Mobility Problems with Predicted Uncertainties in Transportation Network due to Storm Impacts

Ketut Gita Ayu and Pitu Mirchandani
School of Computing, Informatics, and Decision Systems Engineering
Arizona State University
Tempe, AZ 85281, USA
kgita@asu.edu, pitu@asu.edu

Abstract

Disaster such as hurricane, by nature, involves uncertainties in many facets, from the time of its occurrence to magnitude of its impacts. Due to its highly erratic movement, uncertainty during a storm event can quickly cascade. Failure to incorporate these uncertainties when forming any emergency response operations can significantly affect the efficiency and effectiveness of the operations. Understanding that the storm hazards such as strong winds, torrential rain, and storm surge can inflict significant damage on the transport network affecting population's ability to move during/after the storm event, we proposed a cascading network failure model to accentuate this mobility issue. The model takes the scenario-level storm impacts generated by the data-driven probabilistic scenarios model from our previous work as inputs to predict uncertainties in the land transport network states during the storm event. We tested the model on Hurricane Irma case study to determine the mobility states of the Tampa Bay network over the 72-hour time horizon. The proposed model serves as a mean to predict uncertainty in the mobility states over the course of a storm event – a critical factor in forming effective and efficient response operation models.

Keywords
Hurricane, Storm Impacts, Transport Network, Mobility Prediction

1. Introduction

Disaster management aims to lessen the impacts of disaster in terms of fatalities and the potential losses experienced by the society. Disaster such as hurricanes, by nature, involves uncertainties in many facets, from the time of its occurrence to magnitude of its impacts. These uncertainties can substantially influence the effectiveness and efficiency of any actions taken prior and/or during the course of the storm event. Note that, most disaster response actions operate on the road network which is greatly affected by the environment. Since weather is complex and dynamic, it is impractical to examine the impacts of every weather phenomenon (Pisano et al. 2001). Thus, only selected phenomena with significant immediate effects should be considered when determining the changes in the road transport.

During a storm event, uncertainty is largest with respect to the consequences for wind strengths, precipitation patterns, and surge heights (US Climate Change Science Program 2008). Storm surge and intense rainfall affect roads through freshwater inundation and inland flooding whereas wind and rainfall affect vehicle maneuverability and driver capabilities. All of these affect the performance of the road transport system in forms of reduction in traffic speed and roadway capacity, and increase in travel time (Pisano et al. 2001). Disclosing changes in the network and its uncertainties due to these storm impacts could avoid a later loss of credibility if actual result proved to be significantly different from the predicted results. Hence, it is necessary to take justifiable predictions on the changes in the road network and mobility states into consideration when developing any response operations models.

In this paper, we propose a new methodology to predict cascading transportation network failures during a storm event. The procedure takes the storm impacts forecasts to predict changes in the transport infrastructure while simultaneously determining the demand for population movement and potentially safe destinations. The resulting stochastic-dynamic network can then be utilized as basis to form appropriate response operations. The next section of this paper provides a brief methodology; followed by subsections documenting the model details and the corresponding algorithms. Applications of the proposed methodology to determine the mobility states of the Tampa

Bay network during the 2017 Hurricane Irma are presented next. Concluding remarks and future research directions are offered in the last sections of this paper.

2. Methods

2.1. Problem Description

The network consists of n nodes and m arcs. Nodes represent incorporated places, for example, cities, towns, municipalities, and census-designated places. The attributes of a node include geographic (e.g., latitude, longitude, and elevation) and demographics (e.g., population count, household, number of vehicles per households, and housing year built). Google Maps application is utilized to determine the location and the demographics data is retrieved from the 2017 American Community Survey (US Census Bureau 2019).

Arcs represent major, arterial, and connector roads which include interstate highways, turnpikes and most other toll roads, U.S. Routes, and State Roads (FDOT 2013). The arc's elevation is assumed to be within the range of the elevations of its two end nodes, that is, no "valley" arc. The attributes of an arc include its two end nodes, maximum capacity, length, and average travel speed without traffic. The maximum capacity is estimated based on the number of lanes and road type (e.g., interstate, US routes, state roads, county roads). Google Maps application is used to determine these arc attributes. As the predicted storm hazards are at the 27 km x 28 km grid level, their effect on nodes (and arcs) are determined based on the grid(s) in which these nodes (and arcs) reside. An algorithm, not discussed in here, is introduced to determine the grid where the node (and arc) is located.

