TECHNICAL REPORT STANDARD PAGE

1. Title and Subtitle

Quantifying and Improving Time-Dependent Extreme Event Resilience of Road Networks

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P.O. Box 94245
Baton Rouge, LA 70804-9245

5. Report No.

FHWA/LA.17/Enter 3-digit Report No.

6. Report Date

December 2021

7. Performing Organization Code

LTRC Project Number: 21-4TIRE
SIO Number: DOTLT1000370

8. Type of Report and Period Covered

Final Report
July 2020 – June 2021

9. No. of Pages

52

10. Supplementary Notes

Conducted in Cooperation with the U.S. Department of Transportation, Federal Highway Administration

11. Distribution Statement

Unrestricted. This document is available through the National Technical Information Service, Springfield, VA 21161.

12. Key Words

Time-dependent resilience; resource constraints; Bayesian networks; road networks

13. Abstract

A framework to quantify and improve the time evolving resilience of road networks susceptible to extreme events during a long planning horizon has been developed. Herein, for computational efficiency, Bayesian networks were used to quantify resilience while considering performance objectives for the road network defined by the stakeholders, extreme event such as natural hazards, and combinations of mitigation strategies. A linear programming-based resource-constrained project scheduling methodology was employed to identify the combinations of mitigation and response measures that satisfy given monetary and resource constraints. The time dependent resilience quantification method was applied to a small theoretical road network subject to random attacks to assess the connectivity to essential service locations while considering mitigation measures that vary with time, associated costs, and resource constraints. Additionally, preliminary analyses were conducted to apply the framework to the road network in Morgan City, Houma, and Grand Isle region subjected to hurricane hazards to evaluate connectivity to essential facilities. The results indicate that the framework's ability to model and capture the changes in resilience as mitigation measures are implemented over time and filter out measures that do not fit the time varying resource constraints.

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LTRC appreciates the dedication of the following Project Review Committee Members in guiding this research study to fruition.

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SIO No. DOTLT1000370

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Louisiana Department of Transportation and Development
Louisiana Transportation Research Center

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Acknowledgments

PI thanks the Coastal Protection and Restoration Agency for providing hurricane flood hazard data for South East Louisiana.

Implementation Statement

This framework could be used by stakeholders to identify combinations of mitigation and response strategies that satisfy resource constraints and quantify how they enhance the resilience of road networks in real time. Additionally, the proposed research bridges the gap between planning guidelines and resilience assessment frameworks with respect to the considered time horizons.

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Introduction

Regional road networks must be functional after extreme events, such as hurricanes, for post-event rescue and response operations, economic recovery of the region, and for facilitating long term community recovery. Considering the deterioration of infrastructure and the increasing intensity and frequency of climate related events, it is imperative to maintain and improve the performance of road networks for current conditions and future scenarios. In this context, Presidential Policy Directive 21 [1] suggests the use of resilience as a basis for making decisions to improve the extreme event performance of critical infrastructure. Furthermore, planning guidelines by federal agencies, such as the Community Resilience Planning Guidelines (CRPG) released by the National Institute of Standards and Technology (NIST) [2], also suggest the use of resilience for improving the performance of infrastructure systems, such as road networks.

In Louisiana, the Coastal Master Plan (CMP) [3] allocates $50 billion over the next 50 years to improve coastal resilience and reduce flood risk. Specifically, for road networks, the Louisiana Statewide Transportation Plan (LSTP) [4] seeks to invest resources to improve the performance of the transportation infrastructure. All the guidelines and plans, such as the NIST CRPG, the CMP, and LSTP, intend to improve resilience and infrastructure performance according to the objectives defined by stakeholders. However, commonly adopted definitions of infrastructure resilience such as the one proposed by the National Infrastructure Advisory Council (NIAC) [5] only considers "the ability to anticipate, absorb, adapt to, and/or rapidly recover from a potentially disruptive event" without considering stakeholder defined performance objectives. Furthermore, these definitions of resilience only include a time horizon limited to few years. On the other hand, the planning guides consider decadal time scales. Therefore, *there is a gap between time scales considered in planning guidelines and the commonly adopted definitions of resilience*.

Decision making at the decadal time scale needs to consider the interaction effects between different strategies that improve performance. For example, adding new highways, bridges, or lanes, would have impact on the entire road network. However, due to the computational costs associated with resilience quantification considering uncertainties, the effects of different mitigation and response strategies are simply added together linearly without considering the interactions, such as in the Coastal Master plan [3]. *Therefore*, *there is a need for computationally efficient methods for resilience* *quantification considering uncertainties and interaction effects between different mitigation and response strategies*.

Literature Review

Strategic investments and mitigation strategies can gradually improve the resilience of a system against future disasters. For road transportation systems, such risk mitigation strategies often can be very costly and time consuming, and decisions are often constrained by limited financial and human resources. Consequently, systematic prioritization is a critical element for an effective risk mitigation framework. Such a framework requires not only a consideration of the physical condition and structural vulnerability of each individual element in the network, e.g.[6], but also a system perspective that considers the overall pre- and post- disaster operation and functionality of the network as a whole [7]–[9]. Much of the existing literature focuses on bridge fragility and retrofit [10]. For instance, Carturan et al. [11] combined bridge fragility curves with network user equilibrium functions to estimate the total road network delay due to earthquake-introduced damages. Hu et al. [12] proposed a bridge network maintenance scheduling approach that incorporated both individual bridge reliabilities and the network connectivity into a decision optimization formulation. Ghosh et al. [13] presented a two-stage reliability assessment framework for aging bridge networks, including seismic fragilities of individual bridges and correlations among them, and further estimated the network reliability by a revised Markov Chain Monte Carlo simulation.

The most important concepts in the transportation system performance evaluation have included resilience, vulnerability, robustness, reliability, and survivability. These are all technical terms for assessing the security of system operation but differ in their main concerns and angles of view. Among them, the most relevant and representative concepts are vulnerability and resilience, which can cover almost the entire scope of transportation system performance. Bešinović [14] reviewed research progress on the resilience of rail transit in the past 11 years, focusing on quantitative methods and indicators. Leobons et al. [15] summarized the resilience metrics of urban transportation systems and proposed a framework for the use of these indicators, while Hosseini et al. [16] analyzed the resilience of a whole engineering system by dividing approaches into qualitative and quantitative assessments. In addition, the concepts and methods of research on the resilience of transportation systems in recent years have been discussed [17], [18]. Others consider more aspects, such as resilience and vulnerability. Mattson and Jenelius [19] summarized recent research on the resilience and vulnerability of transportation systems by distinguishing different modes of transportation. In the same year, they also summarized the concept and application of the vulnerability of road networks Mattson and Jenelius [20]. In contrast, Reggiani [21] discussed the differences and connections between traffic resilience and vulnerability with connectivity as a bridge. Through a specific case, Gu et al. [22]analyzed the similarities and differences among the reliability, vulnerability and resilience of the transportation network.

In recent years, the research focus of transportation safety has expanded from traditional risk research to safety research and developed towards resilience and sustainability [23]. Traffic vulnerability represents the network's sensitivity to emergencies, and it mainly analyzes the severity of incidents, generally from the perspective of network structure. Traffic resilience analysis includes two aspects: the system's ability to absorb interference and to recover after being disturbed. It emphasizes the overall performance of systems from being damaged to returning to a normal state over a period of time, and the recovery time is one of the important indicators. This is generally considered from a systematic perspective. In terms of analysis difficulty, traffic resilience is more difficult to analyze than vulnerability [21].

Early research on traffic resilience and vulnerability is mainly based on network topology. As a typical networked system, the basic performance of the transportation system is determined by the topological characteristics of the network. Therefore, for a long time, research on network performance based on network topology has been developing continuously. Traffic vulnerability is the focus of the study, while resilience is more focused on the research of operational performance. Graph theory and complex network theory are the main methods for topology research. The steps include three elements of risk analysis: interrupted scenario, probability and event consequence [24].

The study of traffic resilience should not only consider the network's ability to absorb interference but also analyze its ability to recover [25]–[27]. Zhang et al. [28] analyzed the impact of two preparedness and three recovery actions on network resilience. They found that the higher the redundancy of the network is, the better the resilience of the network, while recovery actions are more effective than improving redundancy. The change in the node redundancy rate under network interruption was also analyzed [29]. Chopra et al. [30] considered the changes in the edge redundancy by calculating the number of connected node pairs before and after an edge failure. In addition, there are studies on changing the network topology to improve the system's performance. To improve the connectivity and reliability of the network, Zhang et al. [31] used the nearest-link method to carry out topological intervention on the transportation network and simulate the addition of lines to improve the redundancy of the system. Dunn and

Wilkinson [32] adopted ‘adaptive’ and ‘permanent’ strategies to increase network resilience by changing topological structures. It may also involve a trade-off between the cost of construction and the resilience of recovery [33]. Other ways to add nodes can not only increase the accuracy of the measurement, but also increase the computational cost [34]. Furthermore, many scholars applied network vulnerability to other areas, such as accessibility [35] and understanding the concept of network resilience and vulnerability from the perspective of accessibility [21], [36]. These methods focus on the analysis of travel costs and influences of the user’s choice behavior after the network is disturbed. It can also be used to analyze the vulnerability of the evacuation network in the case of disaster, which is very effective for the site selection of emergency facilities and service facilities under fragile conditions [37], [38].

Methods based on network topology structure often combine simulation methods to carry out the analysis of simulation scenes by simulating the transportation system affected by random failures and malicious attacks [39]. Finally, the changes in topological indicators are measured to identify the important components of the transportation network [40]. In addition, simulation analysis is usually used to study the effectiveness of evaluation models or metrics. Based on Monte Carlo simulation, [41] analyzed and verified the proposed vulnerability metrics in different interrupted scenarios. This method is also often used in the analysis of natural disasters [41]–[43] which is characterized by low occurrence probability and high consequences, and there is not enough real-world data. In this regard, [44] established a micro simulation model of a highway network, which can carry out quantitative analyses on evacuation performance of large regional network under different conditions.

Existing studies have focused on developing methods to quantify damage to bridges and roadways for extreme events [45]. Others have developed process [46] and empirical data [47] based approaches to determine the functionality and restoration time for bridges damaged during extreme events to support network level resilience assessment. Studies at the regional level have been primarily focused on determining the optimal restoration sequence for individual components of the road network. Some studies have also considered retrofit options for bridges and others used multi-objective optimization techniques to develop pareto-optimal fronts with multiple competing objectives such as resilience and economic costs. Overall, none of the existing studies consider decadal time scales for resilience quantification and optimization while including uncertainties. Thus, the novel concept of time evolving probabilistic extreme event resilience will be introduced.

