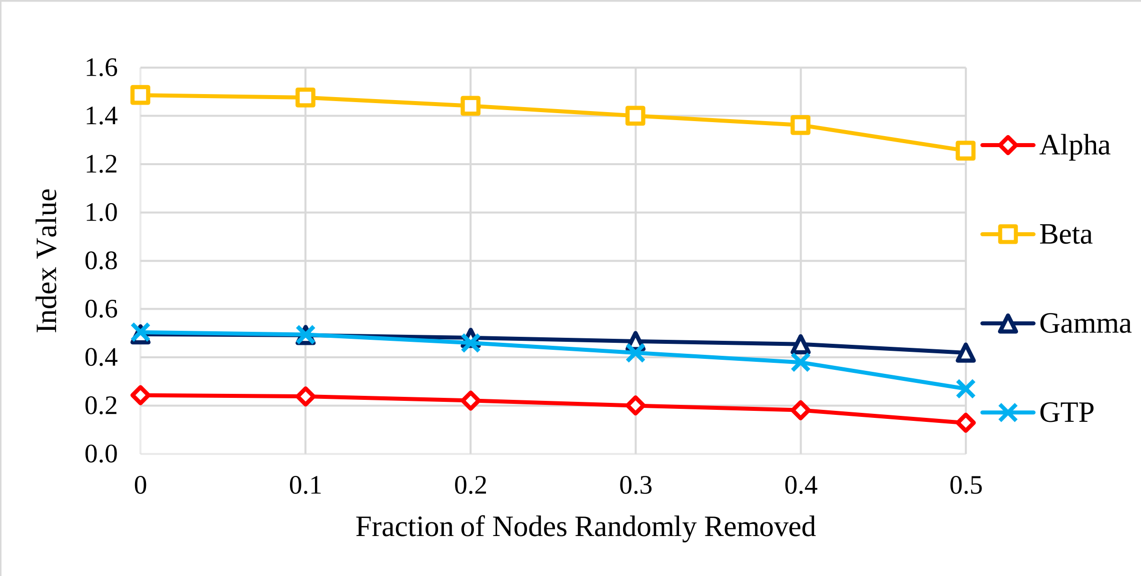


Figure 6.24: Effect of random node removal on connectivity indices of the weighted graph

6.3.3 Targeted Failure Removal

Before performing the directed removal process on the network links and nodes, it is essential to determine the percentage of the susceptible nodes before each scenario is examined. For the typical weekday peak traffic scenario, about 68% of the system's nodes or intersections are at a high exposure to failure. Moreover, 45% of the network's nodes have a high possibility of being disturbed in the scenario that is related to the distribution and location of the buildings (e.g., falling debris, ruptured utility lines, hazardous spills, fires). According to the roads' classification, 32% of intersections are at high priority to maintain the circulation to different critical zones in the city. Also, 26% of the nodes are defined as vulnerable dependent on the geology of the zones and their susceptibility to liquefaction and landslides. Lastly, around 20% of the nodes are considered at higher risk in case of a sea-level rise or floods; this is just a predictable example where no one could know exactly the speed and the wavelength of any tsunami event or how far it would travel inland (i.e., highly dependent on the land topography).

The results of the preliminary simulations of the network's topographical properties between the total undisturbed components and the affected ones reveal that the road classification, the buildings, and the traffic are the most influencing parameters for the system performance. The changes in the disturbed links and segments between the random removal and the targeted removal in the weighted graph cases are shown in Figure 6.25. The calculation of the ratio is based on the links removed in the targeted failure removal over those deleted in the random failure removal. Accordingly, the network's traffic scenario displays more than 30% increase in the number of disturbed links for the targeted event in comparison with the random event. Also, the road class and buildings scenario show a declining trend till the fourth removal where it deviates up after that, meaning the decay of the most weighted connected intersections; though, the ratios still less than the random failure case. These scenarios in the targeted event illustrate more degradation in the network and thus, a reduction in nodal degrees. The remaining two scenarios express an increase in the number of links removed in the random event rather than the targeted one. This tells somehow that the weighted geology and natural hazards cases are not extensively related to the most linked nodes in the graph. The connectivity indices outcomes of the removal targeting the top-weighted components in the stated scenarios are shown in Figure 6.26. It displays a sharper decline of the indices for the targeted removal process in contrast with the random event of the weighted graph.

