NETWORK MODELING OF HURRICANE EVACUATION USING DATA DRIVEN DEMAND AND INCIDENT INDUCED CAPACITY LOSS MODELS

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ABSTRACT

Modeling and simulation of hurricane evacuation is an important task in emergency planning and management. There are two major issues that affect development of a reliable evacuation model. The first one is how to estimate evacuation demand based on socio-economic characteristics, and the second one is how to deal with the uncertainty due to the roadway capacity loss as a result of highway incidents. Either of these factors can affect the planning of optimal evacuation routes due to their spatial-temporal impact on evacuation demand and the roadway network capacity.

This study constructs a scenario-based hurricane evacuation methodology for New York City (NYC) Metropolitan area. In the model, hourly travel demand is generated and distributed to hours following a response curve estimated using empirical data obtained from observed traffic flows prior to landfall of Hurricane Sandy. The study also aims to investigate the impact of various types of incidents on modeling and simulation of hurricane evacuation. Particularly, the incidents that occurred under actual hurricane conditions were examined and their impact on the capacity loss was modeled. The developed incident frequency and duration models were incorporated into the evacuation model used to study traffic conditions under hurricane Sandy in New York City. The results are shown to be consistent with the predictions of the developed evacuation model and observed sensor based travel times as well as zone to zone trip times of NYC taxi data.

Keywords: Hurricane evacuation, modeling and simulation, evacuation demand, traffic incidents, capacity loss
INTRODUCTION

Recent hurricanes such as Irene and Sandy have made hurricane evacuation one of the leading emergency management issues in many coastal areas under the risk of similar hurricanes. An evacuation plan that can ensure timely evacuation of affected residents from the potential impact areas to safer locations is an essential component of an overall emergency management plan. Successful implementation of this important task primarily relies on effective planning of transportation operations prior to the impact of a hurricane. However, this kind of planning process is quite challenging because of the large-scale and complex nature of transportation systems and uncertainties associated with it. Typical issues include “insufficient information about the storm, limited emergency response resources, lack of efficient coordination and effective utilization of available roadway capacity” (1). According to Yazici and Ozbay (2), there are two primary sources of uncertainty in evacuation transportation modeling: (a) randomness in evacuation demand and (b) roadway capacity. Experiences show that the evacuation traffic patterns in terms of volume and departure time might be different than the normal travel condition (3, 4) due to the complicated evacuation decision (5). Likewise, the roadway capacity under emergency condition is largely affected by traffic incidents such as crashes, disabled vehicles and roadway flooding. The randomness of the traffic incident occurrence and characteristics (e.g. duration and severity) further put the timely evacuation needs under pressure. In general, if the traffic volume exceeds roadway capacity on one or more critical roadway segments under the evacuation condition, the evacuation process will be largely delayed due to the problem of oversaturation (reduced capacity and speed) (6). Thus, traffic incidents raise great concern to emergency planners managing an evacuation.

Existing research have showed that the regional transportation planning models have the potential to be used for evacuation modeling. However, these models have to be used with caution as many assumption such as time of day, notice or no-notice, passengers per car, and background traffic in the network should be considered in a way they reflect evacuation specific conditions (7, 8). The probabilistic road capacity constraints are also deemed to affect the evacuation traffic assignment (9, 10). In light of the notable impact of the incidents, some studies such as Robinson et al. (11) and Edara et al. (12) started to tackle the issue by incorporating traffic incident impact in the evacuation models.

Due to the limited number of real-world evacuation cases, more research is needed to understand these issues clearly. Thus, the main objective of this paper is to examine the impact of traffic incidents on evacuation modeling and simulation by examining the most recent hurricane experiences in the Greater New York City metropolitan area. It focuses on the impact of incidents on roadway capacity loss. Unlike the existing studies, the frequency and duration of different types of incidents that occurred under hurricane conditions are studied in this paper. Statistically robust incident generation models are developed and incorporated into a network assignment model to examine the effect of the modeled capacity losses on the modeling results. Results from the model are analyzed against real-world observations. Overall, promising results are obtained from of the enhanced evacuation modeling approach.

