Characterization of the Vulnerability of Road Networks to Fluvial Flooding Using Network Percolation Approach

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ABSTRACT

The objective of this paper is to model and characterize the percolation dynamics in road networks during a major fluvial flooding event. First, a road system is modelled as planar graph, then, using the level of co-location interdependency with flood control infrastructure as a proxy to the flood vulnerability of the road networks, it estimated the extent of disruptions each neighborhood road network experienced during a flooding event. Second, percolation mechanism in the road network during the flood is captured by assigning different removal probabilities to nodes in road network according to a Bayesian rule. Finally, temporal changes in road network robustness were obtained for random and weighted-adjusted node-removal scenarios. The proposed method was applied to road flooding in a super neighborhood in Houston during hurricane Harvey. The result shows that, network percolation due to fluvial flooding, which is modelled with the proposed Bayes rule based node-removal scheme, causes the decrease in the road network connectivity at varying rate.

INTRODUCTION

Transportation systems are of fundamental importance to the normal functioning of societies in developed and developing countries alike. In addition to their everyday transferring of people, goods and services, during the disastrous events, transportation system is crucial for rescuing people and assets, and plays a vital role in repairing and restoring other critical infrastructure systems if they are disrupted (Mattsson and Jenelius 2015). However, transportation networks, especially road networks, are vulnerable to natural and human-made disasters, which could undermine their vital functionality. In order to cope with disruptions efficiently and take active precautionary measures, it is critical to understand the mechanisms with which the disruptions unfold in the transportation network. Graph theory based methods have been devised to assess the vulnerability of the transportation networks, as due to the planar nature of road systems, they tend to lend themselves readily to being represented as graphs. Graph theory reduces a road network to a mathematical matrix, which facilitates the accessibility and connectivity analysis within the road network using available graph theoretic measures and tools. Many studies on this topic, which uses certain network centrality measures, like betweennees centrality, eigenvector centrality, degree centrality, to identify vulnerable or critical locations on the network, indeed exist. However, topology of most of the critical infrastructure networks are intrinsically dynamic and evolving over time, which is especially true during disastrous events. This renders the vulnerability measures based on a single static graph less useful in assessing the temporal performance of the networks under disruptions. In order to address this issue, (Callaway et al.

2000) introduced a generalized concept of network percolation, through which resilience is assessed for a network after possible failure of a node or set of nodes. First introduced in the fields of physics and mathematics, percolation models continuous phase transitions on low-dimensional lattice and could be divided into two broad categories, site percolation and bond percolation (Stauffer and Aharony 2014). The site and bond percolation respectively corresponds to node and edge percolation in the context of networks(Newman 2010). Modelling percolation in road networks requires an estimation of the removal probabilities of the nodes in the network. Most of infrastructure networks, including road networks, are spatially embedded (Bashan et al. 2013) and failure probabilities of their nodes tend to be different due to the heterogeneity of the contexts within which the nodes operate, which requires the node-removal scheme to be able to reflect the difference in the configuration of the environment the nodes are located. In order to achieve this goal, this study proposes a network simulation-based method to capture the propagation dynamics of the fluvial flooding within the road networks.