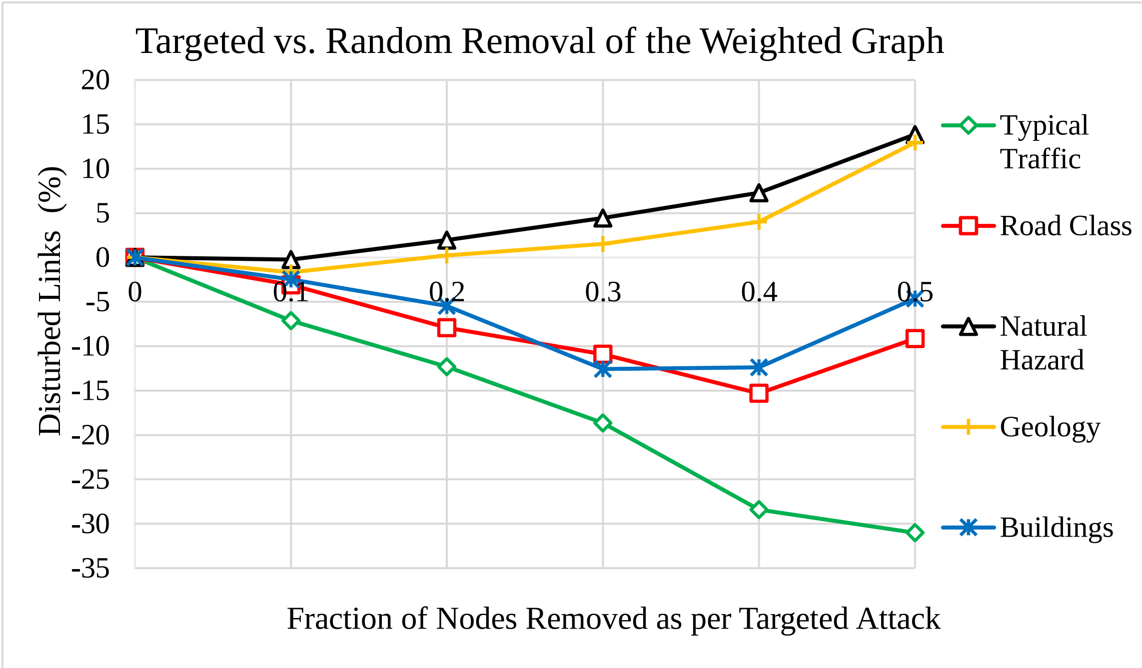


Figure 6.25: Disturbed links variation of targeted over random removal of different weighted graph scenarios

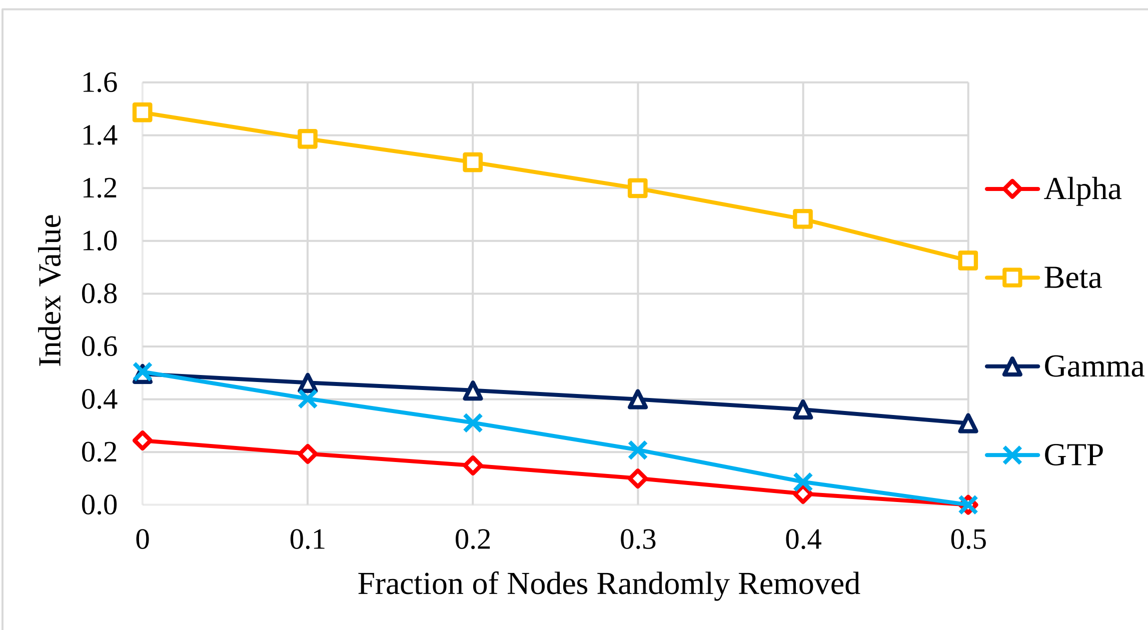


Figure 6.26: Effect of targeted node removal on connectivity indices of the weighted graph