LITERATURE REVIEW

In recent years, numerous studies have been conducted to simulate behavior and impact due to evacuation activities for various extreme events. Silva and Eglese (13) designed a spatial decision support system (SPSS) which links geographic information system (GIS) to evacuation
modeling and enable simulating dynamics of the whole evacuation process. Chiuet al. (1) introduced an approach to transform typical planning network to evacuation network in which evacuation demand, destination and connectors are specified. Lu and Gao (14) developed methodology for estimating evacuation for small regions due to chemical spills using Dynamic Traffic Assignment (DTA), and performed simulation using TransCAD to predict traffic impacts on major roads. Their results show useful predictions of network condition and evacuation performance. A detailed overview of evolutions of highway-based evacuation modeling over past decades is performed by Murray-Tuite and Wolshon (15). Yazici and Ozbay (2) built a system-optimal dynamic traffic assignment model using stochastic modeling approaches which considered probabilistic demand and capacity constraints. The proposed model is proven to be more reliable than deterministic point estimation in evacuation process. Ozbayet al. (8) applied equilibrium assignment tools to evacuation modeling based on multiple scenarios, which are later tested with a case study in North New Jersey. Besides, the study discussed effect of assumption and data input on model estimation. Results presented suitableness to which regional planning models are used in evacuation modeling. One of critical issue in evacuation analysis is to justify the demand of evacuation. Baker (16) identified variables in determining evacuation demand based on post-hurricane sample surveys. These variables include: Vulnerability of Area, housing, prior perception of personal risk, storm-specific threat factor etc., which is shown on his later research (17). An approach to predict coastal flooding and its impact to number of evacuees based on three-dimensional coastal ocean model was proposed by Tanget al. (18), and applied to coastlines of Cape May, New Jersey. Yin et al. (19) introduced a hurricane evacuation demand estimation system using Agent-Based Modeling. The system implemented typical evacuation decisions covering whole evacuation process, including pre-evacuation preparation. Activity-based approach is used in this study to estimate hurricane evacuation for Miami-Dade area.

Ozbay and Yazici (20) evaluated parameters of demand generation under different selections of behavioral response curves using System Optimal Dynamic Traffic Assignment (SO-DTA) applied in Cape May County network. The results showed these parameters changed with different selection of response curves. Thus calibration and validation are necessary. A comprehensive review of demand generation and network loading approaches is presented by Ozbay and Yazici (21).

Besides variability in evacuation demand, estimation of changes in network capacity is another challenge in evacuation modeling process. The non-recurrent traffic incidents such as crashes and disabled vehicles blocking lanes can greatly reduce the roadway capacity. The special characteristics of traffic incidents under evacuation conditions particularly draw more attention as the evacuation process might be delayed and expose the evacuees to additional danger (22). Thus, the impact of these incidents should be carefully addressed in evacuation modeling. For example, Wolshon et al. (23) commented that “incidents such as disabled vehicles are expected to happen during evacuations and reduce the capacity of the roadway and highlighted the need for timely assess the impact of lane closures, weather conditions and incidents”. Fonseca et al. (24) examined multiple evacuation logs for Alabama’s I-65 corridor and highlighted the proportions and duration distributions of three incident types (accident, abandoned vehicle and disabled vehicle) and a traffic incident generation module for evacuation planning was presented. Yazici and Ozbay (10) used dynamic incident generation based on cell transmission model (CTM) to explore spatial variation of shelter capacities caused by probabilistic road capacity constraints, and suggested an approach of evacuation planning which avoids insufficient planning which caused post-disaster problems.

Few studies quantitatively examined incident impact on evacuation. For example, Robinson et al. (11) simulated the impact of incidents including accidents, disabled vehicles and
abandoned vehicles under a hurricane scenario but concluded that they only increased total evacuation time by less than 10%. A follow-up study by Collins et al. (25) tested the hypothesized terrorist attack evacuation as well as hurricane evacuation scenarios and found that the evacuation duration as a result of accidents will be increased by about 8%. Edara et al. (12) simulated the impact of two incidents during hurricane evacuation and found that travel time was greatly increased and throughput decreased. It should be noted that the aforementioned studies did not use empirical incident data under actual evacuation scenarios. Instead, some of them used facility-dependent historical incident data (11), estimated from a generic incident rate model (25), and hypothesized that incidents were generated on high traffic volume segments (12). Fonseca et al. (24) is one of the few studies that developed a more detailed module for incident generation and characterization based on empirical data but with a similar assumption (e.g., incident types) as those in previous studies (11, 26).

