Intermodal Transportation Systems Risk Analysis and Resilience in New Madrid Seismic Zone: the Impact to Mississippi

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ABSTRACT

Being one of the nation's top intermodal hubs, the Memphis area is vulnerable to large scale disasters, especially a large earthquake. This research presents two results. One a framework that visualizes transportation system risk profiles, with a particular focus on earthquakes, and another a model that uses this information to optimize recovery strategies. The first uses data from the United States Geological Survey (USGS) to create a risk probability map that is used to create individual risk profiles that are combined to form a cumulative risk profile. The second is the combination of a constructor, ordering algorithm, and traffic simulator that optimizes recovery strategies. The presented framework and model can be utilized together for simulation purposes, or separately where the first can be used to easily visualize failure probabilities to assist with planning and where the second can be used to determine effective recovery strategies in the aftermath of any disaster, not exclusively a seismic event. This framework and model provide valuable information that can be used to improve the Memphis area infrastructure system by improving infrastructure resilience and emergency recovery strategies and have the ability to be calibrated to any area of concern with minimal effort.

Keywords:

Resilience, Recovery, Neural Network, Critical Link, Risk Probability

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1. Introduction

The transportation infrastructure in the United States plays a vital role in the nation's standard of living and, thus, has a direct impact on the nation's economy. Any destructive impact along this infrastructure system reduces the reliability of travel time causing both private and commercial trip delays. These delays increase fuel consumption, emissions, and congestion while also increasing the amount of time lost in travel, all of which increases transportation environmental and monetary costs driving the economy downward.

Multiple and different problems can cause infrastructure issues from component failures to capacity constraints from increasing traffic volumes. Component failures can be viewed as having the most devastating effect to the transportation infrastructure due to their causing a complete closure in the section affected by this component. These failures can be caused by natural disasters, terrorism, or deterioration. For each of these causes, there are multiple specific models and methods that can be used to predict these events, determine the impacts, and/or determine the best, or optimal, recovery strategies; some of which are introduced in the literature review.

This paper presents an earthquake risk probability framework and a robust recovery strategy optimization model for link failures. The probability framework is developed as an input to the optimization model and focuses on earthquake based failures due to this being the most common failure causing natural disaster in the location of the project's study area, northwest Mississippi. Although this framework was developed solely to create an input for the optimization model, it could be used nationwide to assist in planning and to help visualize the existing risk associated with earthquake events. The optimization model presented in this paper is developed to be robust in the sense that it is not specific to the area or the cause of failure but only requires the failed components to be known and can be made more efficient by knowing some basic network properties. The model is constructed in three parts including a constructor, the algorithm itself, and a traffic simulator which are all explained in section 3. The goal of the model is to be an easily understood, relatively fast, robust recovery model.

The structure of this paper begins by introducing related literature in section 2. Section 3 provides the methodology behind both the probability framework and the optimization model and is divided into subsections to increase the visualization of the proposed framework and model. A case study of northwest Mississippi is presented in section 4 with different earthquake scenarios shown in their appropriate subsections. The conclusions of this research are presented in section 5, and all acknowledgments, references, tables, and figures are then presented in their appropriate sections.

2. Task 1: Literature Review

There are several articles that discuss the areas involved in this research; however, there are few that discuss its scope in entirety. Most of the previously mentioned articles do not focus on Northwestern Mississippi, the area of focus for this research, and few even focus on the New Madrid Seismic Zone. The papers focus on four aspects including risk analysis, resilience evaluation, vulnerable links and infrastructure identification, and strategies for mitigating risk and increasing resilience. Each of the papers focuses on one of these aspects although it may contain more and are separated in this review by each of their primary focus areas.

2.1 Risk Analysis

Gerard Ibarra, Dr. Jerrell Stracener, and Steven Szygenda performed a research project that used a holistic approach and systems engineering to assess risk and cost impacts of highway disconnects. Their research created a methodology applicable to any highway network, and then developed a specific model for the Houston area to assess disconnects associated with an explosion (Ibarra et. al. 2006).

Maria Leung, James H. Lambert, and Alwander Mosenthal adapted the framework of risk filtering, ranking, and management to identify and prioritize critical infrastructures for the purpose of terrorist attacks. The assessment is done at both the system level and the asset-specific level. The framework then performs an in depth analysis of the risk of a specific critical infrastructure (Leung et. al. 2004).

Y. Y. Haimes, J. H. Lambert, S. Kaplan, I. Pikus, and F. Leung created a framework to identify, prioritize, assess, and manage risks. It considers a holistic approach to risk identification, effective judgment, prioritization, event analysis, and the use of a framework to evaluate management options (Lambert et. al. 2002).

Ryan A. Loggins and William A. Wallace "developed a methodology for the rapid estimation and analysis of damage and disruption to interdependent infrastructure systems as a result of a hurricane" (Loggins & Wallace, 2015). The goal was to provide a method for emergency and infrastructure management communities to estimate the effects of damage on multiple infrastructure systems. It is important for these calculations to be performed quickly and accurately in case of a natural or man-made disaster. The model created by Loggins and Wallace assumes that all components in an infrastructure system are independent from each other. In a situation where two infrastructure components are dependent on each other, this model gives the user the ability to input that information. Other inputs that are required for this model include the type of component and the location. Census tracts are used to represent the locations of components because most wind field models provide output at the census tract level. If a higher resolution is desired the model can also accommodate census block groups. Additional data would include the terrain type (open, suburban, city, and heavy trees). To predict damage, a hurricane scenario is selected which includes wind speed, pressure, radius to maximum winds, and the storm track. Maximum gust wind speeds on the region from the hurricane scenario are required to predict the wind damage. This is done using the existing wind field modeling techniques embedded in HAZUS-MH by Vickery et. al. (2009), or the wind speed estimates from the National Oceanic and Atmospheric Administration before a hurricane makes landfall. Both of these models have the ability to calculate the maximum wind speeds that are provided at the census tract level using wind field modeling. Using the maximum wind speeds calculated, the effect these heavy winds have on individual infrastructure components is analyzed. The goal of this research is to simplify the damage prediction process in HAZUS-MH. One simplification was to only include the 32 most common structure types (cellular towers, power transmission types, 1-3 story concrete buildings, prefabricated metal factories, etc.). Also, only damages that inhibited the function of a component were analyzed so the number of damage curves was reduced. Next, to simplify the parameter estimation process, the remaining damage curves of the 32 structure types were fit to a cumulative probability distribution using the *dfittool* in MATLAB (Loggins and Wallace). Terrain type is analyzed along with the wind speed because the surrounding environment also affects the vulnerability of a component. The simulation generates 10th percentile and 90th percentile damage maps for all infrastructure systems one storm at a time. A flood damage predication simulation is also necessary as this is a major issue with hurricanes. This prediction is a simpler than predicating the damaging effects of wind. It is accomplished by using floodplain maps for a given region and assigning each infrastructure element to a certain zone. Existing knowledge of flood patterns is used to predict damage. An infrastructure disruption model is important so that mitigation actions can be taken to lessen the damage of infrastructure. This model uses the infrastructure data and results from the damage predication to predict the effects that will occur. This model is beneficial for infrastructure and emergency managers to predict the demand for work crews and resources before a catastrophic event. Although the data and results described are specific to hurricanes, this methodology can be used for any type of disaster (Loggins & Wallace, 2015).

A team at the Mid-America Earthquake Center performed a study to analyze the severity to infrastructure if a 7.7 earthquake occurred on all three New Madrid fault segments. The earthquake impact assessment was compromised using hazard, inventory, and vulnerability. Hazard includes shaking of the ground and permanent deformation after a quake along with fire and flood. Inventory includes all assets in a certain region including built infrastructure and the population. Vulnerability includes the severity of an earthquake ranked as light, moderate, extensive, and near collapse. The MAE Center developed "transportation network flow models that estimate changes in traffic flow and travel time due to an earthquake." This model was performed for an eight-state study region that is extremely vulnerable to the New Madrid Fault line. Results were able to indicate which states would be most severely impacted by estimating the number of buildings damaged, amount of search and rescue personnel needed, amount of damaged bridges, and the injury and fatality rates. This information would be extremely useful in the case of an earthquake hitting this area, emergency personnel could evaluate how many people would be displaced and determine the amount of aid needed from FEMA along with which routes are shut down due to excessive damage (Elnashai, Jefferson, Fiedrich, Cleveland, & Gress, T., 2009).