Spatial network analysis usually supposes that transportation happens through the shortest accessible paths. However, this is not the case in real networks where people experience longer routes for different subjective reasons. Therefore, determining the redundant routes in case of a disruptive event turn to be a necessity through which alternative paths are found between the OD matrices for a certain length quota beyond the shortest route. Using UNA toolbox, the Redundancy Index is computed. It is the ratio of the sum of the distances of redundant links to the sum of the distances of the shortest route links per every OD pair. This is performed in the corresponding positively weighted and undirected graph of Beirut. For the different set of origins and the specified set of destinations designated by the hospitals and critical emergency centers, the average redundancy index is computed instead. In other words, the removal process is focused on the top-weighted structures that possess the utmost average betweenness centrality and nodal degrees of all the scenarios combined. The stated betweenness centrality of each node in the system is mapped in Figure 6.27. The studied original network dataset should be adjusted through creating a new one after each removal, to carry the analysis of the network's paths of the uppermost weighted structures. Nodes or street intersections could be applied also instead of buildings attributes to define which input points are utilized as origins and destinations to calculate the redundancy magnitudes. As weights are involved in the analysis, the index defines the amount of extra weights discovered on the lengthened redundant routes in contrast with the shortest route. A 5% increase in the redundant paths to the shortest path is applied in the analysis where the redundancy coefficient is set to 1.05. Similarly, the redundancy index which is also interrelated to the primary robustness of the network, reveals the extent of the additional available weighted path length through the OD pairs using a specified redundancy coefficient. For instance, if a 5% coefficient is applied and the redundancy output turns to be equal to "RI = 4", then this indicated that four times more route length turns out to be existing on redundant paths contrasted to the shortest path alone.

Table 6.1 shows the percentage of redundant nodes reachable to critical centers after each targeted removal of the top-weighted scenarios based on network properties. Note to mention that as the redundancy coefficient increases, the paths obtained will increase and thus, more computation-intensive the analysis will become. Yet, in emergency and evacuation situations, there is no place for wasting time through longer routes if the redundant ones are accessible. This requirement is seen through Table 6.1 in which the network is shut down after the disruption of only 40% of its components. Besides, the second fraction removal depicts the weakness in reaching fairly less than half of the available hospitals and critical emergency centers in the city (i.e., 13 destinations), where there is only 44% chance of reaching 13 destinations. This second removal is accompanied by higher standard deviation where the results are more spread out.

Figure 6.28 displays the global connectivity of Beirut hospitals and emergency centers. Note to mention that those centers outside the capital are not fully taken in through the computation which is reflected in their low connectivity outputs. Consequently, it is imperative to assess the network's loss in terms of the average redundancy index following each disturbed portion in the weighted graph. This is illustrated in Figure 6.29 where the network's average redundancy decreases to halve its overall performance after 20% of nodes removal. Therefore, after evaluating the network performance and the efficiency of its various measures through the removal modes of different classified weighted scenarios, the key redundant street nodes and intersections are established and mapped in Figure 6.30. The criterion of critical nodes is mainly based on the average redundancy indices from these nodes to the available hospitals. The vulnerable key nodes are all over Beirut. However, most of the clustered nodes are located along the primary roads in the center and extending toward the westside of the capital. Such points possess low redundancy and constitute around 25% of all the network's components. Correspondingly, the remaining nodes are divided as 70% with moderate and 5% with high redundancy level. This reflects the need to focus on these exposed areas which are more susceptible in case of disasters.

By this means, one of the main relief efforts to mitigate the negative impacts of natural hazard on transport lifeline systems is achieved. This is realized through performing vulnerability analyses and identifying the vital key lifeline connections within the transport system. Such pre-event preparation and planning could significantly reduce the transport infrastructure damage and economic losses. Other strategies could include implementing seismic safety provisions such as strengthening and retrofitting these structures through installing seismic instrumentations. In specific, those illustrated in Figure 6.31 which contain bridges and tunnels that might turn to be a bottleneck to the emergency and evacuation services. Adding to that, improving design standards and methods through continuous research and analysis of the previous similar case studies in the world (i.e., due to the absence of previous events records) will help in response and recovery following the considered hazard. Another measure that compliments the classification of key structures, consists of accessing immediately the pre-selected detours to initiate traffic management control directly after the disaster. An efficient preparation and planning could not be done without raising awareness and improving the people's knowledge on the possible hazards, their implications and the specified movement plans. For a successful recovery, the previous actions require significant coordination and communication between the responsible departments and authorities in the country (i.e., government, municipality, red cross, civil defense, traffic management center, internal security forces...). To finish with, this opens the door for private-public partnerships since the private sector possess substantial resources (i.e., transportation and warehouse assets) which can aid significantly in the recovery development.

