Approach to Modeling Demand and Supply for a Short-Notice Evacuation

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As part of disaster mitigation and evacuation planning, planners must be able to develop effective tactical and operational strategies to manage traffic and transportation needs during an evacuation. One aspect of evacuation planning is the estimation of how many people must be evacuated to provide strategies that are responsive to the number and location of these people. When such estimates are available, it may be possible to implement tactical and operational strategies that closely match the likely demand on the road network during the evacuation. With short notice for an evacuation, people may need to be evacuated directly from current locations. In addition, for some disasters, the spatial extent of the evacuated area may change over time. This problem may be exacerbated by congestion around the evacuated area. An estimation process is proposed for a short-notice evacuation. The method uses on-hand data typically generated through existing travel demand models at many metropolitan planning organizations. It estimates demand using convenient models for trip generation, trip distribution, and travel time generation for these trips, considering a staged evacuation. These demand estimates feed a dynamic simulation model, DynusT, that is used to model the supply characteristics of the roadway network during the evacuation. Such models can be applied using a case study based on a short-notice flooding scenario for Phoenix, Arizona.

In recent years, natural and man-made disasters—hurricanes, flooding, bomb threats, and wildfires—have been frequent worldwide. To help mitigate against the impacts of these disasters, various studies have been conducted to minimize injury and damage. As part of mitigation, the evacuation of people from the affected area in a timely and safe manner is critically important to reduce injury and damage. Planners must be able to develop effective tactical and operational strategies to manage traffic and transportation needs during the evacuation itself.

In planning for an evacuation, it is useful to have some method of estimating how many people must be evacuated to provide strategies that are responsive to the number and location of these people. When such estimates are available, it may be possible to implement tactical and operational strategies that closely match the likely demand on the road network during the evacuation. In traditional evacuation models, it is commonly assumed that people will evacuate directly from their residence. This assumption is grounded in the notion that people will be at home, or will return home, before beginning to evacuate. This assumption may be realistic under conditions where ample time is available to conduct the evacuation (e.g., more than 24 or 48 h, as in the case of a hurricane evacuation).

When the time to evacuate is considerably less, people may need to be evacuated directly from their current locations. The timing and magnitude of certain types of disasters may require faster reactions. People may receive short notice about the emergency and their need to evacuate, providing little or no time to return home before evacuating. In addition, for some disasters, the spatial extent of the evacuated area may change over time. This problem may be exacerbated by congestion around the evacuated area. For example, to manage traffic flows effectively in the event of a short-notice disaster such as a wildfire or flash flood, it may be useful to know which areas must be evacuated first and the likely impact on roadway congestion throughout the region.

Several studies have been conducted on estimating demand characteristics for an evacuation, particularly focusing on the factors of trip generation, trip distribution, and trip timing. Some research has focused on estimating a trip generation model, such as the logistic model and the neural network model, using hurricane survey data (*1–5*). These models estimate a probability of leaving an area as a function of time as the disaster progresses. Other models estimate evacuation demand using socioeconomic data (*6, 7*). Similar to these last two studies, the present study considers the case without existing evacuation survey data for estimating a model of trip generation; existing trip generation data from existing urban planning models are used; such is the common situation faced by most regional transportation and emergency management agencies. In addition, models used for trip distribution for evacuation include the gravity model, the intervening opportunity model, and the multinomial logit model. Finally, a type of logistic model has been used for vehicle loading, describing the time of departure (*6–8*).

Methods of estimating demand for a short-notice evacuation have not been discussed at length in the existing literature. In this paper, an estimation process is proposed for a short-notice evacuation. The method uses "on-hand" data typically generated through existing travel demand models at many metropolitan planning organizations. In this context, the proposed trip generation and distribution models are developed using existing trip matrices based on existing, calibrated travel demand models. It generally assumes that no separate set of behavioral data is available for estimating evacuation demand. Trip matrices are suggested for use as the basis for generating trip distribution; this trip distribution approach was inspired by Southworth (*7*). Additionally, a time-dependent evacuee departure model is proposed that considers a multiple-zone evacuation strategy related to that of Tweedie et al. (*8*).

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The paper proceeds as follows. First, the proposed method and overall framework for the proposed models are introduced. Next, an application of the proposed models for a specific flooding scenario in the metropolitan area of Phoenix, Arizona, is described. Finally, conclusions from this method and areas for future study are discussed.

PROPOSED EVACUATION METHOD

Overall Framework

Demand during a short-notice evacuation may be categorized as evacuation demand or background demand. Evacuation demand refers to the evacuating trips generated in the area around the disaster (defined as the hot zone) and consists of a set of traffic analysis zones (TAZs). Background demand consists of the trips between TAZs outside the hot zone during the evacuation. Some of these trips may interact and interfere with the evacuating trips. The combination of these two types of demand must be estimated and loaded into an evacuation simulation to properly assess traffic performance in a potential emergency scenario.

To generate evacuation demand, one must estimate how many vehicles will originate from the hazardous area (trip generation) and where the vehicles will go (trip distribution). In addition, to simulate an evacuation, it is possible to apply a departure curve for each vehicle (or trip) between a given origin and destination.

