Study of the Network-Wide Impacts of Various Demand Generation Methods under Hurricane Evacuation Conditions

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ABSTRACT

Demand generation and network loading models under hurricane evacuation conditions, which include more guided actions compared to unpredictable disasters, are crucial yet challenging components of evacuation studies. This study has two major goals: (1) Conduct a comprehensive and critical review of demand generation and network loading models under hurricane conditions to understand advantages and disadvantages of available approaches, (2) Assess network-wide impacts of these different demand generation and loading models using an analytical system optimal dynamic traffic assignment model. The review of demand generation and loading models under hurricane conditions revealed the existence of three distinct yet frequently used approaches namely, S-curves, Tweedie’s and sequential logit models (SLM). System Optimal Dynamic Traffic Assignment (SO-DTA) formulation originally proposed by Ziliaskopoulos (25) is then used to model a simplified version of the Cape May network. This multiple origin-single destination SO-DTA case study model is then solved for different demand patterns generated using the three methods described in the first portion of the paper. S-curve and Tweedie’s approaches are found to cause unrealistically large travel time delays mainly due to the fact that they generate demand patterns that are loaded within few hours only. This is clearly not a realistic assumption and is not observed in real data either. On the other hand, demand patterns generated using SLM that are spread over much longer periods of time are found to cause more realistic network delays when they are assigned onto the case study network using the developed SO-DTA model.
INTRODUCTION

Demand generation and network loading models under hurricane evacuation conditions are crucial yet challenging components of an evacuation study. Impacts of various evacuation scenarios can only be estimated by using realistic time-dependent demand generation models. However, unlike traffic assignment models employed to study various evacuation strategies, demand generation has not attracted much attention of the researchers. This is mainly due to the complex nature of evacuation behavior and evacuees’ decision process, which is simply hard to model. Currently used approaches are either very simplistic, like sigmoid curves (S-curves), or data intensive and complex, like logistic regression or artificial neural network (ANN) models. This study has two major goals:

1. Conducting a comprehensive and critical review of the demand generation models under evacuation conditions.
2. Assessment of network-wide performance impacts of widely used demand generation using a system-optimal dynamic traffic assignment model.

COMPREHENSIVE AND CRITICAL REVIEW OF THE DEMAND AND NETWORK GENERATION MODELS

There are several studies conducted (2,3,4,5,11) for investigating the major factors affecting the evacuation behavior, however, there is no consensus about the absolute impacts of those factors on evacuation behavior. Studies are mostly based on surveys, conducted both before and after an evacuation. However, the results obtained in different regions are often found to identify different set of parameters as significant. Furthermore, even two studies based on the same region may give different results. Parameters defined by Baker (11), which summarizes the results of surveys conducted after twelve hurricanes between 1961 and 1989 in almost every state ranging from Texas to Massachusetts, are addressed as a comprehensive review of all the major factors. These parameters are risk level (hazardousness) of the area, actions by public authorities, housing type (being mobile etc.), prior perception of personal risk, and storm specific threat factor (intensity, track etc.). Among those factors, prior risk perception is the most cited factor in the literature. Feeling safe, although it is very difficult to explain how people feel it, is identified to be a major factor for evacuation decision making. Based on behavioral aspects found in the studies, traffic demand models are constructed to mimic the evacuation process to be loaded onto the traffic network (6,7,8,9,10,12).

Widely used estimation method for time dependent demand is the two-staged method employed in evacuation decision support software packages. In the first stage, number of households in pre-specified regions that is expected to evacuate, are estimated using participation rates. These rates are determined by the speed and type of the hurricane, type of housing and proportion of the population that are transient. Multiplication of these rates with the population in pre-specified areas gives the total number of the evacuees at the area. At the second stage, time at which the calculated evacuee number will be loaded on the network is estimated (13). Loading is typically done using so-called response or mobilization curve that estimates the proportion of the total evacuation demand that starts evacuation within each time period. These curves are represented using mathematical functions and formulized to reproduce past evacuation behavior (1).
The most popular loading model is the sigmoid curves (S-curves). S-curve represents cumulative percentage of evacuees at every time period. It is commonly used in practice (1,24). S-curve parameters can be adjusted to mimic different behavioral responses. However they still do not fully reflect the reality since they introduce a time independent continuous process, whereas time-of-day is accepted to affect evacuation decisions and rates. Moreover, S-curves do not allow investigation of specific decision making process of the households and produces aggregate results (12). Nevertheless, S-curves are frequently mentioned in the literature and commonly used in evacuation software packages, such as MASSVAC (16).