Table 1: Percentage of redundant nodes reachable to critical centers after each targeted removal of the top weighted scenarios based on network properties

	Reachable Hospitals and Emergency Centers									
	0	**1**	**2**	**3**	**4**	**5**	**12**	**13**	**28**	**29**
Percentage Removal (%)	Percentage of Redundant Nodes/Total remained Nodes									
0	0	0	0	0	0	0	0	0	1	99
10	4	0	0	0	0	0	0	0	1	95
20	28	7	0	16	0	4	1	44	0	0
30	35	23	32	10	0	0	0	0	0	0
40	64	29	7	0	0	0	0	0	0	0

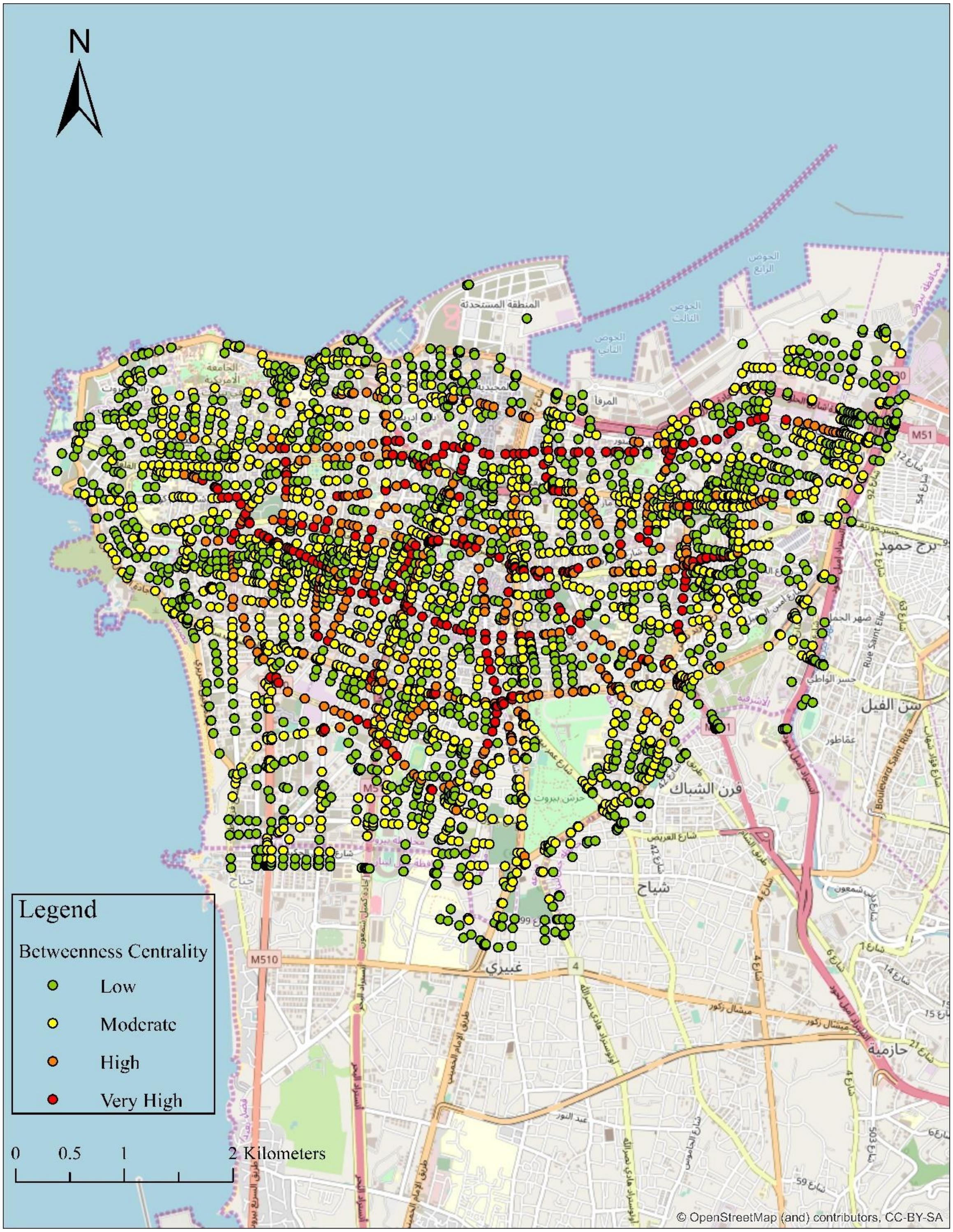


Figure 6.27: Nodal betweenness centrality of Beirut weighted graph

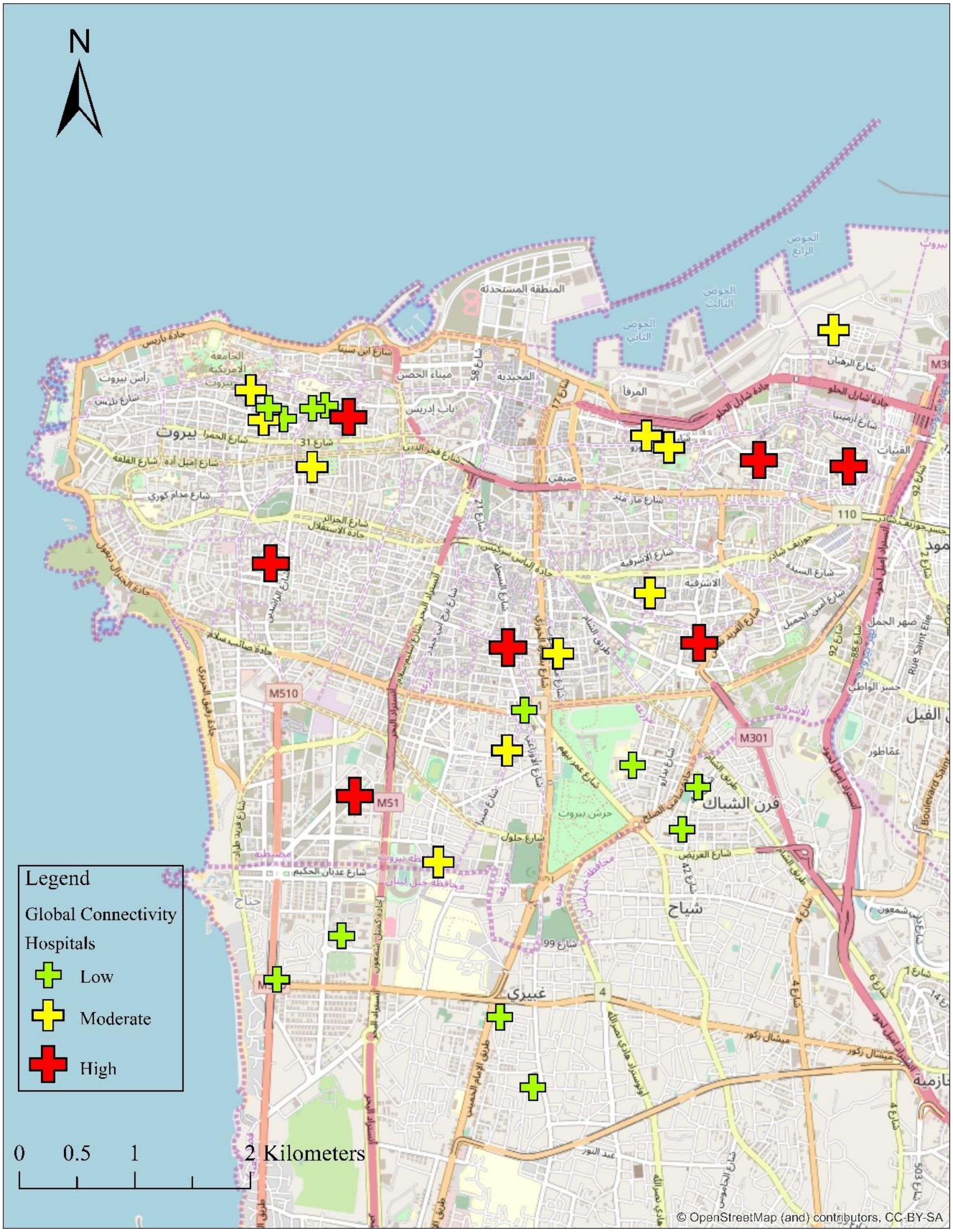


Figure 6.28: Global connectivity of Beirut hospitals and emergency centers

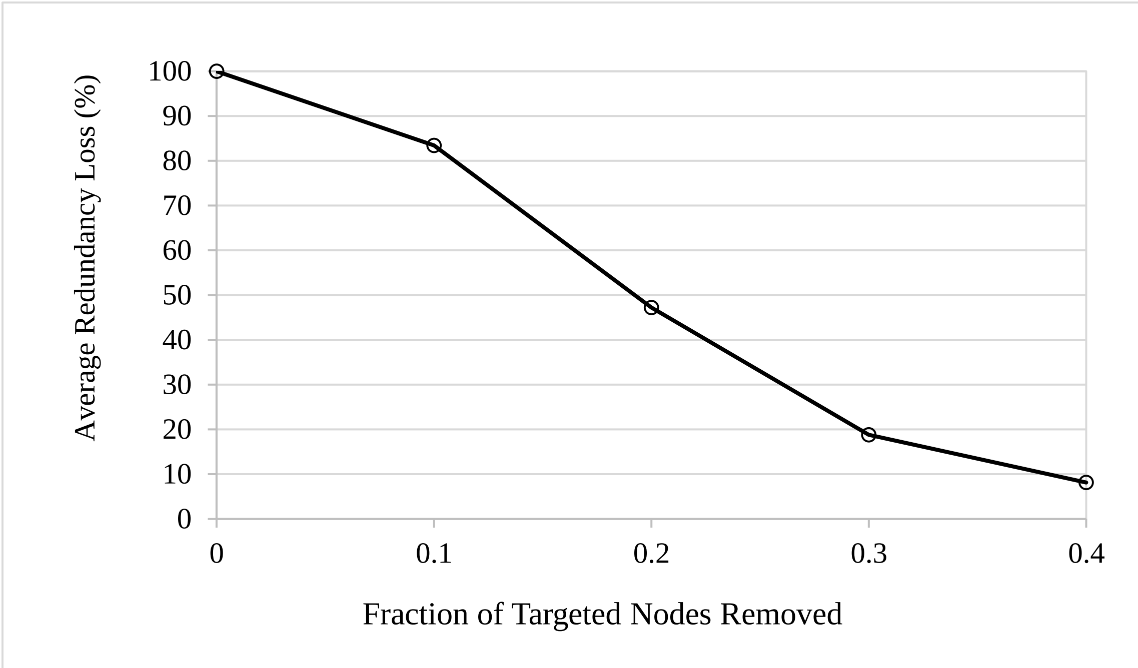


Figure 6.29: Effect of the targeted nodes removed in the weighted graph on the network's overall average redundancy