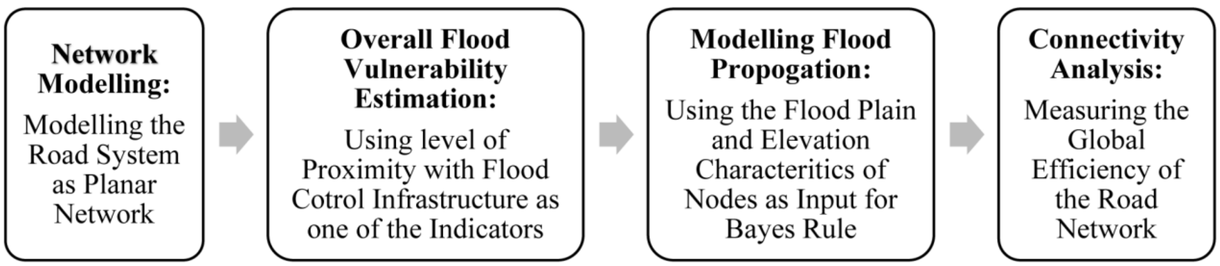

Figure 1 Proposed Framework

LITERATURE REVIEW

Studies on the vulnerability of transportation systems using graph theory have increased significantly in the past decades and graph theory in transportation field has been commonly used to study issues related to travel routing and networks topologies within the transportation network (Monteiro et al. 2012). Based on the inclusion of the temporal dimension in the vulnerability analysis, network topology related methods could be classified into static and dynamic approaches. Some examples of the static approaches that studied the topological vulnerability of transportation networks include the work by (Demšar et al. 2008; Ip and Wang 2011; King et al. 2016; Leu et al. 2010; Porta et al. 2006). Comparatively, number of studies which used dynamic network approaches to study the vulnerabilities in transportation networks are small. A survey on the works used dynamic network approaches to study network vulnerability found that existing studies are either focusing on the theoretical network such as Erdos-Renyi, Scale-Free networks, or power-law networks (Gao et al. 2012; Huang et al. 2011), or they assumed that disruption on the networks are random, such as works on lattice network (Yan et al. 2017), communication tower networks (Parandehgheibi and Modiano 2013) and supply chain networks (Nicosia et al. 2013). This paper will contribute to the body of knowledge by proposing a dynamic network approach, which acknowledges the heterogeneity of the nodes, to assess the temporal change in the network robustness. In another words, instead of just using certain centrality measures to identify "vulnerable" areas in the network, this study considers the compromisation of the road network due to fluvial flooding as a dynamic process and captures the relative targeted nature of flooding locations.

PROPOSED METHODOLOGY

It is possible that different types of flooding (fluvial flooding, fluvial flooding, reservoir flooding, coastal flooding) occur simultaneously during the hurricane and it is a quite challenging to capture the changes in the road networks under all of these flooding with a single model. Therefore, this study aims at capturing the temporal changes in the road network due only to fluvial flooding, which occurs due to the overflow of flood control infrastructure (like rivers, channels and bayous) during heavy rainfall. Figure 1 is the workflow diagram for the proposed methodology.

Road Network Modelling

In this study, modelling of the road network will adopt the primal approach in the network theory, which assumes the nodes are the intersections and links are the road sections. Road networks used for the study are obtained from OpenStreetMap using the OSMnx, which is a Python package developed by Boeing (Boeing 2017). In order to assess the road network connectivity for the general users, this study chosen to focus on the roadways which is used by passenger vehicles, as opposed to a more detailed road network which includes bikeways, walkways and service ways included.

Overall Flood Vulnerability Estimation

As it could be seen from Figure 2, there is a significant positive correlation between the level of flooding a neighborhood experienced and the proximity of the area to flood control infrastructure systems. The four clusters of heavily flooded regions (A, B, C and D) in Figure 2B correspond areas, which are in the immediate vicinity of reservoirs, dams or major bayous (1, 3, 2 and 4) in the Figure 2A. While there could be many other factors contributing to the level of flooding experienced by the neighborhoods, the level of proximity with flood control infrastructure is an important factor for the flooding extent. This paper estimated the level of proximity between flood control infrastructure (dams, bayous and open channels) and road networks, based on the proximity and type of flood control infrastructure located near the road networks. Weights were assigned to the road network in certain super neighborhood (SN) in the below manner (Table 1):

Table 1 Proximity Index with Flood Control Infrastructure

Types of Co-location	Co-location Weight
SN is located within the peripheries of the reservoir/dam	4
SN is adjacent to the dam/reservoir	2
SN contains portion of a bayou	2
SN contains portion of a channel/creek	1

The overall neighborhood proximity index is cumulative, which means if it meets several co-location condition, the proximity index will be the sum of respective co-location scenarios. For example, Super Neighborhood 17 (Eldridge/West Oak) in Houston has the highest flood vulnerability (with overall proximity index of 9) due to the fact that significant part of it is located within a reservoir (Barker), it is adjacent to a reservoir (Addicks), a major bayou (Buffalo) passes through it and it contains channel network. With the same logic, Super

Neighborhood 16 (Memorial) have an overall proximity index of 6 and the level of flooding experienced by this neighborhood is less severe compared to the SN-17.