Another approach for loading transportation networks under evacuation conditions uses the planner’s knowledge and judgment to produce departure time estimation. Mobilization time is the time from issuing of an evacuation order to the time of departure and Tweedie et al. (21) determine mobilization time parameters based on the information obtained from experts in the Civil Defense Office of Oklahoma. Specific amount of time for which given percentages of the evacuating population could normally be expected to be mobilized, is determined according to expert knowledge. Tweedie’s approach suggests a loading function with Rayleigh distribution that has only one independent parameter namely, maximum mobilization time. This is assumed to be the time after which all the evacuees are assumed to leave the danger area. It has S-like shape, like S-curves, however proposed original loading scheme assumes total mobilization time to be 1800 minutes, which is pretty quick compared to S-curve which already has a short loading time span.

Since the dependent variable is discrete (evacuate or not) logistic regression models can also be employed as alternative trip generation models (13). There have also been attempts to model the demand using artificial neural networks (ANN). Mei (9) conducts a detailed analysis of logistic regression and ANN models for hurricane trip generation. He investigates 3 different ANN models, namely back-propagation neural network (BPNN), probabilistic neural network (PNN) and learning vector quantizer (LVQ). The models developed in this study are also compared with a cross-classification type model developed by consultants to estimate the trip generation in Southern Louisiana (PBS&J). Overall, BPNN and logistic regression models are put forward to perform better than the other two models. In his other study (13), feed-forward neural network (FFNN) is also analyzed, and although no clear preference is stated, neural network models are told to perform marginally better than the logistic model. Fu (12), also compares 4 approaches for hurricane evacuation demand, namely Cox proportional hazard models and piecewise exponential models, as subtitles under survival analysis, and sequential logit model (SLM) and sequential complementary log-log model under sequential model title. SLM, which successfully captures the evacuation behavior parameters presented by Baker (11), is stated to perform best among those. Moreover, this model is stated to be transferable, i.e. the model can be applied to different situations in terms of hurricane characteristics and geographic locations. Transferability of SLM and the statistical packages supporting robust estimation of logit models given that data is available, are additional incentives (12). That is the main reason for choosing SLM, among other alternatives, to conduct further analysis.
IN-DEPTH ANALYSIS OF SELECTED EVACUATION DEMAND GENERATION AND LOADING MODELS

Three selected models, namely S-curve, Rayleigh distribution and sequential logit represent different type of approaches that can be used with varying information about the region and its people’s experiences. The general difficulty of acquiring hurricane evacuation data makes it easy to use S-curve for the analysis. Likewise, Rayleigh distribution approximation for evacuation demand proposed by Tweedie (21) is selected for comparison purposes since it mainly relies on professional judgment rather than real data. Main reason behind the popularity of two methods is that they do not need extensive data. Only model among the selected ones that solely relies on real data is the SLM proposed by (12). This model is selected to be able to compare more detailed and representative model with other relatively simplistic yet easy to use models.

Sensitivity Analysis

For defining the effect of model parameters, sensitivity analysis is performed for three selected demand generation models: Tweedie’s Approach, S-curves, and SLM.

Tweedie’s Approach

Tweedie employs Rayleigh distribution to represent evacuation loading onto the network. The formula is:

\[ F(t) = 1 - \exp \left( \frac{-t^2}{1800} \right) \]

In this approach, only parameter to be investigated is number 1800, which is the maximum mobilization time (in minutes), at which all the people will be evacuated. Tweedie finds this number with the help of Civil Defense Office of Oklahoma, which may not be valid for other locations. The evacuation curves according to different maximum evacuation time values are given in FIGURE 1. An important point is that these curves will give time-dependent evacuation rates of total demand, which are determined exogenous to the model.
As shown in FIGURE 1, as the maximum evacuation time increases, the curves become closer to each other. It takes 46, 65, 79, 92 minutes to complete 90% evacuation for maximum evacuation times 900, 1800, 2700 and 3600, respectively. This means that difference in loading pattern is more significant when total evacuation period is short. Note that, although the loading decay (assumed as loading < 0.0001) occurs at 62, 84, 102, 115th minutes, maximum loading minutes occurs at 22, 31, 37, and 43rd minutes for maximum mobilization times of 900, 1800, 2700 and 3600 minutes respectively. Thus it can be concluded that the maximum loading time does not vary in the order of maximum mobilization time parameter.

