Network Modeling of Hurricane Evacuation Using Data-Driven Demand and Incident-Induced Capacity Loss Models

Yuan Zhu
Kaan Ozbay
Kun Xie
Hong Yang
Ender Foruk Morgul

Follow this and additional works at: https://digitalcommons.odu.edu/cee_fac_pubs

Part of the Emergency and Disaster Management Commons, Transportation Commons, and the Transportation Engineering Commons
Network Modeling of Hurricane Evacuation Using Data-Driven Demand and Incident-Induced Capacity Loss Models

Yuan Zhu,1 Kaan Ozbay,2 Kun Xie,3 Hong Yang,3 and Ender Faruk Morgul4

1Inner Mongolia Center for Transportation Research, Inner Mongolia University, Rm A357c, Transportation Building, Inner Mongolia University South Campus, 49 S Xilin Rd, Hohhot, Inner Mongolia 010020, China
2C2SMART Center (A Tier 1 USDOT UTC), Department of Civil and Urban Engineering & Center for Urban Science and Progress (CUSP), Tandon School of Engineering, New York University (NYU), 15 MetroTech Center, 6th Floor, Brooklyn 11201, NY, USA
3Department of Civil & Environmental Engineering, Old Dominion University (ODU), 135 Kaufman Hall, Norfolk 23529, VA, USA
4Apple Inc. Department of Civil & Urban Engineering, Polytechnic Institute of New York University (NYU-Poly), New York, NY, USA

CorrespondenceshouldbeaddressedtoYuanZhu;zhuyuan@imu.edu.cn

Received 28 December 2020; Revised 10 August 2021; Accepted 26 August 2021; Published 3 September 2021

Copyright © 2021 Yuan Zhu et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

The development of a hurricane evacuation simulation model is a crucial task in emergency management and planning. Two major issues affect the reliability of an evacuation model: one is estimations of evacuation traffic based on socioeconomic characteristics, and the other is capacity change and its influence on evacuation outcome due to traffic incidents in the context of hurricanes. Both issues can impact the effectiveness of emergency planning in terms of evacuation order issuance, and evacuation route planning. The proposed research aims to investigate the demand and supply modeling in the context of hurricane evacuations. This methodology created three scenarios for the New York City (NYC) metropolitan area, including one base and two evacuation scenarios with different levels of traffic demand and capacity uncertainty. Observed volume data prior to Hurricane Sandy is collected to model the response curve of the model, and the empirical incident data under actual evacuation conditions are analyzed and modeled. Then, the modeled incidents are incorporated into the planning model modified for evacuation. Simulation results are sampled and compared with observed sensor-based travel times as well as O-D-based trip times of NYC taxi data. The results show that the introduction of incident frequency and duration models can significantly improve the performance of the evacuation model. The results of this approach imply the importance of traffic incident consideration for hurricane evacuation simulation.

1. Introduction

As one of the significant emergency issues, tropical storms, such as Harvey and Irma, caused significant casualty and property damage to the Atlantic coastal area. To alleviate the impact of the hurricanes, an evacuation plan that can ensure timely evacuation of affected residents from the vulnerable zones to safer locations such as shelters is expected. 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 methodology is always difficult because of the large-scale and high complexity of transportation systems with uncertainties. 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 types of challenge in modeling the evacuation traffic: (a) uncertainty in evacuation demand and (b) roadway supply. 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 an emergency condition is largely affected by traffic incidents such as vehicle 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 has shown 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 assumptions such as time of day, issuance and timing of the evacuation order, vehicle occupancy, and nonevacuation traffic (known as 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 limitation of empirical data for evacuation, additional research is expected to clarify these issues. Therefore, this approach tries to quantify and incorporate traffic into the emergency planning models for the metropolitan area of New York City (NYC), utilizing the data regarding the most recent hurricane experience. This study focuses on the impact of incidents on roadway capacity loss. Unlike most of the existing studies, this paper formulates incident frequency and duration models for varied incident types based on the empirical incident data. Then, the statistically robust incident models are imported into a network assignment model to examine the difference in evacuation outcome caused by capacity reduction. Results from the model are analyzed against real-world data during the actual storm.

2. Literature Review

In recent years, numerous studies have been conducted to simulate behavior and impact due to evacuation activities for various extreme events. A detailed overview of evolutions of highway-based evacuation modeling over past decades is performed by Murray-Tuite and Wolshon [13]. Silva and Egelese [14] proposed a spatial decision support system (SPSS) which links geographic information system (GIS) to evacuation modeling and enables simulating dynamics of the whole evacuation process. Chiu et al. [1] introduced an approach to transform the typical planning model to an evacuation model in which specific demand, destination, and connectors are specified. Andrews et al. [15] also used TransCAD to convert a traditional four-step planning model into an evacuation planning model by altering the input to address the traffic demand, and the approach was proved to be effective. Lu and Gao [16] developed a 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. Pel et al. [17] summarized the utilization of DTA on evacuation behavior. Ozbay et al. [8] applied equilibrium assignment tools to evacuation modeling based on multiple scenarios in North New Jersey. In addition, the study discussed the effect of assumption and data input on model estimation. Results presented suitableness to which regional planning models are used in evacuation simulation.