Objective

The goal of this project was to quantify the time evolving extreme event resilience of road networks, efficiently identify resilience improvement strategies, and determine when the strategies can be implemented during the planning considering economic and resource constraints. The framework will enable stakeholders pick best strategies to optimize road network's resilience in real time. For this purpose, the key objectives of this project were:

1. Develop a computationally efficient framework to quantify the resilience of road networks with respect to stakeholder defined performance objectives and measure the change in resilience due to mitigation and response measures for individual network components such as roads and bridges.
2. Formulate a methodology to identify the sequence of implementation for mitigation and response strategies such that resource constraints are satisfied while improving resilience.
3. Determine the time evolving resilience as different mitigation measures get implemented within the considered planning horizon.

Scope

The scope of this research was to develop the time dependent resilience quantification approach and apply it to a regional road network.

Methodology

The methodology for quantifying the time dependent resilience of a road network used in this research consisted of the following key steps:

1. Creating the road network
2. Defining performance objectives
3. Identifying hazards
4. Identifying mitigation measures
5. Selecting feasible mitigation measures
6. Simulating road network's performance
7. Creating the Bayesian network

The following describes each of the steps in detail.

Creating the road network

The first step herein consisted of creating the road network for the region of interest. For this purpose, the locations of all the road in a region can be obtained from sources like the TIGER/Line database [48]. Such databases represent roads in a region using 2-D line features. For further used in connectivity or travel time analyses, road network data often needs to be processed, which could include splitting road at intersections or other important locations, creating a single line to represent a roadway segment between two intersections, or removing unwanted features. Additional attributes can also be added to roads such as their elevation above sea level, speed limit, roadway width, etc. These data can be obtained from a wide variety of data sources such as the state departments of transportation, the US Army Corps of Engineers, or NOAA.

Next, the road network could be represented mathematically using a graph theory based approach. First, nodes are created for intersections, bridges, or other points of interests such essential facilities, evacuations zones etc. Roadways between nodes are represented as links. The nodes and links are represented mathematically using an adjacency matrix of size $n \times n$ (n is the number of nodes). Initially, all entries in the adjacency matrix are set to zero. A link from nodes i to node j is represented by marking the element $A_{ij} = 1$, i.e., the value at row i and column j is marked as 1. If the link represents a two way road, then, the element A_{ji} is also marked as 1. This process is repeated for all the links in the network to obtain an adjacency matrix corresponding to the road network. This adjacency matrix can be further used for connectivity analysis. Additional details on links such as free flow speed limit, travel demand data, lane width, etc. can be obtained for calculating travel time.

Identifying hazards

In the context of extreme events, for quantification of the resilience of road networks appropriate hazards need to be identified. For this purpose, the significant hazards affecting the region of interests can be considered. For a given hazard, different intensities should be considered, e.g., various return period events. For a given hazard and associated return period, data on hazard severity over the region needs to be obtained. E.g., for flooding hazards, data on flood depth maps can be obtained for different return period events. If multiple hazards are considered, their joint occurrence should also be considered, if necessary. For example, in case of bridges wind and wave hazard may be correlated and should be considered together. Data of hazards can be obtained from several sources such as FEMA and USGS. Stakeholders can select the hazard(s) and the associated return periods for resilience quantification.

Defining performance objectives

Planning guidelines by federal agencies, such as the Community Resilience Planning Guidelines (CRPG) released by the National Institute of Standards and Technology (NIST) [2] suggest the use of performance objectives for infrastructure systems to evaluate their resilience against extreme events. These performance objectives can be on initial damage, immediate post event functionality, restoration time, a combination of multiple metrics, or other performance metric relevant to the community.

For a road network, performance objectives could relate to initial damage to infrastructure such as bridges and roads. Other performance metrics could include initial connectivity within the region to emergency services such as hospitals, fire-station, and police station. Additionally, connectivity to essential facilities such as grocery stores, pharmacies, schools, and evacuation zones. In addition to initial connectivity, evolution of connectivity over time and corresponding cumulative loss in connectivity over time can also be used a metric for defining performance objectives. In addition to these metrics, travel time and distance within the road network immediately after the extreme event and its evolution can also be used. These metrics can be further converted into social metrics such as the number of lost trips and opportunity.

The threshold for these metrics, i.e., an acceptable level of performance, can be defined either deterministically or probabilistically. A strict threshold e.g., 90% connectivity in the network represents a deterministic threshold. However, 95% chance of 90% connectivity represents a probabilistic threshold. These thresholds can also vary with time, i.e., the thresholds can become stricter with time and may also vary with the severity of the event. For example, the thresholds for a 100 year event may be different than the thresholds for a 500-year event, which reflects the expectation that a more severe event would cause greater damage. Stakeholders can select the thresholds, their nature (deterministic vs. probabilistic), and associated return periods.

Identifying mitigation measures

Resilience of a road network can be improved by using several approaches. The first approach involves mitigating the hazards before their occurrence. Such measures include hardening infrastructure to make them less susceptible to hazards. For this purpose, infrastructure could be hardened, e.g. retrofitting bridges to prevent their failure, elevating roads and improving draining to prevent flooding. Alternatively, the susceptibility of the road network could be reduced by regional level hazard mitigation efforts, e.g. levees and dikes. Additionally, adding redundancy within a road network can also improve their performance in terms of maintaining connectivity to different essential service facilities.

Several measures can be taken during or immediately after the occurrence of a hazard or an extreme event. These include having crews ready to partially re-open damaged or blocked roads and bridges, having spare components available to repair damaged infrastructure. Such measures can help reduce the initial drop in performance due to damages to the roadway infrastructure and help maintain connectivity for essential services.

Resilience not only considers initial damage but also how long it takes to restore the system to a normal state. Therefore, resilience can also be improved by faster restoration of the infrastructure. These measures could include establishing contracts apriori for repairing damaged infrastructure in the aftermath of an extreme events.

These measures can be considered based on short, medium, and longterm considerations. However, stakeholders need to identify a set of potential options considering local considerations.

Selecting feasible mitigation measures

Mitigation measures that satisfy resource and other constraints need to be selected from the set of all potential mitigation measures. Considerations should also be given to the availability and requirement of resources over time. To select the mitigation options that satisfy overall and temporal budgetary and resource constraints a linear programming formulation of multiproject and job-shop scheduling problems proposed by Pritsker (1969) was employed. The formulation uses binary (0 or1) variables to indicate whether or not a job is completed at a given time. Three objectives were considered in the scheduling approach (a) minimize time for completion for each projects; (b) minimize the time by which all projects are completed (i.e., minimize makespan); and (c) minimize total lateness or lateness penalty for all projects. For these considerations, equations were developed to ensure that a schedule meets the constraints on resources, precedence relations between jobs, job splitting possibilities, project and job due dates, substitution of resources to perform the jobs, and concurrent and nonconcurrent job performance requirements

The following describes the mathematical formulation of the RCPSP procedure. G_i indicates the due date, and x_{it} is a Boolean variable that is 1 if the job is completed at time t and 0 otherwise. Minimizing throughput time for a single project is equivalent to maximizing the number of periods remaining after the project is completed (e_i is the time when project i is completed), where this number of periods is $\sum_{t=e_i}^{G_i} x_{it}$. Therefore, the objective function for minimizing the sum of the throughput times for all projects can be written as

$$Maximize\ z = \sum_{i=1}^{I} \sum_{t=e_i}^{G_i} x_{i_t} \tag{1}$$

The second objective function minimizes the time by which all projects are completed, i.e., minimize makespan. For this prupose, x_t is defined as: $x_t = 1$ if all projects are completed by period t, or zero otherwise.

Minimizing makespan then corresponds to maximizing:

$$z = \sum_{t=max\ e_i}^{max\ G_i} x_t \tag{2}$$

A sequencing constraint is required when a job cannot be started until one or more other jobs have been completed. For example, on project i, assume job m must precede job n. In any given period, the amount of resource k used on all jobs cannot exceed the amount of resource k available (more than one type of resource can be considered e.g. money and labor). This procedure is implemented in Python.

Simulating road network's performance

Road network's performance assessment during an extreme event is essential for resilience quantification. For this purpose, first, components that are either damaged or not functional due to the hazard need to be identified. For example, roads that are flooded can be identified by comparing the flood depth with the elevation of the roadway and using an appropriate threshold to determine if a road is usable. Damage to components, such as bridges, can be ascertained using fragility models, which provide the probability of damage at a given hazard intensity.

Once the non-functional components of the road network are identified, the adjacency matrix of the road network should be changed to reflect the damages. For example, if the link connecting nodes i and j is flooded and can not be used then the corresponding elements (A_{ij} and A_{ji}) in the adjacency matrix need to be assigned zero values. Once the adjacency matrix is updated to reflect damage, analysis can be performed to assess the performance of the road network. Herein, connectivity based analysis was performed to understand connectivity to essential service facilities. Specifically, a depth first search [49] was employed to determine the cluster of nodes that were connected. If a source node and an ESF location are in the same cluster then the node has connectivity to the ESF, else the ESF will not be accessible from that node.

The connectivity analysis approach can also be used to estimate connectivity as the links and nodes in a road network are restored. Furthermore, the same approach can be used to incorporate the effects of mitigation strategies. After a mitigation activity is complete, the failure probability of a link can be updated, which can be used for damage assessment.