2.2. Cascading Network Failure Model

The approach begins with predicting the change in the transport network upon considering individual storm impact and then assimilate them to generate the predicted overall impacts over the time horizon. In here, we assume the coming hurricane is a 24-hour 100-year storm event and its attributes and associated hazards over the study area at every time step are available. We also assume that the predicted storm hazards are independent of each other. Two possible cases: threshold case and probabilistic case, are then considered. In the threshold case, the algorithm takes a preset threshold value for an impact to be considered significant. Its output is a deterministic spatial-temporal mobility states, for example, a node is safe or unsafe and an arc is traversable at normal, reduced, or zero capacity. In the probabilistic case, the mobility states are expressed in a form of piecewise function with probability of occurrences (e.g. probability of a node being safe, probability of an arc being traversable at normal, reduced, or zero capacity). Outputs from the network failure model is the probabilistic predicted changes in the transport network states over time. Emergency responders can use the resulting network as basis in developing or evaluating their response operation models. See Figure 1 for the schematic illustration of the cascading network failure approach.

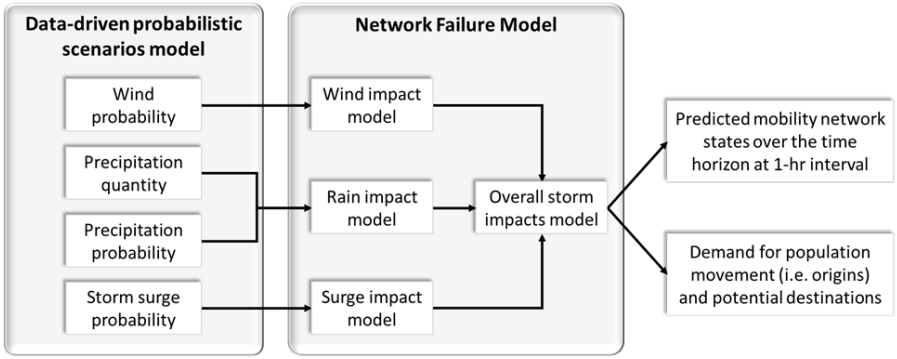


Figure 1. The Cascading Network Failure Modeling Approach

The cascading network failure model is comprised of three sub-algorithms, each generates the individual spatial-temporal predicted impact (i.e. wind, precipitation, storm surge), and one sub-algorithm that assimilates the individual impacts to generate the overall storm impacts unto the network. These sub-algorithms will be discussed separately in the following sequence: the algorithm for 1) wind speed impact, 2) rain impact, 3) storm surge impact, and 4) overall storm impacts. We utilize Naylor and Finger's 3-step approach to validate the algorithm. In the face validation, we use visualization comparison and reasonableness of the outputs, data source reliability and statistical distribution for assumption validation, and the visualization comparison for spatial aspect for the input-output validation.

2.2.1. Wind Impact Algorithm

High winds commonly occur during strong weathers, such as hurricanes. When the 1-minute average surface winds are sustained at least 40 mph or 34.8 knots for one hour or longer, the National Weather Service (NWS) issues high wind warnings and watches as any unsecured outdoor objects could easily blow away and cause damage or injury (NHC 2018). Damages caused by the high winds include downed trees and power lines, building or structure collapses, and flying debris. These wind damages lead to transportation disruptions, power outage, uninhabitable places, and injury or death – altering the state of both nodes (i.e. safe or unsafe) and arcs (i.e. traversable or not) in the transport network.

Recall that a node represents a city, town, village, or census-designated place. A node is unsafe when buildings and structures in the node are expected to be damaged by the high wind. That is, the predicted maximum sustained wind speed (MWS) exceeds the wind design speed of the buildings and structures, commonly referred to as the ultimate design wind speed, V_{ult}, which its value can be obtained from the state's building code. This building code regulates all buildings or structure, or any appurtenances connected or attached to such buildings or structures and is based on the national model building codes and national consensus standards. For example, Florida Building Code provides discussion in detail about the design wind speed for buildings and structures that fall in each risk category. By assuming that all buildings and structures in the nodes comply with the code, we can determine the respective V_{ult} accordingly.

To determine the maximum wind speed (MWS) in a node, we first define the hurricane winds' radial structure which can be represented using piecewise continuous wind profiles (Kossin et al. 2007, Willoughby et al. 2006). That is, inside the eyewall, wind increases in proportion to a power of radius while outside the eyewall, the wind decays exponentially. As the strongest wind within the storm occurs at the eyewall, a node that is located inside the eyewall, at any moment as the storm moves, is expected to experience the maximum wind speed. A node that is located outside the eyewall, the MWS can be estimated using exponential decay function. Let x be the distance to the storm center and y be the wind speed. Note that, the radius of 64-kt or R_{64} and MWS can be retrieved from the National Hurricane Center (NHC) forecast advisory (NHC 2016) whereas the radius of the maximum wind, R_{max}, can be computed using equation in Quiring et al. (2011). Using these two (x, y) points (R_{max}, MWS) and $(R_{64}, 64)$, we can generate the decay function by substituting the x and y of the two points into the equation $y = ax^b$ and solving for the parameters a and b. The maximum wind speed that a node is expected to experience can be computed based on its radial distance to the storm center.