One of the critical issues in evacuation study is to justify the demand for evacuation. Baker [18] identified variables in determining evacuation demand based on posthurricane sample surveys. These variables include vulnerability of area, housing, prior perception of personal risk, and storm-specific threat factor, which is shown in his later research [19, 20], the latter created a disaggregate model to address time-dependent choices of evacuation destination. A comprehensive review of demand generation and network loading approaches is presented by Ozbay and Yazici [21]. An approach to estimate the impact of evacuees under landfall situation based on a three-dimensional coastal ocean model was proposed by Tang et al. [22] and applied to the coastlines of Cape May, New Jersey. Yin et al. [23] introduced a hurricane evacuation demand estimation system using Agent-Based Modeling. The system implemented typical evacuation decisions covering the whole evacuation process, including pre-evacuation preparation. An activity-based approach is used in this study to estimate hurricane evacuation for the Miami-Dade area.

Besides variability in evacuation demand, estimation of changes in network capacity is another challenge in the evacuation modeling process. The roadway capacity can be significantly reduced by the traffic incidents such as downed trees, flooding, or debris. The influence of these nonrecurring incidents during evacuation is crucial as it may delay the evacuation process and lead to additional danger to the evacuees [24]. Thus, in evacuation modeling, the impact of incidents should be considered qualitatively. For example, Wolshon et al. [25] stated 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 [sic] the impact of lane closures, weather conditions and incidents.” Fonseca et al. [26] analyzed evacuation records for Interstate 65 in Alabama and analyzed the varied incident types with proportions and duration distributions. Based on that, they developed a methodology to generate the incidents for the evacuation model. Yazici and Ozbay [10] used dynamic assignment based on cell transmission model to explore the spatial variation of shelter capacities caused by probabilistic road capacity constraints and suggested an approach of evacuation planning which avoids insufficient planning which caused postdisaster problems.

Few studies quantitatively evaluated incident-induced network changes on emergency evacuation. For example,
Robinson et al. [11] simulated the hurricane scenario to explore the impact of disabled and abandoned vehicles, but the results showed that the changes in total evacuation time are negligible. Edara et al. [12] estimated two kinds of incidents and their impact under an evacuation simulation scenario, and the result illustrated a significant increase in evacuation time and a decrease in throughput. It is noticeable that the aforementioned studies are based on hypothesis rather than empirical incident data from actual evacuation circumstances. Collins et al. [27] simulated the fictitious evacuation scenarios of terrorist attacks and hurricane evacuation and the results reveal that accidents can increase the evacuation time by 8%. On the contrary, others used facility-based empirical incident data [11], predicted from a generic incident rate model [27], and assumed that segments of high traffic volume can yield more incidents [12]. Fonseca et al. [26] developed a more specified methodology for incident creation and categorization based on historical data but with a hypothesis resembling previous studies [11, 28]. More recently, Robinson et al. [29] evaluated the impact of the incident on hurricane evacuation by setting up a simulation model with historical incidents. The results revealed that traffic incidents extended the travel times of evacuees involved, but the impact of overall evacuation performance is negligible.

Several challenges are raised in the previous studies for the simplification on the evaluation of the incident impact on evacuation simulation. First, the hurricane-specific incident records may not be available or collectable. For example, due to the gust during the storm, down tree is a major type of incident under hurricane conditions [30]. However, this impact is yet to be addressed in detail. Second, it is difficult to collect the wide range factors such as weather conditions and roadway physical inventory, which are needed in incident modeling under an evacuation scenario. In addition, it is difficult to validate the simulation of incident impact since it is difficult to collect empirical data of incident impact in different stages. Without proper consideration of these critical issues, the performance and credibility of the proposed models will be negatively affected.

3. Data and Tools

3.1. Data and Tools for Evacuation Modeling. The network and demand used in this study are derived from a large-scale network model, NY Best Practice Model (NYBPM) [31]. The original model was a typical 4-Step trip generation module for the planning of daily travel based on the TransCAD 6.0 [32] platform. This planning model includes the latest physical and socioeconomic information such as network and socioeconomic attributes for 28 counties for NY metropolitan area. The macroscopic traffic network and traffic analysis zones (TAZs) of the original model are utilized.

In this study, the time-dependent degradable network and evacuation demands are generated based on a macroscopic traffic network of 53399 links and more than 4000 traffic analysis zones (TAZs) in the original planning model. The evacuation demand is developed by adding evacuation trips that modified original daily OD demands to reflect expected evacuation behavior of the affected populations given their location and characteristics such as auto-ownership, number of residents per household, and evacuation preference.

One advantage of generating the evacuation model based on the NYBPM Second Generation (NYBPM 2g) model is that the regional planning model provides period-based well-calibrated trip tables. For the convenience of hourly assignment, the trip tables are distributed into hourly ones based on the hurricane evacuation response curve, which is modeled using traffic counts from Transportation Operations Coordination Committee (TRANSOCOM). 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 postprocessing 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, as shown in [8].