S-Curves

S-curves according to Radwan et al. (20)’s formula used in evacuation software packages like TEDSS and MASSVAC are shown in FIGURE 2 and the formula is:

\[
P(t) = \frac{1}{1 + \exp[-\alpha(t - H)]}
\]  

where:

\( P(t) \): Cumulative percentage of total trips generated at time \( t \).
\( \alpha \): Response of the public
\( H \): Half loading time.
H represents the time at which half of the vehicles in the system are loaded onto the network. It defines the midpoint of the loading curve, and can be adjusted according to disaster characteristics (9).

![Cumulative Evacuation and Percentage Loading Graphs for S-Curve with Half Loading Time=90 Minutes and Changing Alpha Parameters](image)

**FIGURE 2** Cumulative Evacuation and Percentage Loading Graphs for S-Curve with Half Loading Time=90 Minutes and Changing Alpha Parameters

In FIGURE 2, different S-curves with varying \( \alpha \) parameters are shown. All curves intersect at \( H \), which was kept fixed. As \( \alpha \) parameter increases, the response is more concentrated near \( H \) value. Low \( \alpha \) value gives more homogeneous loading percentages. The time it takes for 90% evacuation, with \( H=90 \) minutes, is 101, 98, 96, and 95 minutes for \( \alpha \) values of 0.2, 0.3, 0.4, and 0.5 respectively. This is an expected result since \( \alpha \) value determines the response rate and as it increases, time to reach high percentages gets lower and also becomes less distinguishable from curve obtained from a close \( \alpha \) value.

Half loading time is also important since it determines the time which maximum loading occurs (FIGURE 2). A change in \( H \) shifts S-curve in horizontal direction, also changing the time of the maximum loading. In other words, half loading time parameter changes the timing of the evacuation, without changing the behavior of the evacuees.

**Sequential Logit Model (SLM)**

A sensitivity analysis for evacuation probabilities is conducted in (12). In the model, each random utility function \( U_i^c \) (utility of household not to evacuate at time \( i \), \( c=continue \)) and \( U_i^s \) (utility of household to evacuate at time \( i \), \( s=stop \)), are assumed to be composed of systematic component \( x' \beta \), which represents the explanatory variables,
and an error term, i.e. $U = x^\prime \beta + \varepsilon$. Also the utility differences $U_i^c - U_i^a$ are assumed to be independently logistic distributed. Then the probability of a household to evacuate at time $i$ given that it has not evacuated earlier can be expressed as:

$$P(i)_{s, c} = \frac{e^{x^\prime \beta}}{1 + e^{x^\prime \beta}}$$

where $x^\prime \beta = V = -2.8238 - 0.7995 \times \text{dist} + 1.4512(2.0244) \times \text{TOD} + 0.1463 \times \text{speed}$

$$+ 0.5401 \times \text{orderper} + 0.7809 \times \text{flood} + 1.6496 \times \text{mobile}$$

where $\text{dist}$: A function of distance to the storm at time $t$

$\text{TOD}$: Time of the day, periods used – night, morning, afternoon.

$\text{speed}$: Forward speed of the hurricane at time $t$

$\text{orderper}$: 1 if perceived evacuation order, 0 otherwise

$\text{flood}$: 1 if the residence is likely to be flooded, 0 otherwise

$\text{mobile}$: 1 if a mobile home, 0 otherwise

Two coefficients, 1.4512 and 2.0244 are used for morning and afternoon, respectively. For night since TOD=0, utility function is not affected. These coefficients basically state that people are more likely to evacuate in the afternoon, morning, and night, with decreasing order respectively.