To determine all of the parameters that were described in Volume I of the New Madrid Seismic Zone study, the MAE Center used HAZUS modeling. To perform this, inventory of all transportation infrastructure (bridges, roads, etc.) is collected, soil conditions and date are analyzed and collected, and all wastewater, potable water, or oil facilities locations are collected. The program also needs to know of all the nodes and links in the desired network. This data can be collected from the NBI database which will also display the number of bridges. Structural vulnerability functions are then used to determine the probability of a section in a network failing. Building capacity curves are constructed based on the capacities of buildings in the affected area. HAZUS models are created to analyze different vulnerabilities such as bridges or buildings. The HAZUS model uses realistic ground movements that the New Madrid Seismic Zone could potentially have. This gives for accurate results in preparing for an earthquake (Elnashai, Jefferson, Fiedrich, Cleveland, & Gress, T., 2009).

Savary et al. introduced a traffic assignment model to assess the impact of a disruption of a section of highway. The total travel time spent by the travelers on the road network, total distance covered by the travelers on road network, total vehicle operating costs borne by travelers on the network, and toll charges were used as indicators in the model. The researchers compared the variation of these indicators with disruption of different highway segments, and analyzed the consequences of the road disruption on the transportation network. Based on different consequences of the disruption of the links, the components of transportation network that should be protected in priority were decided. Further, the modified robustness index of a studied segment was validated (Savary et al. 2014).

2.2 Resilience Evaluation

Michel Bruneau, Stephanie E. Chang, and et al. performed research on quantitatively assessing seismic resilience. Their research created a framework to quantitatively assess resilience and relies on the complimentary resilience measures. This research also provides quantitative measures of robustness, resourcefulness, and redundancy (Bruneau et. al. 2003).

Li Zhang and Mingzhou Jin developed a framework for measure of resilience calculations for intermodal transportation systems. Mobility, accessibility, and reliability were the selected evaluation characteristics. A formula was also created to evaluate the quantitative values of measures of resilience (Zhang et. al. 2009).

Therese McAllister describes the importance of resilience in infrastructure systems against natural, technological, and human-made hazards to avoid significant damage in communities. Negative effects of damage to essential infrastructure systems includes the disruption of a communities economic patterns and the rate of recovery. A hazard event such as a hurricane, flood, earthquake, etc., could have such a negative impact on a community that it causes the permanent relocation of businesses. Typically, if the damage on a community is lesser, the time to full recovery decreases which allows the community to continue its level of economic growth. If mitigation of hazard effects occur prior to a damaging event, the level of damage, time, and cost of recovery could be reduced. For this to occur, there must be a way to create resilient infrastructure. "Community resilience requires disaster preparedness and emergency response plans which rely on the availability of buildings and infrastructure systems," (McAllister, 2015). To evaluate the resilience of a community, design, mitigation, and recovery alternatives should be addressed with a risk-informed methodology. This risk analysis should include all possible consequences including losses and recovery costs due to damage caused by a natural disaster. To make this assessment easier to evaluate, it is beneficial to understand that most disasters occur independently of each other (some exceptions may include a storm surge following a hurricane or a tsunami or fire following an earthquake). These exceptions pose a significant challenge in risk assessments due to the fact that they will most likely have damage beyond expected of the initial disaster. McAllister's ideology is that a "resilient community considers the role of buildings and infrastructure systems in meeting the desired levels of operations and functionality before, during, and after disruptive hazard events, and prioritizes activities needed to achieve such performance."

To accomplish this, three things are required: assessment methods to characterize the performance of existing buildings and infrastructure systems, guidance to support developments of risk-informed performance criteria, and standards to provide consistent reliability basis for designing buildings and infrastructure systems (McAllister, 2015).

Osei-Asamoah and Lownes evaluated the resilience of surface transportation networks by using examples of the US Highway and Interstate network. They were able to simulate this by using biological (slime mold) and real transportation networks. They also analyzed the relationship between resilience performance measures and complex network structural metrics to see how they influence network resilience to disruptions. To test this, links are subjected to random attacks and failures and the performance and topological resilience to disruptions of the link network is evaluated. From this study, it was clear that the existing infrastructure has vulnerabilities such as lack of link redundancy and adaptive capabilities in the surface transportation networks. According to Osei-Asamoah and Lownes, it was also established that the "average degree of the network and density have a strong influence on structural resilience performance measures after disruptive events, while the average clustering coefficient does not display a strong correlation with the structural performance of the network post disruption" (Osei-Asamoah & Lownes, 2014).

Zhang, Huang and Wen proposed that a widely accepted method for evaluating measures of resilience (MOR) had not been formed. In their research, the intermodal network resilience was defined as the ratio of the reduction of the performance of the intermodal system after the disaster, with respect to the pre-disaster performance of the system. A lower value of MOR meant the system was more resilient to disruption. A case study of the Mississippi Gulf Coast intermodal network after Hurricane Katrina was included in this research. It was shown that the resilience of the intermodal network was weak one week after the hurricane but it increased in subsequent weeks. However, this method of calculating resilience cannot be used for another disaster, due to the lack of knowledge about other kinds of disasters (Zhang et al. 2010).

2.3 Vulnerable Links and Infrastructure Identification

MAP Taylor and GM D'Este performed a study on network reliability. The purpose of this study is to analyze the vulnerability of a network. They define network vulnerability as network weakness and consequences of a failure. To analyze vulnerability, points of weakness and links where network failures will have substantial adverse effects are anticipated. The idea is to suggest cost effective remedial measures such as protecting vulnerable links or adding links. To perform this study, MAP Taylor and GM D'Este applied their research to the Australian National Highway Systems Network and analyzed the vulnerability for travel between two selected pairs of capital cities. Travel distance represented travel cost and a threshold link probability value was set. The minimum path cost and expected path cost of the full network are compared with those of the degraded network (when a specific link is cut). The ratios indicate the differences in travel costs of a full versus degraded network system which can then be used to predict the potential for greater adverse impacts if a link is broken. Using this information it is possible to select a reasonable alternative path in case of a network failure. Taylor and D'Este discovered that there are potential benefits from the development and application of a methodology to assess risk and vulnerability in transport systems. These benefits include social and economic by managing the impacts of a network failure to minimize more severe consequences (D'Este, G M & Taylor, M A P, 2003).

Murray and Matisziw assert that it is important for disaster response teams to be aware of transportation network vulnerabilities. Knowing and assessing these vulnerabilities can benefit response teams in disaster planning. Murray and Matisziw created a model on a path-based approach using PAC. This model analyzed flow vulnerability similar to other models. The difference is in this model, only one and two step *i-j* paths need to be specified. By only analyzing the *i-j* path, computational and solution times were significantly less. This provides for a faster response time in a disaster by emergency response teams. Although this model has certain benefits over existing models, it also has limitations such as: it assumes all network paths are viable for *s-t* interactions (Matisziw & Murray, 2007).

Darren M. Scott, David C. Novak, Lisa Aultman-Hall, and Feng Guo created a new approach to identifying critical links in their research called the Network Robustness Index (NRI). Instead of the traditional highway planning methods that involve the volume/capacity ratio, the NRI considers network flows along with link capacity and network topology. Having a reliable source of data is also important for this method to work. It is known that a failure of one or more network links can have a significant effect on travel-time and economics in the area. Therefore, it is important to identify critical network links to improve reliability in transportation networks. It is also important to understand that one network link failure has the ability have system wide effects. This research team believes that the highway systems in the United States should be extremely connected so that in case of one link failure, the entire system does not fail. The NRI evaluates the "importance of a highway segment to the overall system as the change in travel-time cost associated with rerouting all traffic in the system should that segment become unusable." Instead of calculating travel times based on free-flow speeds, it is calculated based on link performance functions for a more realistic and therefore beneficial measure. The NRI model begins by calculating the flow and travel-time using the "user equilibrium assignment model." Next, the model disables each link in the network one by one. As each link is disabled, the program finds an alternate route for traffic to move throughout the network. Upon applying this model to examples, the research team proved that the v/c ratio and the NRI model provide different results.