3.2. Traffic Incidents. The incident data of major expressway and highway of the NY metropolitan area were collected from TRANSOCOM. The dataset contains all traffic incidents from the beginning to the aftermath of Hurricane Sandy. Detailed information about the dataset can be found in Xie et al. [30]. According to statistics, there are 354 incidents during 84 hours before the landfall, and there are six types of incidents, as presented in Table 1. It can be seen that accident is the major type of incident, followed by downed trees. These two types account for more than half of all the incidents.

Incidents 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.

4. Hurricane Evacuation Modeling

The basic strategy for the modeling approach is shown in Figure 1. Under the evacuation condition, the travel demand consists of both assumed background traffic and evacuation demand. Unlike most of the previous studies that assume stable highway capacity based on the roadway characteristics, the roadway capacity in this study is dynamically modeled as a function of simulated incidents.

4.1. Scenarios and Assumptions. In this study, three simulations are developed and evaluated, namely, base scenario, evacuation scenario without capacity loss, and evacuation
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 on 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

---

**Table 1: Type of incidents during evacuation period.**

| Incident Type     | Proportion |
|-------------------|------------|
| Accident          | 31.88      |
| Debris            | 8.12       |
| Disabled vehicle  | 19.71      |
| Downed tree       | 24.93      |
| Flooding          | 5.80       |
| Others            | 9.57       |

**Table 2: Capacity loss caused by various incident types.**

| Incident Type     | Shoulder blocked (%) | One lane blocked (%) | Two lanes blocked (%) | Three lanes blocked (%) | Four lanes blocked (%) |
|-------------------|----------------------|----------------------|-----------------------|-------------------------|------------------------|
| Accident          | 23.60                | 19.45                | 35.77                 | 17.22                   | 3.96                   |
| Debris            | 14.29                | 28.57                | 14.29                 | 28.57                   | 14.29                  |
| Disabled vehicle  | 26.36                | 12.92                | 29.75                 | 29.58                   | 1.38                   |
| Downed tree       | 1.96                 | 18.63                | 69.61                 | 7.84                    | 1.96                   |
| Flooding          | 0.00                 | 11.76                | 88.24                 | 0.00                    | 0.00                   |
| Others            | 3.98                 | 23.88                | 52.24                 | 14.43                   | 5.47                   |

---

**Figure 1: Procedure of network-wide demand and degradable capacity modeling.**
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 p.m. to 12:00 p.m. on the second day. It is consistent with the issuance of a government mandatory evacuation order for Hurricane Sandy on 12:00 p.m. 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. Specifically, Zone 1 in NYC and Long Island is the Mandatory Evacuation Zone, and the trips towards these two zones (blocked trips) are not allowed in the model. The identification of the evacuation zones for NYC and LI can be depicted in Figure 2.

### 4.2. Steps of Model-Based Evacuation Analysis

The following steps are used to test the evacuation model:

1. Identify the evacuation zones based on the NYC flooding evacuation zones of year 2012 and TAZ attributes, and estimate the zonal evacuation demand based on model assumptions and socioeconomic data.
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.
3. Develop scenarios based on normal and evacuation situations.
4. Modify trip tables based on evacuation demand and then modify the highway network to capture capacity losses due to incidents.
5. Run network assignment model in TransCAD using the hourly based quasi-dynamic assignment method for different scenarios.
6. Analyze assignment results and summarize evacuation times and network performance with and without capacity losses.

### 5. 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 a non-evacuation condition are prepared using period-based trip tables. There are four periods in the planning model, namely, AM (morning peak), MD (midday), PM (evening peak), and NT (night) periods. 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. The following hourly calibration coefficient is used:

\[
\text{Coeff}_{HR} = \frac{\text{Prop}_{HR}}{\sum \text{Prop}_{HR}} \text{ original}
\]  

(1)

where Coeff\(_{HR}\) is the coefficient factor to adjust the original trip table and Prop\(_{HR}\) is the 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. \(\sum \text{Prop}_{HR}\) is the cumulative percentage of the period, that is, periodic percentage of daily volume. \(r_{\text{original}}\) is the fraction of hour within the period (e.g., for MD period, \(r_{\text{original}} = 1/5\)). Therefore, the adjusted hourly volumes of the trip table, \(TTHR_{\text{actual}}\), can be calculated as

\[
TTHR_{\text{actual}} = TT_{\text{Period}} \times r_{\text{original}} \times \text{Coeff}_{HR}.
\]  

(2)

The calculated hourly volume is used as input of the base case scenario and to determine background trips.

The next step is the 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 is made based on hourly volume and directions, and three different assumptions of background traffic rate (percentage of background trips remains in network) are made:

1. Set 100% background traffic percentage for safe interzonal trips, that is, trips inside safe zones, which start and end at TAZs that belong to safe zones.
2. Set 75% background traffic percentage for evacuation intrazonal trips. These include trips from evacuation zones and risky zones to safe zones.
3. Set 0% for trips towards evacuation zones. All trips to evacuation zones are set to zero.

The following task is identifying total evacuation demand. We first identify the population in evacuation zones based on socioeconomic data. Since census data of 2010 show the population of each census tract, we can calculate TAZ population as the sum of the 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 has the lowest. In the next step, the 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:

\[
D_i = N_i \times \text{Evac}_{a} \times \text{VO},
\]  

(3)

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

The 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,

\[
\text{Evac}_{AB} = \text{Evac}_{\text{total}} \times \frac{BG_{AB}}{\sum BG_{AX}}, \quad (4)
\]

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 demand modeling can be shown in Figure 3.