Signs of the variables are as intuitively expected, since increasing distance will decrease the probability of evacuation, and increase in all other variables increases the evacuation probability. Among all variables, TOD has the largest absolute value, and it affects the evacuation considerably. “Mobile” and “flood” are the next two important parameters according to their impact on the utility function. From the data set used for model estimation, the values of dist ranges from 0 to 7 and have a ratio of 270 between two extreme values, making dist the most influential variable in the model (6).

One point that can be discussed in SLM is that high-risk households tend to leave their houses first. Fu (6) states that high-risk households tend to live near water or low-lying areas and, therefore, probably have longer evacuation distances, so their early leave is reasonable. However, one would expect that the people would tend to wait for making their final evacuation decisions after being sure about hurricane’s path, its intensity, and also stay to protect their houses. These latter points were not incorporated in this model but stated in the literature (11). Overall, SLM succeeds to capture behavioral aspect for many of the possible scenarios. However, it fails in case of high-risk household, especially when mobile home is under consideration.

Besides the facts stated by (6), for this study, the evacuation percentage output of SLM are estimated with Monte Carlo simulation for comparison with the participation rates in the literature. For this purpose, artificial samples were generated with alternating attributes for evacuation order, flood risk, and housing type. Each sample was assumed to be subjected to same hurricane characteristics. The simulation results can be seen in FIGURE 3.
As shown in FIGURE 3, SLM gives about 90% participation rate for mobile households with flood risk, and which received evacuation order. According to behavioral studies conducted by Federal Emergency Management Agency & Army Corps of Engineers (24), relatively higher participation rates for high-risk households are reasonable. However for low risk households, without any evacuation order, the participation rate predicted by the model is about 25%. This is assumed to be about 10-15% at most in the behavioral studies. Although the model estimate is higher than the assumption, it still gives a value that lies on the safe side. It should also be noted that these participation rates are also assumptions, so it may be misleading to decide about a model’s accuracy only relying on those assumptions.

Since the evacuation is assumed to last for 3 days, the beginning period is also analyzed if it has any effect on evacuation behavior. It is found that participation rate do not change (around 1-3%) in case of starting evacuation in the morning or afternoon. The most diverse evacuation numbers (12-16%) between different starting periods are obtained for two extreme cases; high risk (mobile home-flood risk-received evacuation order) and low risk (not a mobile home-no flood risk-no order received) houses.

For Cape May County, which will be investigated with a case study in the next section, the difference of about 12-16% is equal to a difference of roughly 5,000-7,000 households out of total 42,148 households (22). This is equal to about 11,000-16,000 people according to U.S. Census statistics. Overall, it can be said that SLM is sensitive to the starting period of evacuation, especially for extreme cases, like high-risk and low-risk households.
Case Study: Cape May, New Jersey

SLM is employed for estimating the evacuation demand for Cape May County where the last major hurricane made a direct landfall in 1821. Below are some important facts about Cape May County (22,23). These facts are used in the simulation.

- Number of housing units=93541 → Used as total number of houses in the area in the simulation
- Number of mobile houses=2807 → Used to determine the percentage of mobile houses together with total number of houses
- Number of households=42148 → Total number households to be evacuated
- Water area=365.09 mi² → Used to determine the households with flood risk
- Total area=620.28 mi²

Following assumptions are made for the demand simulation under evacuation conditions:
- Total number of evacuations is equal to 42148 households, where there are total of 93541 housing units.
- Houses are evenly distributed in the county, so that the proportion of mobile homes over total number of houses applies to whole county to represent the mobile home probability. Likewise, water area over total area represents the proportion of households exposed to flood risk.
- All attributes are assigned independently, since no joint statistics like mobile home-flood risk is present.