The NRI accounts for spatial relationships and rerouting possibilities according to the network's topology, the OD demand and individual highway segment capacities. After applying the NRI to different examples and comparing data using the v/c ratio, the team proved that the NRI is more beneficial than the v/c ratio and the NRI is a valuable measure (Scott, Novak, Aultman-Hall, and Guo, 2005).

Pamela Murray-Tuite and Hani Mahmassani also performed research that created a methodology to identify vulnerable networks. Their method works by assigning damage values to the disruptions in certain links and the critical infrastructure is determined by that with the maximum amount of damage by being disrupted. The damage is assigned based on certain traffic conditions, roadway characteristics, and the availability of other paths. The study focused on behavior rules of evacuees along with existing transportation infrastructure, the availability and sharing of information to differentiate her simulation model. A vulnerability index was developed to determine the importance and connectivity of roads. Their methodology states that evacuation plans cannot be accurately determined without studying the behavior of the evacuees along with the resilience of the transportation infrastructure. To effectively develop a method to evaluate the evacuation of a city, Tuite and Mahmassani proposes that locations should be analyzed using the vulnerability index, evacuee behavior is known, and there are continuous developments in information and communication technology. Using a household's decision making rules and a transportation network consisting of known nodes and arcs, the evacuation time can be predicted for every household with the known information. The vulnerability index will identify the most vulnerable link which aides in redirecting traffic for evacuation purposes. Using this information developed in this research, authorities can accurately predict where additional roads could be built to divert traffic away from highly vulnerable links. These methods could also be used for drivers to adjust their routes based on given travel time. The main use of this research leads to determining the locations of schools, government buildings, etc. for adequate safety measures in case of an emergency evacuation (Mahmassani & Murray-Tuite, 2005).

Ukkusuri and Yushimito claimed that the criticality of facilities in the transportation network (i.e. link nodes) was important since it impacted driving decisions. They assumed that every driver would seek to minimize his individual travel time and applied the Frank-Wolfe algorithm to assess the criticality of facilities in transportation networks to prove that their revised way of criticality measurement out-performed the V/C ratio measurement, which does not include use behavior. Their methodology, however, is a heuristic approach using network science with travel time being the performance measure (Ukkusuri et. al. 2009).

Rinaldi, Peerenboom, and Kelly researched how to identify, analyze, and understand the interdependencies among the major components of infrastructure. To accomplish this, it is necessary to understand physical dependencies, cyber dependencies, geographic dependencies, and logical dependencies. Physical dependency is defined by having the inputs and outputs of two agents physically linked. Cyber dependency is defined by relying on information being sent to and from an information infrastructure. Geographic dependency is defined by infrastructure having state changes due to local environmental changes. Logical dependency is defined as the factor if human decisions that play a role in the outcome of events. To model or simulate how these interdependencies affect infrastructure is a complex problem that would involve six major categories including: types of interdependencies, infrastructure environment, coupling and response behavior, infrastructure characteristics, types of failures, and state of operations. This is an extremely complex simulation and Rinaldi, Peerenboom, and Kelly have only just begun. Their research begins the study of interdependencies and needs more research before a usable model is created (Rinaldi, Peerenboom, & Kelly, 2001).

Khaled et al. claimed that the criticality of an infrastructure element (i.e. link, yard) was based on the time delay incurred after the disruption of that element. Their modified heuristic solution approach was first applied into the network to get the total transportation cost. Then each element of the network was excluded separately; the residual traffic was re-routed in the approach and a new transportation cost was calculated. The criticality of each specified element was obtained by the comparison of the two costs. However, their methodology differs from the normal methods in that it applied a model which took capacity into consideration at both the yards and links and considered the relations of speed and volume at links. Therefore the methodology used in this study was applicable under an event of disruption. However, the researchers pointed out that their model was rarely used in realistic application because of the complexity, but the model would be helpful to the development of better preparation and response plan to cases of disruption (Khaled et al. 2015).

Khademi et al. claimed that the previous studies about post-disaster vulnerability rarely made the distinction between operability, connectivity and accessibility, which led to the assessment of vulnerability of roads imprecise. In the case study of Tehran, the researchers used their own methodology to introduce the concepts of redundancy and isolation index. In their research, for medical and relief trips, the cases with a higher trip-type isolation index were more vulnerable to the catastrophic earthquake. However, the regions with a lower redundancy index represented the regions had a large number of rescue facilities and less damage. In future studies, the potential goals could be maintaining the accessibility to a specified vertex of the transportation network, reducing the number of casualties and so on. According to the researchers, based on this study, all these objects could be done through building more mathematic formulas (Khademi et al. 2014).

Mattsson and Jenelius did a review of numerous studies about vulnerability and resilience of transport systems. Based on their review, there seemed to be no consensus on the definitions of resilience and vulnerability, as well as their relations to relevant notions such as robustness, fragility, and risk. Furthermore, the authors distinguished the two traditions of vulnerability analyses, which were a topological vulnerability analysis of transport network and a system-based vulnerability analysis of a transport network. The authors also argued that the cross-disciplinary collaboration between researchers, operators and other stakeholders was desirable to strengthen the mutual learning and transform the knowledge to practical plans which could enhance the resilience of transportation network (Mattsson et al. 2015).

2.4 Strategies for Mitigating Risk and Increasing Resilience

Karaca developed a regional earthquake loss methodology that emphasizes economic interdependencies at regional and national scales. To accomplish this feat, the first step is to evaluate all regional and national losses after an earthquake. Next, quantifying the uncertainty on the losses through loss risk curves including data from seismicity, attenuation, and fragilities is necessary. Losses can be defined as damage to buildings and transportation components, functionality losses, changes in levels of economic activity, and the speed of the recovery process. Once all aspects of loss are evaluated, the effectiveness of alternative mitigation strategies must be assessed. This study produced a large amount of data that can be compared, but for a more accurate evaluation of the effectiveness of alternative mitigation options, a more detailed analysis with many more earthquake scenarios would be beneficial (Karaca, 2005).

Riccardo Rossi, Massimiliano Gastaldi, and e. al. designed a procedure to identify the optimum action plan. This research was focused particularly on earthquakes in post-emergency situations. A network risk curve is also derived through this research (Rossi et al.).

Silvana V. Croope and Sue McNeil developed a framework for a decision support system, referred to as the Critical Infrastructure Resilience Decision Support System (CIR-DSS), to reduce the vulnerability of infrastructure systems. They discovered that to make a system resilient to disasters, the performance of a system must continually be improved over the years to lower the impact of a disaster. The CIR-DSS model was organized by 1) obtain infrastructure information 2) obtain system performance measures 3 and 4) degrade system performance because of a disaster 5-7) improve system performance and step 8) assess system performance. The scenarios tested were assess based on "infrastructure projects developed just to recover from damage because of a disaster and infrastructure projects developed to recover from damage because of a disaster and to be able to withstand future similar events." According to the results, the CIR-DSS model provides beneficial solutions that affect not only infrastructure but also society and the economy (Croope & McNeil, 2011).

Chang researched "a method to develop a systematic approach for risk modeling and disaster management of transportation systems in the context of earthquake engineering." The goals of Chang's research were to improve transportation infrastructure resilience, allow emergency response teams to select optimal routes for teams to get to certain areas, estimate traffic congestion in extreme events, and find ways to protect these systems. This research is important because after a devastating event such as an earthquake, emergency personnel need to be able to get to the affected area to aid in evacuating people as quickly as possible. This is impossible if the transportation infrastructure fails. One method that has proven effective in mitigating potential catastrophic losses of transportation systems is retrofitting existing bridges. While this is an extremely effective measure, it is too costly and impractical to apply to every existing bridge. Therefore, it is important to prioritize the infrastructure that is vital to a transportation system. This study chose to study the New Madrid Seismic Zone which is located in the Central United States because this area is the most vulnerable region to seismic hazards in the U.S. and the chance of an earthquake in the near future is high. This area is vulnerable because infrastructure has not been built to withstand an earthquake due to the low occurrence rate as opposed to Japan or California. Chang's model includes "an integrated simulation model of travel demand that accounts for damage of bridge and building structures, release of hazardous materials, and influences of emergency shelters and hospitals." The purpose of this model is to assess traffic patterns post-earthquake and evaluate the failure of a transportation network. Chang's model proved that an existing similar model (NBSR by MAE Center) was not sufficient enough for a large infrastructure system. To improve their model, Chang implemented optimization techniques and OD-dependent performance metrics. Once the existing model reached an acceptable efficiency level, it was proven that an increased infrastructure budget would improve seismic retrofit programs. Using this model, emergency personal are able to model risks, evaluate post-earthquake damage, and assess the reliability of transportation infrastructure. This will aide emergency personal in decision-making for the planning, construction, and operation for future hazardous events (Chang, 2010).