6. Incident-Induced Simulation

This section proposes a generation method of the degradable network under a hurricane condition, more specifically, simulated the hourly based dynamic incident-induced capacity loss. Based on the aforementioned incident data, two models are built. The first model investigates the relationship between incident occurrence and the roadway geometry, and the second one addresses the correlation of incident type and duration. Then, the models are applied to the whole network to estimate the network-wide capacity reductions. The details of this modeling approach are available in [36] by the authors of this article.

6.1. Modeling Incident Frequency. This subsection explores the relationship between incident occurrence in the presence of evacuation and roadway attributes such as link length and traffic volume. Each incident was geocoded in the GIS Shapefiles and matched to the roadway sections where it had been detected. The incident frequency model for each roadway section can be retrieved. Negative binomial (NB) models are widely used to model event frequencies [37, 38], for they can address the nonnegative and discrete nature of incident occurrence and have been proved effective for the overdispersed data by introducing an error term [39]. The NB model can be expressed as follows:

\[
f_i \sim \text{Negbin}(\theta_i, r) \ln(\theta_i) = \alpha X_i, \quad (5)
\]
where \( f_i \) is the observed incident frequency for roadway 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 under hurricane evacuation are shown in Table 3. According to the \( p \) values, all the estimates can be regarded as significant at the 95% level except for 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 overdispersion of data and the necessity of adopting the negative binomial model.

6.2. Modeling Incident Duration. Duration distributions vary for different incident types. A lognormal model can be used to express the relationship between incident duration and type, as previously used in [30, 40, 41]. The model can be expressed as

\[
\ln(d_j) \sim \text{Normal}(\mu_j, \sigma^2) \mu_j = \beta Z_j, \tag{6}
\]

where \( d_j \) is the observed duration for incident \( j \), \( \mu_j \) and \( \sigma \) are the mean and standard deviation of the normal distribution for incident \( j \), \( Z_j \) is the explanatory variables representing types of the incidents, and \( \beta \) is the vector of regression coefficients to be estimated. The results of incident duration model are shown in Table 4. According to statistics of coefficients in Table 4, estimations of accidents, debris, and disable vehicles are negative, which imply that they have shorter duration than other incidents like downed tree and flooding.

6.3. Simulation of the Incidents and Network Capacity Loss. Once the incident models are generated, hourly based simulation of roadway capacity loss can be conducted by applying the link capacity reduction in the planning model. Monte Carlo simulations are utilized to generate random observations that follow estimated distributions [42]. This section describes the procedure for incidents simulation, and the methods to generate a continual capacity loss for the simulation network.

The first step is to clean the simulation network. The original network in NYBPM 2g model involves 53399 traffic links, including centroid connectors, external connectors, and PTZ connectors (public transit). Since these connectors are not actual roadways and do not apply to the incidents,
they should be removed. For each roadway link, the mean value of incident $\theta_i$ is linearly correlated to the roadway attributes as parameters in Table 3; then, the incident frequency $f_j$ for the remaining 40442 links can be estimated using $\theta_i$ and dispersion parameter $r$. Based on $f_j$, simply apply Monte Carlo simulations to determine whether an incident will occur for link $i$.

The previous step generates a list of network-wide incidents for each hour. In order to predict the capacity loss, other attributes of the incidents need to be completed. These attributes include incident type, duration, number of blocked lanes, and side of the affected link. First, types of incidents are simulated using the percentages in Table 1. Once the types are determined, the durations of the incidents can be simulated using the incident duration model shown in Table 4, where mean $\mu_i$ is dependent on incident type, and the logarithm of the incident is normally distributed with mean $\mu_j$ and standard deviation $\sigma$. Other attributes of the incident that need to be specified are the number of affected lanes and directions, which is simulated using Table 2. For example, for an accident, the probability of blocking two lanes is 35.77%. Capacity losses caused by the blocking shoulder and each individual lane are assumed to be 1000 and 2000 veh/h, respectively. Then, directions of the incidents are simulated. More specifically, for each two-way roadway where the incident occurs, assign a side of the link according to the directional volume ratio. Therefore, the link can be identified as one-way if the capacity of the other side is zero. Another issue is the overlapped incidents’ impact. 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. The output of this step is the complete incident list that contains fields of incident type, capacity loss, and direction for each hour. Figure 4 shows a sample output of incident simulation of a certain hour, including locations and type of incident.

Considering the differences in incident durations and types, the incident lists cannot be used directly to reduce the capacity of the links. More specifically, the roadway capacity is affected not only by the incidents occurring in the current hour but also by the active ones occurring in previous hours. These attributes are time-dependent so that a mechanism of life-cycle management of incidents is necessary. Moreover, combined impacts of the incidents should be considered, since multiple incidents may be active simultaneously for a certain location and side.

