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An agent-based modeling system for travel demand simulation for hurricane evacuation

Weihao Yin [a], Pamela Murray-Tuite [a,*], Satish V. Ukkusuri [b], Hugh Gladwin [c]

[a] Department of Civil and Environmental Engineering, Virginia Tech, 7054 Haycock Road, Falls Church, VA 22043, USA
[b] School of Civil Engineering, Purdue University, 550 Stadium Mall Drive, West Lafayette, IN 47907, USA
[c] Department of Global and Sociocultural Studies, Florida International University, 3000 NE 151st St, North Miami, FL 33181, USA

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ABSTRACT

This paper presents an agent-based travel demand model system for hurricane evacuation simulation, which is capable of generating comprehensive household activity-travel plans. The system implements econometric and statistical models that represent travel and decision-making behavior throughout the evacuation process. The system considers six typical evacuation decisions: evacuate/stay, accommodation type choice, evacuation destination choice, mode choice, vehicle usage choice, and departure time choice. It explicitly captures the shadow evacuation population. In addition, the model system captures pre-evacuation preparation activities using an activity-based approach.

A demonstration study that predicts activity-travel patterns using model parameters estimated for the Miami-Dade area for a hypothetical category-4 hurricane is discussed. The simulation results clearly indicate the model system produces a distribution of choice patterns that is consistent with sample observations and existing literature. The model system also identifies the proportion of the shadow evacuation population and their geographical extent. About 23% of the population outside the designated evacuation zone would evacuate. The shadow evacuation demand is mainly located within 5 km of the coastline. The output demand of the model system works with agent-based traffic simulation tools and conventional trip-based simulation tools.

1. Introduction

Hurricane evacuation is a highly complex and dynamic process, which is generally modeled using optimization and simulation-based tools (Pel et al., 2012). Simulation abstractions of the evacuation process require accurate representations of evacuation demand, which is governed by many factors, such as the hurricane trajectory, warning system, and household characteristics (Baker, 1991; Gladwin et al., 2001; Murray-Tuite and Wolshon, 2013; Urbina and Wolshon, 2003). This paper presents an agent-based model system that captures household evacuation travel decisions and converts them into activity plans.

During an evacuation, households encounter a series of related decisions: whether to evacuate, when, to where, and by which mode, among other decisions. These decisions lead to the ultimate evacuation trips which constitute a large proportion of the evacuation demand. However, the demand also includes trips derived from pre-evacuation preparation activities,

* Corresponding author. Tel.: +1 703 538 3764; fax: +1 703 538 8450.
E-mail addresses: alexyin@vt.edu (W. Yin), murraytu@vt.edu (P. Murray-Tuite), sukkusur@purdue.edu (S.V. Ukkusuri), gladwin@fiu.edu (H. Gladwin).

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which can span several hours or days (Wolshon et al., 2009). These activities generate local traffic that was ignored in most previous evacuation simulation studies, which generally assumed no pre-evacuation activity travel, possibly due to data unavailability. However, before they leave, households usually make purchases (e.g., fuel and food) for their evacuation trips, which generate local traffic that contributes to overall congestion. In the no-notice context, preparation activities (e.g., family gathering) have a significant effect on evacuation time and traffic patterns (Liu et al., 2014; Murray-Tuite and Mahamassani, 2004) and some such effects are anticipated for hurricane evacuation as well (although at a lower magnitude). Therefore, pre-evacuation activity travel should be considered in the demand representation. Furthermore, incorporating the activities allows assessment of the implications of supply shortages, such as the gas stations running out of fuel.

Agent-based modeling and simulation (ABMS) is a useful approach to represent the complicated evacuation decision-making process. ABMS employs autonomous agents that can interact with the artificial surrounding environment (North and Macal, 2007). An agent has a set of attributes and behavioral characteristics. The attributes define an agent's identity and the behavioral characteristics define what an agent does (North and Macal, 2007). When a household is modeled as an agent, typical attributes include household size, number of children, and number of senior citizens. Agents' behavioral features can include decision rules to select actions, adaptation capabilities to learn from experiences, perceptual capabilities to sense surroundings, and optional internal mechanisms to project decisions' potential consequences (North and Macal, 2007). For evacuation decision modeling, the behavioral characteristics can be constructed using econometric models and other findings from evacuation behavioral studies.