The simplified consideration of traffic incident impact on evacuation modeling adopted in these studies may be attributed to several challenges. First, the actual incident records under hurricane conditions may not be available. For example, none of them carefully considered the impact of downed trees on roadways, which occur much more frequently during hurricane conditions than non-hurricane conditions (27). Second, modeling traffic incidents under an evacuation scenario requires a wide range factors such as road geometry and weather condition, which are usually difficult to collect. Moreover, the empirical observations of actual incident impact in different stages of the actual evacuation process needed for validating the simulation results are hard to obtain. The failure to address these important issues can greatly affect the performance and accuracy of the developed evacuation models.

DATA AND TOOLS

Data and tools for evacuation modeling

In this study, a large-scale macroscopic network model of the New York metropolitan area was used in TransCAD 6.0 (28). This network modeling effort builds on the recent work conducted by one of the authors of this paper presented in (29-31). The network and zone structure of OD matrix used in this study is based on the NYBPM 2g network. The evacuation demand is developed using various assumptions that modified original daily OD demands to reflect expected evacuation behavior of the affected populations given their location and socio-economic characteristics such as auto-ownership, number of residents per household, etc.

There are several unique features of this network model. Firstly, the model reflects the latest traffic analysis zones (TAZs), road network configuration, and socio-economic data in the NY metropolitan area. Another distinct characteristic of the model is that it uses the well-calibrated background traffic demand trip tables available from the NY Best Practice Model (NYBPM) (32), which covers 28 counties in the Tristate area and involves more than 22 million population and 53399 traffic links. For the purpose of hourly assignment, the original period-based (AM Peak, Midday, PM Peak and Night Period) trip tables are modified into hourly ones based on empirical highway volume data from Transportation Operations Coordination Committee (TRANSCOM). These datasets also include volume of critical corridors during evacuation period of Hurricane Sandy, which is used for building evacuation response curve. The methodology of constructing the response curve presented in Li and Ozbay (4) ensures that the network assignment model can capture the change of evacuation responses in a time-dependent manner.
As mentioned above, prior to network assignment, a critical step is to estimate and distribute evacuation demand to trip tables. Considering large computing requirements of modifying trip tables (4000 rows and columns for each table, 24 hourly matrices for each scenario), we developed a pre and post-processing tool named Trip Demand Matrix Generation (Tridmatrix) tool. Tridmatrix is written in Java, and it can generate hourly evacuation demand for designed evacuation zones in minutes. These output trip tables are then imported into TransCAD for performing quasi-dynamic traffic assignment method described in (8).

Incident Data

Incident data of the interstate, US and New York State highways in New York City and its surrounding areas from Oct. 1st 2012 to Jan. 31st 2013 were obtained from TRANSCOM. Figure 1 shows the areas with incident data available and the whole network used for capacity loss simulation. More detailed description of this dataset is given in Xie et al. (27). A total of 354 incidents occurred during the evacuation period (12 AM, Oct.26th, 2012- 12 PM, Oct.29th, 2012) before Sandy’s landfall. Those incidents can be classified as six different types including accident, debris, disabled vehicle, downed tree, flooding and others. The proportion for each incident type during evacuation period is presented in Table 1. According to Table 1, accidents and downed trees are the major incident types during the evacuation period, and account for over 50% of all the incidents.

![Figure 1 Areas with incident data available and the whole simulation network](image_url)
Accidents can temporarily reduce highway capacities by blocking shoulders or lanes. The amount of capacity loss caused by incidents varies across different incident types. Based on historical data, the capacity loss caused by various incident types is shown in Table 2. It can be noticed that incidents such as accident, debris, and disabled vehicle are likely to block more lanes.

<table>
<thead>
<tr>
<th>Type of incident</th>
<th>Shoulder blocked</th>
<th>One lane blocked</th>
<th>Two lanes blocked</th>
<th>Three lanes blocked</th>
<th>Four lanes blocked</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accident</td>
<td>23.60%</td>
<td>19.45%</td>
<td>35.77%</td>
<td>17.22%</td>
<td>3.96%</td>
</tr>
<tr>
<td>Debris</td>
<td>14.29%</td>
<td>28.57%</td>
<td>14.29%</td>
<td>28.57%</td>
<td>14.29%</td>
</tr>
<tr>
<td>Disabled vehicle</td>
<td>26.36%</td>
<td>12.92%</td>
<td>29.75%</td>
<td>29.58%</td>
<td>1.38%</td>
</tr>
<tr>
<td>Downed tree</td>
<td>1.96%</td>
<td>18.63%</td>
<td>69.61%</td>
<td>7.84%</td>
<td>1.96%</td>
</tr>
<tr>
<td>Flooding</td>
<td>0.00%</td>
<td>11.76%</td>
<td>88.24%</td>
<td>0.00%</td>
<td>0.00%</td>
</tr>
<tr>
<td>Others</td>
<td>3.98%</td>
<td>23.88%</td>
<td>52.24%</td>
<td>14.43%</td>
<td>5.47%</td>
</tr>
</tbody>
</table>