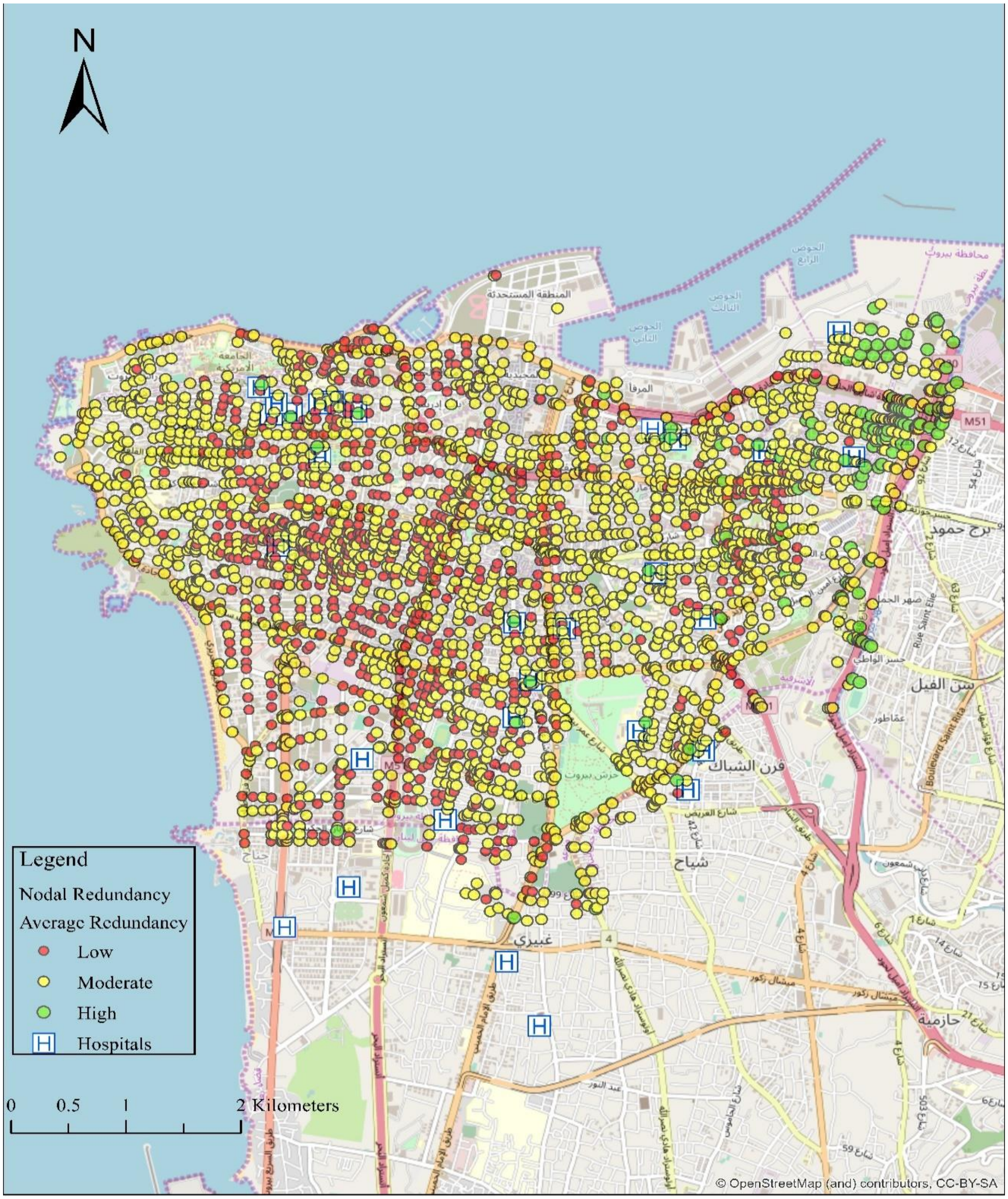


Figure 6.30: Nodal average redundancy of Beirut intersections to the accessible hospitals