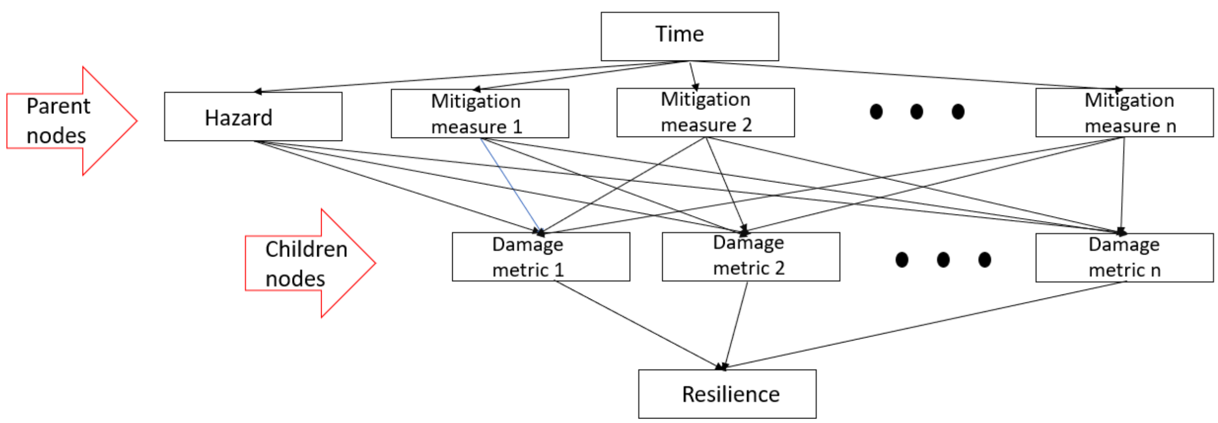
In this process, uncertainties in hazards and damage probabilities can be propagated using Monte Carlo Simulations (MCS). In these simulations, large number of values for the hazard and damage conditions are generated and for each random combination, the entire performance assessment is repeated. After the uncertainties are propagated, the probabilities of accessing ESF nodes from various source node can be obtained by calculating the percentage of simulations where the source and ESF are connected.

Creating the Bayesian network

Propagating uncertainties using Monte Carlo Simulations can be prohibitively time consuming for large road networks. Furthermore, real time estimates of the effectiveness of mitigation strategies would facilitate informed decision making. However, the network level simulations are computationally expensive. Therefore, Bayesian networks were employed herein to enable real time assessment of connectivity in road networks with and without several mitigation measures.

A Bayesian network consists of a directed graph where a link between two nodes denotes a probabilistic relation [50]. For example, Figure 1 shows a schematic version of the Bayesian network that was developed in this study. Herein, a link between two nodes implies conditional dependence between them. Node from the where the link originates is called the parent node and the node where the link terminates is called a child node. For example, the node *Hazard* is one of the parent nodes for *Damage metric 1*. The values at the child node are conditionally dependent on the values at the parent node. This relation is defined using conditional probability tables.

Figure 1. Schematic Bayesian network



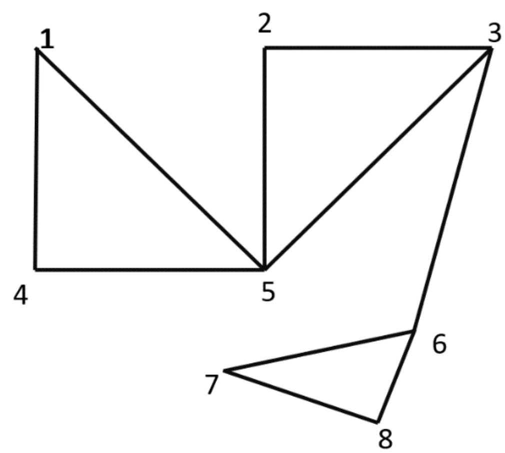
Herein, the conditional probability tables for Bayesian networks were obtained from the results of the Monte Carlo simulations performed to assess the performance of the road network. Herein, the Monte Carlo simulations and the Bayesian networks were implements in Python.

Application to a hypothetical network

Road network

As a proof of concept for the methodology has been demonstrated using a miniature model road network shown in the Figure 2. The road network is the same one used by Novak & Sullivan (2014).

Figure 2 Model miniature road network



The emergency service facility nodes (ESFs) are nodes 2 and 5 in this model network. The ESF nodes signify locations of great importance that need to be accessible from other points in the network in the event of emergencies – i.e., hospitals, schools, public buildings, buildings that are designed as community hazard shelters, fire stations, police stations etc. The link weights and node weights used for this network are given in Table 1. Herein, a link between nodes i and j is referred to as lij. The weight associated to nodes can be considered as the importance of the node. For real network, the weights can be determined based on population or other criteria defined by the community. The link weights can be considered as a proxy for travel time on the link.

Table 1 Link and node weights

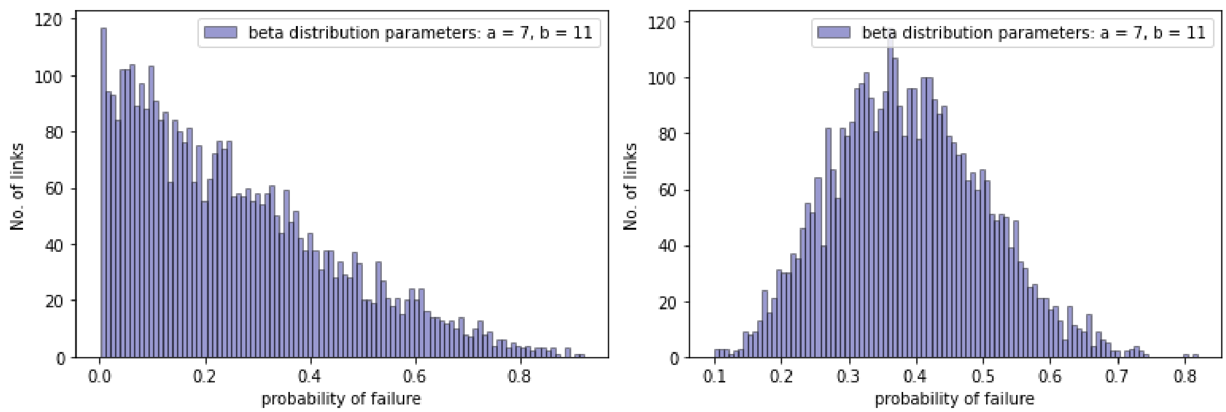
Link designation (links are defined by edge nodes)	Link weights	Node designation	Node weights
l14	5	n1	0.5
l15	8	n2	1
l23	3	n3	0.6
l25	4	n4	0.8
l36	8	n5	0.85
l45	6	n6	0.2
l53	8	n7	0.25
l67	5	n8	0.5
l68	3		
l78	4		

Hazard information

Herein, random link failure was considered as the main hazard. Probabilities of failure values were assigned to each individual road in the network. The probability of failure reflects the susceptibility of a roadway link to become non-functional due to a hazard event.

In the case of the miniature model road network, probabilities were assigned to the roads by sampling a beta distribution. The parameters of the beta distribution can be adjusted to reflect different hazard severity levels. Herein, two levels of hazard severity were considered: H1 and H2. For Hazard H1, the probability of failure was simulated using a beta distribution with parameters a = 1 and b = 3. For Hazard H2, which is more severe,the probability of failure was simulated using a beta distribution with parameters a = 7 and b = 11. The Figure 4 displays the distribution for the probabilities of failure for the two hazards.

Figure 3: (a) Hazard H1 probability of failure distribution for roads using beta distribution with parameters a = 1 and b = 3, (b) Hazard H2 probability of failure distribution for roads using beta distribution with parameters a = 7 and b = 11



When applying this method to a full-scale road network, adaptations have to be applied depending on the nature of the hazard in question and the mode of failure for those hazard types. For example, when considering hurricane induced inundation of roads, flood data would have to be collected from appropriate sources, like the Coastal Protection and Restoration Authority (CPRA).

Mitigation options

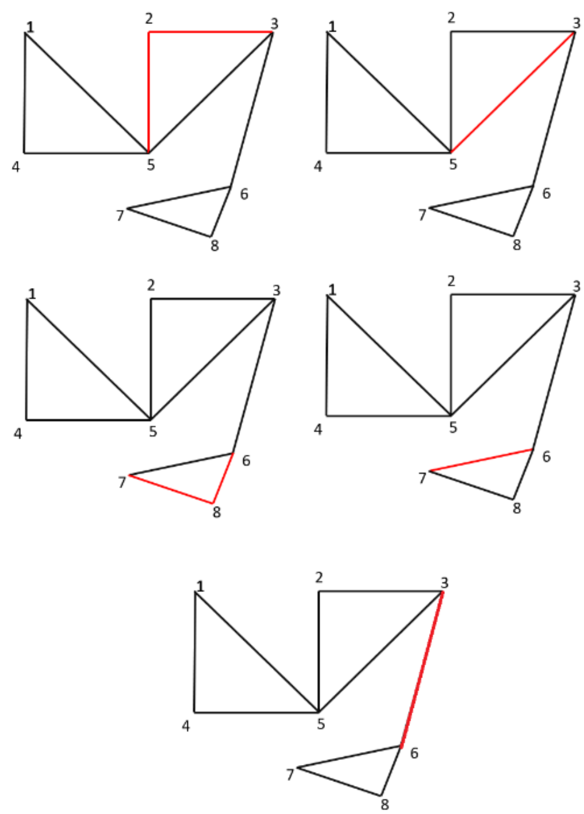
Mitigation options were selected to reduce the probability of failure of the road network and enhance the connectivity of the nodes to emergency service facility nodes (ESFs). Ideally, in a real network, with thousands of roads and billions of combinations for possible mitigation options, it would come to the stakeholders – people who actually live in the area under question to provide guidance regarding the sets of possible mitigation options. The developed framework would then be applied to those select mitigation options to narrow down the optimum mitigation measure that minimizes losses and maximizes connectivity.