We define, in the "threshold" case, a node is unsafe only if the following two conditions are met: (1) the maximum wind speed exceeds the design speed, i.e. $MWS \geq V_{ult}$, and (2) the probability of wind speed exceeds 64 knots exceeds the threshold value α, i.e. $P(\text{wind speed} \geq 64kt) > \alpha$. Otherwise, we claim that the node is safe. In the "probabilistic" case, we define the probability of a node being unsafe as the probability of wind speed exceeds 64 knots when the predicted maximum wind speed value exceeds its design speed, $P(\text{node is unsafe}) = P(\text{wind speed} \geq 64kt, MWS \geq V_{ult})$. In summary, when $MWS \geq V_{ult}$, the probability of a node is safe, $P(\text{node is safe}) = 1 - P(\text{wind speed} \geq 64kt, MWS \geq V_{ult})$ and when the $MWS < V_{ult}$, then the node is safe, i.e. $P(\text{node is safe}) = 1$, regardless of the value of the 64-kt wind speed probability.

High winds can play a major role in vehicle operations as it can decrease their stability and control. As tropical storm-force winds (34-kt) are strong enough to be dangerous, evacuation process are commonly terminated before the onset of the tropical storm-force winds (NHC 2015, Wolshon et al. 2005). The federal highway regulation regulates bridge closure when the sustained wind speed blowing across reaches 39 mph or 34 knots (I-95 Corridor Coalition 2013). Based on these facts, an arc can be either traversable or untraversable. In the "threshold" case, if the probability of wind speed of at least 34 knots blowing across the arc exceeds the threshold value α (i.e. $P(\text{wind speed} \geq 34kt) > \alpha$), then the arc is untraversable. Whereas in the "probabilistic case", the probability of an arc being untraversable is the 34-kt wind speed probability itself. As an arc can reside across several grids, in the "threshold" case, we define an arc is untraversable if it is untraversable in at least one of its segments. For example, if arc L_{ij} is in grid $\{G_1, G_2\}$, then arc L_{ij} is traversable only if it is traversable in both grids. In the "probabilistic" case, we use pessimistic approach and set the probability of arc L_{ij} being untraversable as the maximum of its probability being untraversable over all segments.

2.2.2. Rain Impact Algorithm

Potential roadway flooding comes from storm surge for coastal areas and torrential rain for inland areas. Rain of any intensity decreases traffic speed and roadway capacity which result in higher crash risk and increase in travel time. Heavy rain in particular can produce very low visibility, lane submersion, flooded underpasses, and damage to roadbeds (Pisano et al. 2001) altering the state of both nodes (i.e. safe or unsafe) and arcs (i.e. traversable at normal attribute value, traversable at reduced attribute value, or untraversable) of the transport network.

A node is considered unsafe if flooding due to torrential rain is expected to occur. That is, the *predicted rainfall intensity* r *exceeds the design storm drains* ω of the node. The storm drain is designed to drain excess rain and ground water from impervious surfaces (Chow et al. 2003). Plumbing section in the state's building code provides discussion on storm drainage that is based on 100-year hourly rainfall rate (in inches/hour). Hence, assuming the drainage system of the nodes comply with the plumbing regulation listed in the building code, we can specify the storm drains of the nodes in the network according to their whereabouts.

The available spatial-temporal rainfall data is in the form of precipitation amount (QPF) expected to fall in a 6-hour interval (inches/6-hour), while the storm drains discharge rate is at hourly interval (inches/hour). To match the units, we need to convert the 6-hour QPF to hourly rain rate. One option is by assuming that the QPF value is uniformly distributed within the 6-hour interval, but this approach underestimates the maximum rainfall rate which is critical in determining potential flooding of an area. The other possible approach is to utilize *design storm* to create distribution of rainfall intensity over the time horizon. Design storm represents storm precipitation pattern where its amount corresponds to rare frequencies (i.e. "worst case scenario"). It is constructed based upon historical precipitation data or general characteristics of precipitation in the surrounding regions (USDA-NRCS 2015). The design storm is used in the design of hydrologic systems in most jurisdictions in the United States. It can be defined by a *design hyetograph*, an isohyetal map, or a value for precipitation depth at a point (Chow et al. 2003). Design hyetograph specifies the *time distribution of rainfall during a storm* while isohyetal map specifies the spatial pattern of the precipitation. As our interest is the *temporal distribution of rainfall intensity*, we utilize design hyetograph to generate the distribution.