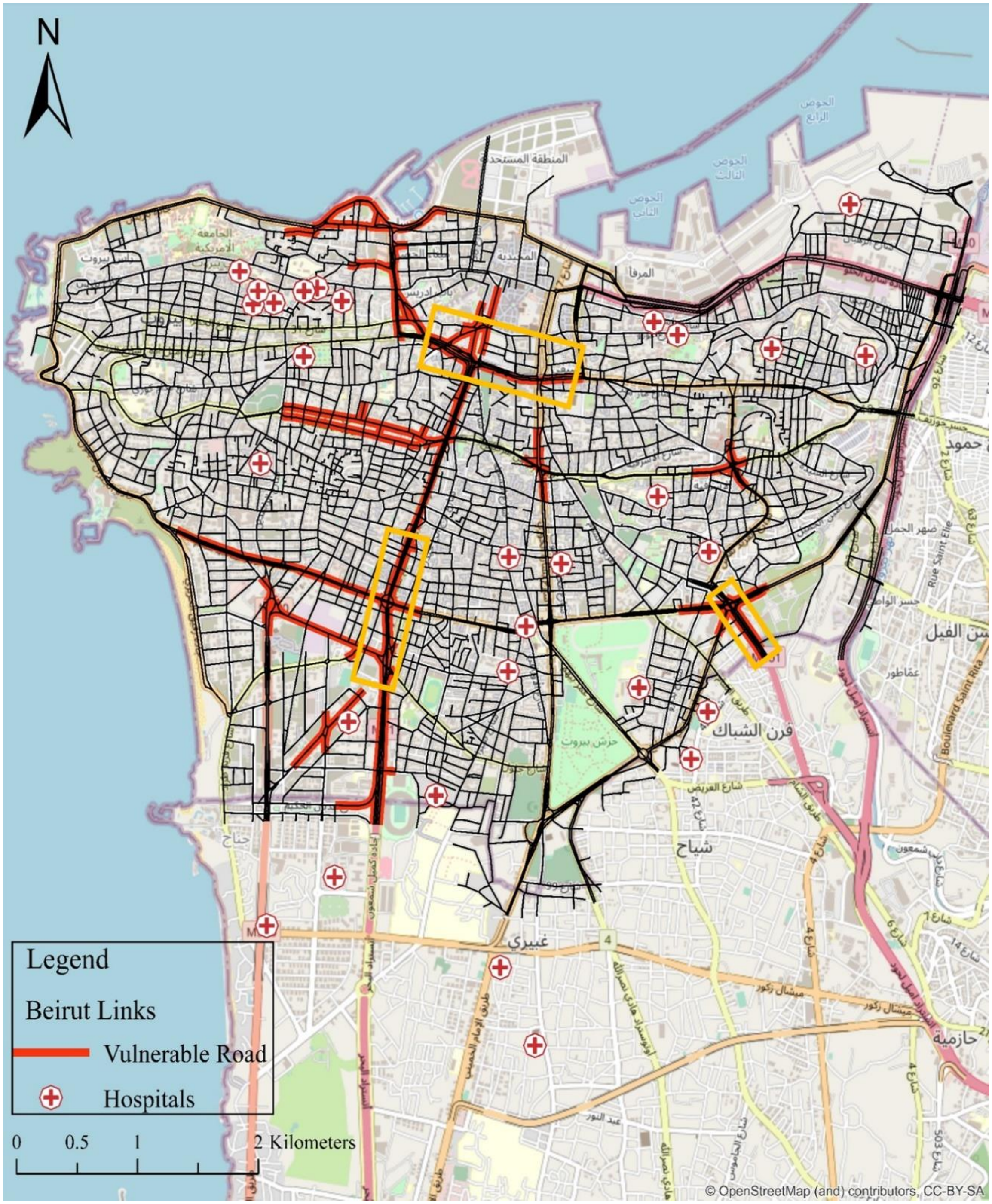


Figure 6.31: Major vulnerable links and intersections (the highlighted three rectangle zones show the riskiest areas).