To manage the life cycle of the incidents, this approach maintains an active incident table with the same columns with the incident lists. The table is updated each hour by adding the new incidents of the current hour from the incident list and deleting the incidents that are no longer active. After the insertion and deletion, take a snapshot table of the hour. The incident deletion is determined by the duration field, which decreases by one unit every hour. Once the duration became zero, the incident is removed from the table. The impact of multiple incidents in the same location is another issue that needs to be addressed. This approach keeps both incidents in the table and presumes that only the one that has greater impact (high capacity loss) is in effect. Once the one with higher impact is expired and the other one is still alive, activate the other incident. This approach does not apply to the concurrent incidents on the different sides of the same link, in which case both incidents can be effective simultaneously.

The snapshot tables generated from the previous approach indicate the capacity loss and direction of the designated links. So, the time-dependent degradable simulation network can be built by simply reducing the capacity by the values in the snapshot table for each hour within the study period. If the capacity loss is greater than the original capacity of the link, the remaining capacity is set to 100. This is to meet the requirement of convergence in the macroscopic assignment model.

The final step is to run the evacuation simulation based on the modified planning model based on the time-dependent demands and degradable networks. Similar to the study of Ozbay et al. [8], a quasi-dynamic traffic assignment approach covering NYC metropolitan area is created in TransCAD. Three simulation runs are made for the scenarios. Specifically, the base scenario only considers background traffic without eliminating the blocked trips, and the highway network capacity is stable. The two evacuation scenarios have the same evacuation demand, including both evacuation and background demands, subtracted by the blocked trips. The only difference for the two scenarios is the presence of the incident impact.

7. Result and Discussion

7.1. Evaluation of Simulation. In this step, simulated incident frequency and durations are evaluated by comparing with the observed data. Tables 5 and 6 summarize the percentages of incident types simulated from the incident frequency and duration models, which agree with the observed incident data shown in Tables 1 and 2.

The histograms of the simulated and observed duration of incidents (unit: hours) are shown in Figure 5, which also shows the consistency between observed data and modeled result.

7.2. Validation by Comparison with Observed Postdisaster Taxi Data. The travel times for trips leaving Manhattan are compared to observed taxi travel times as validation of the model. In NYC, most of the yellow cab trips occur inside Manhattan, so it is practical to use yellow cab trips to compare with the simulation trips in Manhattan. To be consistent with the evacuation direction, the taxi trips from TAZs inside Manhattan to safe zones outside Manhattan are selected. To make the average trip results comparable, the sampling of modeled trip results is necessary to guarantee the identical number of modeled trips and observed taxi data for the same O-D pair. This is done by selecting all qualified taxi trips for each hour, picking the same number and attributes of modeled trips, and then calculating mean travel times for both datasets.
Figure 6 shows the hourly and average travel time (unit: minutes) for evacuation scenarios without a capacity loss (first row), with capacity loss (second row), and observed travel time (third row). The zones colored in grey indicate no taxi trip data available for the time selected. For the colored zones, if there are no additional trips in the following hour, the average travel times are assumed to be unchanged. Based on Figure 6, the travel times for Midtown are significantly higher than downtown and Harlem, and the travel times for the east side of Manhattan are lower than the west. These reveal the spatial characteristics and different levels of vulnerability for zones in Manhattan. Additionally, travel times for that capacity loss scenario are slightly higher and closer to the empirical times. Such conclusions can also be

Table 5: Type of incidents during evacuation period simulated from models.

|                  | Accident (%) | Debris (%) | Disabled vehicle (%) | Downed tree (%) | Flooding (%) | Others (%) |
|------------------|--------------|------------|----------------------|----------------|--------------|------------|
| Proportion       | 20.00        | 11.76      | 25.88                | 25.88          | 2.35         | 14.11      |

Table 6: Simulated shoulder/lane blockage caused by various incident types.

|                   | Shoulder blocked (%) | One lane blocked (%) | Two lanes blocked (%) | Three lanes blocked (%) | Four lanes blocked (%) |
|-------------------|----------------------|----------------------|-----------------------|------------------------|-----------------------|
| Accident          | 23.53                | 23.53                | 47.06                 | 5.88                   | 0.00                  |
| Debris            | 10.00                | 30.00                | 10.00                 | 40.00                  | 10.00                 |
| Disabled vehicle  | 36.36                | 4.55                 | 36.36                 | 22.72                  | 0.00                  |
| Downed tree       | 0.00                 | 27.27                | 59.09                 | 4.55                   | 9.09                  |
| Flooding          | 0.00                 | 0.00                 | 100                   | 0.00                   | 0.00                  |
| Others            | 0.00                 | 8.33                 | 75.00                 | 8.33                   | 8.33                  |
quantified in Table 7 where MAE and RMSE values are computed as the normalized evacuation times for each TAZ. The values are all lower in the capacity loss model.

The similarity to taxi data can also be graphically shown using the temporal distributions of travel times, shown to be consistent between datasets in Figure 6. It is also illustrated the temporal difference: travel times are closer at the time when the evacuation order is issued, and then empirical travel times become worse than the model at night. On the morning of the second day, travel times are again getting closer. The results also reveal that in the late stage of evacuation, the evacuation time from empirical data is slightly higher than the model.