The hyetograph is developed by the Natural Resource Conservation Service (NRCS) or previously Soil Conservation Service (SCS) based on the analysis of observed storm events (USDA 1986). As the patterns in precipitation of event storms have been changing over the past decades, NOAA Atlas 14 is introduced to replace the SCS design hyetograph developed in 1961 (Merkel and Moody 2015). NOAA Atlas 14 incorporates precipitation data through 2011 and utilizes data from more weather stations. It is the official U.S. Government source of precipitation frequency estimates on temporal distribution of heavy precipitation (HRWC's Climate Resilient Communities Project 2016, Perica et al. 2018, USDA-NRCS 2017). Volume 9 of NOAA Atlas 14, for example, was released in 2013 for Midwest and Southeast (MSE) regions. A rainfall distribution map with six rainfall distribution patterns are generated to cover the Midwest and Southeast regions. These distributions are named MSE-1 through MSE-6 (Merkel and Moody 2015). These MSEs provide ratio of accumulated rainfall distribution at 1-hour interval of a 24-hour 100-year storm event. The temporal rainfall distribution is then estimated by multiplying the ratio with the predicted accumulated rain over the 24-hour interval.

Table 1. Rain Impacts on Roads

Element (reduction)	Light rain	Heavy rain
Average speed	3-13%	3-16%
Free flow speed	2-13%	6-17%
Volume	5-10%	14%
Capacity	4-11%	10-30%

In the "threshold" case, a node as unsafe (or flooded) when the rain rate exceeds node's storm drains discharge rate and the probability of precipitation (PoP) exceeds the threshold value α. The duration of flooding depends on the node's previous state, i.e. flooded or not. When the previous state is flooded, we need to consider the accumulated rain to be discharged by the storm drains. For example, if the rain rate on a node with storm drain rate ω, 4 in/h at time (t) and $(t+1)$ are 6 and 3 in/h, respectively, then the status of the node at time $[t, (t+1)]$ is [unsafe, unsafe] instead [unsafe, safe] due to the rain accumulated by time $(t+1)$. In the "probabilistic" case, the probability of a node

being unsafe is the rain probability when the rain rate exceeds the storm drains discharge rate, that is $P(\text{node is unsafe}) = P(\text{rain}, r_t > \omega)$ where r_t is the rainfall intensity at time t.

The Federal Highway Administration (FHWA) provides documented operational practices under various weather threats such as rain, snow, and fog (FHWA 2017, Hranac et al. 2006). The FHWA define rain impacts on roads in terms of reduction in speed, volume, and road capacity (see Table 1). The rainfall is classified as light rain when the rate is 0.01 to 0.25 in/h and heavy rain when the rate is greater than 0.25 in/h. Hranac et al. (2006) claimed that capacity reduction remains constant and not affected by the rain intensity when it is in range of 0 to 0.67 in/h. Moreover, a 2 to 3 in/h rain is claimed to typically create minor street flooding and cumulative of 8-10 inches within an hour or two usually severely flooded roads and overflowed canals (Kaye 2013). Based on these facts, we define three arc states: *untraversable*, *traversable at reduced* value, or *traversable at normal* value. For simplicity purpose, throughout the discussion, let's assume that the arc attribute we are interested in is its capacity. The reduced value can be computed using the piecewise function according to the findings from the literature. This piecewise function represents the relationship between rainfall intensity and reduction in arc's attribute and is summarized in Table 2 below.

Table 2. Piecewise Function of Rainfall Intensity and Reduction in Arc Capacity

Rain type	Rain rate (in/h)	% reduction	Relationship
Very light rain	$r < 0.01$	0	Constant
Light to heavy rain	$0.01 \leq r < 0.67$	4 – 11	Linear
Very heavy rain	$0.67 \leq r < 2.00$	11 – 30	Exponential
Torrential rain (minor flooding)	$2.00 \leq r < \omega$	30 – 100	Exponential
Torrential rain (major flooding)	$\omega \leq r$	100	Constant

The piecewise function provides information only on the amount of capacity changes. By incorporating the precipitation probability information, we can define the state of an arc in both cases as follow. In the "threshold" case, when the rain probability exceeds the threshold value α (i.e. $PoP > \alpha$), depending on the rainfall intensity at that particular time step, the arc can be traversable at its maximum capacity (rain rate $r < 0.01$ in/h), at reduced capacity (0.01 in/h $\leq r < \omega$ in/h) , or untraversable ($r \geq \omega$ in/h). Otherwise, the arc is traversable at its maximum capacity. In the "probabilistic case", the PoP value represents the probability of the arc having such capacity. As an arc can be across several grids, the arc capacity is determined as the minimum capacity over all its segments and its associated occurrence probability.

2.2.3. Storm Surge Impact Algorithm

Storm surge poses significant risk to transport network due to the immediate flooding on the infrastructure and damage caused by water force. The amount of inundation inland caused by the surge is controlled by the elevation of the land (US Climate Change Science Program 2008). For example, in a 5 feet surge, a land at elevation of 3 feet will receive as much as 2 feet of inundation but a land at elevation above 5 feet will expect no inundation. During each period of inundation, roads are impassable affecting the state of both nodes (i.e. safe or unsafe) and arcs (i.e. traversable at normal attribute value or untraversable) of the transport network.