Generated evacuation demand should be combined with the existing background demand to synthesize the total demand for an evacuation simulation. Background demand is generated from a typical day's travel patterns, which can be estimated from well-calibrated travel demand models for some baseline year and network condition. This background demand excludes the demand generated by zones in the evacuation area. In generating evacuation demand, one should consider the evacuation start time. Traffic patterns will be considerably different whether a disaster occurs midday, during the morning rush hour, or late in the evening. For this reason, a useful estimate of evacuation demand will specifically consider time-of-day demand data. According to time of day, it may also be possible to analyze the worst-case (from a traffic perspective) timing for each disaster. For instance, the worst case in a downtown area could be at 11 a.m. or 12 noon, when the maximum people have accumulated downtown. In this case, the demand should be accumulated until 11 a.m. or 12 noon from the morning peak.

Finally, the total demand for an evacuation simulation is produced by combining evacuation demand with background demand. This process provides the interactions between the background and evacuation travel behavior during the evacuation.

Trip Generation and Trip Distribution Models

Data

Calibrated trip matrices (by time of day and by trip purpose) are the starting point of the demand-estimation process. Matrices include trips from each origin TAZ to each destination TAZ for every time of interest *t* and for a given trip purpose *p*. The Maricopa Association of Governments (MAG) in Maricopa County, Arizona (greater Phoenix area), provided the trip matrices. For trip generation, 2006 trip matrices were received covering a full day (24 h) for all purposes: home-based work (HBW), home-based other (HBO), and non-home-based (NHB). Time-of-day trip matrices also were received, covering all trip purposes for the morning peak (6–9 a.m.), midday (9 a.m.–3 p.m.), afternoon peak (3–6 p.m.), and night (6 p.m.–6 a.m.). Ideally, these matrices would be broken out by trip purpose and by time of day. Instead, the trip-purpose matrices were factored by the time-of-day matrices to estimate trips by trip purpose and by time of day.

Evacuation Trip Generation Model

For the model description, O is defined as the set of TAZs that must be evacuated on short notice; D is the set of all other TAZs not in the set O; and T is the set of periods in the day that occur up to and including the time when a disaster occurs, for a given evacuation scenario. For trip generation, the proposed model consolidates the intended travel of household vehicles out of the evacuation area, minus the number of vehicles that have exited the area earlier in the day, plus the number of vehicles that have entered the area earlier in the day. All the vehicles existing in the evacuation zone at that time are assumed to be evacuated, equivalent to the total number of evacuating vehicles. Mathematically, the proposed model is expressed as

$$G_i = V_i \cdot H_i - \sum_{t \in T} \sum_{j \in D} Q_{ij}^t + \sum_{t \in T} \sum_{j \in D} Q_{ij}^t \qquad \forall i \in O \tag{1}$$

where

G_i = number of vehicles in zone i at the start of the evacuation,
V_i = average vehicles per household in zone i,
H_i = number of households in zone i, and
Q_{ij}^t = vehicles departing from flooding zone i to other zone j during time of day t.

The first term of Equation 1 is the total number of vehicles generated from evacuation zone i, based on an average vehicle ownership rate in the zone (V_i) multiplied by the total number of households in zone i. The second and third terms represent the total outgoing vehicles from zone i and the total incoming vehicles to zone i, respectively, before starting the evacuation. Although this approach for trip generation is similar to that of Southworth in terms of estimating demand considering in-and-out trips, the proposed model is different because it is based on time-of-day data, not socioeconomic data (*7*).

In many cases, the time-of-day trip matrices may actually be in-person trips and are separated by vehicle occupancy, considering drive alone, two-person (2) carpools, and three-person-or-more (3+) carpools. A simple mathematical procedure can be applied to sum these three trip tables, dividing by the average vehicle occupancy to get the necessary vehicle count, as

$$Q_{ij}^t = q_{ij}^{t,1} + \frac{q_{ij}^{t,2}}{2} + \frac{q_{ij}^{t,3+}}{3.5} \tag{2}$$

where $q_{ij}^{t,k}$ is the person trips with k people per vehicle, from zone i to zone j for time of day t. Equation 2 converts person trips to vehicle trips. An average of 3.5 people was applied for the 3+ vehicle occupancy. To apply this model, it is assumed that evacuees do not have sufficient time to return home or go to some other places to pick up another person. In other words, this model is appropriate for short-notice evacuations.

Evacuation Trip Distribution Model

The proportions from an existing trip distribution matrix may be used to distribute traffic from the evacuation area to appropriate destinations. For 81.8% of the trips, destinations considered in evacuations are the homes of friends or relatives and hotels or motels (*1, 4*). According to Mei's literature review, 55% to 68.8% of evacuees traveled to the homes of relatives or friends, 13% to 26% to hotels or motels, and 3% to 12% to public shelters (*3*). Given the predominance of trips to friends or relatives and hotels or motels, one approach would be to apply the destinations according to a social or recreational trip purpose. Because it would seem to apply to more than 80% of the trips during the evacuation, this method may be most appropriate for trip distribution. Of course, it may be questionable; it was chosen simply on the basis of previous research. Other assumptions are possible using the existing trip matrices from a regional planning model (e.g., some evacuees may head for home, if home is outside the evacuation area).

If a home-based social or recreational trip matrix is available, then this information can be used as follows:

$$D_{ij} = G_i \frac{q_{ij}}{\sum_{j \in D} q_{ij}} \tag{3}$$

where

D_{ij} = vehicle trips from zone i in the evacuation area to zone j outside of the area,
G_i = generated vehicle trips from zone i before starting the evacuation, and
q_{ij} = vehicle trips from i to j for the given trip table.