Table 2 Capacity loss caused by various incident types

HURRICANE EVACUATION MODELING

The basic strategy for the network-wide evacuation modeling approach is shown on Figure 2. Under the evacuation condition, the trip tables consist of both assumed background traffic and evacuation demand. Unlike most of the previous studies that assume static highway capacity based on the roadway characteristics, the roadway capacity in this study is dynamically modeled as a function of simulated incidents.
Scenarios and Assumptions

In this study, three scenarios including one base and two evacuation scenarios are developed and evaluated. The base scenario uses calibrated hourly trip table and network links based on the regional planning model. The two evacuation scenarios simulate actual Hurricane Sandy conditions, a Category 1 Hurricane which occurred in the east coast in October, 2012. The Hurricane made the landfall on New Jersey and caused serious damage to NYC and Long Island. Other than the background travel demand, the evacuation demands in both scenarios are generated based on population and assumed evacuation rates in the evacuation areas in NYC and Long Island. The hourly OD matrices are estimated using the empirical evacuation curve that is based on the actual observed traffic demands in the study area. Moreover, as stated in (8), incremental assignment is implemented by keeping residual traffic and passing them to the following assignment period. This makes the traffic assignment quasi dynamic. One evacuation scenario considers the impact of capacity loss based on the incident generation model whereas the other one does not incorporate incident impacts.

The key assumptions considered in this study are as follows. Firstly, the modeled evacuation period is defined as 24 hours from 12:00 pm to 12:00 pm of the second day. It is
consistent with the issuance of government mandatory evacuation order for Hurricane Sandy on 12:00 pm October 28, 2012, one day before the hurricane’s landfall (33). Secondly, the direction of actual evacuations varied in different administrative areas. For NYC, the residents are assumed to leave six evacuation zones to safe zones. For Long Island, the residents are evacuated from four evacuation zones to safe zones. Specifically, Zone 1 in NYC and Long Island is the Mandatory Evacuation Zone, and the trips towards these two zones are not allowed in the model.

**Steps of Model Based Evacuation Analysis**

Following steps are used to test the evacuation model:

*Step 1:* Identify the evacuation zones based on the current NYC flooding evacuation zones and TAZ attributes; and estimate the number of people that need to be evacuated based on the socio-economic data and model assumptions.

*Step 2:* In this step, both existing highway network and trip tables are modified based on hourly empirical data to perform hourly assignments for the total evacuation duration namely, 24 hours.

*Step 3:* Develop scenarios based on normal and evacuation situations. In this study, three scenarios including one base scenario and two evacuation scenarios are implemented.

*Step 4:* Modify trip tables based on evacuation demand and then modify highway network to capture capacity losses due to incidents.

*Step 5:* Run network assignment model in TransCAD using the quasi-dynamic assignment method described in Ozbay et al. (8) for each hour based on different scenarios and obtain results including the performance of network links and evacuation times between each O-D pairs of the study network.

*Step 6:* Analyze assignment results and determine evacuation times from evacuation zones to safe zones and the performance of the network with and without capacity losses.

**MODELING OF HOURLY EVACUATION DEMAND**

A step by step process is explained in this section which determines the evacuation demand.

In the beginning, hourly trip tables under non-evacuation condition are prepared using period-based trip tables (AM Peak, Midday, PM Peak and Night Period). These period-based trip tables are divided into equal parts in terms of hours. Then trip tables are calibrated using TRANSCOM data, since the hourly traffic may not be evenly distributed for each period during the evacuation process. Following hourly calibration coefficient is used:

\[ Coef_{HR} = \frac{\sum Prop_{HR}}{\sum Prop_{HR}} / r_{original} \]  