H.W. Ho and Agachai Sumalee design an optimal recovery plan by utilizing a continuum transportation system. The goal of this research is to provide a faster recovery period after a disaster that causes damage to transportation and building infrastructure. The continuum transportation system model is excellent in finding alternative routes after a disaster, impacts of the disaster, and the demand for emergency and reconstruction services. This method can be used in analyzing "wide-area disruptions and represents all possible alternative spaces for network recovery" (Ho & Sumalee, 2014). The design of optimal recovery plan is formulated as a bi-level model and the optimal recovery plan of road density, housing unit, and CBD's after a disaster is formulated as an upper level model. According to Ho and Summalee, "the upper level model will be formulated as an optimization problem with the weighted sum of total travel cost and total travel demand of the whole recovery process as the objective function and available budget as the constraint. The lower-level model, which is a quasidynamic model over the recovery period, is proposed to determine the path choices, travel costs, and the corresponding sensitivity information at different times of the recovery period for solving the upper-level model." The Newtonian algorithm is used to solve this model. This optimal recovery plan design can be analyzed through research in different directions. Optimal changes would include decreasing the problem size and computation time for authorities to have a faster response time in rebuilding transportation and building infrastructure (Ho & Sumalee, 2014).

Trejo et al. investigated three plausible strategies to maintain the post-seismic operations of bridges: high-strength reinforcement, precast bridge columns supported on drilled shafts, and concrete-filled tubes for columns of bridges. For the high-strength reinforcement, a team of designers tested with two columns, C1 and C2, which had same exterior dimensions and similar moment capacities. C1 was reinforced with Grade 60, and C2 was reinforced with Grade 80. The two columns experienced both visual (i.e. cracking, concrete spalling and bar fracture) and observations (i.e. column lateral displacement, column curvature and column tilt) under cyclic loading. In their findings, the Grade 80 reinforcing steel has similar displacement ductility and resistance compared to steel reinforced with Grade 60. Furthermore, the Grade 80 reinforcing steel had smaller dissipation of hysteretic energy than the Grade 60 reinforcing steel. Also, for the other parts, based on their conclusions, a new connection system of a precast concrete column and a drilled shaft using “wet” socket could have high performance in high seismic regions. The construction of concrete-filled tubes was also a practical method for structural constructions including bridge, and the construction can restrain the spalling of concrete and local buckling of the tubes (Trejo et al. 2014).

The goal of a study by Hitchcock was to review the historical and temporary policies employed in Alabama for the rapid restoration of transportation network after natural disasters. In case studies of the state of Alabama, several factors such as prepared participants, proper planning, and hands-on training exercises are important for time and cost efficient transportation network renovate and reconstruction. The researchers also had pointed out several recommendations for preparations for natural disasters such as the development of supplemental resource capabilities and doing emergency preplanning workshops (Hitchcock 2008).

Ellis and Vessely introduced that geotechnical data visualization (GDV) was valuable for the mitigation of hazards and response to the consequence of disasters. This study specified the hazards faced with transportation personnel determined the types of geotechnical data and visualization to the hazards and evaluate the effectiveness of different GDV tools. The study showed that the visualization of geotechnical data was important in terms of improvement of damage assessment, design of repairs and long-term recovery from the hazards. However, when using the GDV tools, there were still challenges for the transportation personnel to overcome, such as unjustifiably expensive of specific tools (Ellis and Vessely 2015).

According to Edrissi, Nourinejad and Roorda, during disasters, the distribution of humanitarian supplies is vital to save lives. In their research, a new reliability measure to evaluate link importance values is discussed. Under a specified budget, the researchers considered both the importance and the failure probabilities of the links to decide which links should be retrofitted to improve the performance of the network. Furthermore, an emergency response plan (ERP) was developed to assign a limited supply to the regions which encountered the disaster, to ensure that the survivor count could be optimized. The researchers also pointed out that in the future, the inclusion of the joint failure probability of multiple links could be considered to improve the realism of the model in this study (Edrissi et al. 2015).

2.5 REDARS 2

Werner et al. produced a software program called REDARS TM 2 SRA, which was designed mainly for seismic risk reduction. When used in pre-earthquake assessment, the software will combine financial, legal, and political aspects, and also the individual effectiveness of different options, to identify how different options can reduce losses aroused by disruption of traffic flows due to earthquakes. Compared to the past strategies which usually did not consider the effectiveness of alternative decisions, the REDARS TM 2 SRA methodology and software has filled the gap and increased the accuracy of assessment. The software can also be used as a post-earthquake response tool to select one from alternative strategies to mitigate the traffic congestion and restore the functionalities of transportation system. The software was designed as a module package so that any further improvements can be made through adding new modules in the future. Although the program works well and performs its intended task, it lacks the flexibility to be useful outside of a specific niche (Werner et. al. 2006).

Moore, Ioannou, Bardet, Park, Cho, and Abadi studied the risks and recoveries of transportation systems in megacities as a result of extreme events such as earthquakes. Using REDARS software, they were able to estimate the disruption level of earthquakes on roads and bridges and predict which pieces of infrastructure fail as well as the recovery time to repair that section of infrastructure. They created an integrated model that consists of macroscopic terminal simulator, microscopic traffic simulator, and terminal cost model to estimate how traffic flow changes in the event of an earthquake and to evaluate the economic impact. By estimating the bridge damage, costs and times to restore traffic flows throughout the system and economic losses due to earthquakes, the model is able to successfully identify critical failed transportation links. Based on the scenarios they analyzed, the integrated model was proven efficient (Moore, Ioannou, Bardet, Park, Cho, & Abadi, 2013).

2.6 Contribution

The simple reconstruction model is flexible enough to be used for any failure mechanism. The inputs of the presented models are readily available across the United States and are typical data most DOT's already have on hand and all the essential software used to run this model is available as open source software. The models presented in this research look to solve the flexibility issues of the current available models.

3. Model Development

The framework, shown in Figure 1, is divided into two separate parts. The first is a probability framework that is used to obtain and visualize multiple probabilities relating to Earthquake events; however, it is primarily used to predict the bridges that will experience failures in a given earthquake scenario within the context of this research. This framework is divided into three subsections. The first uses USGS resources to create an earthquake probability map, the second, a local magnitude model, utilizes the Lillie Empirical Formula shown as Equation 1, a well-known earthquake magnitude formula, to transform the epicenter magnitude into the equivalent magnitude that is felt at individual bridge locations, and the third, a failure determination model, uses USGS qualitative data to predict bridge failures.

$$M_L = \log_{10} A - 2.48 + 2.76 * \log_{10} \Delta \quad (1)$$

Where:

M_L is the Richter magnitude, A is amplitude or maximum ground displacement, and Δ is the distance in km (Richter Magnitude Scale).