As we assume population is concentrated in a node, it is important to know whether or not the node is inundated due to the storm surge. We define a node is unsafe (i.e. inundated) if the *predicted surge height exceeds the node's elevation* and safe otherwise. As an arc represents a road connecting two nodes, it is unreasonable to traverse along the arc if any of its end nodes is inundated. Based on these assumptions, we define the states of nodes and arcs as follow. In the "threshold" case, a node is unsafe (or inundated) if the occurrence probability of surge height surpasses the node's elevation exceeds the threshold value α. In other words, $P(\text{surge height} \geq \text{elevation}) > \alpha$. An arc is traversable at its normal attribute value (e.g., maximum capacity) only if both of its end nodes are safe. In the "probabilistic" case, the probability of a node being unsafe is defined as the probability of surge height surpasses the node's elevation, that is $P(\text{node is unsafe}) = P(\text{surge height} \geq \text{elevation})$, whereas the probability of an arc being untraversable is equivalent to the maximum of the probabilities of its end nodes being unsafe. Considering an arc can be across several grids, in the "threshold" case, an arc is untraversable if it is untraversable in at least one of its segments whilst in the "probabilistic" case, the probability of arc L_{ij} being untraversable is the maximum of its probability being untraversable over all segments.

2.2.4. Overall Storm Impacts Algorithm

To this end, we define the individual storm impacts on nodes and arcs of the transport network. As we assume these storm impacts are independent of each other, we can define the impacts of wind, rain, and surge altogether on the transport network using basic probability theory. For the "threshold" case, a node is safe only if it is safe in all impacts and unsafe otherwise, whereas the arc's attribute value (e.g. capacity, travel speed) is equivalent to the minimum value across all impacts.

For the "probabilistic" case, a node is safe only if it is safe in all impacts. Recall that the wind impact as well as the storm surge impact results in an arc be either traversable at its normal attribute value or untraversable. The impact of rain, on the other hand, can result in variation in the arc's attribute value ranging from untraversable to traversable at its normal value. Fortunately, this variation is binary, aka traversable at a "reduced" value when precipitation occurs or traversable at its normal value when no rain is expected to occur. Define three possible arc state: (a) traversable at its *normal* value, (b) traversable at a *reduced* value, and (c) *untraversable*. As the storm impacts are assumed independent, eight possible events constitute the sample space of the possible combinations along with their occurrence probabilities can then be determined using probability theory.

3. Hurricane Irma Empirical Study

The Florida Regional Planning Councils (RPCs) are quasi-governmental organizations comprised of local governments to address problems and plan solutions that are greater than local scope (FRCA 2019). The RPCs are required to exercise regional cooperation in growth management programs and in emergency preparedness program planning and hurricane evacuation and recovery planning (Tampa Bay RPC 2018). In this research, we limit the scope of the transport network being evaluated to the Tampa Bay RPC (see Figure 2) which covers six counties, Citrus, Hernando, Hillsborough, Manatee, Pasco, and Pinellas. The Tampa Bay network has 152 nodes and 271 arcs with line thickness represents the arc capacity (see Figure 35). The nodes represent incorporated places such as cities, towns, villages, and census-designated places while the arcs represent major, arterial, and collector roads connecting the nodes. Dummy nodes are added around the border of the Tampa Bay region as exit/entry nodes between Tampa Bay and its surrounding RPCs. Dummy nodes are also added in selected intersections where there is more than one main road that connects the same two end nodes. Each node has location information (e.g., latitude, longitude, elevation, grid number where it resides) and demographic data (e.g., population, housing, number of vehicles), except the dummy nodes which only have the location information. The location and demographic data are retrieved from Google Maps and 2017 American Community Survey, respectively.

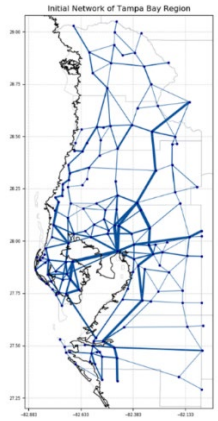


Figure 2. Transport Network of Tampa Bay Region

All buildings and structures in the network are assumed comply with the 2010 Florida Building Code (FBC). The FBC regulates all buildings or structure or any appurtenances connected or attached to such buildings or structures in the State of Florida (FBC 2010). The 2010 edition of the FBC introduced significant changes to wind load design, particularly in the presentation of the wind speed maps. No changes to the wind speed maps were observed from the 2010 edition to the latest one, 2017 FBC. Since the 2017 edition was issued in December 2017, we refer to the 2010 FBC to define the wind design speed of a node. Chapter 16 in the 2010 FBC discusses in detail about the wind speed requirement, the ultimate design wind speed, V_{ult}, for buildings and structures that fall in each category.