(1)

where \( Coef_{HR} \) is the coefficient factor to adjust the original trip table, \( Prop_{HR} \) is hourly percentage of daily traffic volume coming from TRANSCOM data. This reflected different travel patterns of background traffic on weekdays and weekends, and the percentage is different. \( \sum Prop_{HR} \) is cumulative percentage of the period, that is, periodic percentage of daily volume. \( r_{original} \) is fraction of hour within the period. (E.g. for MD period, \( r_{original} = 1/5 \)). Therefore, the adjusted hourly volumes of the trip-table, \( TTHR_{actual} \) can be calculated as:

\[ TTHR_{actual} = TTP_{period} \cdot r_{original} \cdot Coef_{HR} \]  

(2)
The calculated hourly volume is used as input of base case scenario and to determine background trips. The next step is estimation of background trips. According to Urbanik II (34), background traffic includes trips present during evacuation but irrelevant to evacuation activities. In this approach, estimation of background trips are made based on hourly volume and directions, and three different assumptions of background traffic rate (percentage of background trips remains in network) are made:

- (a) Set 100% background traffic percentage for safe inter-zonal trips, that is, trips inside safe zones, which start and end at TAZs that belong to safe zones.
- (b) Set 75% background traffic percentage for evacuation intra-zonal trips. These include trips from evacuation zones and risky zones to safe zones.
- (c) Set 0% for trips towards evacuation zones. All trips to Evacuation Zones are set to zero.

Next task is identifying total evacuation demand. We first identify population in evacuation zones based on socio-economic data. Since census data of 2010 shows population of each census tract, we can calculate TAZ population as the sum of population in included census tracts.

Assumption of evacuation rates is made next for areas within different evacuation zones. Zone 1 has the highest evacuation rate whereas zone 6 the lowest. In the next step vehicle occupancy assumption is made according to (35), where 1 person/vehicle is used. Evacuation trips are now generated based on all these assumptions described in the previous steps using the following equation:

\[ D_i = N_i \times Evac_a \times VO \]  

where \( D_i \) denotes total daily evacuation trips generated by TAZ \( i \), \( N_i \) is population of TAZ \( i \), \( Evac_a \) is evacuation rate for evacuation zone category \( a \) to which TAZ \( i \) belongs. VO is the assumed vehicle occupancy.

Following step is to split the evacuation demands into each hour using the estimated evacuation response curve, where the outcome output is hourly zonal evacuation demands. After that, destinations of evacuation demands are assigned. The distribution of destinations for evacuation trips will follow the trip percentage for background travels, since the background travel patterns can be considered as an indication of travel preference and familiarity, which can contribute to the selection of evacuation destinations. Therefore assignments are based on proportion of original background trips from evacuation and risky zones to safe zones. For example, for evacuation zone A and non-evacuation zone B:

\[ Evac_{AB} = \frac{Evac_{total} \times BG_{AB}}{\sum BG_{AX}} \]  

where, \( Evac_{AB} \) stands for evacuation trips from TAZ A to TAZ B, \( Evac_{Total} \) is all evacuation trips that start from TAZ A, \( BG_{AB} \) denotes background trips from TAZ A to TAZ B, and \( \sum BG_{AX} \) stands for the sum of all background trips from TAZ A to all other zones X. Finally, the modified trip tables are calculated by adding evacuation demands to background trips. The procedure implemented for Approach 2 can be shown in Figure 3.
This section introduces an hour-by-hour capacity loss simulation procedure, where the impacts of incidents on highway capacity are simulated. The empirical incident data during hurricane Sandy is obtained, processed and then used for modeling incident frequency and duration. The empirical data as well as the estimation results of the incident frequency and duration models are used as inputs to the incident-induced capacity loss simulation.

Modeling Incident Frequency

This subsection investigates the relationship between incident frequency during evacuation and highway features such as road length and traffic volume. Each incident was geocoded in the GIS map and was matched to the highway sections where it had been detected. The incident frequency during evacuation period was obtained for each highway section. Negative Binomial (NB) models are widely used to model event frequencies (36, 37). NB models can accommodate the nonnegative, random and discrete features of incident frequencies and have been proved better dealing with the over-dispersed data by introducing an error term (38). The NB model can be expressed as follow:

\[ f_i \sim \text{Negbin}(\theta_i, r) \]

\[ \ln(\theta_i) = \alpha X_i \]