The proposed trip distribution model in Equation 3 distributes the generated vehicles (G_i) from a zone in the evacuation area on the basis of the fraction of trips distributed from zone i to zone j, out of all trips leaving zone i. For person–trip matrices, an additional equation (similar to Equation 2) is necessary to convert person trips to vehicle trips:

$$q_{ij} = \bar{q}_{ij}^{1} + \frac{\bar{q}_{ij}^{2}}{2} + \frac{\bar{q}_{ij}^{3+}}{3.5} \tag{4}$$

where $\bar{q}_{ij}^{k}$ are the person trips with k people from zone i to j for the HBO trip table. Again, the average 3.5 people is used for the vehicle occupancy of 3+ people. Additionally, to prevent distributing vehicles to the disaster area, vehicle trips q_{ij} is set equal to zero for every $j \in O$ in the area being evacuated.

Timing of Evacuation Decision and Departure Curve

Another consideration during an evacuation is the timing of vehicle departures. In an evacuation scenario, evacuee behavior will depend on perceptions of the hazard level. One might argue that, in an emergency situation, all people in the evacuation area will evacuate as soon as possible. Yet if they have more information about the possible hazard and the timing of that hazard according to their location, they may change their resulting departure behavior slightly. If they perceive that more time is available to evacuate and that delaying departure may convey possible advantages, they may delay departure. However, this scenario assumes that the arrival time of the disaster is predictable and that information can be clearly transmitted to evacuees with some geographic precision. These assumptions are mere conjecture for the purposes of the model, which is sufficiently flexible that other assumptions about departure times can be tested easily.

If the severity and the dispersion of the disaster can be estimated in both time and space, it may be possible to estimate the number of vehicles departing at a given time. For modeling purposes, the level of severity according to its geographical area is called a contour. For instance, evacuees in Contour 1 may need to be evacuated more urgently than evacuees in Contour 2.

For modeling purposes, the rate of departure is estimated for vehicles in each contour from the evacuation area. Estimated vehicle departure times are critical when loading vehicles into a transportation network for simulation. These studies use the departure curve from Equation 5, which is based on the Rayleigh cumulative density function defined by Tweedie et al. (*8*).

$$F_i(t) = 1 - \exp\left(\frac{-t^{a_i}}{b_i}\right) \tag{5}$$

where $F_i(t)$ is the cumulative density function of vehicle departures and a_i and b_i are the parameters for each contour i. When estimating parameters a_i and b_i for contour i, it may be necessary to constrain the parameter value such that 100% of the evacuees in contour i should have left their origins well in advance of the disaster striking the area. This assumption may be reasonable for evacuee behavior in each contour. Conversely, the two parameters could be estimated by finding appropriate values where 100% of the evacuees have departed by a given time. This approach is recommended when the direction and severity of the disaster can be predicted. In this case, if the evacuation can be effectively managed to restrict departures (i.e., to stage the departures) for multiple contours, this strategy may be an efficient way to reduce traffic congestion around the evacuation area.

Traffic Simulation and Assignment Model

Innovative evacuation modeling capabilities were built on Dynamic Urban Systems for Transportation (DynusT), a mesoscopic dynamic traffic-simulation and assignment model. DynusT has been developed for years and has been applied to various regionwide traffic-simulation modeling applications, including mass evacuation (*9–14*).

The traffic assignment process in DynusT involves interplay of the simulation model and the time-dependent shortest-path and flow-redistribution component (Figure 1). DynusT can compute the equilibrated route selection for travelers departing at different times. This capability is used primarily to assign the background traffic to routes in the network. During the iterative computational process, the time-dependent link travel time and intersection delays are input into the time-dependent shortest path algorithm. From the shortest path results, the new flow distribution and routing policies are computed in a time-dependent traffic assignment procedure based on the method of isochronal vehicle assignment (Y.-C. Chiu and E. Nava, Method of Isochronal Vehicle Assignment for Simulation-Based Dynamic Traffic Assignment, submitted for publication in *Transportation Research, Part B*, 2009; and Y.-C. Chiu and J. A. Villalobos, Incorporating Dynamic Traffic Assignment into Long-Range Transportation Planning with Daily Simulation Assignment and One-Norm

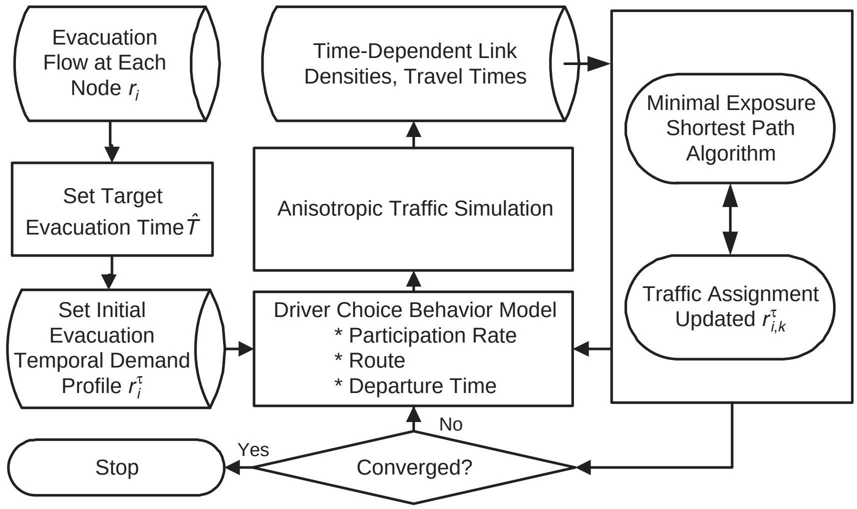

FIGURE 1 General algorithm structure of the DynusT model (*11*).