Four risk categories are assigned to reflect current understanding of the nature of occupancy and risk to human life in the event of damaged or failure. Buildings and structures with a low hazard to human life are assigned to Risk Category I while the ones with substantial hazard are assigned to Risk Category III. Essential facilities where their availabilities are necessary to cope with an emergency are assigned to Risk Category IV. All other buildings and other structures do not fall into any of the aforementioned three categories are assigned to Risk Category II with residential, commercial, and industrial buildings as the examples. The wind design speed, V_{ult}, for buildings and structures over Florida that fall in Risk Category II is depicted in Figure 3 which is equivalent to Figure 1609.3(1) in the 2010 FBC. The V_{ult} of a node can then be defined by assuming that all buildings and structures comply with the FBC.

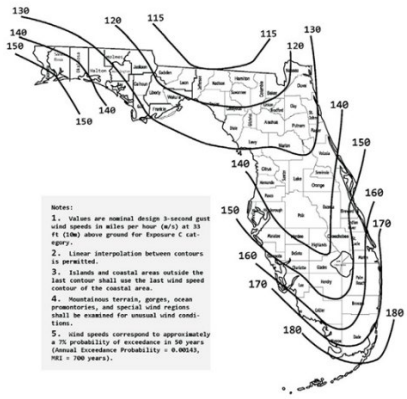


Figure 3. Ultimate Design Wind Speed for Buildings and Structures in Risk Category II

Chapter 11 in the building code of the 2010 Florida Building Code: Plumbing (FBCP) also provides discussion on storm drainage that is based on 100-year hourly rainfall rate (inches/hour) as indicated in Figure 1106.1 in the 2010 FBCP. By assuming that the storm event being studied is a 24-hour 100-year storm and the drainage system in Tampa Bay area complies with the 2010 FBCP, we can specify the storm drains of the nodes in the network according to their whereabouts in Figure 4. For example, the storm drains discharge rate ω in Lee county is 4.5 in/h whereas in Levy county is 4.25 in/h.

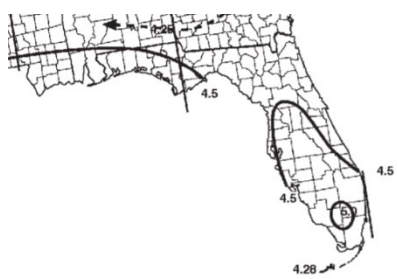
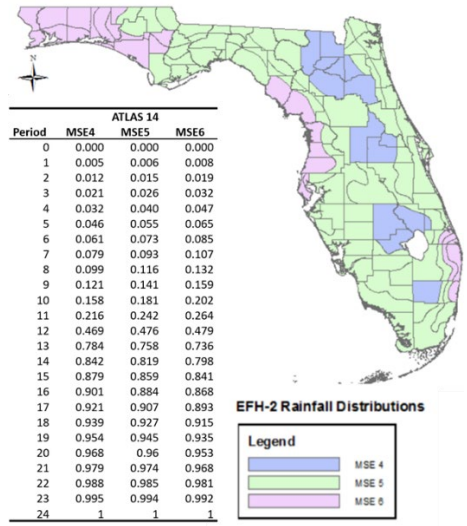


Figure 4. 100-Year Hourly Rainfall in Inches (Figure 1106.1 in 2010 FBCP)

Volume 9 of NOAA Atlas 14 was released in 2013 for Midwest and Southeast (MSE) regions. A rainfall distribution map with six rainfall distribution patterns are generated to cover the Midwest and Southeast regions. These distributions are named MSE-1 through MSE-6 (Merkel and Moody 2015). As can be seen in Figure 5, the MSE-4, MSE-5, and MSE-6 are the rainfall distribution patterns for locations in Florida. The MSEs provide ratio of accumulated rainfall distribution at 1-hour interval of a 24-hour 100-year storm event. Hence, the temporal rainfall distribution can be computed by multiplying the ratio with the predicted accumulated rain over the 24-hour interval.

The arcs connecting the nodes are mostly major, arterial, and collector roads. Some local roads are included if it is the only road that connects the nodes. Each arc has its normal capacity, distance, average travel speed, and the grid(s) where it lays on. Google Maps is again used to determine the arc attributes except the capacity. As capacity varies

according to the travel speed and road size, we define the maximum arc capacity according its road type (e.g., interstate, US route, state road, county road, or local) and the number of lanes. This maximum capacity is estimated using FDOT real-time traffic counts during Hurricane Irma. For simplicity purpose, the storm impacts are represented as weight factor. The arc capacity can then be estimated by multiplying the weight factor with its maximum capacity during normal condition.