FIGURE 4 Different evacuation loading patterns generated for Cape May County
FIGURE 4 shows predicted evacuation pattern for Cape May with various S-Curves and SLM. Participation rate is predicted by the SLM to be 42% for the whole county. Four different response curves are generated. S-curves 1 and 2 represent three-day long loading scenarios, where S-curve-3 is the commonly employed S-curve with short loading duration. S-curve 4 is also a three-day long loading curve where each daily part resembles S-curve 3. Thus S-curve 4 is the reproduction of S-curve 3 assuming equally divided participation rates for each day. For S-curves 1 and 2, parameters are chosen as $\alpha_1 = 0.002$ and $\alpha_2 = 0.004$, with $H = 8$ hours for both curves. For each daily loading pattern, parameters of S-curves 3 and 4 are $\alpha = 0.04$, $H = 12$ and $\alpha = 0.01$, $H = 9$, respectively. Although parameters are adjusted to replicate long evacuation durations, S-curve 1 and S-curve 2 shown in FIGURE 4 fail to accurately represent a realistic evacuation pattern. S-curve 1 achieves to represent a more realistic evacuation pattern better than S-curve 2 but it does not reach 100% at the end of the evacuation period. Also, it underestimates the first half of the evacuation percentages, whereas it overestimates the second half. Quick loading S-curve 3 shows a distinctively different behavior compared to first two curves, because it loads all the evacuees onto the network in less than one day. Curve 4 incorporates some kind of a time-of-day dependency. Overall, S-curves, although widely used in the literature because of their simplicity, are found to represent the evacuation demand patterns rather poorly. Reader should note that the evacuation pattern produced by SLM is assumed to represent the evacuation pattern most realistically and other model performances are compared with its performance. This kind of an assumption is unavoidable since there is no real evacuation data present for Cape May County. SLM was chosen as the most realistic demand generation approach because of the reasons mentioned before, i.e. its capability of capturing widely agreed evacuation behavior parameters and extensive real-world hurricane data used to validate it by Louisiana State University researchers (12).

ASSESSMENT OF THE NETWORK-WIDE PERFORMANCE IMPACTS OF DIFFERENT DEMAND GENERATION AND LOADING MODELS

The final outcome of different demand generation and loading models cannot be fully understood by just studying the shape of loading curves. Total time needed to evacuate people out of danger area is the most important outcome of these models. This insight can be obtained by using a realistic network supply model that incorporates the outcome of the specific demand model. For example, two models with distinctly different shapes, but resulting in exactly same clearance times, will have no difference as far as the modeler is concerned. On the other hand, two different loading scenarios giving inconsistent results in terms of average delays can point out to important theoretical problems related to these models in terms of failure to represent the real life conditions. Thus, there might be a need for the use of a new and more appropriate model.

For network clearance time and delay analysis, system optimal dynamic traffic assignment (SO-DTA) formulation proposed by Ziliaskopoulos (25) is employed for modeling network supply. The reason for selecting SO-DTA model is due to the fact that during evacuation, the traffic flow will be controlled by emergency officials, whose aim is to clear the area as quickly as possible. This goal can only be achieved by adopting a SO traffic assignment scheme. Ziliaskopoulos (25) formulates a linear programming
problem for single destination network, making use of Daganzo’s cell transmission model (26,27). His formulation minimizes the total time that the cells are occupied and in this setup, the final clearance time can be considered as the time when there are no occupied cells. There is no legal mechanism to enforce the exact timing of the mobilization of each household. Assuming that the evacuees are not safe until they reach the destination, the algorithm minimizes the time that those evacuees are considered to be unsafe. Thus, average travel time, as a period of time spent outside shelter, corresponds to a risk exposure measure for the problem and will be used to evaluate the evacuation performance.

As the application region, Cape May County, NJ, was chosen. Simplified version of Cape May highway network (FIGURE 5) obtained from NJ Office of Emergency Management (18) was modeled based on Daganzo’s cell-transmission theory as a multiple origin and single destination network. According to this modeling approach, evacuees are assumed to depart from two origins in the coastal region, all heading to the same single destination, which is inland.

FIGURE 5 Depiction of the simplified Cape May evacuation network used in the analysis (Source: NJ Office of Emergency Management)

For the cell representation, the cell capacities and speeds under evacuation conditions were estimated based on real-world counts, obtained from evacuation studies (29). Cell transmission model is capable of introducing time-dependent flow rates that
change depending on the congestion levels. However, to keep the model as simple as possible, also considering the inaccuracy of traffic flow models under highly congested networks like the evacuation case, average values for flow rates and speeds are assumed to remain constant throughout the simulation, except the reduced capacity case scenario explained below. Average speeds and flows are assumed to be 30 mph and 1000 vphpl. Physical capacity of cells to accommodate cars was assumed to be 200 vehicles per mile.