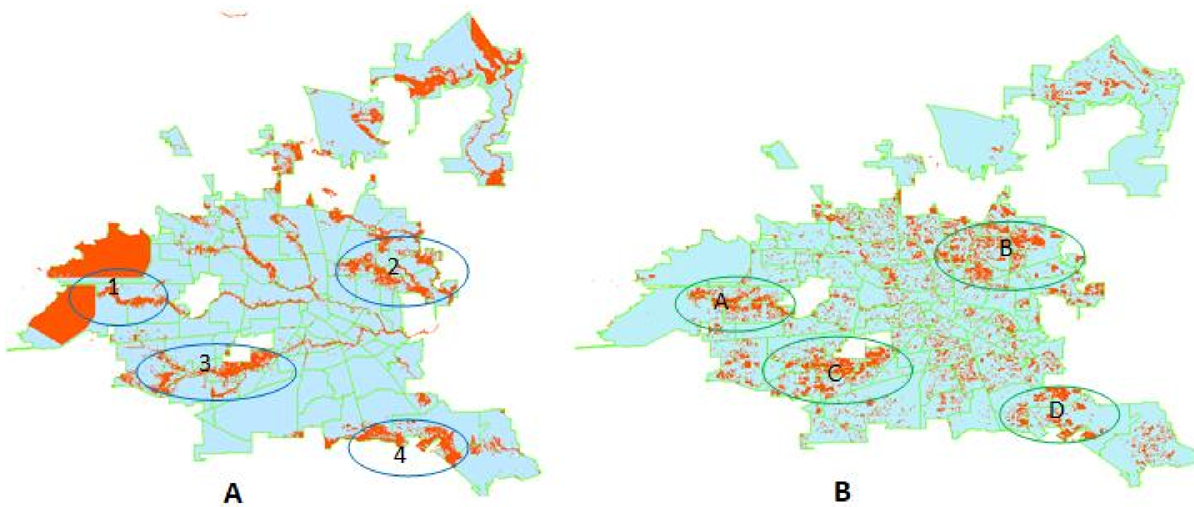

Figure 2 A: Location of the Flood Control Infrastructure in Houston(source:HCFCD); B:Flooding Experienced at Different Location in Houston (source:COHGIS)

The super neighborhood this study focused on is called Memorial, which is located in the Energy Corridor region in Houston and one of the areas whose road network suffered heavily from the fluvial flooding during the past hurricane Harvey. This neighborhood has an overall co-location index of 6. While proximity with flood control infrastructure is an important indicator for the level of inundation, many other factors, like topography of the area, availability of unpaved green space in the vicinity, are simultaneously at play. In the end, this study used the ratio of the area covered by flood water and total area at the peak of the inundation as the proxy for the portion of the nodes in the road network removed during flooding, which is about 60%.

Flood Propagation in Road Network

While the co-location interdependency with the flood control infrastructure provides insights about the overall level of flooding an area could experience at a macro-level, the sequence of the flooding and closure of roads in the area are largely affected by factors like the types of flood-plain and relative elevation of the nodes in the road network. Therefore, this paper uses this information as the proxy for the likelihood of a node being an initiation point for the flood, which means nodes located in flood-prone areas (located in 100-year flood plain) with lower elevation having a higher chance of being removed first. It is also noteworthy to mention that, to certain extent, flood in the road network also spreads in a way that a disease does, a flooding of an adjacent node could lead to the flooding of the certain road nodes. Therefore, this study will estimate the prior probability of nodes being flooded based on the flooding status of the adjacent nodes and grade level of the street between these nodes, which will be used to update initial flood plain and elevation-based probability of nodes being removed. Bayesian rule is used to update the probability and obtain the posterior probability of nodes being removed.

Due to the fact that there are numerous factors which could cause the road network to be flooded, there is an uncertainty about what areas get flooded first (i.e., places on the road network where the flooding originates). In order to identify where the flood initiates, a fuzzy inference method is used. Two groups of variables (See Table 2 for variables and their possible values) are introduced to estimate the initial removal probability (See Table 3 for an example). The rational is if a certain node in the road network is located in a highly flood-prone area and its elevation is low, there is a high chance for it being removed from the road network first. The elevation data for the nodes in the road network is retrieved using Google API on OSMnx.