Origin–Destination Calibration Formulation, submitted for publication in *Transportation Research, Part A,* 2009). The vehicles with updated routes are then input into the traffic simulator to assess the performance. The process is repeated until some convergence criteria are satisfied or the maximum number of iterations is reached.

The vehicle-simulation mechanism follows anisotropic mesoscopic simulation logic in that individual vehicles are generated with individual attributes such as departure time, origin, destination, occupancy, vehicle type, and evacuation route (*15, 16*). During the simulation, a vehicle's movement follows a speed–density relationship—a widely known correlation between speed and density that describes traffic flow—to ensure that the millions of simulated vehicles exhibit realistic traffic flow characteristics at the macroscopic level. Furthermore, individual vehicles have decision rules in response to traffic conditions and information (*11*). Several innovative behavioral rules in response to information include the following:

- Travelers scheduled to depart after the disaster occurs may (*a*) change departure time or route because of congestion information broadcasted by the emergency agency or (*b*) cancel the trip if all possible routes are blocked by the disaster. If all routes to intended destinations are blocked by the disaster, then the trip is cancelled.
- If all possible routes are blocked by the disaster, then en route travelers whose origins are not inside the disaster zone would return home (or to one of several shelters if the return-home route is blocked).
- Travelers passing a dynamic message sign or listening to a radio broadcast may change to an alternate route if the current route is congested and the vehicle is permitted to take other routes. These routes are not computed using accurate network travel times but a synthesis of experienced travel time and real-time information with only partial network coverage (*17*).

Another unique modeling feature is the time-dependent activation and decommissioning of contraflow lanes at a designated time during simulation, modeled by including a coupling counterdirectional dummy link in each directional freeway (or arterial) main lane or ramp lane.

CASE STUDY: PHOENIX FLOOD

Description of Scenario and Contours

As a case study, the proposed method was applied to the Phoenix metropolitan area. The regional network data set obtained from MAG included not only the extensive freeway network in Maricopa County, Arizona, but also the major and minor arterial streets. This network has 2,006 zones, 4,432 nodes, and 11,658 links.

A flooding scenario is assumed. To the northeast of Phoenix, several dams feed the Salt River, which eventually flows through the Phoenix area. In the event of a catastrophic series of dam failures along this system, flooding would occur along the Salt River, and people living and working around the river would have to be evacuated to safe areas. In the most difficult evacuation scenario, the Salt River would start flooding at noon. From this scenario, emergency managers in the Phoenix, Arizona, metropolitan area developed five flooding contours. Contour 1 is the first area to flood, and the water is highest in Contour 5 (Figure 2). Evacuees in Contour 1 must begin evacuating right away and have only 90 min to complete evacuation, whereas those in Contour 5 have more time to get to a safe area before flooding danger becomes imminent. The flooding area includes a total of 298 TAZs.

In a typical scenario, right after the start of flooding at noon, a warning would be broadcasted to citizens for 30 min. Evacuees in Contour 1 would need to be evacuated by 2 p.m. (during the first 90 min after the warning starts), Contour 2 by 2:30 p.m., Contour 3 by 3:30 p.m., Contour 4 by 4:30 p.m., and Contour 5 by 5:30 p.m. (a total of 300 min or 5 h to leave the area that will flood last) (Figure 3). It is assumed that the evacuation starts in all contours after the warning. All evacuees can start moving before the flooding period for their contours.

Evacuation Demand Results

Trip Generation Model

Trip matrices provided by MAG were used to configure the trip generation and trip distribution model. They included 24-h trip matrices