In summary, this section validates the model with the empirical data, and the evacuation model with incident-induced capacity loss matches the empirical data well but still tends to underestimate actual evacuation times for certain time periods. Several issues such as demand assumptions or other hurricane-related circumstances may lead to inconsistencies.

### Table 7: Validation results of evacuation scenarios.

| Models                                      | MAE   | RMSE  |
|---------------------------------------------|-------|-------|
| Taxi data vs. evac. scenario without capacity loss | 2.895 | 4.612 |
| Taxi data vs. evac. scenario with capacity loss | 2.524 | 4.289 |

7.3. Comparison of Evacuation Times. With the capacity loss model validated, it is applied to provide insight on evacuation times for different evacuation zones to demonstrate how it impacts a model that ignores incident impact.

First, the impact on evacuation times for trips generated from designated risky zones to safe zones is quantified using the network model.
Figure 7 shows the evacuation travel time from each zone category of each simulation scenario. The analysis is based on six evacuation zones in NYC and four evacuation zones in Long Island (LI). The results imply that average travel times vary depending on the location of the evacuation zones.

As shown in Figure 7, during the evacuation period, there are two peak periods. The first peak period happens at
the p.m. peak of the first day and the second is at the a.m. peak of the second day. For the base scenario, the difference between travel times in two peak periods is insignificant for evacuation zone 1 in NYC and LI. Moreover, for evacuation scenarios, the p.m. peak periods have higher travel times. That is attributed to the large volume of evacuation in the initial hours of evacuation.

In the first couple of hours of the evacuation period, the average travel times for all 10 categories of zones are the highest. For zone 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 p.m. where evacuation demand and background traffic are the heaviest, and the highest evacuation travel times for evacuation zones in NYC and LI are estimated to be 45 and 38 minutes, respectively. After the first eight hours, the p.m. peak period is finished and the travel times for all zones for both evacuation scenarios decrease, and travel times approach their base scenario values around midnight.

For some zones like zone 4 in NYC, the travel times for the evacuation scenario without capacity loss are even lower than the base scenario at 12 a.m. This may be because the evacuation demand is even less than the 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 a normal level in the 23rd 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 have higher values than the other two scenarios, whereas the travel times of the evacuation scenario with full capacity are close to the base scenario travel times.

8. Conclusion

This study constructs a scenario-based hurricane evacuation model that incorporates a robust incident estimation module for NYC and LI. The demands of the evacuees are generated based on the demographic data and are distributed to each hour based on the empirical evacuation response curve. Incident frequency and duration models are generated based on the empirical data of the highway incident during Hurricane Sandy. Three macroscopic scenarios based on the planning models are created to evaluate the impact of the incident on the evacuation time predictions. The results imply that the roadway incident can have a strong negative impact on the evacuation process, especially introducing a significant increase for these OD pairs from evacuation to safe areas.

Despite the highlighted improvements after considering 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 be expected to vary based on specific events. For the incident modeling, some of the events, such as flooding or downed trees may be related to the place, and a spatial modeling approach may be useful to improve the incident generation module. 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 yet possible to accurately assess whether introducing incident-induced capacity loss to the network model yielded more accurate travel time estimates for all the links in the network.

Thus, other relevant data of empirical link attributes that can help conduct this comparison would be useful to conduct a network-wide evaluation. In addition, further study needs to examine the capacity loss for cascading failures to develop an enhanced simulation module that can address the interdependency of multilayer networks. 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 the unique modeling approach described in this paper [43].

Data Availability

There are no linked research datasets for this submission because the authors do not have permission to share data.

Disclosure

The contents of this paper reflect the views of the authors who are responsible for the facts and accuracy of the data presented herein. The contents of the paper do not necessarily reflect the official views or policies of the agencies. An early version of this manuscript was presented in Transportation Research Board 95th Annual Meeting of Transportation Research Board (43).

Conflicts of Interest

The authors declare that they have no conflicts of interest to disclose.

Authors’ Contributions

Yuan Zhu developed the methodology, worked on software, wrote the original draft, and visualized the study. Kun Xie carried out formal analysis and investigated the study. Kaan Ozbay supervised the study and reviewed and edited the article. Hong Yang conceptualized and validated the study. Ender Faruk Morgul: conceptualized the study and carried out data analysis.

Acknowledgments

This study was partially supported by the Young Scientists Fund of the National Natural Science Foundation of China (Grant no. 61903205) and Young Scientists Fund of Natural Science of Inner Mongolia (Grant no. 2019BS07002). The
work was partially funded by New York State Resiliency Institute for Storms & Emergencies (NYSRISE) and NSF CRISP: Type 1: Reductionist and Integrative Approaches to Improve the Resiliency of Multi-Scale Interdependent Critical Infrastructure and the project on A Decision-Support System for Resilient Transportation Networks funded by NYU Provost Global Seed Fund Grants. It was also partially supported by C2SMART, a Tier I UTC at New York University funded by U.S. Department of Transportation. The authors would like to acknowledge TRANSCOM for providing incident data.

References

[1] Y.-C. Chiu, H. Zheng, J. Villalobos, and B. Gautam, “Modeling no-notice mass evacuation using a dynamic traffic flow optimization model,” IIE Transactions, vol. 39, no. 1, pp. 83–94, 2007.