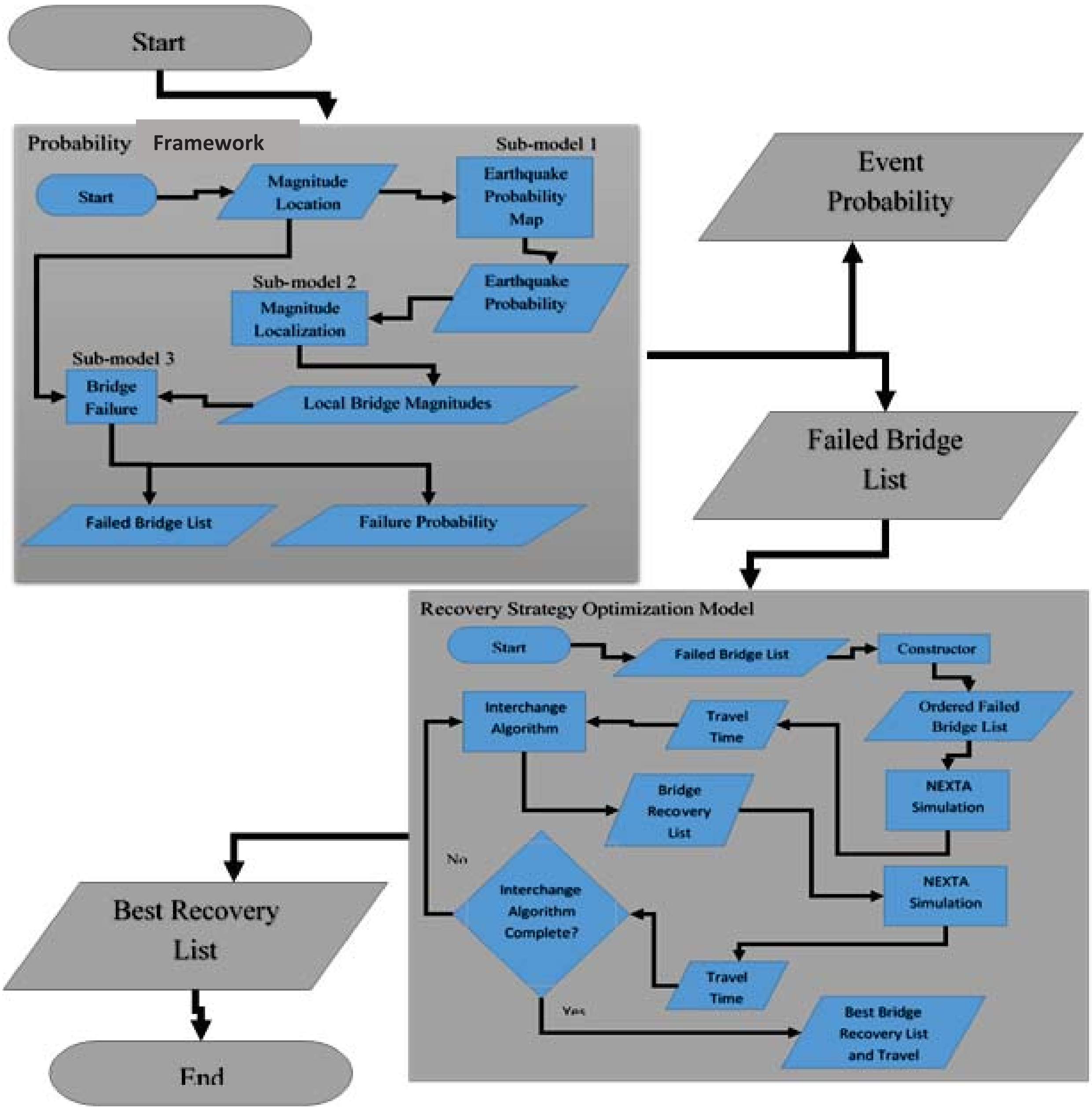


FIGURE 1 Research Framework and Model

The second component of the overall framework, the recovery model, optimizes the order in which the failed bridges obtained from the probability framework output are brought back online to minimize the total impact of an earthquake event or any multiple bridge failure event to the transportation network. This model is divided into three components as well. The first is a constructor that takes the randomly ordered list of failed bridges provided by the probability framework in this research and reorders them to attain a better solution. The second and third components, the solution algorithm and traffic simulator, work simultaneously to determine a good reconstruction strategy. Each aspect of the total framework are explained in their related sections below.

3.1 Task 2: Determine the Risk Profiles

Before creating the risk probability framework, the area of concern, the area in which an earthquake event of a given magnitude has the potential of damaging structures within the study area, must be determined. From the USGS's Magnitude / Intensity Comparison, it is determined that a local magnitude of 5.0 would be the minimum earthquake event considered damaging, and to simplify the scope of the research only earthquakes with an integer magnitude were considered (Magnitude / Intensity Comparison). Equation 1 cannot be used due to $\log_{10}(0)$ being undefined; thus another common method is utilized, the original Richter nomogram shown in Figure 2. Equation 2, which is only valid for a distance of zero, was then created from the nomogram. This equation is then rearranged to determine the amplitude associated with a 5.0 magnitude earthquake, which is deemed the minimum damaging amplitude. Equation 1 is then rearranged to solve for distance given the minimum damaging amplitude and a range of integer magnitudes from 5.0 to an upper bound on the magnitude. The lower bound of this range is explained previously while the upper bound is determined by finding the maximum magnitude with probability greater than zero within a reasonable distance of the study area. For each of the resulting distances, a damage distance is determined by adding the previous resulting distance to the distance from the most extreme point of the study area to the centroid of the study area (assuming the study area is of an irregular shape). Once this damage distance is determined, a circular area is formed for each magnitude with the centroid being the study area centroid and a radius equal to the damage distance. These circular areas are deemed the areas of concern for the associated magnitude with the largest of them being the entire area of concern. They represent the area where an earthquake can occur that has the potential to create the minimum damaging amplitude in at least one location within the study area. It should be noted that both earthquake equations used here were developed in rocky geological formations and may actually underestimate the distance damage may propagate from the epicenter in softer (clay) geological formations.

$$M_L = \log \frac{A}{0.2} \qquad (2)$$

The three sub components of the risk probability framework are explained individually bellow and combined to create an event based input for the reconstruction optimization model.

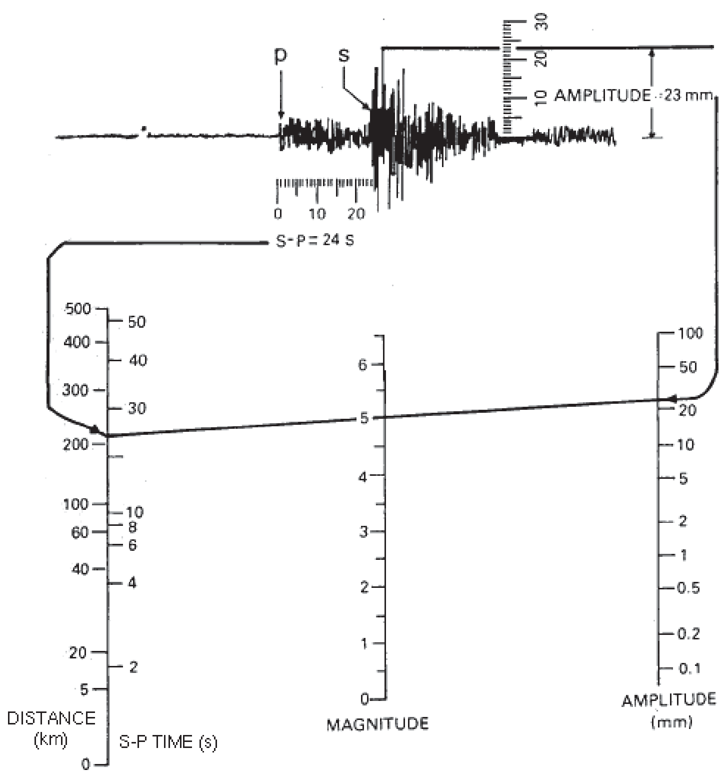


FIGURE 2 Richter Magnitude Nomogram with Example (What Is Richter Magnitude?).

3.1.1 Earthquake Occurrence Probability

The first component of the probability model is created by determining the probabilities of damaging earthquakes occurring in the areas of concern within one hundred years. To do this multiple USGS custom hazard maps are created (2009 Earthquake Probability Mapping). An example can be seen in Figure 3. For each integer magnitude, enough custom hazard maps are created to cover the entire corresponding area of concern. Each map is then imported and georeferenced into ArcGIS's ArcMap software. A polygon shapefile is created for each existing probability, for the example in Figure 3 this range would be from 0.01 to 0.25; however, these shape files were only created within the given magnitude's area of concern because no event outside of this area can damage the study area regardless of the occurrence probability based on the assumptions of the framework previously explained. A layer of all United States cities is then overlaid over the resulting layers and joined, so that each city data entry was given a probability column for each magnitude. This is done again to simplify the model by limiting the locations to consider an earthquake occurring; however, the relative accuracy remains due to the high density of cities and towns within the area of concern. For areas with a relatively low density of cities, this simplification may result in significant accuracy reductions.