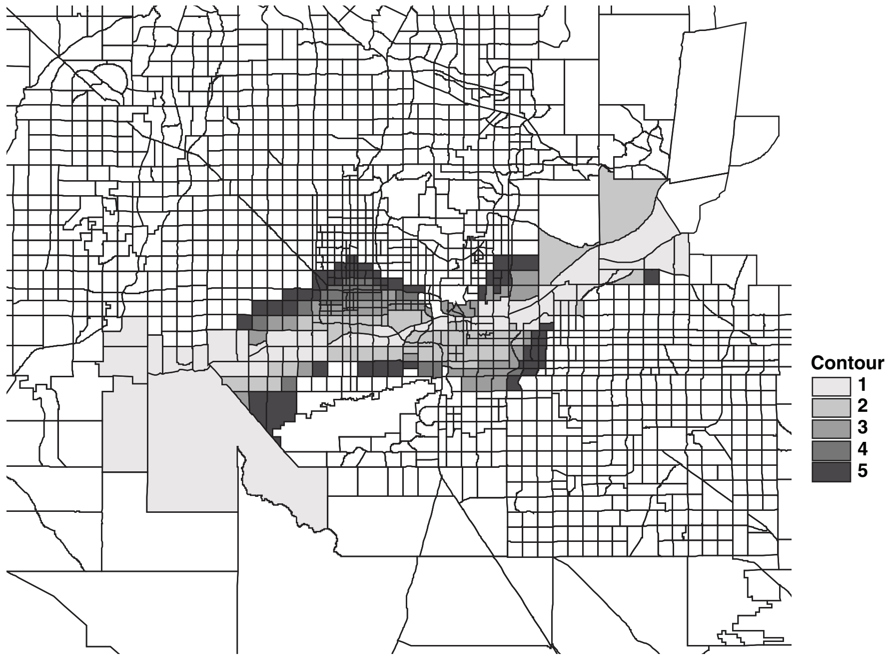

FIGURE 2 Flooding contours.

from 2006 for each trip purpose (HBW, HBO, and NHB) and separate time-of-day matrices (with combined trip purposes) for the morning peak, midday, afternoon peak, and night. The time-of-day matrices were factored to account for trip purpose, by time of day.

With the MAG matrices, the trip generation model was applied in Equations 1 and 2, using the time-of-day trip matrices for morning peak and midday. With flooding starting at noon, the full morning peak trip table and one-half of the midday trip table were used (because the timeframe for midday travel is 9 a.m. to 3 p.m.). Equation 1 was applied directly; however, the vehicle occupancies were given for larger subareas, containing many TAZs, because of insufficient zonal information. The average number of vehicles available per household for each municipal planning area is as follows: Avondale = 1.71, Mesa = 1.68, Phoenix East = 1.35, Phoenix West = 1.61, Phoenix South = 1.71, Scottsdale = 1.70, Tempe = 1.70, Gila River Indian Community = 1.74, and Salt River Reservation = 1.74 (*18*).

Trip generation results are shown in Figure 4*a.* The model generates a total of 425,089 vehicles in the flooding area (i.e., 425,089 vehicles to be evacuated). Most originate in the center of the metropolitan area, including downtown Phoenix, Tempe, and parts of Mesa and Scottsdale.

Trip Distribution Model

A 2006 HBO trip matrix was applied to approximate evacuation travel behavior for the trip distribution model. The HBO matrix was used because no further details on trip purpose were available; however, the intention was to be as close as possible to the likely origins and destinations for social and recreational trip purposes to reflect people traveling to friends' homes.

For selected zones, zero trip origins were in the HBO matrix (i.e., a zero in the numerator of Equation 3), but generated trips (G_i) were.

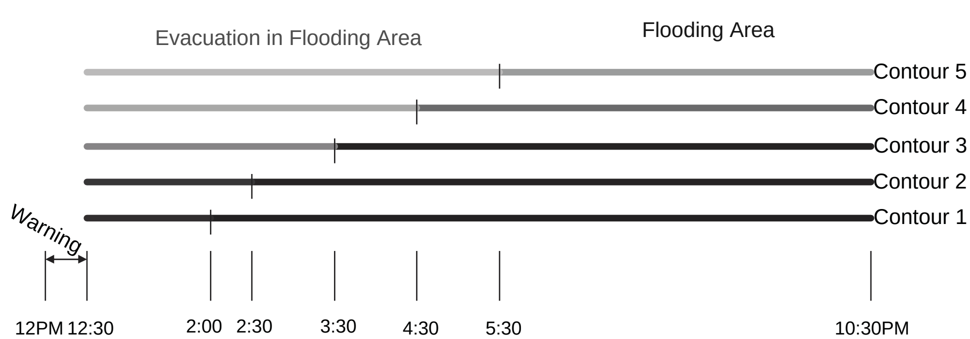

FIGURE 3 Evacuation timing, by contour.

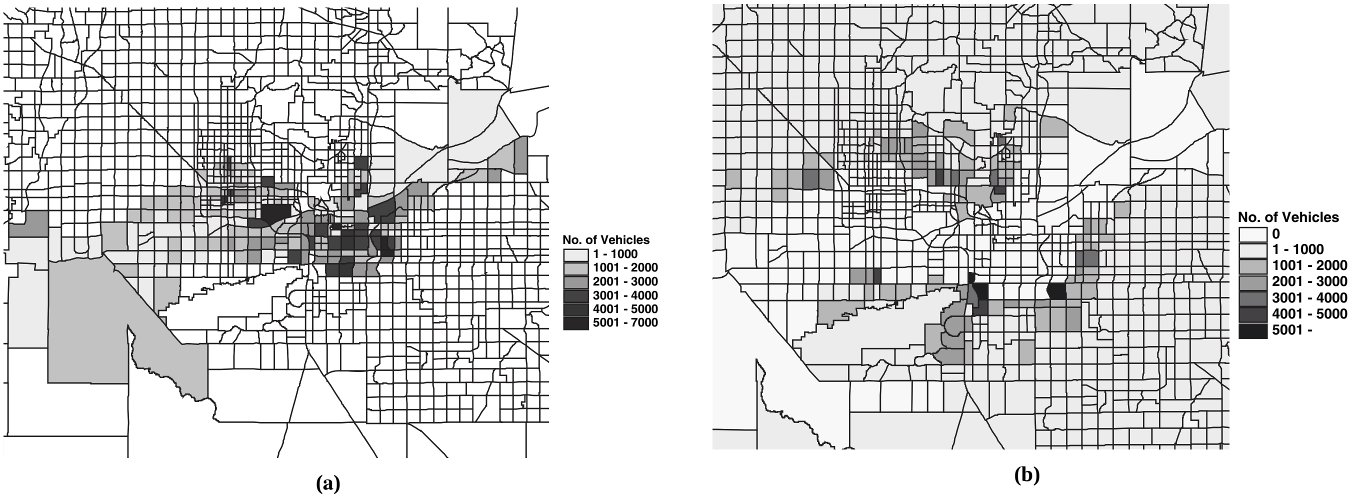

FIGURE 4 Model results: (*a*) trip generation from origin and (*b*) trip distribution at destination.