Table 2 Variables and Their Possible Values

Variables	Possible Values		
	Low Probability	Medium Probability	High Probability
Flood Plain (Flood Control Infrastructure) Variable	Non-floodplain	500 year flood plain	100 year flood plain
Elevation Variable	Fourth quartile	Third quartile	First & Second Quartile

Table 3 Example of Fuzzy Rule for Initial Probability for Node Removal

IF	Flood Plain	AND	Elevation	THEN	Probability P(A)
If	100 year	And	First & Second quartile	Then	Very high
	100 year		Third quartile		High
	100 year		Fourth quartile		Medium

As to the estimation of the prior probability, which intends to models the possible propagation trends (directions) for the flood in the road network, two variables are used as input for the fuzzy inference model. The two variables are the status of the adjacent nodes and the type of grade between the adjacent node and the node in question. Two possible values are considered for the first variable, which are (1) there is at least one adjacent node which has already been flooded;(2) there is no adjacent node which has already been flooded. Similarly, binary values (positive or negative) are considered to the street-grade variable. For example, if the slope for the road section which is connecting one of the flooded adjacent nodes and grade of the road section is negative, then there is a high chance for that node being removed next (See Table 4 for an example). The data for grade types between every two adjacent nodes in the road network is retrieved using Google API using OSMnx tool in Python.

Table 4 Example of Fuzzy Rule for Prior Probability for Node Removal

IF	An Adjacent Node	AND	Street Grade	THEN	P(B)
If	Flooded	And	Negative	Then	High
	Not flooded		Positive		Low

Using below Bayesian rule, the posterior probability ($P(A|B)$) of certain node being removed is obtained by updating the initial probability after each removal phase.

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

where: $\mathrm{P}(\mathrm{A})$: the initial probability; $\mathrm{P}(\mathrm{B})$: the prior probability

Connectivity Analysis under Fluvial Flooding Disruption

Global efficiency of the network is a measure which could be used to assess the level of connectedness in the network, which also has been used in the context of transportation network (Mattsson and Jenelius 2015). It is defined as below (Newman 2010):

$$GE = \frac{1}{N(N-1)} \sum_{s \neq t} \frac{1}{Z_{st}}$$

where GE : global efficiency; N : number of nodes;

Z_{st} : the length of the shortest path between nodes s and t.

CASE APPLICATION AND RESULTS

The proposed methodology is applied to the Memorial super neighborhood road network in the Energy Corridor Region of Houston (Figure 3). Nodes in the network have heterogenic elevations levels, as it could be seen from Figure 3 (maximum elevation is above 32 meters and minimum is about 15 meters). This road network contains 1388 nodes and 3280 edges. Due to a lack of accurate GIS data, approximation was made for the boundaries of the flood plains. The simulated node removal is compared with the observed temporal closure of the road network in this neighborhood and the results showed that there is a high level of similarity in the areas impacted.