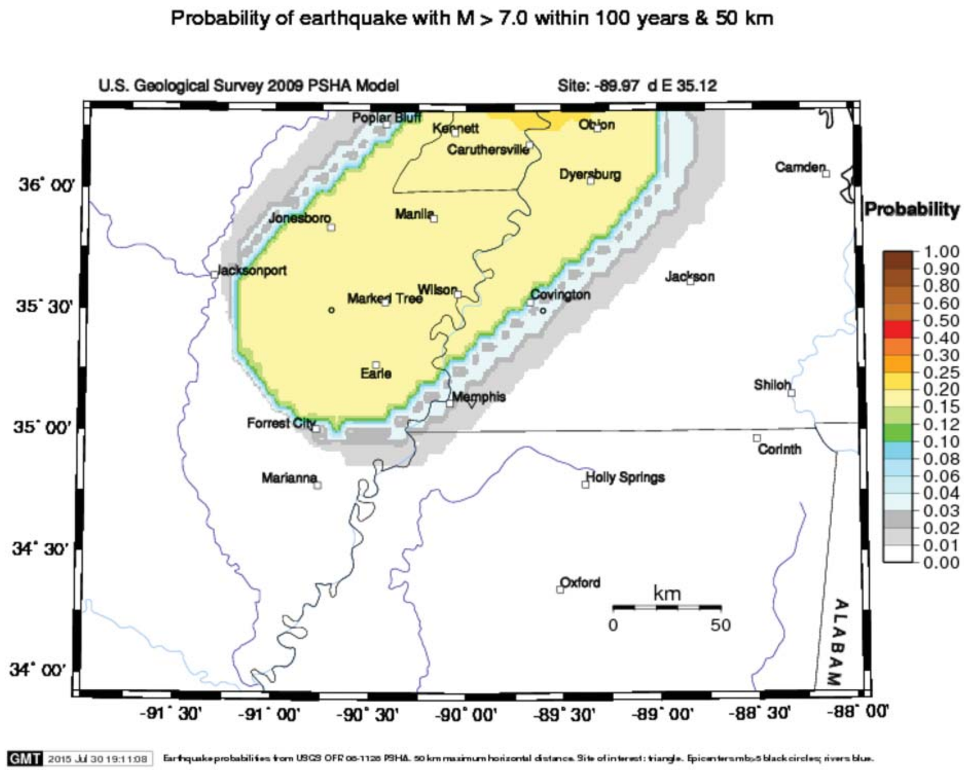


FIGURE 3 USGS custom hazard map in the Memphis area (2009 Earthquake Probability Mapping)

3.1.2 Local Magnitude Determination

The second component of the probability model calculates the relative magnitude felt at each bridge location resulting from an earthquake of a known magnitude at a given location. Equation 1 is rearranged and solved for the amplitude felt at each bridge location, and Equation 2 is used to solve for the relative magnitude felt at each bridge location. The resulting magnitude is then rounded to the nearest integer magnitude.

3.1.3 Bridge Failure Probability

The final component of the probability model first converts qualitative damage information from USGS associated with each earthquake magnitude into quantitative probabilities as shown in Table 1. Each bridge is then assigned a random number between 0 and 1. This random number is used in conjunction with the magnitude results from the second component to determine whether or not the bridge has failed. For example, if the magnitude result of a given bridge is a 5.0 and this bridge has a random number less than 0.2 the bridge is deemed as failed; otherwise it is deemed undamaged. The resulting failed bridges are then simplified into failed links simply by deeming a link failed if it contains a failed bridge. This simplification is valid because all connections between links in this research occur at the link head or link tail. No connections occur mid-link meaning that a link with a failed bridge would be impassible.

Within this component, the event probability is also calculated. This probability is determined using the definition of conditional probability shown as equation 1.The probability of failure for each bridge, i, is based on a given earthquake's magnitude, location, and occurrence. Assuming that the failure of bridge i is independent of the failure of bridge j allows the probability of the exact scenario to be calculated as shown in equation 2.

$$P(A|B) = \frac{P(A \cap B)}{P(B)} \tag{1}$$

$$P(Scenario\ A) = P(M, L, O) \times \prod_i P_f(i|M, L, O) \times \prod_j P_{nf}(j|M, L, O) \tag{2}$$

Where:

M = Magnitude of Earthquake

L = Location of Earthquake

O = Occurrence of Earthquake

i = all failed bridges

j = all non-failed bridges

P_f = Probability of failure

P_{nf} = Probability of non-failure

TABLE 1 Qualitative to Quantitative Earthquake Magnitude Scale

Magnitude	Qualitative Damage (Magnitude / Intensity Comparison)	Quantitative Bridge Failure Probability
1.0	Typically not felt	0
2.0	Typically not felt / May be felt by few on upper level floors	0
3.0	Felt by few usually on upper level floors/ May be felt in	0

	vehicles similar to a large truck passing	
4.0	Felt by most/ Some ceramic or glass items may be broken	0
5.0	Felt by all/ Damage negligible in well-designed buildings/ Damage slight to moderate in ordinary designed structures/ Heavy Damage in poorly designed structures	20
6.0	Heavy damage to non-specially designed structures / Partial collapse of structures may occur	50
7.0	From the same as a 6.0 to major structural damage even collapse	80
8.0	Major structural damage even collapse	100

3.2 Task 3: Dynamic Multimodal Traffic Assignment Model

A previously developed assignment model, Network Explorer for Traffic Analysis (NEXTA) a micro-scopic traffic simulator, was used. NEXTA is an open source GUI, a powerful tool that allows users not only to dynamically simulate traffic patterns in a network but also to visualize those patterns as well as the attendant effects, such as congestion, emissions, and safety. In addition, NEXTA provides a "learning" functionality for traffic wherein traffic patterns change in response to stimuli such as construction and congestion (Taylor and Zhou 2013). This degree of power, precision, and flexibility allows NEXTA users to simulate a wide variety of scenarios quickly. For the requirements of this research, NEXTA's work zone functionality is used in conjunction with NEXTA's Route Choice Behavior Model. With this combination, NEXTA allows the user to set special events on multiple links with start time, end time, capacity drop percentage, and speed limit changes (Taylor and Zhou 2013). These inputs allow the simulation of the reconstruction of all the failed links to be performed simultaneously. For this research, as a proof of concept, only one link will be brought back online at a time and each link will have the same repair period; however, the inputs can be altered to simulate multiple bridges being repaired simultaneously or varying repair times for different bridges.

3.3 Task 4 and 5: Development of Resilience Evaluating Module and Ranking Measures

The goal of the reconstruction optimization model is effectively formulate a good (preferably optimal) order in which to rebuild each failed bridge while being robust enough to handle multiple situations. The idea is for the model to be as simple as possible to enhance its robustness allowing it to be used for a variety of situations instead of being only useful for seismic failures. This model is also divided into three components one of which is the traffic assignment module presented in section 3.2. The recovery strategy optimization model is held together by several small programs to achieve communication between the three components. The constructor releases its updated failed link list to the interchange algorithm and NEXTA where the traffic assignment simulation is performed. NEXTA then returns the average travel time to the interchange algorithm which provides an altered failed link list to NEXTA after determining the best existing order. This loop is repeated until the interchange algorithm ends after parsing the entire list. The interchange algorithm then returns the generated best bridge recovery list to the user. The three components are described individually in their corresponding sections.

3.3.1 Bridge Link List Constructor

The constructor is used to ensure a good result as the simplicity of the algorithm does not ensure optimization and can get stuck in a local optimum. To create the constructor, six different data are selected to be used to develop the constructor. These data relate to critical link determinations, are easily attained, and include link length, posted speed limit, number of lanes, daily flow rate, link type, and average travel time. Connectivity, capacity, and flow rate are commonly used to determine the criticality of links. Connectivity shows the availability of detour routes, capacity provides a physical measure of the number of people that can be served instantaneously, and flow rate provides a measure of the people served over time whether existing or attainable. The structure of the network in this research with no mid-link connections allows link length to be used as an estimate of connectivity since shorter links denote more connections and thus more links in any given area. The number of lanes and link type (local collector, urban arterial, interstate, etc.) is closely associated with capacity, and the posted speed limit, daily flow rate, and average travel time are directly related to either the existing or attainable flow volume.