In this model, cut sets were used to identify mitigation options using the concept of cut sets, which is defined as a unique combination of component failures that cause a system to fail. Thus, reducing the probability of failure of the links in the cut sets will significantly reduce the likelihood of disconnection in the network. In the context of mathematical graphs, a cut set is a set of edges (or nodes) which when removed will disconnect the network, forming at least two disjointed networks. For the purposes of demonstration, the following edge cut sets were selected. Note that these are not an exhaustive list of all edge cut sets in the entire road network. Figure 4 shows the different cut sets that were selected in this demonstration. Herein, it is assumed that mitigating the failure of a link reduces the failure probability 50%

Table 2 Mitigation options

Mitigation option	Cut sets of links
M 1	[l15, l67, l53, l36]
M 2	[l14, l45, l67, l53, l36]
M 3	[l15, l68, l78, l53, l36]
M 4	[l15, l67, l23, l25, l36]
M 5	[l14, l45, l68, ll78, l53, l36]
M 6	[l15, l68, l78, l23, l25, l36]
M 7	[l14, l45, l67, l23, l25, l36]
M 8	[l14, l45, l68, l78, l53, l36]
M 9	[l14, l45, l68, l78, l23, l25, l36]

Figure 4 The lines shown in red are the possible alternate cut sets; for each row, either disconnecting the left cut set or right cut set would disconnect a portion of the network; link l36 is the smallest cut set as its removal alone is a major dysconnectivity



Each task was divided into subtasks to operate the RCPSP algorithm in the following section. The reasoning was that each subtask is treated as a 1-unit time long stretch of the whole task. The tasks themselves were assumed require time directly proportional to the length of the road the task represents. Resources requirements are assigned to subtasks of each task using a random number generator (rng). For the sake of reproducibility the rng was seeded with the number 2021. The subtask resource requirement thus obtained for each mitigation option are as follows:

Table 3 Subtask resource requirement for each mitigation option

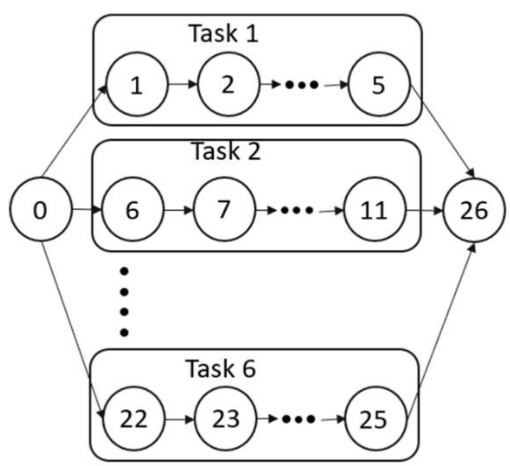
m1	m2	m3	m4	m5	m6	m7	m8	m9	m10	m11	m12	m13	m14	m15	m16	m17
18	18	18	13	18	13	18	18	18	18	18	18	18	13	13	18	18
19	19	19	26	19	26	19	19	19	19	19	19	19	26	26	19	19
23	23	23	25	23	25	23	23	23	23	23	23	23	25	25	23	23
14	14	14	25	14	25	14	14	14	14	14	14	14	25	25	14	14
20	20	27	19	27	19	27	27	27	27	27	27	27	19	19	27	20
19	19	28	19	28	19	28	28	28	28	28	28	28	19	19	28	19
22	22	20	19	20	19	20	20	20	20	20	20	20	19	19	20	22
20	20	26	14	26	14	26	26	26	26	26	26	26	14	14	26	20
20	20	29	18	29	18	29	29	29	29	29	29	29	18	18	29	20
20	20	28	20	28	20	28	28	28	28	28	28	28	20	20	28	20
20	20	25	14	25	14	25	25	25	25	25	25	25	14	14	25	20
15	15	27	27	27	27	27	27	27	27	27	27	27	27	27	27	15
19	19	19	14	19	14	19	19	19	19	19	19	19	14	14	19	19
21	21	27	18	27	18	27	27	27	27	27	27	27	18	18	27	21
15	15	22	15	22	15	22	22	22	22	22	22	22	15	15	22	15
15	15	26	29	26	29	26	26	26	26	26	26	26	29	29	26	15
19	19	20	16	20	16	20	20	20	20	20	20	20	16	16	20	19
24	24	20	29	20	29	20	20	20	20	20	20	20	29	29	20	24
16	16	20	18	20	18	20	20	20	20	20	20	20	18	18	20	16
14	14	20	19	20	19	20	20	20	20	20	20	20	19	19	20	14
17	17	15		15	23	15	15	15	15	15	15	15	23		15	17
	15	19		19	27	19	19	19	19	19	19	19	27		19	
	14	21		21		21	21	21	21	21	21	21			21	
	16	15		15		15	15	15	15		15					
	20	28		28		28	28	28	28		28					
	18	15		15		15	15		15		15					
	22	26				26										
	19	19				19										
	15	24				24										
	20	16				16										
	24	14				14										
	21															

Selection of feasible mitigation measures

The Resource Constrained Project Scheduling Program (RCPSP) algorithm described in the previous section was used to identify the mitigation options that satisfy the resource constraints. Table 3 show the resource constraints and the resources and time needed for each mitigation option. The following discusses the implementation of the RCPSP algorithm for the selected road network.

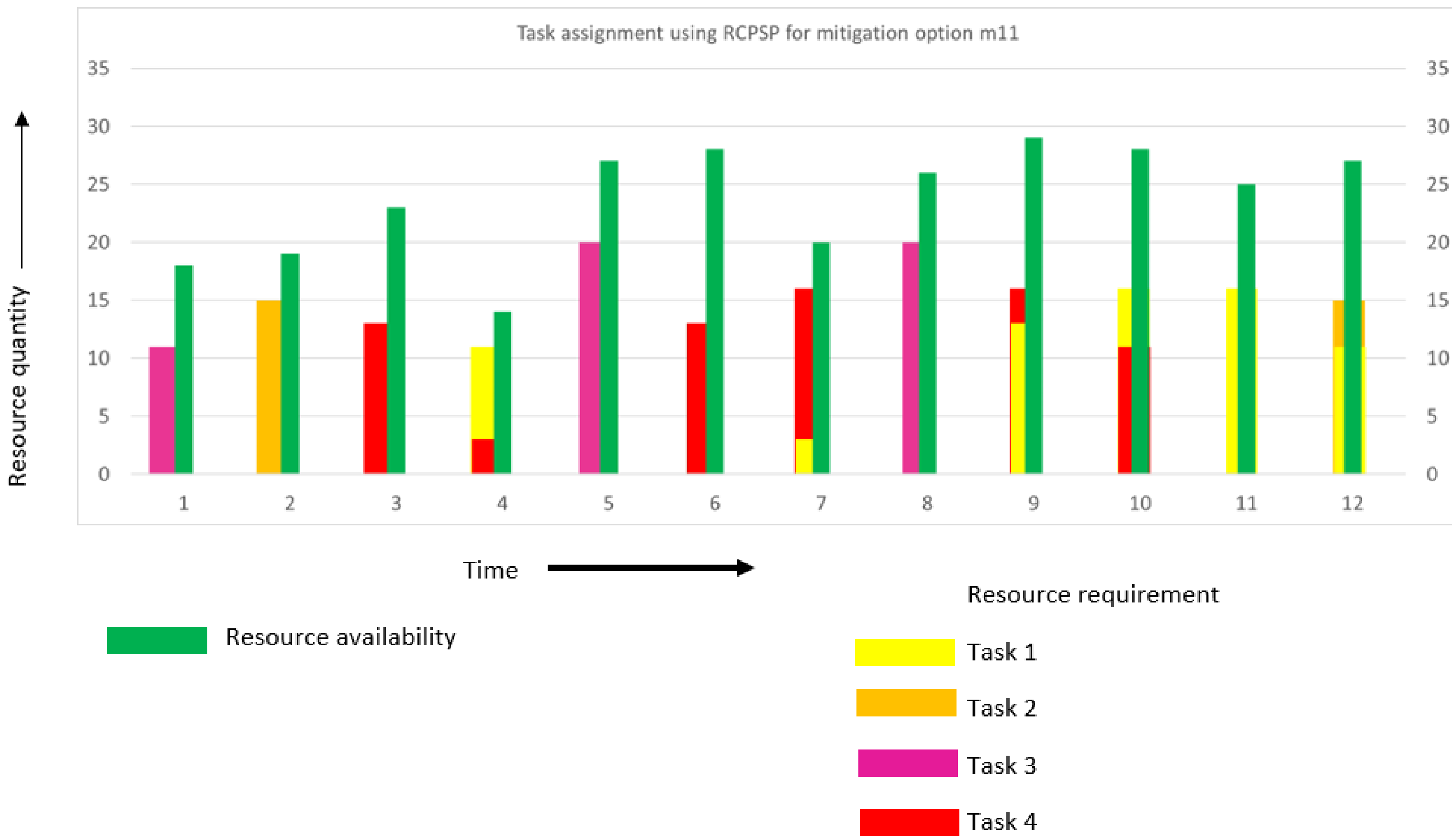
For example, mitigation option M8 consists of six links that need to be improved – these are 6 independent tasks in the algorithm. Each task (improvement of a link) is divided into multiple subtasks, each spanning a period of 1 unit time. All the larger tasks are connected to placeholder "subtasks" at the beginning and the end of all processes to signify the start and end of tasks. The subtasks in each task have a precedence order. As shown in the Figure 5, subtask 2 cannot be started before the completion of subtask 1. Task 1, which is the improvement of road l14 will not take effect until the completion of all the subtasks 1 through 5. Once all the subtasks of a task are completed, the probability of failure of that road is reduced for a particular hazard scenario. If in mitigation option M8, improvement operations of l14 are completed after 5 years, the probability of failure of l14 is reduced. For the model road network, the reduction in probability of failure is a factor (0.5) that is multiplied to the original probability of failure of the roads after the requisite time has passed for the mitigation measure to take effect.

Figure 5 Task and subtask precedence of mitigation option M8 for RCPSP algorithm



The Figure 6 shows the task scheduling for mitigation option M1 utilizing the RCPSP algorithm. The wider dark purple bars in the chart represent the available resources at each time step. The slimmer colored bars represent the resources required for each task. As can be seen, the tasks are completed in the allotted time without exceeding the resource constraint at any timestep. Similar analyses are performed for the other mitigation options. It is found that the mitigation measures M2, M5 and M8 do not have valid solutions in the assumed resource constraints and given timeframe of 12 years.

Figure 6 RCPSP algorithm results for mitigation option M1



Performance assessment of the road network

Monte-Carlo simulations were performed to determine the expected number of nodes still connected to the ESFs in the network after failure of roads using the depth first search approach described in the previous section. Herein, the failure of a road as modeled by simulating a random number (u) between zero and 1 for each link. This random number was compared against the probability of failure. If u was less than the failure probability, then the link is considered to be damaged and removed from the network. This process was repeated 1000 times to propagate the uncertainties in failure of links. The same process was used when mitigation measures were considered.

Bayesian network setup

The Bayesian network is setup from the results obtained in the Monte Carlo simulations for all time, hazard, mitigation measure combinations. The Figure 1 conceptualizes the Bayesian network that was developed herein. Time is the primary parent node to which the hazard and mitigation nodes were linked. These secondary nodes are child nodes of the time node but are themselves parent nodes to the selected damage metric – expected connected (to ESFs) node count and the cost of mitigation.