[2] A. Yazici and K. Ozbay, “Evacuation network modeling via dynamic traffic assignment with probabilistic demand and capacity constraints,” Transportation Research Record: Journal of the Transportation Research Board, vol. 2196, no. 1, pp. 11–20, 2010.

[3] J. Li, K. Ozbay, and B. Barton, “Effects of hurricane Irene and sandy in New Jersey: evacuation traffic patterns,” in Proceedings of the Transportation Research Board 93rd Annual Meeting, Washington, DC, USA, January 2014.

[4] J. Li and K. Ozbay, “Empirical evacuation response curve during hurricane Irene in Cape May County, New Jersey,” Transportation Research Record: Journal of the Transportation Research Board, vol. 2376, no. 1, pp. 1–10, 2013.

[5] A. Yazici, S. Demiriuk, K. Ozbay, and J. A. Carnegie, “Use of feature selection and variable ranking in classification and regression tree evacuate decision model,” in Proceedings of the Transportation Research Board 91st Annual Meeting, Washington, DC, USA, January 2012.

[6] A. G. Hobeika, S. Kim, and R. E. Beckwith, “A decision support system for developing evacuation plans around nuclear power stations,” Interfaces, vol. 24, no. 5, pp. 22–35, 1994.

[7] M. A. Yazici and K. Ozbay, “Reliability of evacuation performance measures with respect to demand and capacity uncertainties,” in Proceedings of the International Symposium on Transportation Network Reliability (INSTR2007), The Hague, Netherlands, 2007.

[8] K. Ozbay, M. A. Yazici, S. Iyer, J. Li, E. E. Orguven, and J. A. Carnegie, “Use of regional transportation planning tool for modeling emergency evacuation: case study of northern New Jersey,” Transportation Research Record: Journal of the Transportation Research Board, vol. 2312, no. 1, pp. 89–97, 2012.

[9] M. A. Yazici and K. Ozbay, “Importance of information collection and dissemination for evacuation modeling and management,” in Proceedings of the Intelligence and Security Informatics, p. 370, May 2007.

[10] M. A. Yazici and K. Ozbay, “Impact of probabilistic road capacity constraints on the spatial distribution of hurricane evacuation shelter capacities,” Transportation Research Record: Journal of the Transportation Research Board, vol. 2022, no. 1, pp. 55–62, 2007.

[11] R. M. Robinson, A. J. Khattak, J. A. Sokolowski, P. Foytik, and X. Wang, “Role of traffic incidents in hampton roads hurricane evacuations,” in Proceedings of the Transportation Research Board 88th Annual Meeting, Washington, DC, USA, November 2009.

[12] P. Edara, S. Sharma, and C. McGhee, “Development of a large-scale traffic simulation model for hurricane evacuation—methodology and lessons learned,” Natural Hazards Review, vol. 11, no. 4, pp. 127–139, 2010.

[13] P. Murray-Tuite and B. Wolshon, “Evacuation transportation modeling: an overview of research, development, and practice,” Transportation Research Part C: Emerging Technologies, vol. 27, pp. 25–45, 2013.

[14] F. N. d. Silva and R. W. Eglese, “Integrating simulation modelling and GIS: spatial decision support systems for evacuation planning,” The Journal of the Operational Research Society, vol. 51, no. 4, pp. 423–430, 2000.

[15] S. Andrews, H. Wang, D. Ni, S. Gao, and J. Collura, “Development and implementation of an adapted evacuation planning methodology in the framework of emergency management and disaster response: a case study using TransCAD,” Journal of Transportation Safety & Security, vol. 2, no. 4, pp. 352–368, 2010.

[16] X. Lu and S. Gao, “Using travel demand forecasting software for emergency planning in small and medium-sized regions,” in Proceedings of the Transportation Research Board Annual Meeting, Washington, DC, USA, 2010.

[17] A. J. Pel, M. C. Bliemer, and S. P. Hoogendoorn, “A review on travel behaviour modelling in dynamic traffic simulation models for evacuations,” Transportation, vol. 39, no. 1, pp. 97–123, 2012.

[18] E. J. Baker, “Predicting response to hurricane warnings: a reanalysis of data from four studies,” Mass Emergencies, vol. 4, pp. 9–24, 1979.

[19] E. L. Samson, “Hurricane evacuation behavior,” International Journal of Mass Emergencies and Disasters, vol. 9, no. 2, pp. 287–231, 1991.

[20] G. Cheng, C. Wilmot, and E. J. Baker, “Development of a time-dependent disaggregate hurricane evacuation destination choice model,” Natural Hazards Review, vol. 14, no. 3, pp. 163–174, 2013.

[21] K. Ozbay and M. A. Yazici, “Study of networkwide impact of various demand generation methods under hurricane evacuation conditions,” in Proceedings of the Transportation Research Board 85th Annual Meeting, Washington, DC, USA, January 2006.

[22] H. Tang, S. L.-J. Chien, T. Marouane et al., “Prediction of coastal flooding and evacuation demand estimation considering climate change,” in Proceedings of the Transportation Research Board 92nd Annual Meeting, Washington, DC, USA, January 2013.