Three different scenarios were investigated with three demand models described before:
1. Base scenario: Loading the empty network.
2. Shadow evacuation scenario: Loading the network with initial traffic representing the evacuees loading to network before the evacuation order is given by the authorities.
3. Reduced capacity scenario: Loading the network with reduced link capacities to investigate the sensitivity of different loading schemes due to capacity losses.

For the base scenario, the network is assumed to be initially empty. For the second scenario, initial traffic is introduced to all cells in the network as 15% of cell capacity to represent the shadow evacuation. Shadow evacuation terminology is used for both the percent of evacuees who leave before officials issue an evacuation order (9) and for the case of evacuation near threatened areas even though the evacuees are not necessarily in danger (30). In our analysis, we use the former definition to represent the traffic due to evacuees who leave before officials issue an evacuation. For the third scenario, network is assumed to suffer a capacity loss due to storm surges and flooding. Both flow and cell capacities are assumed to decrease continuously from the beginning till the end of the analysis (48 hours), which can be considered as the landfall of hurricane. Another important point is that contraflow was assumed for all links in the network. For example 6 lanes of the Garden State Parkway, which has 4 lanes in each direction under regular operation conditions, were assumed to be utilized for the evacuation in one direction. Likewise for other roads with two lanes in each direction, 3 lanes in the direction of evacuation were used instead of 2 lanes.

Three scenarios were run with different participation rates. First, the total number of evacuees found from SLM was assumed to be valid for all other loading models. However, one drawback of the sequential model is its sensitivity to total evacuation period. For the one-day evacuation scenario, participation rate is estimated as 20-25 percent. This is due to the fact that the model was developed using evacuation data over several days and time-of-day coefficients were determined accordingly. This dependency of evacuation period raises the major question of the transferability of the model to other areas.

Since the evacuation rate estimated using SLM for one day is low, the system handles the demand easily and neither initial traffic nor reduced capacity affect the system clearance times except the for Rayleigh distribution. This is due to the fact that evacuation demand based on Rayleigh distribution loads the network very quickly during initial period. For other loading schemes, the shadow evacuation is discharged before the high loading values are assigned onto the network and clearance times are not affected.

The participation rate obtained from SLM does not allow full investigation of the effects of different scenarios, since network capacity is not fully utilized. Thus, a higher
participation rate assumed independent of the SLM output was also employed. 50% participation rate rather than 20-25% is more justifiable for a coastal region like Cape May. Moreover, SLM gives 42% participation rate for 3 days long evacuation. An additional 8% increase in demand can be attributed to tourist population in Cape May region. Additional runs are not necessary for S and Rayleigh curves since participation rate is introduced externally to these models. However for the SLM, the curve for one day long evacuation is adjusted and shifted up to reach 50% at the end of the one day period (FIGURE 6). Parameters of the S-curve are set to $\alpha = 0.04$, $H = 5$ for quick loading case, $\alpha = 0.04$, $H = 5$ for long span loading S-curve. Maximum mobilization time for Rayleigh distribution is assumed to be 1800 minutes.

![FIGURE 6 Loading curves that are used for Cape May County network performance analysis](Image)

Clearance and average travel times obtained from the analysis are summarized in TABLE 1.
TABLE 1  Clearance times and average travel times in hours for one-day evacuation with different scenarios

<table>
<thead>
<tr>
<th>Clearance and Average Travel Times (hours)</th>
<th>Base Scenario</th>
<th>With 15% Shadow evacuation</th>
<th>Capacity Drop of 30%</th>
<th>Capacity Drop of 50%</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Low P.R</td>
<td>High P.R</td>
<td>Low P.R</td>
<td>High P.R</td>
</tr>
<tr>
<td>Sequential Logit Model</td>
<td>28.5 (1.86)</td>
<td>45 (11.08)</td>
<td>28.5 (2.03)</td>
<td>45 (11.25)</td>
</tr>
<tr>
<td>S-Curve (Quick loading)</td>
<td>22 (4.02)</td>
<td>40 (17.9)</td>
<td>22 (4.19)</td>
<td>40.5 (18.08)</td>
</tr>
<tr>
<td>S-Curve (Long loading period)</td>
<td>25.5 (1.7)</td>
<td>39.5 (9)</td>
<td>25.5 (1.87)</td>
<td>39.5 (9.17)</td>
</tr>
<tr>
<td>Tweedie’s Approach</td>
<td>19 (4.46)</td>
<td>38 (19.18)</td>
<td>20 (5.3)</td>
<td>39 (20.82)</td>
</tr>
</tbody>
</table>

Some important observations based on the clearance time results are summarized below.