In the actual formulation of the Bayesian network, hazard and mitigation measures are treated as independent parent nodes like the time node i.e., they are not treated as child nodes of time. This is because although they are derived from time, that relationship was predetermined by the RCPSP algorithm so there was no need to add it into the actual formulation of the Bayesian network.

The expected node count child node will have a conditional probability table reliant on all its parent nodes. For each time, hazard and mitigation measure combination, there will be a probability value for connected nodes and one for disconnected nodes; these probability values when multiplied by the number of nodes in the road network will return the expected values. The following table shows a sample conditional probability table for Hazard scenario H1, Mitigation measures M0, M1, M3, M4, M6, M7, M9 and Times t=3 to t=12.

Table 4 Conditional probability table for Hazard scenario H1, Mitigation measures M0, M1,M3, M4, M6, M7, M9 and Times t=3 to t=12

Hazard type	Mitigation measure	Time	Conditional probability of connected(p1) and disconnected (p2)		Hazard type	Mitigation measure	Time	Conditional probability of connected(p1) and disconnected (p2)	
h1	m0	t3	p1	0.653917	h1	m9	t7	p2	0.249375
h1	m0	t3	p2	0.346083	h1	m0	t8	p1	0.653917
h1	m1	t3	p1	0.729167	h1	m0	t8	p2	0.346083
h1	m1	t3	p2	0.270833	h1	m1	t8	p1	0.752375
h1	m3	t3	p1	0.738917	h1	m1	t8	p2	0.247625
h1	m3	t3	p2	0.261083	h1	m3	t8	p1	0.747125
h1	m4	t3	p1	0.735083	h1	m3	t8	p2	0.252875
h1	m4	t3	p2	0.264917	h1	m4	t8	p1	0.745875
h1	m6	t3	p1	0.738333	h1	m4	t8	p2	0.254125
h1	m6	t3	p2	0.261667	h1	m6	t8	p1	0.751125
h1	m7	t3	p1	0.754458	h1	m6	t8	p2	0.248875
h1	m7	t3	p2	0.245542	h1	m7	t8	p1	0.7495
h1	m9	t3	p1	0.748125	h1	m7	t8	p2	0.2505
h1	m9	t3	p2	0.251875	h1	m9	t8	p1	0.752625
h1	m0	t4	p1	0.653917	h1	m9	t8	p2	0.247375
h1	m0	t4	p2	0.346083	h1	m0	t9	p1	0.653917
h1	m1	t4	p1	0.747125	h1	m0	t9	p2	0.346083
h1	m1	t4	p2	0.252875	h1	m1	t9	p1	0.75075
h1	m3	t4	p1	0.75125	h1	m1	t9	p2	0.24925
h1	m3	t4	p2	0.24875	h1	m3	t9	p1	0.75625
h1	m4	t4	p1	0.745	h1	m3	t9	p2	0.24375
h1	m4	t4	p2	0.255	h1	m4	t9	p1	0.74925
h1	m6	t4	p1	0.746	h1	m4	t9	p2	0.25075
h1	m6	t4	p2	0.254	h1	m6	t9	p1	0.749375
h1	m7	t4	p1	0.749875	h1	m6	t9	p2	0.250625
h1	m7	t4	p2	0.250125	h1	m7	t9	p1	0.750875
h1	m9	t4	p1	0.742625	h1	m7	t9	p2	0.249125
h1	m9	t4	p2	0.257375	h1	m9	t9	p1	0.749125
h1	m0	t5	p1	0.653917	h1	m9	t9	p2	0.250875
h1	m0	t5	p2	0.346083	h1	m0	t10	p1	0.653917
h1	m1	t5	p1	0.75	h1	m0	t10	p2	0.346083
h1	m1	t5	p2	0.25	h1	m1	t10	p1	0.74825
h1	m3	t5	p1	0.7505	h1	m1	t10	p2	0.25175
h1	m3	t5	p2	0.2495	h1	m3	t10	p1	0.74875
h1	m4	t5	p1	0.743375	h1	m3	t10	p2	0.25125
h1	m4	t5	p2	0.256625	h1	m4	t10	p1	0.751125

Hazard type	Mitigation measure	Time	Conditional probability of connected(p1) and disconnected (p2)		Hazard type	Mitigation measure	Time	Conditional probability of connected(p1) and disconnected (p2)	
h1	m6	t5	p1	0.742625	h1	m4	t10	p2	0.248875
h1	m6	t5	p2	0.257375	h1	m6	t10	p1	0.748
h1	m7	t5	p1	0.75025	h1	m6	t10	p2	0.252
h1	m7	t5	p2	0.24975	h1	m7	t10	p1	0.750375
h1	m9	t5	p1	0.7505	h1	m7	t10	p2	0.249625
h1	m9	t5	p2	0.2495	h1	m9	t10	p1	0.746875
h1	m0	t6	p1	0.653917	h1	m9	t10	p2	0.253125
h1	m0	t6	p2	0.346083	h1	m0	t11	p1	0.653917
h1	m1	t6	p1	0.750875	h1	m0	t11	p2	0.346083
h1	m1	t6	p2	0.249125	h1	m1	t11	p1	0.74825
h1	m3	t6	p1	0.745375	h1	m1	t11	p2	0.25175
h1	m3	t6	p2	0.254625	h1	m3	t11	p1	0.750375
h1	m4	t6	p1	0.747	h1	m3	t11	p2	0.249625
h1	m4	t6	p2	0.253	h1	m4	t11	p1	0.74825
h1	m6	t6	p1	0.7525	h1	m4	t11	p2	0.25175
h1	m6	t6	p2	0.2475	h1	m6	t11	p1	0.74725
h1	m7	t6	p1	0.746	h1	m6	t11	p2	0.25275
h1	m7	t6	p2	0.254	h1	m7	t11	p1	0.74975
h1	m9	t6	p1	0.7505	h1	m7	t11	p2	0.25025
h1	m9	t6	p2	0.2495	h1	m9	t11	p1	0.751
h1	m0	t7	p1	0.653917	h1	m9	t11	p2	0.249
h1	m0	t7	p2	0.346083	h1	m0	t12	p1	0.653917
h1	m1	t7	p1	0.746875	h1	m0	t12	p2	0.346083
h1	m1	t7	p2	0.253125	h1	m1	t12	p1	0.74575
h1	m3	t7	p1	0.7485	h1	m1	t12	p2	0.25425
h1	m3	t7	p2	0.2515	h1	m3	t12	p1	0.746
h1	m4	t7	p1	0.748	h1	m3	t12	p2	0.254
h1	m4	t7	p2	0.252	h1	m4	t12	p1	0.751125
h1	m6	t7	p1	0.746875	h1	m4	t12	p2	0.248875
h1	m6	t7	p2	0.253125	h1	m6	t12	p1	0.748375
h1	m7	t7	p1	0.75175	h1	m6	t12	p2	0.251625
h1	m7	t7	p2	0.24825	h1	m7	t12	p1	0.74725
h1	m9	t7	p1	0.750625	h1	m7	t12	p2	0.25275
h1	m9	t7	p2	0.249375	h1	m9	t12	p1	0.746625
h1	m0	t8	p1	0.653917	h1	m9	t12	p2	0.253375

Results

Figure 7 displays the effect of the various mitigation options over time on the connectectivity of the network after hazard scenario H1. The Figure 8 shows the same but for hazard scenario H2. The dotted light blue line m0 is designates the case when no improvements options have been applied to the road network – this acts as a control baseline. As can be plainly observed, the number of nodes connected to ESFs after hazard events does not vary over time for this condition,remaining constant about 5.3 for H1 and 4.25 for H2. The mitigation options m2, m5 and m8 are not present in the results as the RCPSP algorithm found those options impossible in the given time and resource constraints. In Figure 7, the mitigation option m15 represented by the dark blue line experiences one of the eraliest rises in connectivity at around the 6 unit time mark, which aligns with the fact that this mitigation option has one of the earliest completion of mitigation tasks – mitigation of road l25 is completed by time step 6 in this mitigation option. Similar trends are observed for the other mitigation options as well, for example, m16 represented by the orange line, experiences jumps at time step 9 and 11, the time steps at which the mitigation measures for this option are completed.

Overall, m1, m12 and m13 show the greatest ultimate improvements in expected number of nodes connected to ESFs post hazard, with $E[n] = 7.54$. The cluster of mitigation options just beneath are m14, m15, m16 and m17 with $E[n] = 7.07$ at the least to 7.27 at the highest. The remaining form another cluster of mitigation measures that plateau at $E[n] = 5.9$. It is of note that some of the mitigation options which improved more roads performed worse than others. The key takeaway here is that the mitigation measures which included a crucial link – l36 – consistently performed best in terms of connectevity. It is noted that this link serves as the minimum cutset for network.

The trends observed for hazard H1 are consistent in Figure 8 which displays the results for hazard H2. The main difference is that since hazard H2 has higher probabilities of failure assigned to each road to emulate a more dangerous hazard, the base expected connected node count drops for all mitigation measures. The most effective measure in this scenario is m10, with $E[n] = 7.15$.