VII. CONCLUSIONS, LIMITATIONS, and FUTURE PERSPECTIVES

7.1 Conclusions

Civil infrastructure systems such as transportation networks create the backbone of modern cities. It is of paramount importance to analyze their current resilience state which allows preparedness, absorptiveness, and adaptation for the probable upcoming disruptive events especially for those critical systems which are more susceptible to natural hazards and whose disturbance will profoundly affect the network's operation. Correspondingly, it is vital to identify the network's key components and have adequate knowledge to the most vulnerable networks through developing and evaluating criteria and performance metrics for an effective prioritization. Therefore, this thesis is devoted to providing network analysis functionalities for vulnerability assessment in transportation networks with respect to natural disasters. Infrastructure systems are entities that hold a networked nature appropriate for rigorous statistical and mathematical analysis (i.e., Graph Theory tools). The novel methodology in this thesis offers measures for understanding the urban graph, and to justify the necessity for expanding the network resilience by making it more fault-tolerant. In that manner, more insights into resilience quantification approaches for infrastructure systems are presented to detect the strengths and weaknesses through a mathematical framework that could respond efficiently to the resilience quantification requirements. By combining GIS derived spatial data and network concepts, the vulnerability of transportation networks is evaluated, and so the engineering resilience is defined along its aspects by a quantitative approach and statistical modeling of the topological graph properties. The graph-theoretic properties are examined to illustrate the behavior and distribution of Beirut network subject to various damage combination scenarios (i.e., random and targeted attacks). The spatial resilience of the entire network is evaluated through the assessment of the network's redundancy, robustness, and efficiency metrics based on the topological and connectivity parameters. Centralities results have offered comprehensive statistical and spatial knowledge about significant classes of local and global centralities measures. As indicated by the average centralities and degrees, the more redundancies built into the system, the better the resilience level.

Any infrastructure disruption directly threatens the economy, the governance, the security, and the confidence of the population. Following proper planning, and strategic resource allocation through mitigation priorities can diminish the sustained losses by a substantial amount and reap the most effective benefits. Thus, this thesis pinpoints the network's key components that have an important influence on the safety and reliability of the entire road network structure. These findings will help the authorities in disaster preparedness, risk mitigation emergency management, and post-disaster recovery plans. In this manner, policymakers are better able to direct and optimize resources by prioritizing the critical network components, thereby, decrease the period of the recovery process and maintain the system functionalities. To the author's knowledge, this thesis is the first one to assess the transportation network of Beirut under various random and targeted failure scenarios to quantify the resilience of the network structures. Yet, the presented effort is just the primary step towards a better understanding of complex dynamic processes in transport networks through approaches from complex network theory. The next section will outline some of the research limitations, and tasks to continue advancing the study of engineered networked systems.

7.2 Limitations and Future Perspectives

Resilience is a subject of growing concern lately. Starting within the scientific literature as a descriptor of the ecological behavior, it is extended to reach other domains in economics and engineering. Even with the recognition of the significance of this subject, researches that can be developed to real-world conditions are fairly sparse. This thesis, which has tangible benefits to society, sets to create a framework for resilience quantification through spatial and statistical analysis. Yet, it is limited to undirected transportation networks with specific topological properties. Also, particular scenarios are assessed due to the absence of previous records of the considered hazards. So, future research is required to focus on the extension of the proposed methodology to directed, weighted, and metric graph which reflects advanced aspects of the transportation network. Similarly, such extension can improve the computational tools to graph of great dimensions and analyze additional graph properties and alternative topological measures of different types of transportation networks. Correspondingly, other performance indicators and network characteristics could be studied and embedded for an enhanced vulnerability modeling for spatial networks.

Finally, further recommended extensions could include a detailed network flow and traffic demands studies along with the change in driver behavior in the post-event. Future topics could tackle the development of models to investigate and capture the various effects of different climate change scenarios (e.g., higher temperatures, higher storm surges, severe flooding…) on the reliability and capacity of transportation networks. As well, the development of models to explore cascading susceptibility within the interdependent critical infrastructure systems, will help to recognize the impact of interdependencies among critical systems that could promote a better understanding of the links between infrastructure systems in the dynamic built environment and their robustness and resiliencies.

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