For example, special zones (such as Arizona State University or Sky Harbor Airport) are not included in the HBO trip table. In these cases, rather than estimating zero origin–destination trips, the equivalent value was used from the appropriate time-of-day matrix (e.g., the midday trip table), which covers all trip purposes. It was an approximation because more detailed data for special generators were not available.

Trip distribution results are shown in Figure 4*b*. The HBO matrix is used mainly to distribute the generated vehicles, and the time-of-day matrix is applied for only 47 zero-origin cells in the HBO matrix. Evacuee destinations are distributed mainly along the boundary of the flooding area. Southworth comments that evacuees select their destination from four choices, one of which is the closest safe destination (*7*); model results seem to support the view that evacuees usually choose the nearest destination. Considering that the HBO matrix is based on the trip distribution, this result may be reasonable.

Vehicle Departure Curve

The evacuee departure curve for each contour can be applied to the trip distribution results following Equation 5. Evacuees who are located close to the river (e.g., in Contours 1 and 2) may evacuate in haste, whereas those farther from the river (e.g., in Contours 3, 4, and 5) may evacuate less hurriedly. This model offers only one way to estimate departure time; other models could be tested with better empirical evidence from short-notice evacuations.

Results from the proposed models for the cumulative departure rate over time are shown in Figure 5 (in which F(t,i) = $F_i(t)$, as in Equation 5). Because the evacuees in Contour 5 have more time to evacuate, their departure pattern curve is flatter than those for evacuees from other contours. As modeled (assuming some basic information scenarios), evacuees depart from their origins at least 1 h earlier than the predicted flooding time. Evacuees in Contours 1 and 2 depart quickly because they are next to the river, and those in Contours 3 to 5 depart less quickly.

In Figure 5, Time 0 corresponds to 12:30 p.m., the flood announcement. Evacuees in Contours 1 and 2 depart within 30 min and 60 min, respectively; these two patterns are assumed to reflect immediate departures for these evacuees. Evacuees in Contours 3, 4, and 5 leave gradually. All evacuees in the flooding area depart within 240 min (4:30 p.m.). The parameters for a_i and b_i used in Equation 5 are presented in the following table:

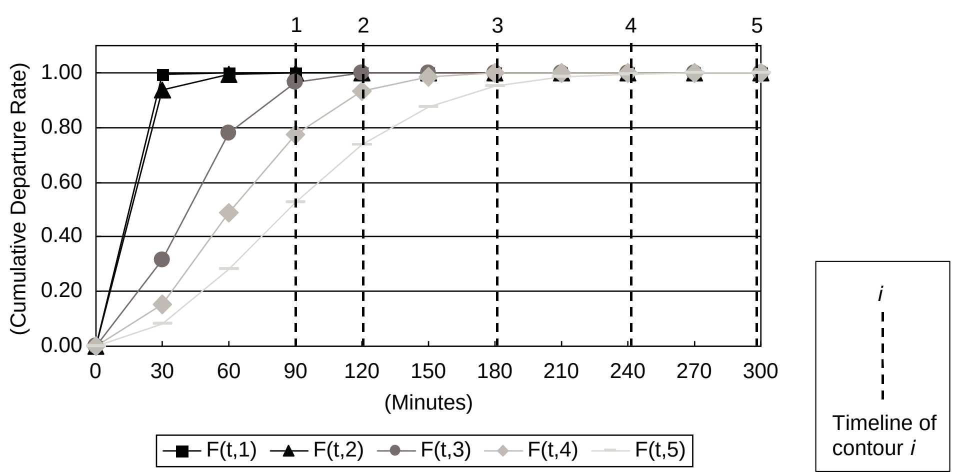

FIGURE 5 Departure curves, by contour.