Figure 7 The expected number of nodes connected to ESFs over time for different mitigation options for Hazard H1 a=1, b=3

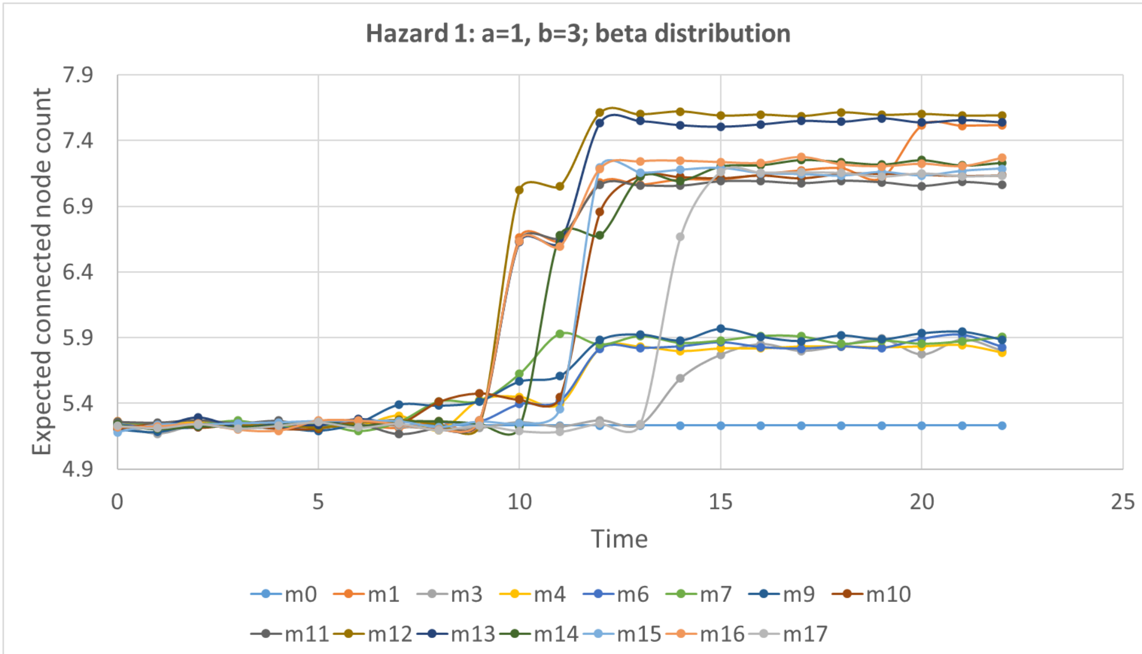


Figure 8 The expected number of nodes connected to ESFs over time for different mitigation options for Hazard H2 a=7, b=11

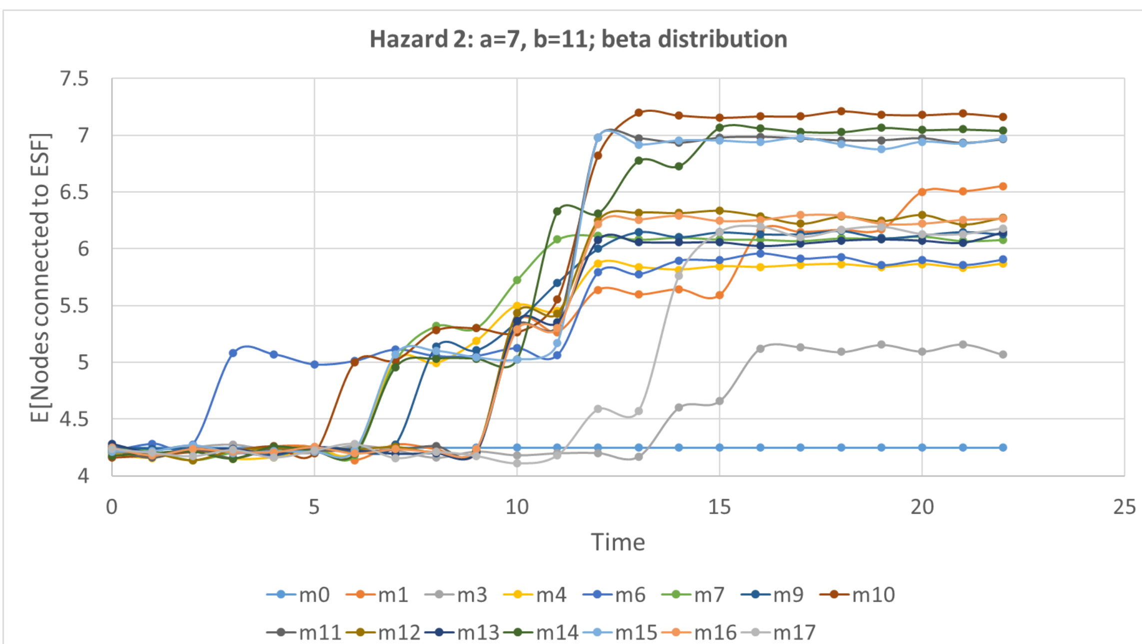


Figure 9 compares the effects of the two hazard scenarios on the effectiveness of mitigation measure m10, which was established as one of the best options. It is observed that initially, there is a large difference in performance between the two hazard cases, but after time step 5 the gap is significantly closed and then completely closed at time step 11. This is as expected because the first task completed in m10 is the improvement if road l68 which is completed at time step 5. Therefore, before time step 5, the performance was purely governed by the hazard scenario. The next improvement task is completed at timestep 7 and then the rest are completed in quick succession at 10, 11 and 12. This explains the closing of the gap between the two hazard scenario performances at time step 11 as well as the jump in performance at time step 12. After all mitigation measures are completed, there is no difference in performance regardless of hazard.

Figure 9 Comparing the effects of hazard h1 and h2 on mitigation option m10

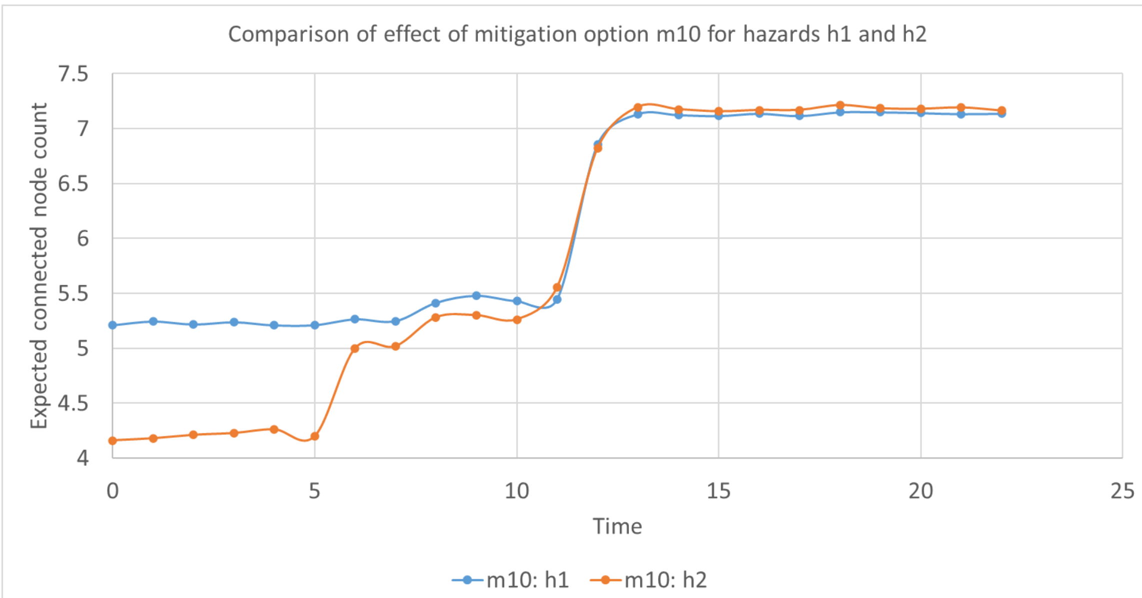


Figure 10 shows the improvement of performance of the network as the tasks for mitigation option m10 are completed. The blue dotted line indicates the expected connected node count at each time step and the black bars indicate the completion of a task. Note that this is displayed for hazard H2. As discussed previously, the tasks are completed at time steps 5, 7, 10, 11 and 12. The improvements in performance are also seen right after the completion of tasks.

Figure 10 Expected connected node count for mitigation option m10 compared against completion of the five tasks in the mitigation process

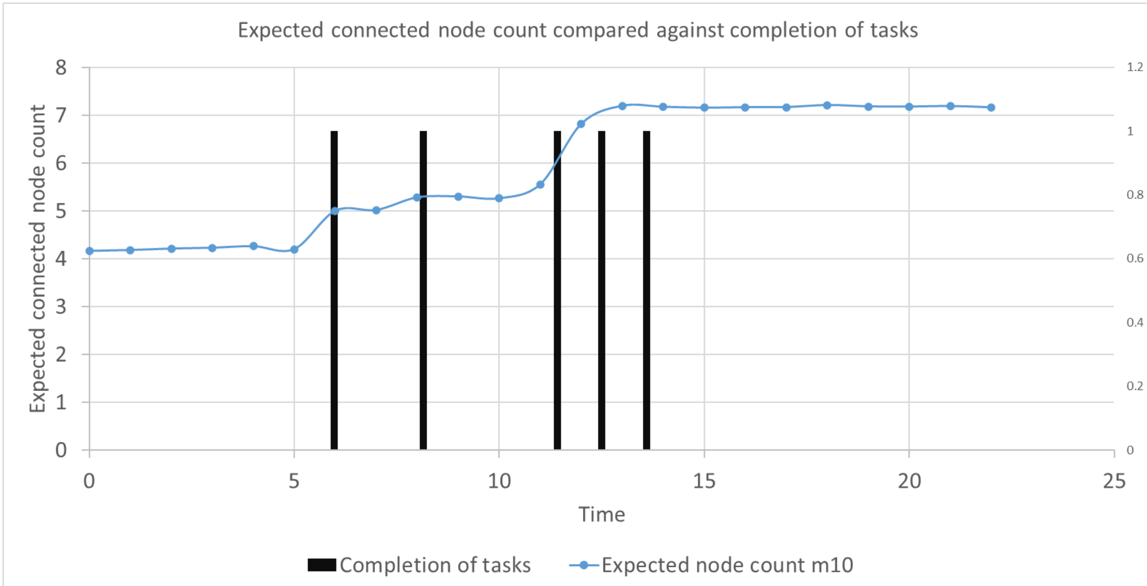
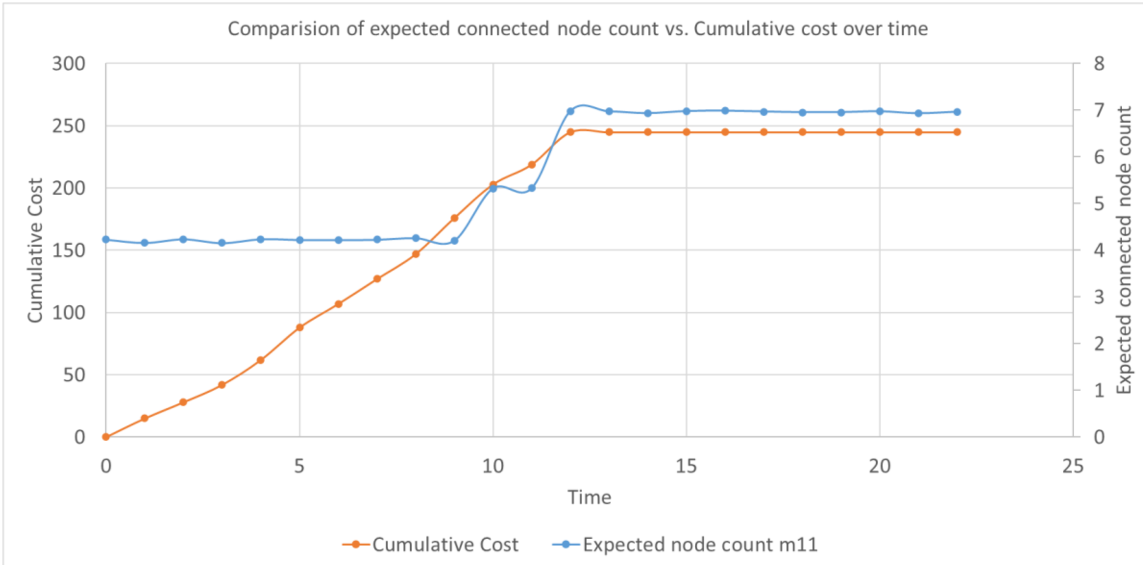


Figure 11 compares the cumulative cost of repair tasks for mitigation option m11 against the expected connected node count over time when considering hazard scenario H2. For mitigation option m11, the forst task l36 is completed at time step 9 and the remaining task l15, l23 and l25 are completed at timestep 11 at once. Thus two jumps in performance are observed corresponding to those times. The cumulative expenses for the tasks steadily increase until the final task has been completed then it plateaus.