where \( f_i \) is the observed incident frequency for freeway section \( i \), \( \theta_i \) is the expectation of \( y_i \), \( X_i \) is the vector of explanatory variables, \( \alpha \) is the vector of regression coefficients to be estimated, and \( r \) is the dispersion parameter.
The modeling results of the incident frequency model during the evacuation period are shown in Table 3. A widely used statistical measure p-value was used to test the significance of variables. According to the p-values, all the estimates can be regarded as significant at the 95% level except the variable interstate which is significant at 90% level. The estimated dispersion value (r=0.4523) is significantly different from 0. This shows strong evidence of over-dispersion of data and the necessity of adopting the negative binomial model. The developed incident frequency model will be used to predict the probability of incident occurrence for each highway section in the capacity loss simulation.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Estimate</th>
<th>SD</th>
<th>t-value</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-9.6449</td>
<td>3.4485</td>
<td>-2.797</td>
<td>0.00516</td>
</tr>
<tr>
<td>Logarithm of volume</td>
<td>0.6349</td>
<td>0.2608</td>
<td>2.434</td>
<td>0.01493</td>
</tr>
<tr>
<td>Logarithm of length</td>
<td>0.6450</td>
<td>0.2520</td>
<td>2.560</td>
<td>0.01048</td>
</tr>
<tr>
<td>Road type</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Interstate</td>
<td>0.8697</td>
<td>0.4860</td>
<td>1.789</td>
<td>0.07355</td>
</tr>
<tr>
<td>Others</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Dispersion r</td>
<td>0.4523</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 3: Estimation results for the incident frequency model

Modeling Incident Duration

Duration distributions vary for different incident types. The relationship between the incident type and duration can be explored using a lognormal model \((27, 39, 40)\). A lognormal model assumes a linear relationship between the logarithm of incident durations and explanatory variables. It can be expressed as:

\[
\ln(d_j) \sim \text{Normal}(\mu_j, \sigma^2) \\
\mu_j = \beta Z_j
\]

where \(d_j\) is the observed duration for incident \(j\), \(\mu_j\) and \(\sigma^2\) are the mean and variance of the normal distribution, \(Z_j\) is the explanatory variables (dummy variables indicating the incident types), \(\beta\) is the vector of regression coefficients to be estimated.

The results of incident duration model are shown in Table 4. According to the p-values, all the estimates are found to be statistically significant at 95% level. According to coefficients in Table 4, accidents, debris and disable vehicles are expected to have shorter duration than other incidents; while duration of incidents such as downed tree and flooding tend to be shorter. These modeling results will be used to generate the duration for each incident in the capacity loss simulation.
<table>
<thead>
<tr>
<th>Parameters</th>
<th>Estimate</th>
<th>SD</th>
<th>t-value</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>4.4430</td>
<td>0.0387</td>
<td>114.83</td>
<td>&lt;0.0001</td>
</tr>
</tbody>
</table>

**Incident Type**

- **Accident**: -0.9017, 0.0419, -21.52, <0.0001
- **Debris**: -1.0964, 0.0729, -15.05, <0.0001
- **Disable vehicle**: -1.3014, 0.0445, -29.25, <0.0001
- **Downed tree**: 1.5352, 0.0934, 16.43, <0.0001
- **Flooding**: 0.5894, 0.1563, 3.77, 0.00016
- **Others**: -

Normal distribution variance \( \sigma^2 \) = 1.192

### Table 4: Estimation results for the incident duration model

#### Capacity Loss Simulation

The empirical incident data, incident frequency and incident duration, are used as inputs for simulating incident-induced capacity losses for the whole study network (40442 links) during the time period that covers 24 hours before Hurricane Sandy’s landfall. A widely used Monte Carlo simulation method is adopted to generate observations randomly from specified distributions (41). The simulation procedure to generate capacity loss is described below:

**Step 1**: Use the incident frequency model shown in Table 3 to estimate the expectation of incident frequency \( \theta_i \) for link \( i \). Incident frequency \( f_i \) is generated from a negative binomial distribution with \( \theta_i \) as the mean and \( r (0.4523) \) as the dispersion parameter. Repeat the above procedure to generate \( f_i \) for all the 40442 links.

**Step 2**: For each incident, generate incident type using the type proportions listed in Table 1. For example, the probability of generating an accident is 31.88% according to its proportion shown in Table 1.

**Step 3**: Use the incident duration model in Table 4 to estimate the normal distribution mean \( \mu_j \) for incident \( j \). The logarithm of incident duration \( \ln(d_j) \) is generated from the normal distribution with mean \( \mu_j \) and variance \( \sigma^2 (1.092) \). The duration \( d_j \) for all the incidents can thus be computed using this approach.