	ATLAS 14		
Period	MSE4	MSE5	MSE6
0	0.000	0.000	0.000
1	0.005	0.006	0.008
2	0.012	0.015	0.019
3	0.021	0.026	0.032
4	0.032	0.040	0.047
5	0.046	0.055	0.065
6	0.061	0.073	0.085
7	0.079	0.093	0.107
8	0.099	0.116	0.132
9	0.121	0.141	0.159
10	0.158	0.181	0.202
11	0.216	0.242	0.264
12	0.469	0.476	0.479
13	0.784	0.758	0.736
14	0.842	0.819	0.798
15	0.879	0.859	0.841
16	0.901	0.884	0.868
17	0.921	0.907	0.893
18	0.939	0.927	0.915
19	0.954	0.945	0.935
20	0.968	0.96	0.953
21	0.979	0.974	0.968
22	0.988	0.985	0.981
23	0.995	0.994	0.992
24	1	1	1

Figure 5. NOAA Atlas 14 Volume 9 Rainfall Distribution for Florida

5. Results and Discussion

We define 15 instances generated by the simulation model correspond to NHC advisory number 34 to 48 as our test cases[1] because no storm surge data of Hurricane Irma is available for the other advisories. For the threshold case, the algorithm first convert the probabilities to binary state based the preset value α of an impact to be considered as significant, i.e. if $P(\text{occurrence}) > \alpha$, then $P(\text{occurrence}) = 1$. For the wind speed probabilities, α varies according to the forecast periods and wind types (Brown 2013, NWS 2019).

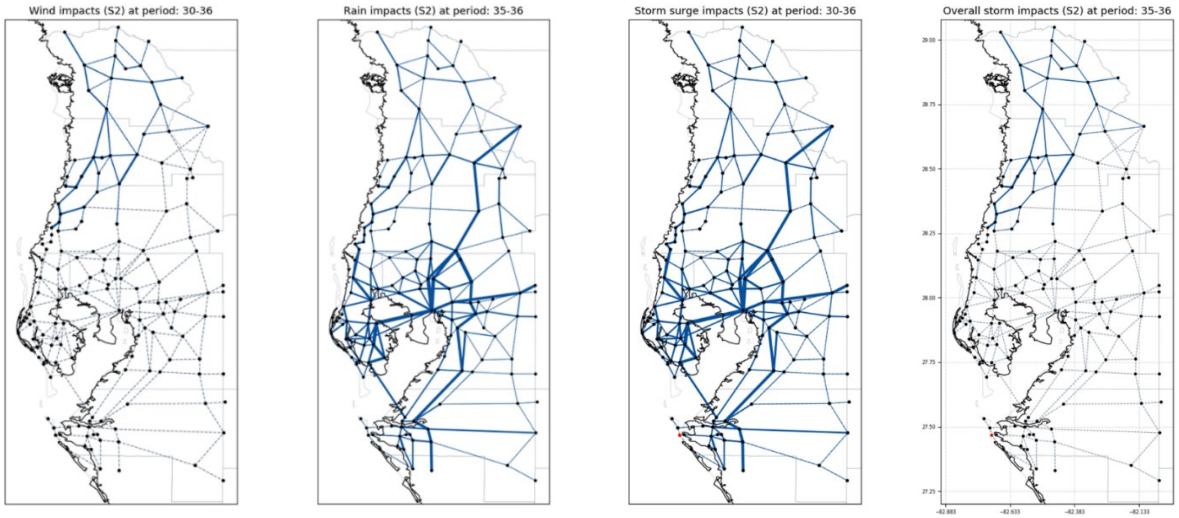
In here, we set $\alpha = 0.35$ and $\alpha = 0.20$ for the wind speed probabilities of a tropical storm and hurricane, respectively, $\alpha = 0.60$ for the precipitation (NWS 2018, WPC 2016), and $\alpha = 0.10$ for the storm surge because the NHC uses a 10% probability of occurrence as a first-cut threshold for the surge watch/warnings (Cangialosi et al. 2018). No preset value is defined in the probabilistic case. The overall runtime of the algorithm is approximately 8 minutes on average. The wind and rain impact algorithms have larger runtime because these two algorithms have to generate the associated wind graph and rainfall distribution, respectively, for each grid prior determining the status of the network. Note that, the algorithm generates not only the state of the transport network over the time horizon, but also provides information on the origins and potential destinations for evacuation. Zooming into advisory 40, according to the predicted state of the network over time, population in Bradenton Beach must be evacuated by 49 h in all scenarios except in scenario 2. We also observe variations on the evacuation time and origins among scenarios (see Table 3) which underlines the importance of incorporating uncertainty when determining response actions particularly in evacuation.