The advantages of the ABMS framework over conventional trip-based demand modeling approaches in evacuation modeling are threefold. First, the households have different characteristics which lead to different behaviors. Even if the households have identical characteristics, they may choose different actions due to unobserved taste (preference) variation (Train, 2002). The agent is a useful abstraction capable of handling such behavior, especially for capturing shadow evacuation, largely due to households' different perceptions of risk. However, an aggregate demand modeling technique, usually applied in trip-based simulation models, generally fails to recognize taste variation. Second, ABMS can capture the evacuation decisions and preparation activity travel in a consistent and integrated manner. Households, the agents, are the actual entities that make evacuation decisions and they are also the trip-makers that conduct pre-evacuation travel and the ultimate evacuation trips. In comparison, the analysis units of conventional trip-based simulation models are individual trips generated at the level of traffic analysis zones (TAZs). This discrepancy renders coherent modeling of decision-making and trip-making behavior difficult, if not impossible. Finally, agents can interact with the external environment, such as hurricane characteristics. The external environment abstraction in the ABMS framework allows incorporation of these aspects of the evacuation process. Therefore, the ABMS framework is particularly suitable for simulating households' behaviors and exploring emergent collective phenomena in evacuation (Zhang et al., 2009).

In prior evacuation ABMS studies, the agent assumed different appearances in different transport simulation applications. Some studies (e.g., those using the microscopic simulation package VISSIM) defined agents as cars that follow a certain car-following logic (PTV, 2011). Adopting this convention, Chen et al. (2006) evaluated various evacuation scenarios for the Florida Keys using VISSIM. They generated evacuation demand at the level of evacuation zones. Other studies that considered cars as agents focused on evacuation route choice. For example, Handford and Rogers (2011) considered agents' familiarity with local routes. Zhang et al. (2009) explicitly dealt with the risk-taking preference for evacuees in route choice by categorizing the households as "normal" and "greedy" agents in hurricane evacuation.

A few studies considered decision-making entities as agents, an alternative to defining cars as agents. Notable examples include Wolshon et al. (2009), Montz et al. (2011), and Montz and Zhang (2013) who applied the ABS package TRANSIMS (Ley, 2009) to hurricane evacuation. Though the households were modeled as agents, the households' decisions and behavior were still treated at the aggregate level. A simplifying assumption was made regarding the evacuation trips and departure time- the departure time distribution was not associated with evacuees' characteristics, rather departure time was assigned based on a zone-level sequential logit model (Montz et al., 2011). A similar approach was used with regard to destination choice and they did not consider pre-evacuation preparation activities explicitly.

ABMS has also been used in pedestrian evacuation (e.g., Lämmel et al. (2010), Liu et al. (2008)). Santos and Aguirre (2004) provided a comprehensive review of the simulation-based evacuation models for pedestrian evacuation in buildings. Though the applications of ABS to hurricane evacuation have been limited, ABS has received attention in general transportation planning for daily commutes (e.g., Balmer et al., 2006; Balmer et al., 2009).

This paper applies the ABMS approach to develop a model system that generates evacuation demand, including pre-evacuation preparation activities in addition to a series of evacuation decisions. This paper makes the following contributions:

- The proposed system is among the first comprehensive agent-based evacuation demand model systems. It differs from previous TRANSIMS applications in that it relies on stochastic simulation with agents completely characterized by household-level behavioral models and findings. It flexibly represents evacuation decisions by allowing different behavioral model specifications and modeling orders.
- It explicitly captures shadow-evacuation demand, leading to a more realistic representation of the evacuate-stay choice.
- It statistically considers the choice of the number of evacuation vehicles through explanatory factors.
- It explicitly models pre-evacuation trips using an activity-based approach. The incorporation of the pre-evacuation trips enhances the accuracy of the demand representation.