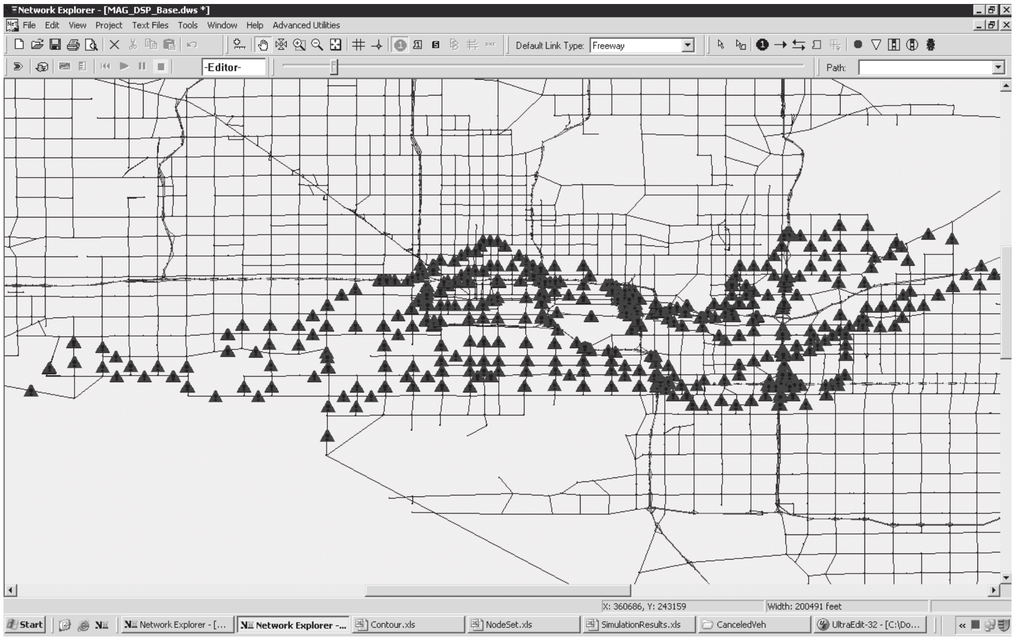

FIGURE 6 Flooding contours modeled in DynusT.

	Contour				
Parameter	*1*	*2*	*3*	*4*	*5*
a_i	1.00	1.00	2.00	2.00	2.00
b_i	0.09	0.18	0.66	1.50	3.00

The loading rate on the network within 30 min is 50% of the total evacuees (around 200,000 vehicles). If all evacuees try to leave as soon as possible, then the initial loading rate would be higher than 50%, which would cause considerably more network congestion.

Simulation Results

The DynusT simulation package was used to test generated demand. In preparation, an incident link list was produced on the MAG network, mainly to control the traffic flow coming into the hazard area. Red triangle flags were set for all the links crossing the water boundary according to the timing of flooding for each contour (Figure 6).

Next, total simulation time was set as 600 min (Figure 3). Evacuations for all contours were executed until 300 min (5:30 p.m.), and flooding stopped at the point with the highest water. After this point, evacuees from the flooding zones continued to move to their destinations. Then, evacuation demand was generated according to the departure curve (Figure 5) and the background demand matrices generated by zeroing out all entries with origins or destinations in the hot zone (evacuation area). Vehicles corresponding to both evacuation and background demand were generated separately using the appropriate demand matrices. Background demand was assumed to follow a dynamic traffic assignment (DTA) equilibrium, in which the path assigned to each vehicle is retained. Background traffic used this habitual path before further en route diversion. The vehicles generated from the evacuation demand matrices, however, were not solved to DTA equilibrium, which assumes a considerable amount of additional information for evacuating drivers.

About 4.8 million vehicles were generated for the simulation, assuming that 30% of the background demand would forego travel entirely during the flood. Approximately 422,336 vehicles were generated from the evacuation demand itself, according to Equation 1. (Numbers in Tables 1 and 2 are slightly different because of rounding in the simulation.)

Figure 7 shows the results for full demand; every dot indicates the arrival time of a vehicle originating from a contour in the evacuation area. For example, the vehicle at the highest point starts in Contour 2 and arrives at the house of a friend or family member or at a hotel about 100 min after the start of the evacuation (2:10 p.m.). Arrival rates are generally skewed to the left around 100 min, indicating that evacuees in each contour arrive at their destinations by spending the least time traveling as possible. The arrival times of vehicles in Contour 5 are relatively high (more than 150 min). Vehicles may be detoured, because Salt River flooding would divide Phoenix into two parts, north and south, and congestion may affect the whole area.

A baseline case (Baseline) and two strategies (Info and Contra) were generated for more applications. Baseline includes background

TABLE 1 Number of Generated Vehicles and Travel Times for Strategies

Statistic	Baseline	Info	Contra
For All Demand			
Total vehicles generated (veh)	4,803,811	4,803,811	4,803,811
Total travel time (h)	1,767,847.25	1,583,170.88	1,586,623.75
Average travel time (min)	22.08	19.77	19.82
For Evacuee Only			
Total vehicles generated (veh)	422,336	422,336	422,336
Total travel time (h)	501,681.99	384,970.70	393,770.21
Average travel time (min)	71.27	54.69	55.94

TABLE 2 Percentage of Vehicles Reaching Safe Nodes from Each Flooding Area

Strategy	Contour 1 by 90 min (%)	Contour 2 by 120 min (%)	Contour 3 by 180 min (%)	Contour 4 by 240 min (%)	Contour 5 by 300 min (%)
Baseline	77.9	64.3	97.3	98.6	99.9
Info	81.9	73.3	99.6	99.8	100.0
Contra	81.9	70.9	99.0	99.5	99.9

and evacuee demand as well as roadway closures for the flooding simulation; it is assumed that a radio broadcast may be updated every 15 min. The Info strategy uses a more frequent radio broadcast (5 min). In addition to the 5-min radio updates, the Contra strategy implements contraflow on three major arterials for movements south from the hot zone. The basic statistics from the simulation for these three cases are listed in Table 1. Compared with Baseline, the Info strategy performs better than the Contra strategy in terms of total travel time for all demand and for evacuee demand. The reason for this counterintuitive result is that contraflow facilities were not well designed and created significant queuing and congestion at the downstream end of each contraflow facility.