**Step 4**: Generate number of blocked lanes caused by each incident according to 错误!未找到引用源。 For example, for an accident, the probability of blocking two lanes is 35.77%. Capacity losses caused by blocking shoulder and each individual lane are assumed to be 1000 and 2000 veh/h, respectively.

**Step 5**: For each incident, determine which side of the highway gets affected according to the ratio of traffic volumes in different directions. This step is skipped for incidents located on one-way roads.

**Step 6**: Repeat step 1 through step 5 to generate highway capacity losses for the 24 hour period before Hurricane Sandy’s landfall.

**Step 7**: Check the overlap of incidents’ impacts. For the cases that multiple incidents are generated at the same side of the same link, the capacity loss for that direction of the link is assumed to be the maximum of the capacity losses caused by all of those incidents.
For each hour, there are active incidents, which include ones happened in current hour and ones occurred in previous hours and still affective. Figure 4 shows sample output of incident simulation of certain hour, including locations and type of incident.

Figure 4 Sample results of incident simulation

Incorporation of Incidents into the Network Model

Incident simulation described in detail in the previous section generates an incident list for each hour. Each list includes simulated incident location, type, duration, direction as well as the corresponding capacity loss due to lane closure. If the duration of an incident is more than one hour, it will still be effective in the next hour. Also, for some links, there may be more than one incident occurrence during the same period. Thus, the following modeling assumptions are followed:

(a) Maintain an active incident list. For each hour, insert the simulated incidents of the current hour to this list. In the next hour, first subtract duration of all active incidents by 1 (1 unit: 1 hour). If the duration of certain incidents becomes zero then remove these incidents from the list. Remaining ones will be simulated in the next hour.

(b) In each hour, reduce capacity of links from original roadway capacity based on the impact of the active incidents in the list. In same hour, only one incident is allowed for the same direction of a link. So if two simulated incidents occurred on the same link simultaneously, only the one causing more capacity loss will be considered during current hour. If the incident with
more capacity loss was cleared in the next hour and the other incident was still effective, then capacity loss in the next hour will be based on the remaining incident.

(c) Incidents simultaneously presented in different directions of the same link are independently considered.

RESULT AND DISCUSSION

Comparison of Evacuation Times

First, the impact of incidents on evacuation times for trips generated from designated risky zones to safe zones are quantified using the network model.

Figure 5 shows the evacuation travel time from each zone category of each simulation scenarios. The analysis is based on six evacuation zones in NYC and four evacuation zones in Long Island. The results show that the average travel times vary depending on the location of the evacuation zones.

As shown in Figure 5, during the evacuation period, there are two peak periods. The first peak period happens at the PM peak of the first day and second is at the AM peak of second day. For the base scenario, the difference between travel times in two peak periods is insignificant for evacuation zones 1 in NYC and LI. Moreover, for evacuation scenarios, the PM peak periods have higher travel times. That is attributed to the large volume of evacuation in the initial hours of evacuation.

In first couple of hours of the evacuation period, average travel times for all 10 categories of zones are highest. For zones 1 in both NYC and LI where evacuation is mandatory, evacuations have caused significant increases in travel times. The highest average travel time is observed at 3 pm where evacuation demand and background traffic are the heaviest, and highest evacuation travel time for evacuation zones in NYC and Long Island are estimated to be 45 and 38 minutes, respectively. After first eight hours, PM peak period is finished and the travel times for all zones for both evacuation scenario decrease, and travel times approach to their base scenario values in the midnight.

For some zones like zone 4 in NYC, travel times for the evacuation scenario without capacity loss are even lower than the base scenario in 12 am. This may be due to the fact that the evacuation demand is even less than number of trips blocked whose directions are towards evacuation zones. The outcome of this modeling assumption is fewer total trips compared to the base scenario. The travel times increase again 17 hours after the evacuation order. This can be attributed to the, residual evacuation demand in the morning. Then the times fall to normal level in the 23th hour.