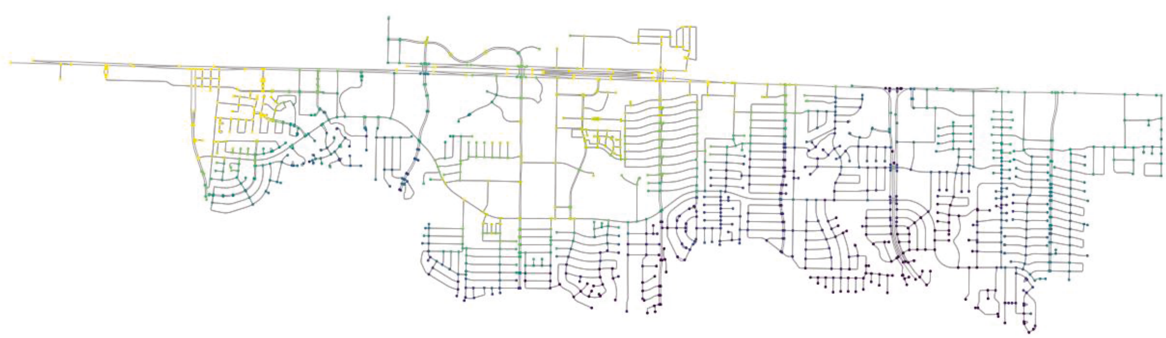

Figure 3 Road Network Elevation in Memorial Super Neighborhood Houston

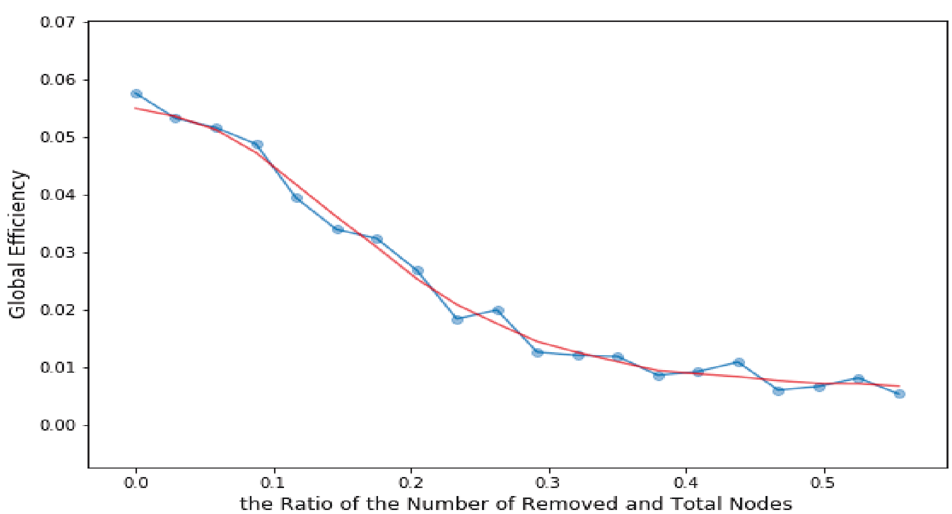

Figure 4 Road Network Connectivity as Flood Propagates

Figure 4 shows the temporal (approximated) changes in the connectivity (global efficiency) of the road network as the fluvial flood expands within the road network. This simulated result corresponds to the road closure in this neighborhood which started on Aug 25, 2017 and peaked (about 60% of the roadways closed) on Aug 29, 2017. As it could be seen in the Figure 4 (the blue dots represents the simulated result and the red one is fitted to the data with polynomial regression), there is a dramatic drop in the connectivity after about 10 percent of the nodes being removed and this trend continues until node removal portion reaches about 20 percent, after which the network probably becomes too fragmented and the further removal of nodes has little impact on the overall connectivity. A few cases were global efficiency of the road network seemingly increase after further nodes are removed are because global efficiency is also impacted by the changes in network size. Therefore, the level of reduction in the global efficiency due to node-removal is smaller than the positive impact the smaller-size have on the global efficiency.

CONCLUSION AND FUTURE WORK

This study proposed a probability-based simulation framework to model the percolation process in the road networks during a fluvial flooding. A highly non-linear relationship between the node removal ratio and the global efficiency of the road network is observed. One of the advantages of this study is its utilization of the publicly available big data (like planar network structure, node elevation and street grade) about road network. This study also has an intermediate finding that there is a positive correlation between proximity index and the level of inundation experienced, which means disruptions caused by hurricane induced flooding on the road networks could not be treated as random events. In the meantime, there are rooms for improvements. For example, this study only considered and modeled the fluvial flooding that is due to the overflow of the flood control infrastructure, while it is possible that multiple types of flooding occur simultaneously during a hurricane. More variables and parameters could be introduced to paint a more comprehensive picture of the disruptions caused by different types of flood. Using a connectivity measure which is not impacted by, or could account for, the varying network size will provide a more accurate sense of the change in the road network connectivity. It is also possible to relate the depth of flooding in the road network with the travel speed to develop a more accurate model about the impact of the flooding on the traffic flow.

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