Because the main goal of this study is to save lives from the flooded area, the most important objective is to evacuate as many people as possible. To do that, the number of vehicles that can reach safety should be determined. A total of 183 safe nodes were installed around the last contour (Contour 5). If a vehicle arrived at a safe node, that vehicle was assumed to be safe from the flooding.

Table 2 shows the percentage of vehicles reaching safe nodes from the five flooding contours for the Baseline, Info, and Contra strategies. For instance, in the Baseline scenario, 97.3% of the vehicles from Contour 3 arrived at predefined safe nodes by 180 min. Slightly more vehicles (99.6%) reached safe nodes in the Info scenario and slightly fewer in the Contra scenario. The number of vehicles passing the safe nodes were around 72,000, 121,000, 82,500, 45,000, and 100,000 for Contours 1, 2, 3, 4, and 5, respectively.

Not all evacuees reached the safe nodes for this scenario, especially for the demand in Contours 1 and 2. The results also show that even though vehicles from Contours 3, 4, and 5 had more evacuation time, the contraflow strategy might not work well in this case. Again, the cause might have been the congestion occurring at the end of the contraflow facilities.

CONCLUSIONS AND AREAS FOR FUTURE RESEARCH

To estimate demand for short-notice evacuation, this study proposed trip generation and distribution models that primarily use trip matrices used in traditional travel demand models. The proposed trip generation model is appropriate for estimating the origin of evacuating vehicles, considering the timing of a disaster by taking advantage of time-of-day trip matrices. This method is appropriate under the assumption that evacuees react swiftly to a short-notice evacuation and may not return home before beginning to evacuate. For trip distribution, a model was proposed using home-based social trips (in our case, HBO trips) and time-of-day matrices. The outcome of the trip distribution model reflects previous notions suggested by Southworth (*7*).

As a shortcoming, the proposed model is based principally on trip matrices. For trip generation, more aggregate vehicle availability data were used instead of more specific zonal data. The results should improve with zonal vehicle availability data. The use of social and recreational trip data (instead of HBO trip data) may produce more reliable estimates of travel demand for trip distribution.

The most problematic assumption to date in the present model has been the multiple-contour departure curve, which assumes a phased evacuation strategy in and around the evacuation area. This kind of

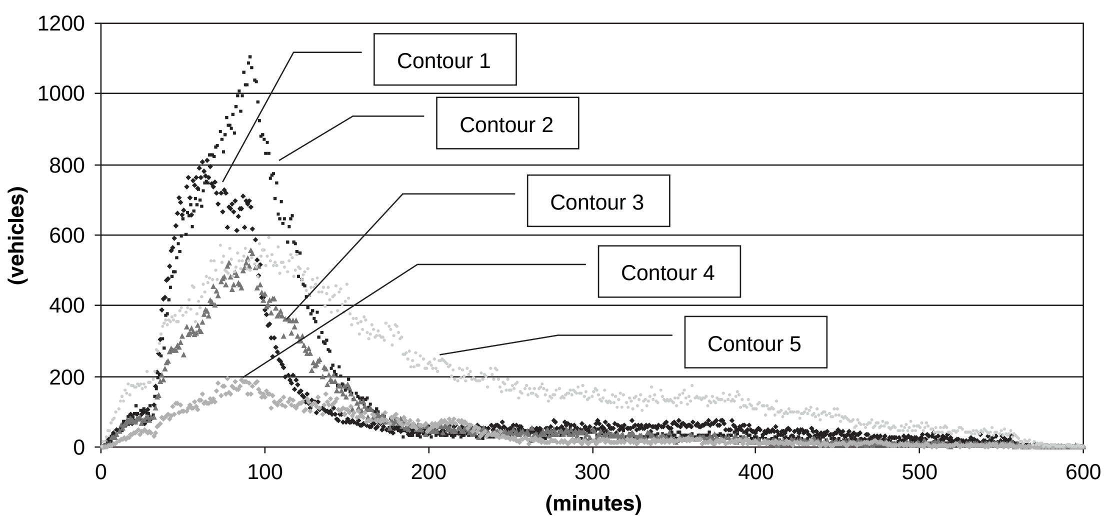

FIGURE 7 Arrival curves, by contour.

behavioral model uses exponential departure curves, which have been used in previous studies with single-stage evacuations. However, their use in short-notice evacuations may be questionable, especially if perceptions of the danger level of the disaster are high. The authors have hypothesized that some of this panic-like reaction can be mitigated with information, perhaps justifying the choice of these departure curves. Nonetheless, the need for more research into the efficacy and likely behavioral response to phased evacuations is great.

Perhaps most important, the proposed method is perhaps inferior to other methods that require more detailed data or more sophisticated modeling techniques. Explicit revealed or stated preference data could be used to develop and calibrate more detailed models of travel demand in these evacuation scenarios. As another alternative, detailed activity-based models also could be used to help estimate demand in such short-notice disasters (*19*). Although the authors believe that the approach proposed in this paper has merit in using existing metropolitan travel demand tools, these more advanced modeling approaches are likely to be more useful and accurate in the long term as they become more commonly used.

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