Using these selected six data, the constructor is formulated. Originally, a weighted average was developed empirically based on multiple small (5 to 10 link) optimum failed link lists. This constructor, however, failed to scale to larger link lists; therefore, a neural network is designed using MATLAB and used as the constructor. A diagram of this neural network consisting of 10 neurons and 2 layers is shown in Figure 4.

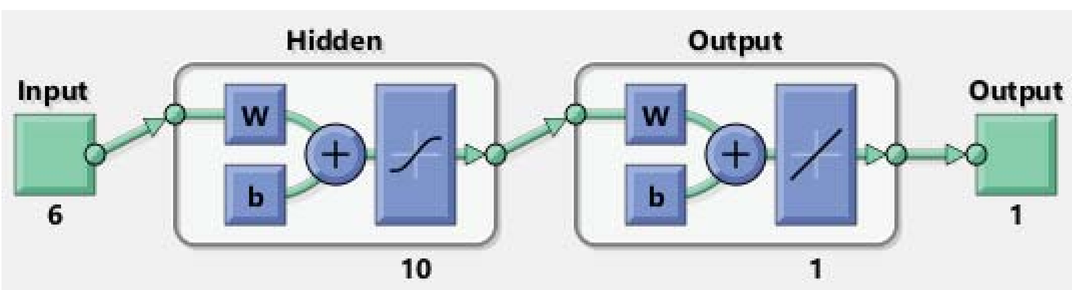


FIGURE 4 Constructor Neural Network Diagram

3.3.2 Solution Algorithm

The second component of the optimization model is an ordering algorithm. To maintain the goal of robustness through a simple model, the ordering algorithm used is a simple interchange algorithm, a variation of bubble sort. This algorithm compares the results of the previous list (1,2,3,4,5 for example) with the results of a list where two elements are swapped (1,2,4,3,5). If the previous list is deemed more efficient, the algorithm switches the next pair of elements and continues; however, the algorithm switches the previous pair if the change is accepted as more efficient. This continues until the algorithm parses the entire list minimizes travel time, TT, which is the conditional function shown in equation 3. This algorithm has an average time complexity of O (n^2) and a total of n! permutations of the list which is also a reason the previously mentioned constructor is needed to attempt to make the time complexity approach the best time complexity of O (n).

$$TT_L = \begin{pmatrix} \sum_{V=1}^{TV} AVTT_V \ \ for\ L = 1 \\ \vdots \\ \sum_{V=1}^{TV} AVTT_V \ \ for\ L = n! \end{pmatrix} \tag{3}$$

Where:
TT_L = Total Network Travel Time for L
TV = Total Number of Vehicles
V = Vehicle V
L = Failed Bridge List Permutation L
n = number of entries in L
$AVTT_V$ = Average Vehicle Travel Time of V from its origin to destination

4. Task 6: Memphis Seismic Zone Case Studies

First the study area of this case study is defined as Northwest Mississippi; however, this area is precisely determined by data availability within the general area of interest. From the Northwest Mississippi TransCAD traffic network model's availability through the Mississippi Department of Transportation (MDOT) and their relative locations to both the Memphis intermodal hub and the New Madrid Fault, four counties in Northwest Mississippi (Desoto, Tate, Tunica, and Marshall) are chosen as the study area and can be seen highlighted in red in Figure 5.

The risk probability framework is then developed for this study area. The first step of this framework is to develop the associated area of concern for each magnitude of interest. For this case study, a 5.0 magnitude earthquake is chosen as the minimum magnitude of interest as explained in section 3.1 and the upper magnitude bound is determined to be an 8.0 by the USGS custom earthquake probability mapping tool, since it yields the probability of a 9.0 magnitude or larger earthquake to be effectively zero in all areas surrounding the study area of this base case (2009 Earthquake Probability Mapping). Using Equation 2, the damaging amplitude, which is that of a 5.0 magnitude earthquake at a distance of 0km from the particular location of interest, is determined to be 20000mm. Plugging this damaging amplitude back into Equation 1 and solving for distance for each magnitude integer from 5 to 8 yields the following distances respectively: 14km, 33km, 75km, and 173km. These distances are then added to the distance from the centroid of the study area to its most extreme point which in this case is 65km. These combined distances makeup the damage distance which is used as the radius of a circle with a centroid at the center of the study area. These circles are the areas of concern for each associated magnitude and are shown in Figure 5.