Sequential color scheme is used in the visualization to analyze the underlying arc's attribute value, i.e. normal capacity, reduced capacity, and zero capacity. We set five classes to represent the changes in the arc's attribute over time where the lighter the color implies the attribute value decreases and dashed line implies that the arc is impassable. Figure 6 provides example of the individual and overall storm impacts on the Tampa Bay region network in one scenario at time 36 h for advisory number 40.

[1] Courtesy of Shaurya Jaisinghani for compiling the dataset

Table 3. Evacuating Nodes for Each Scenario along with its Required Vacant Time

Scenario	Evacuated by	Origin(s)
1	49 h	Bradenton Beach
2	43 h	Bradenton Beach
	49 h	Cortez, Holmes Beach, Longboat Key
	55 h	Anna Maria, Aripeka, Hernando Beach, Jasmine Estates, South Pasadena, St. Pete beach, Tierra Verde
3	49 h	Anna Maria, Bradenton Beach, Cortez, Holmes Beach, Longboat Key, Spring Hill, St. Pete Beach, Tierra Verde
	55 h	Aripeka, Hernando Beach, Jasmine Estates
4	49 h	Anna Maria, Bradenton Beach, Cortez, Holmes Beach, Longboat Key, South Pasadena, St. Pete Beach, Tierra Verde
	55 h	Aripeka, Hernando Beach, Jasmine Estates



(a) (b) (c) (d)

Figure 6. Individual and Overall Storm Impacts in Scenario 2 at 36 h

6. Conclusion and Future Works

Road transport network is the backbone of moving people and goods in the United States and its operational activities are greatly affected by the weather conditions. During a storm event, the importance of road transport amplifies as it becomes primary means for evacuation and other response operations. Being able to predict the potential changes in the transport network due to the storm impact is of interest to decision makers to arrive at founded response operations. Since a large part of disaster response operations use transportation networks, which are greatly impacted by the weather conditions, a network failure model introduced in this research aims to predict the network states for a given set of weather forecasts over the course of a disaster event. We use the model to determine the mobility states of the Tampa Bay network over the time horizon during Hurricane Irma. It takes the spatial-temporal weather profiles from the simulation model to determine the mobility states of the Tampa Bay area network. The resulting stochastic dynamic network that explicitly represents uncertainties in the predictions of the network states during a storm event can then be utilized to derive the appropriate response operations.

When predicting the mobility states, the model compares the node's elevation with the storm surge height to determine whether evacuation should be issued for population residing in that node. Since choosing the appropriate elevation is important, it is possible to define the elevation of a node using the center of population distribution approach as

opposed to using directly the one available in Google Maps (as done in the models in this research). Moreover, the current impacts model assumes that buildings, structures, and storm drainage comply with the current building code. Yet, per demographic data, vast majority of the buildings and structures are built in much earlier years. Upon comparing the building codes which are generated every four years, it was found that the wind load requirement can vary significantly during these years. Hence, it may be better to utilize the year structure built in order to better represent the impacts on building structures.

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Biography

Ketut Gita Ayu is an assistant professor at BINUS University. She received B.S. and M. S. degrees in Industrial and Systems Engineering from Georgia Institute of Technology, Atlanta, GA, and Ph.D. in Industrial Engineering from Arizona State University. She served as the department chair of the Industrial Engineering undergraduate program in BINUS University, Jakarta, Indonesia from 2008 to 2015. She is actively involved as program committee, track chair, and reviewers in the 2017 INFORMS Transportation Science and Logistics and past IEOM conferences. She was a recipient of CIDSE Doctoral Fellowship 2020, Best Logistics Track Paper in IEOM 2015, and Outstanding Scholastic Achievement and Excellence from the Golden Key National Honor Society. She is a senior member of IISE, a member of INFORMS, and currently served as the ABET program evaluator for Industrial Engineering program. Her areas of interest include optimization, transportation, and humanitarian logistics.

Pitu Mirchandani received the Sc.D. Operations Research from Massachusetts Institute of Technology in 1975. He is the chief scientist at Center for Accelerating Operational Efficiency (CAOE), a Department of Homeland Security Center of Excellence. He is a professor of Computing, Informatics, and Decision Systems Engineering (CIDSE) at Arizona State University and holds the AVNET Chair for Supply Chain Networks. He is also a senior sustainability scientist within the Julie Ann Wrigley Global Institute of Sustainability and the director of Advanced Transportation and Logistics: Algorithms and Systems (ATLAS) Research Laboratory. His areas of expertise include optimization, decision-making under uncertainty, real-time control and logistics, application interests in urban service systems, transportation, and homeland security. He is a Fellow in IEEE and in editorial boards of: IIE Transactions on Scheduling and Logistics; Transportation Science; Advanced Transportation; Industrial Mathematics; Transportmetrica. He is a recipient of “2007 Member of the Year” by the ITS Arizona Society for contributions to ITS in the State of Arizona.