Figure 11 Cumulative Cost of repairs compared against Expected node count for mitigation option m11



Application to road network in South East Louisiana

The framework developed and tested on the model miniature road network is being applied on a real-life road network. The road network selected for this purpose is around Houma City in the Terrebone Parrish of Louisiana, extending to Morgan City in the West, Grand Isle in the south and I-10 in the Northeast. The resulting network has 4392 total nodes and 4916 edges. To reduce complexity of computation some of the roads in the networked are trimmed. The following links were removed from the network if: there were more than 1 road connecting 2 points in the network, the road represented a cul-de-sac that connected to the same point or, the road was significantly short and connected a single node to the larger network. There are five hospitals in the area, which represent the Emergency Service Facilities (ESFs). Figures Figure 12, Figure 13,Figure 14, and Figure 15 show the road network along with the ESFs. Herein, connectivity to ESF was considered to the objective of the road network.

Figure 12 Full scale road network with hospitals shown in blue H-marked icons

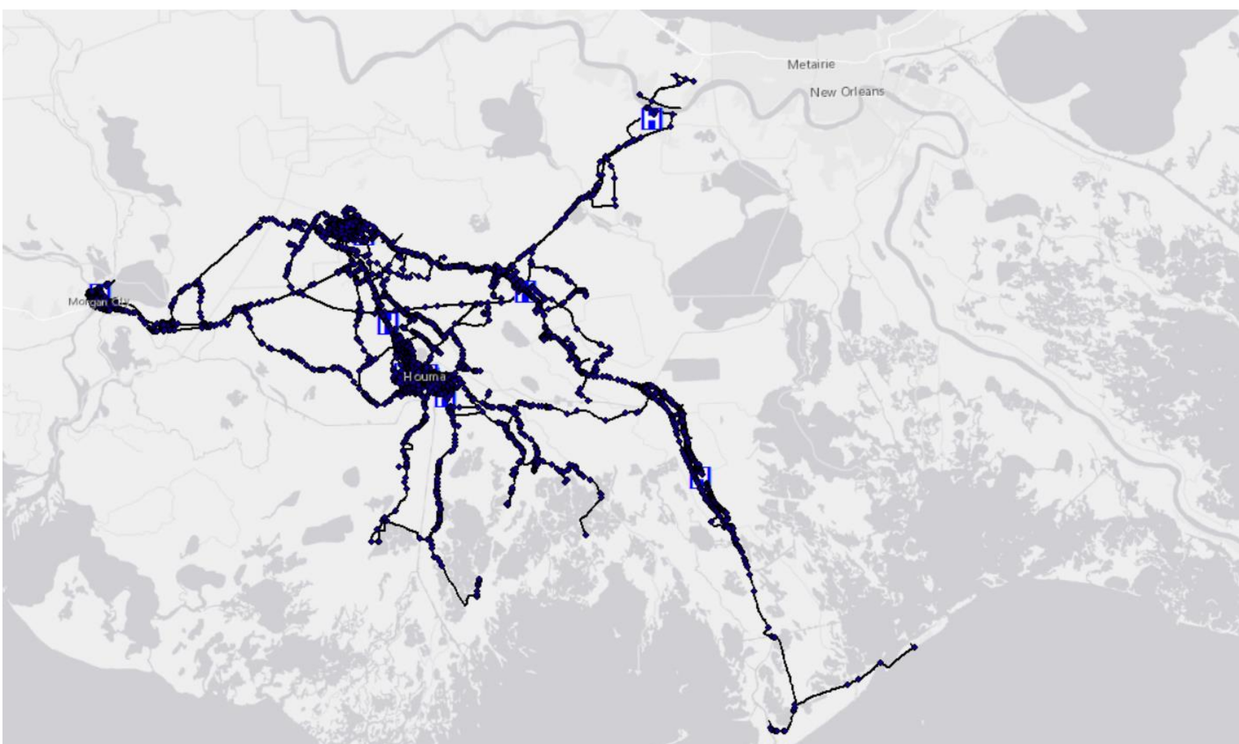


Figure 13 Full scale road network with public schools shown in green flagpole icons