The modeling results show that the evacuation scenario with capacity loss has higher travel times than the evacuation scenario without capacity loss assumptions. Especially in the last 6 hours of evacuation, the travel times for the capacity loss scenario has higher values than the other two scenarios whereas the travel times of the evacuation scenario without capacity loss are close to the base scenario travel times.
Figure 5 Comparisons of zonal travel times for different scenarios (in minutes)
Comparison with Taxi Data

Besides evacuation times for all the trips, we are also interested in evaluating travel times for trips leaving Manhattan. This comparison is also used as validation of model. The following section compares the zonal-level average travel times for trips in each TAZ, that is, trips from each TAZ in Manhattan to evacuation zones in the other four boroughs in NYC.

In comparing taxi trips and model trips, there is the important issue that the dataset from model and taxi data are not directly comparable, because taxi data only include part of taxi travel, and model data includes all trips on network (passenger cars, trucks, buses, taxi etc.) We must make sure the data used to compare model and empirical travel times have the same sample size, and each trip used for calculation has identical origin and destination pair. The study tracks available trips from taxi data and identifies an average trip for the same O-D pair within same time period from the model output of the evacuation scenario with capacity loss. Detailed procedure of data processing to achieve this goal is given below.

Step 1: Define Study Area, and fetch all trips within the study area from taxi dataset. In this paper, only trips from all 318 TAZs in Manhattan and to safe zones in Brooklyn, Queens, Bronx and Staten Island are included. Any trip with null or incorrect value will also be eliminated.

Step 2: Determine corresponding periods for model and empirical data. The evacuation scenarios with/without capacity loss simulate 24 hours of traffic network from midday, one day before the hurricane, which matches taxi trips from 12pm, Oct 28 to 12 pm, Oct 29.

Step 3: Subdivide the taxi dataset to each hour, and find corresponding trips from the model dataset. For example, if there is a trip from zone 1 to zone 500 from taxi data between 3pm to 4pm, also identify an average trip with the same OD from model. Each trip in modified dataset includes original trip information, and one extra column of model travel times.

Step 4: Calculate average travel times for each TAZ based on the modified dataset described in Step 3.
Figure 6 shows the average daily evacuation times for two evacuation scenarios and empirical taxi data. It can be seen that travel times for Harlem and downtown areas are lower than Midtown, and travel times for east side of Manhattan is shorter than the east side for all scenarios. Compared with the scenario with full capacity, travel times for capacity loss scenario is significantly higher, and more realistic.

It’s shown that the distribution of travel times is consistent for both model and empirical data sets. It is also observed that the actual travel times for whole the Manhattan are higher than the ones generated by the model. Figure 7 compares the hourly variations of model and taxi data. It can be seen that average travel times are closer at the beginning of evacuation, and then actual condition becomes worse than the conditions simulated by the model for the midnight period. After 17 hours, travel times are again getting closer to each other in the AM period. It can be concluded from abovementioned figures that the current evacuation model with capacity loss due to incidents follows the actual travel times quite accurately but tends to underestimate actual evacuation times for certain time periods. This can be due to both modeling assumptions and specific characteristics of taxi data.

Figure 7 Comparison of network wide travel time for incident-induced model and taxi data

CONCLUSION

This study proposed to incorporate a novel incident generation module with a network evacuation model. A statistically robust incident simulation module was developed based on the empirical data collected during an actual hurricane namely, Sandy, in the NY metropolitan area. Three scenarios are developed using the integrated evacuation model to test the impact of the incidents on the predicted evacuation times. The results suggest that incident-induced capacity loss can significantly increase travel times during the hurricane evacuation, especially for these OD pairs from evacuation zones to safe zones.

Despite the highlighted improvements after incorporating the impact of incidents in the network model, more work is needed to examine the accuracy and realism of these results. The study made various assumptions regarding evacuation rates and background traffic percentages. Although these values based on our assumptions were calibrated using empirical data, they may
are expected to vary based on specific events. Also, since fewer than usual taxi data points are
available for a significant percentage of network links mainly due to the reduction in demand prior
to the hurricane’s landfall, it was not possible to accurately assess whether incorporating incidents
into the network model yielded more accurate travel time estimates for all the links in the network.
Thus, other relevant travel time data that can help conduct this comparison would be valuable to
conduct a network-wide evaluation. In addition, the estimated capacity loss for different types of
incidents should be further examined to develop an enhanced incident simulation module as part of
the network evacuation model. It is however important to note that hurricanes are very rare events
in the NY/NJ area and the availability of future data for this and any other region with a very low
hurricane occurrence rate can be a problem. We hope that similar data can be obtained from other
regions of the US and used to improve unique modeling approach described in this paper.

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