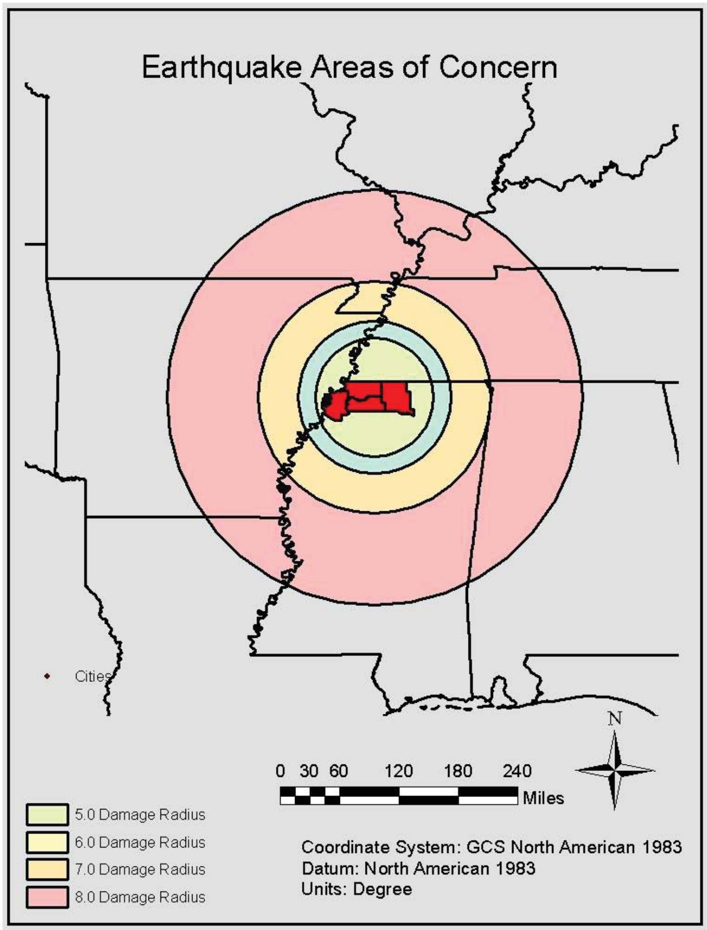


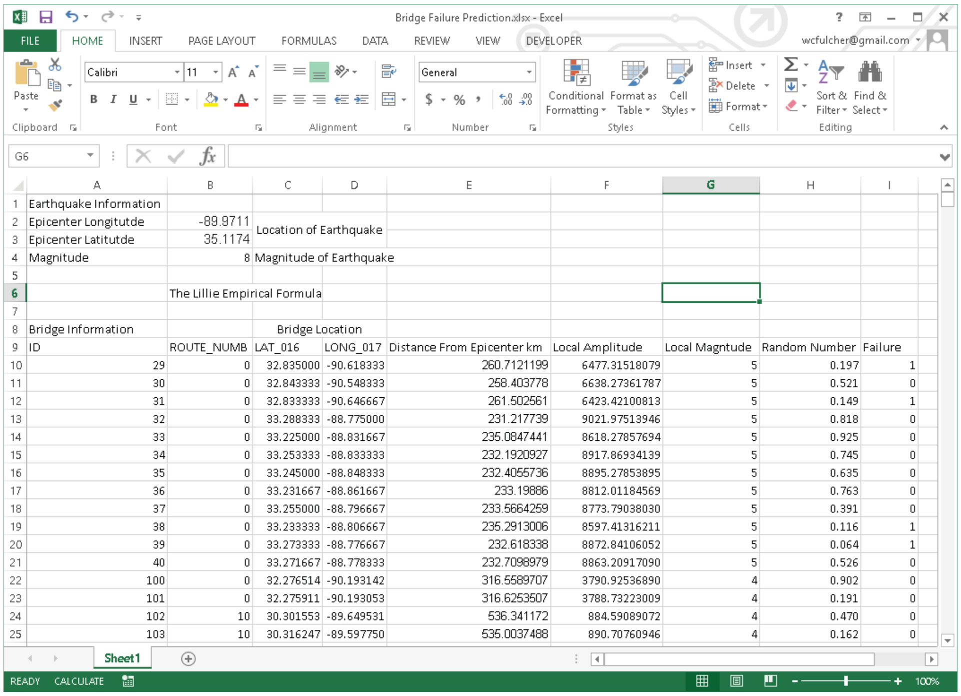
FIGURE 5 Earthquake Areas of Concern

The earthquake occurrence probability portion of the framework is then created. For each magnitude, custom probability maps are created from the USGS Custom Earthquake Probability Maps Tool (2009 Earthquake Probability Mapping) spanning the entire associated area of concern. An example is shown in Figure 3. Each of these maps are then imported into ArcGIS and shape files are created corresponding to each probability within the area of concern. These layers are then joined to an overlaid United States' city layer to associate the probabilities for each magnitude associated with a particular city.

The local magnitude at each bridge location is then determined by solving Equation 1 for the local amplitude and then using Equation 2 to determine the associated magnitude rounded to the nearest integer value. A random number is then assigned to each bridge and each bridge is either deemed as failed or unaffected based on the probabilities shown in Table 1. An example of both of these steps is shown in Figure 6. The failed bridges, those with a value of 1 in the failed column, are compiled into a list and the associated link list is found. The link association is created in ArcGIS by joining the link layer with the bridge layer yielding the link information on each bridge entry. These failed list links are then run through the reconstruction optimization model whose results are presented in the following subsections separated by location.

4.1 Hernando, Mississippi

This scenario represents an earthquake occurring within the study area and is tested with magnitudes of 5, 6, and 7 which have the 100 year occurrence probabilities of 0.08, 0.02, and 0.00 respectively. The 7.0 is tested regardless of its probability being statistically zero to provide a large failure list to ensure the reconstruction model functions properly with a large number of bridge failures. The three scenarios provide failure link lists of length 24, 123, and 257 respectively. The best achieved order's lost travel time and the computation time are shown in Tables 2, 3, and 4 for five random lists and the list developed by the constructor. The constructor not only provides the minimum lost travel time but also provides the fastest results.



	A	B	C	D	E	F	G	H	I
1	Earthquake Information								
2	Epicenter Longitutde	-89.9711	Location of Earthquake						
3	Epicenter Latitutde	35.1174							
4	Magnitude	8	Magnitude of Earthquake						
5									
6		The Lillie Empirical Formula							
7									
8	Bridge Information		Bridge Location						
9	ID	ROUTE_NUMB	LAT_016	LONG_017	Distance From Epicenter km	Local Amplitude	Local Magntude	Random Number	Failure
10	29	0	32.835000	-90.618333	260.7121199	6477.31518079	5	0.197	1
11	30	0	32.843333	-90.548333	258.403778	6638.27361787	5	0.521	0
12	31	0	32.833333	-90.646667	261.502561	6423.42100813	5	0.149	1
13	32	0	33.288333	-88.775000	231.217739	9021.97513946	5	0.818	0
14	33	0	33.225000	-88.831667	235.0847441	8618.27857694	5	0.925	0
15	34	0	33.253333	-88.833333	232.1920927	8917.86934139	5	0.745	0
16	35	0	33.245000	-88.848333	232.4055736	8895.27853895	5	0.635	0
17	36	0	33.231667	-88.861667	233.19886	8812.01184569	5	0.763	0
18	37	0	33.255000	-88.796667	233.5664259	8773.79038030	5	0.391	0
19	38	0	33.233333	-88.806667	235.2913006	8597.41316211	5	0.116	1
20	39	0	33.273333	-88.776667	232.618338	8872.84106052	5	0.064	1
21	40	0	33.271667	-88.778333	232.7098979	8863.20917090	5	0.526	0
22	100	0	32.276514	-90.193142	316.5589707	3790.92536890	4	0.902	0
23	101	0	32.275911	-90.193053	316.6253507	3788.73223009	4	0.191	0
24	102	10	30.301553	-89.649531	536.341172	884.59089072	4	0.470	0
25	103	10	30.316247	-89.597750	535.0037488	890.70760946	4	0.162	0

FIGURE 6 Example of Local Magnitude and Bridge Failure Determination

TABLE 2 Hernando 5.0

Random Lists					
A	B	C	D	E	Constructor
Best Order's Total Travel Time					
14.88	14.5474	14.878	14.7731	14.5027	14.4141
Computation Time					
5 h 45 mins	5 h 45 mins	5 h 50 mins	5 h 48 mins	5 h 49 mins	5h41mins

TABLE 3 Hernando 6.0

Random Lists					
A	B	C	D	E	Constructor
Best Order's Total Travel Time					
17.5535	17.4734	17.2056	18.6476	17.7038	17.2131
Computation Time					
11h54m	12h03m	11h58m	11h49m	12h01m	11h43m

TABLE 4 Hernando 7.0

Random Lists					
A	B	C	D	E	Constructor
Best Order's Total Travel Time					
28.3412	29.4105	29.4125	28.7314	28.4511	28.1245
Computation Time					
29h21m	29h25m	29h33m	29h21m	29h32m	28h55m

4.2 Memphis, Tennessee

This scenario represents an earthquake occurring just outside of the study area and is tested with magnitudes of 6 and 7 which both have a 100 year occurrence probability of 0.06. The two scenarios provide failure link lists of length 28 and 171 respectively. The best achieved order's lost travel time and the computation time are shown in Tables 5 and 6 for five random lists, the list developed by the constructor, and in the 7.0 magnitude event the optimum list. The constructor provides the closest results to the optimum and requires significantly less computation time than the random scenarios. The optimum results show that the initialization of the traffic analysis model accounts for the majority of the computation time.

TABLE 5 Memphis 6.0

Random Lists					
A	B	C	D	E	Constructor
Best Order's Total Travel Time					
15.7113	15.8147	15.2722	15.9295	15.9915	14.9571
Computation Time					
6h25mins	6h27mins	6h18mins	6h22mins	6H24mins	6H05mins

TABLE 6 Memphis 7.0

Random Lists						
A	B	C	D	E	Constructor	Optimum
Best Order's Total Travel Time						
21.4863	22.2063	22.9263	21.3838	21.5491	21.2148	21.1723
Computation Time						
22H43M	23H12M	22H54M	23H42M	23H21M	22H21M	22H03M

4.3 Jonesboro, Arkansas

This scenario represents an earthquake a distance away from the study area and is tested with a magnitudes of 8.0. This event has a 100 year occurrence probabilities of 0.03. The scenario provides a failure link list of length 103. The best achieved order's lost travel time and the computation time are shown in Table 7 for five random lists and the list developed by the constructor. The constructor not only provides the minimum lost travel time but also provides the fastest results.

TABLE 7 Jonesboro 8.0

Random Lists					
A	B	C	D	E	Constructor
Best Order's Total Travel Time					
18.3109	19.3145	18.4938	18.8309	18.4756	18.2451
Computation Time					
18h48m	18h06m	18h41m	18h19m	18h31m	18h04m

5. Conclusions

The case study proves the concept of the methods presented in this research. The constructor provides an initial list that will provide better results than average although the results are not guaranteed to be optimal due to the nature of the algorithm. To achieve optimality, however, the algorithm complexity could be increased; although, this could prevent the model from being used in other situations. Due to the input requirements of the presented model, it can be used in almost any failure situation regardless of the failure cause. The presented methodologies in the field will typically be used separately where the probability visualization framework can be used for planning purposes to better understand the actual probabilities associated with earthquake events or to create the probabilities of a particular failure event from a given earthquake event by combining the probabilities of all possible bridge failures and the event itself and where the reconstruction model can be used to provide a good reconstruction order to minimize the effect on travel time.

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