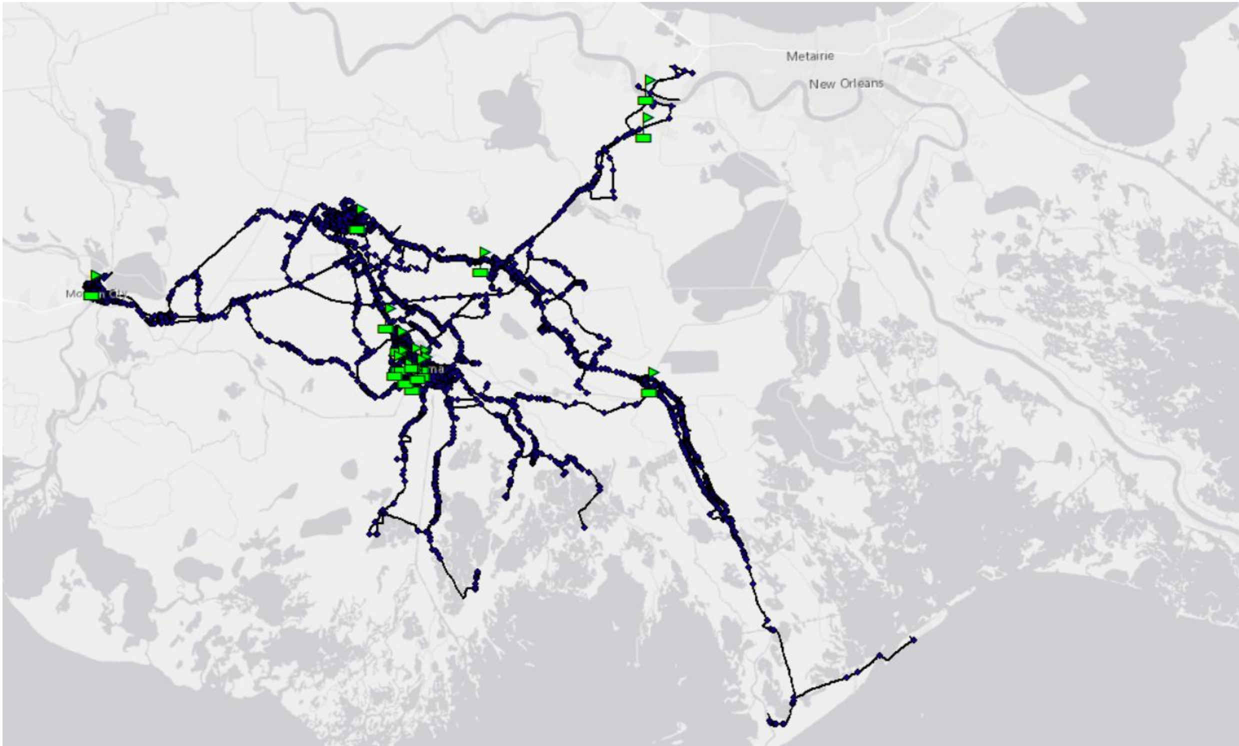


Figure 14 Full scale road network with police stations shown in red badge icons

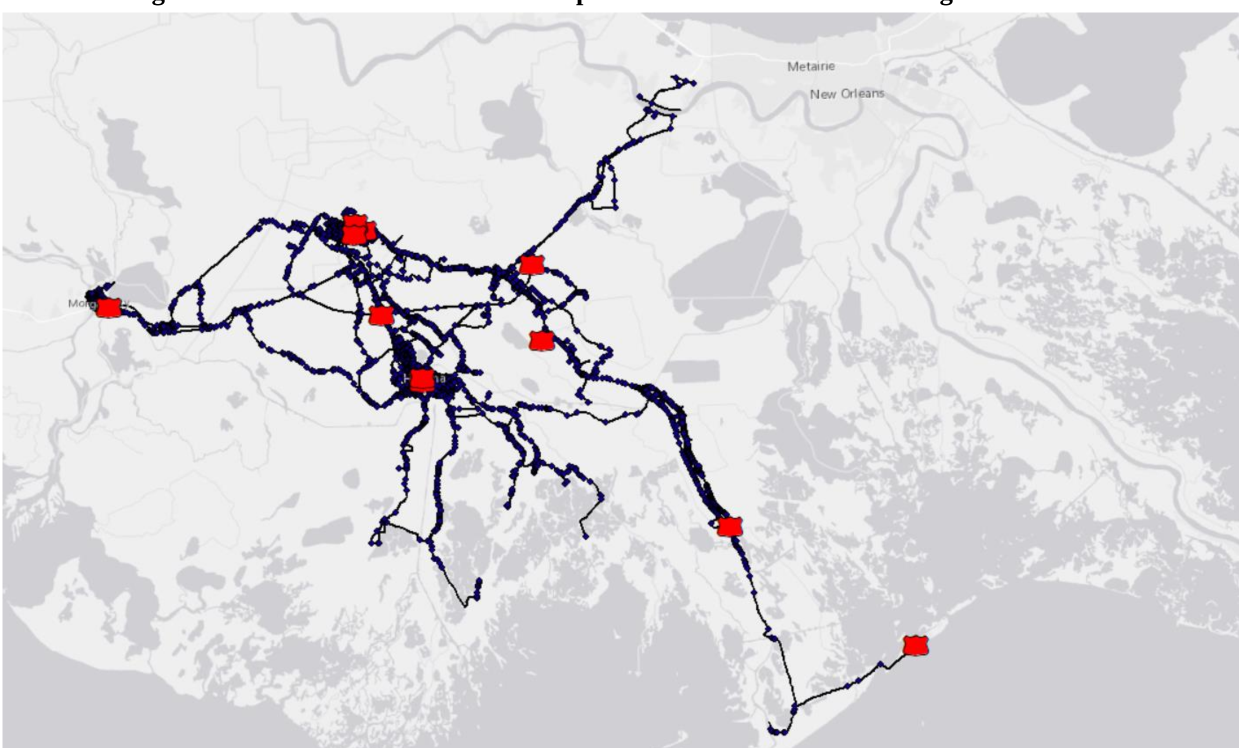
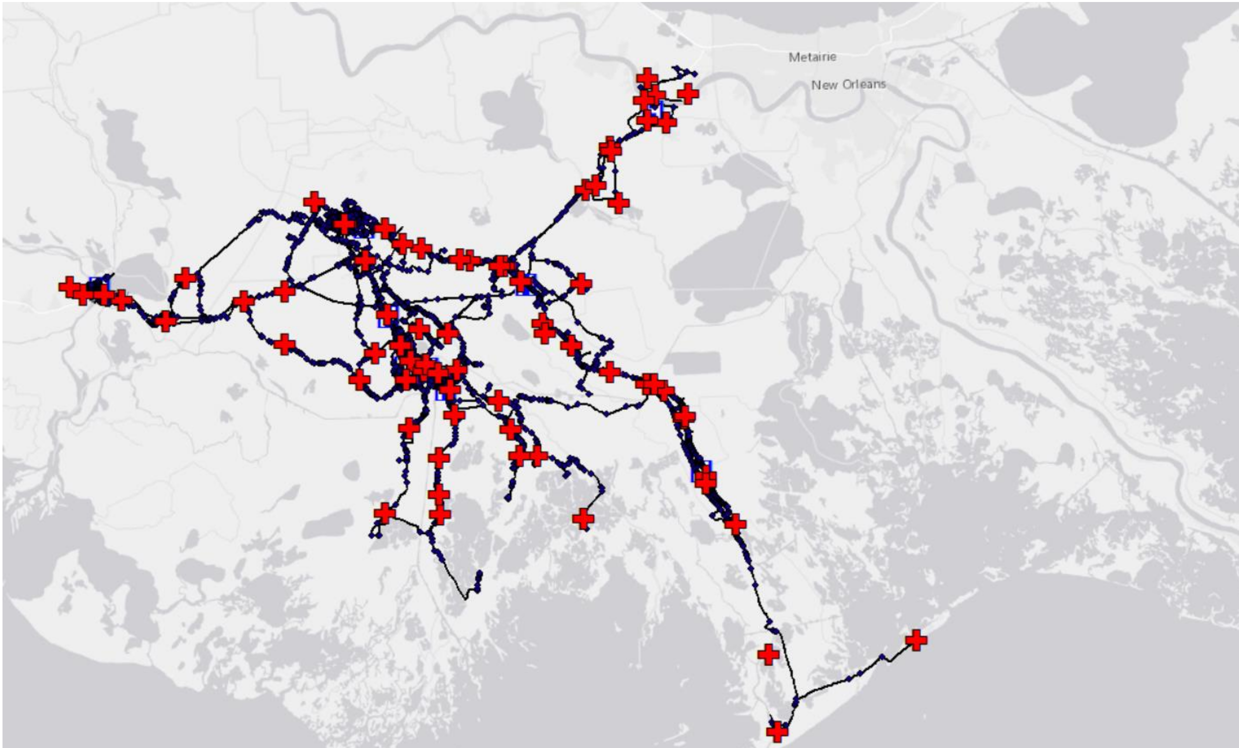


Figure 15 Full scale road network with fire stations shown with red cross symbols



Hurricane induced flood hazard was considered for the region. Flood hazard data was provided by Coastal Protection and Restoration Authority [52]. The data provided has flood depths for an array of coordinates in the study area. Since flood depth is not a deterministic quantity, the values were represented as 10 percentile, 50 percentile and 90 percentile – a probability density function (pdf) is generated using these values. For the provided data, a lognormal distribution is selected as it best emulates the expected distribution of flood depth values. The flood depths are also available for return periods of 10 years, 50 years, 100 years, 250 years, 500 years and future conditions considering subsidence. Once the appropriate pdf has been selected, a mean flood depth is assigned to the roads in the network. This is done by dividing the roads into points at 10-meter intervals – each point is assigned a flood depth depending on the geospatially nearest coordinate.

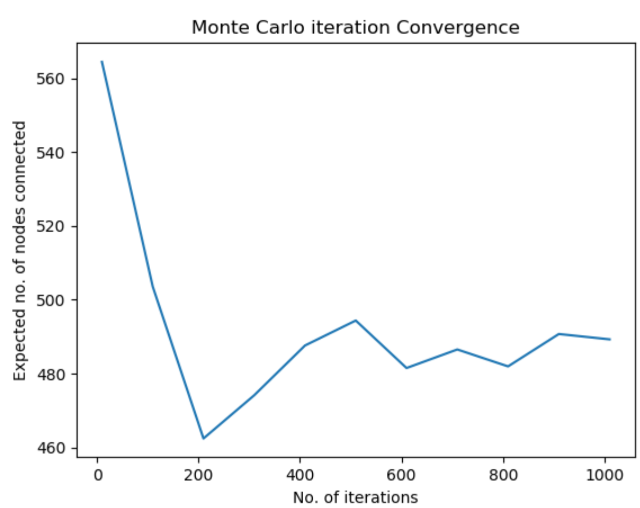
Next, 30 cm threshold was selected to determine if the roadway link will be functional or not. However, since the flood depths are probabilistic, the probability of flood depth exceeding the threshold were obtained using the probability density function of flood depths assigned to each link.

In order to select the mitigation options cutsets were employed. Paths were chosen that have the most importance in terms of maintaining connectivity in the road network. The costs and time associated with these mitigation options were based on the length of roads.

The mitigation options were then evaluated using the Resource Constrained Project Scheduling Algorithm (RSPSP) which determines if the mitigation measure is viable in the given time period and resource constraint and if it is, the timeline for effectiveness of the mitigation measure. The mitigation measures that were thus chosen are then applied on the road network. Initially Monte Carlo simulations were performed to determine the number of nodes connected to ESFs. To determine the number of simulations required for convergence, the expected post hazard node count is determined using a beta distribution (a=1, b=3) for probability of failure of the roads. Figure 16 shows that 3000 iterations are enough for convergence. The expected number of nodes connected to ESFs after failure with no mitigation options applied was 484.

Ongoing simulations are quantifying the expected number of nodes connected to the ESF locations for different return periods, future conditions, and mitigation options. The expected connected node count and the associated cost and time will be used to develop conditional probability tables for the Bayesian network.

Figure 16 Convergence of Monte Carlo simulation for full scale road network



Conclusions

A Bayesian network based framework was proposed to assess the time evolving resilience of road networks. The framework considers performance objectives for the road network, time evolving hazards, mitigation measures, and resource constraints. Herein, connectivity to essential service facilities (ESF) was considered to the performance objective for road networks. A graph theory based approach was used to assess connectivity in the road network. Hazards were modeled probabilistically to determine the loss of functionality of roadway link in the aftermath of extreme events. Mitigation measures were identified based on the topology of road networks. Next, a linear programming based approach was used to identify the options which satisfy the total and temporal resource constraints. With the mitigation options, Monte Carlo Simulations were performed to determine the likelihood of accessing ESF nodes. Since computational simulations require a lot of time and cannot be performed in real time, the data from the simulations were used to develop a Bayesian network. Decision makers can use the Bayesian network to understand the effects of various mitigation measures on the resilience of road networks in real time. This approach was applied to a small hypothetical road network to assess resilience in terms of connectivity to essential service facilities to demonstrate the approach. Based on this application, the following conclusions can be drawn:

- The results show that improvement in connectivity is not necessarily related to the number of roadway links that are rehabilitated. The effect on connectivity is primarily dependent on the importance of the links. Therefore, mitigation measures that target critical roadways can significantly improve the resilience of the road network.
- Application of the RCPSP method to select feasible mitigation measures show that mitigation measures should not only meet economic constraints for the entire mitigation action, but should also meet the resource and other constrains during the implementation phase. Finally, the results of selecting feasible mitigation measures also show that timespan for the mitigation options should also be carefully selected to prevent elimination of a large number of potential mitigation strategies.
- Preliminary analysis for the road network in South East Louisiana shows that around 3000 Monte Carlo simulations are needed to achieve convergence in the results for the number of nodes connected to essential service facilities. However, such simulations are computationally expensive and can not be performed in real

time. Since Bayesian networks can provide results in real time they provide a viable alternative to such simulations to aid informed decision making in real time.

Ongoing work is focused on applying the approach to the road network in Houma, Morgan City, and Grand Isle region for hurricane induced flood hazards.

Recommendations

Based on the implementation of the approach to the small road network and preliminary results for the large road network in Southeast Louisiana, the following is suggested:

- Community level stakeholders and decision makers need to determine the performance objectives of the road networks and set expectations for the performance. These objectives and expectations and will help identify suitable mitigation options for the road network.
- Selection of hazards and corresponding return periods for resilience quantification and enhancement should consider the not only the hazards for present conditions but also for future conditions. Furthermore, the expected performance for the road network should also vary with the return period of the hazard.
- Mitigation options for the road network should also be identified at the community level to incorporate local knowledge and minimize impacts on low income and marginalized communities.

Acronyms, Abbreviations, and Symbols

Term	Description
ESF	Essential Service Facilities
MCS	Monte Carlo Simulations
NAIC	National Infrastructure Advisory Council
NIST	National Institute of Standard and Technology
CMP	Coastal Master Plan
LSTP	Louisiana Statewide Transportation Plan
CPRA	Coastal Protection and Restoration Authority

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