[23] W. Yin, P. Murray-Tuite, S. V. Ukkusuri, and H. Gladwin, “An agent-based modeling system for travel demand simulation for hurricane evacuation,” Transportation Research Part C: Emerging Technologies, vol. 42, pp. 44–59, 2014.

[24] G. P. Moynihan, D. J. Fonseca, T. Brumback, and H. Fernandes, “Evacuation decision support system for road incident detection and characterization,” Journal of Homeland Security and Emergency Management, vol. 6, no. 1, 2009.

[25] B. Wolshon, E. Urbina Hamilton, M. Levitan, and C. Wilmot, “Review of policies and practices for hurricane evacuation. II: traffic operations, management, and control,” Natural Hazards Review, vol. 6, no. 3, pp. 143–161, 2005.

[26] D. J. Fonseca, Y. Lou, G. P. Moynihan, and S. Gurupackiam, “Incident occurrence modeling during hurricane evacuation events: the case of Alabama’s I-65 corridor,” Modelling and
[27] A. J. Collins, P. Foytik, E. Frydenlund, R. M. Robinson, and C. A. Jordan, “Investigating the impact of traffic incidents on large-scale emergency evacuation times using a generic incident model,” in Proceedings of the Transportation Research Board 93rd Annual Meeting, Washington, DC, USA, January 2014.

[28] N. Zou, S.-T. Yeh, G.-L. Chang, A. Marquess, and M. Zezeski, “Simulation-based emergency evacuation system for Ocean City, Maryland, during hurricanes,” Transportation Research Record: Journal of the Transportation Research Board, vol. 1922, no. 1, pp. 138–148, 2005.

[29] R. M. Robinson, A. J. Collins, C. A. Jordan, P. Foytik, and A. J. Khattak, “Modeling the impact of traffic incidents during hurricane evacuations using a large scale microsimulation,” International Journal of Disaster Risk Reduction, vol. 31, pp. 1159–1165, 2018.

[30] K. Xie, K. Ozbay, and H. Yang, “Spatial analysis of highway incident durations in the context of Hurricane Sandy,” Accident Analysis & Prevention, vol. 74, pp. 77–86, 2015.

[31] New York Metropolitan Transportation Council, Best Practice Model, New York Metropolitan Transportation Council, New York, NY, USA, http://www.nymtc.org/project/bpm/bpmindex.html.

[32] Caliper TransCAD—transportation planning software, http://www.caliper.com/tcovi.htm.

[33] City of New York. Mayor bloomberg issues order for mandatory evacuation of low-lying areas as hurricane sandy approaches, http://www.nyc.gov/portal/site/nycgov/menuitem.c9093b9a57bb4e3d3a2fc701c789a0/index.jsp?pageID=mayor_press_release&catID=1194&doc_name=http://www.nyc.gov/html/om/html/2012b/pr377-12.html&cc=unused1978&rc=1194&ndi=1.%202012.

[34] T. Urbanik II, “Evacuation time estimates for nuclear power plants,” Journal of Hazardous Materials, vol. 75, no. 2–3, pp. 165–180, 2000.

[35] University of South Florida, State Averages for Private Vehicle Occupancy, Carpool Size and Vehicles Per 100 Worker, University of South Florida, Tampa, FL, USA, http://www.nctr.usf.edu/clearinghouse/censusavo.htm.

[36] Y. Zhu, K. Ozbay, K. Xie, and H. Yang, “Modeling of incident-induced Capacity loss for hurricane evacuation simulation,” in Proceedings of the 2019 IEEE Intelligent Transportation Systems Conference (ITSC), pp. 613–618, IEEE, Auckland, New Zealand, October 2019.

[37] S. P. Miaou and H. Lum, “Modeling vehicle accidents and highway geometric design relationships,” Accident Analysis & Prevention, vol. 25, no. 6, pp. 689–709, 1993.

[38] M. Poch and F. Mannering, “Negative binomial analysis of intersection-accident frequencies,” Journal of Transportation Engineering-Asce, vol. 122, no. 2, pp. 105–113, 1996.

[39] K. Xie, X. Wang, H. Huang, and X. Chen, “Corridor-level signalized intersection safety analysis in Shanghai, China using Bayesian hierarchical models,” Accident Analysis & Prevention, vol. 50, pp. 25–33, 2013.

[40] T. F. Golob, W. W. Recker, and J. D. Leonard, “An analysis of the severity and incident duration of truck-involved freeway accidents,” Accident Analysis & Prevention, vol. 19, no. 5, pp. 375–395, 1987.

[41] A. Garib, A. Radwan, and H. Al-Deek, “Estimating magnitude and duration of incident delays,” Journal of Transportation Engineering, vol. 123, no. 6, pp. 459–466, 1997.

[42] C. Z. Mooney, Monte Carlo Simulation, SAGE Publications, Thousand Oaks, CA, USA, 1997.

[43] Y. Zhu, K. Ozbay, K. Xie, H. Yang, and E. F. Morgul, Network Modeling of Hurricane Evacuation using Data Driven Demand and Incident Induced Capacity Loss Models, Transportation Research Board, Washington, DC, USA, 2016.