- Increase in participation rate (P.R) affects the models with shorter loading periods more than the ones with longer loading periods. Quick loading S-curve and Tweedie’s model double the clearance time with doubled P.R. where the clearance times for other two models a minimum 55% increase is observed.

- For high participation rates, the overall clearance times are close for all loading models. However for low P.R the clearance times differ considerably. This is mainly due to the fact that when the system is not congested, the clearance time depends on the loading timing of the vehicles rather than the network capacity. For networks operating at capacity, the clearance times become more dependent on the network characteristics.

- Shadow evacuation does not affect the clearance times considerably. The effect is valid only when the demand model loads the network quickly just after the initiation of the evacuation process, e.g. Rayleigh distribution and quick loading S-Curve.

Although clearance time is an important parameter for evacuation studies, it is not the best measure to compare the realism of demand models, since it mainly depends on the timing of the loading. Due to the nature of the SO optimization problem, timing of the last loading onto the network, impacts the length of the overall clearance time. Thus, investigating clearance times only can give a general idea about the reliability of the total network discharge process, but not the time-dependent congestion on the network. In SO-DTA model, vehicles are not moved forward until there is available capacity in the downstream cells. In other words, bottlenecks can occur anywhere in the network but corresponding delay or queue mainly occur in source cells by the vehicles waiting to be loaded onto the network. Although close clearance times are obtained, different demand models inherently cause different average individual delays. To investigate the performance of different models in terms of average travel times, the total occupancy of the network, which is the objective function of the optimization problem to be minimized, is divided by the total number of vehicles. From the risk exposure perspective, average travel time can be interpreted as the average time between their homes and the hurricane shelter where the evacuées are exposed to risk. Likewise, queuing delays can be interpreted as the duration of extra risk exposure on the evacuées.
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Analysis shows that an average of 17%, 48%, 17% and 61% of the total evacuee population wait in the queue to be loaded onto the network in source cells, for SLM, quick loading S-curve, long span loading S-curve and Rayleigh distribution, respectively. These numbers show the similar patterns with respect to average travel times (TABLE 1 in parenthesis). SLM and long span S-curve give similar results for both average travel time and queuing time. Quick loading S-curve and Rayleigh distribution produce large queue lengths and large travel delays. Note that, the SO-DTA model does not force vehicles to move forward if there is not enough time for all the loaded vehicles to leave the network. Since there is a heavy computational burden for every time step added to the analysis, the optimization was limited to 48 hours. Thus, average travel times could not be computed for the scenarios that require more than 48 hours of clearance time.

CONCLUSIONS

The purpose of this study was to conduct a comprehensive and critical review of demand generation and network loading models under hurricane conditions to understand advantages and disadvantages of available approaches, and to assess the network-wide impacts of different demand generation and loading models using an analytical SO-DTA model.

Average travel times obtained from the case study show that regardless of the clearance times, quick loading models produce unrealistic evacuation delays. Especially when demand is high, although final network clearance times are close, average travel time for the vehicles loaded using Rayleigh distribution or quick loading S-curve is almost doubled compared to SLM and smooth loading S-curve. Effect of shadow evacuation also becomes more apparent. If the fact that sequential logit model can better mimic the evacuation behavior is taken granted, it can be concluded that quick loading S-curve or Rayleigh distribution both cause large delays that are not consistent with real traffic conditions. If the distances in Cape May region are considered along with the 30 mph speed assumption, it should take about 1.5-2 hours to travel between the two most distant points of this network. However, even for the low demand loading scenario, quick loading S-curve and Tweedie’s approach give about 4 hours of average travel time where SLM and smooth loading S-curve give reasonable values around 2 hours.

In conclusion, S-curve with quick loading parameter, which is a popular loading scheme used in evacuation software packages, and Rayleigh distribution approach predict unreasonable delays. Average travel times are found to be up to 18-22 hours, which are almost the same amount of time that loading takes place. Those high travel times show that neither the Rayleigh distribution nor the quick loading S-curve can represent the real evacuation behavior.

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