- The output of the model system is evacuation demand represented by activity plans, which can be used for both agent-based traffic simulation tools, such as TRANSIMS and MATSIM, and mesoscopic trip-based simulation tools, such as Dynus-T (Chiu et al., 2010).

The survey data used for developing the model components came from three telephone surveys: a post-Hurricane Ivan, hypothetical hurricane in Miami, and post-Hurricane Wilma survey. In the post-Hurricane Ivan survey, 3200 households participated from Florida, Alabama, Mississippi, and Louisiana. Information collected included household socio-demographics, past hurricane experience, and evacuation decisions. The Miami Beach survey asked for evacuation decisions for a hypothetical hurricane among the Miami Beach residents. It also requested up to five of the most important, travel-involving activities that respondents would participate in prior to departing for their ultimate evacuation destinations through open ended questions (in-home activities were reported often as well). The Hurricane Wilma data were collected via an online-survey and included 287 responses from Key West, Florida regarding pre-evacuation trips, among other evacuation decisions. Additional details of the surveys can be found in previous papers (e.g., Hurricane Ivan – Hasan et al., 2013; Miami Beach survey – Yin et al., 2013b; Hurricane Wilma – Noltenius, 2008).

The remainder of this paper is divided into four sections. Section 2 presents the modeling framework and discusses the specific modules of the model system. Section 3 discusses the implementation of the simulation-based model system. Section 4 presents a sample application to the Miami-Dade area and the last section provides conclusions.

2. Modeling framework

The discussion of the modeling framework is organized into three sections. The first section discusses the overall agent-based modeling framework. The second section presents the modeling framework for the evacuation decision module, followed by the modeling framework for the pre-evacuation activity module.

2.1. Overall agent-based modeling framework

To develop an agent-based representation of households' travel demand in the evacuation process, it was essential to recognize that this demand is derived from the desire to achieve goals like "going to a safer place" and to participate in various activities such as "shopping for medicine before evacuation." This goal achievement and activity participation were the common threads of the entire evacuation process and were characterized by a series of decisions that are generally made by a household, represented by an agent. An agent's behaviors were described by several related econometric or statistical models.

The simulation framework consisted of two related modules: the evacuation decision module, shown in Fig. 1, and the pre-evacuation activity module, depicted in Figs. 2–4. The evacuation decision module captured important decisions that a household generally would make during the evacuation process, as identified by Murray-Tuite and Wolshon (2013). In total, six decisions were sequentially captured in the modeling framework. These decisions included whether to evacuate for the approaching hurricane, accommodation type choice, evacuation destination choice, evacuation mode choice, and departure time choice for their ultimate evacuation trip. If a household would use personal vehicles as the evacuation mode, they would also need to choose the number of vehicles to take. The pre-evacuation activity module captured households' decisions about engaging in preparation activities such as buying food, gas, and supplies. The outcomes of the evacuation decision module affected the preparation activities for the upcoming evacuation, which were captured by the pre-evacuation activity module. Specifically, the departure time was translated into the activity planning horizon during which a household would perform various evacuation preparation activities that may require travel. Other decision outcomes were also used in different components of the pre-evacuation activity module, as discussed below.

The pre-evacuation activity module adopted an activity-based approach, which viewed the pre-evacuation activity-travel from a tour-stop perspective. Activity-based models have been widely used for regular planning purposes (Pendyala and Ye, 2005), such as the modeling system developed by Bhat and Singh (2000), Bhat et al. (2001, 2002). However, evacuation activity travel behavior differs from that under normal conditions. Regular planning activity travel models have generally focused on a 24-h planning horizon while evacuation preparation activities usually have spanned days and involved activities that allowed evacuees to effectively plan for evacuation. During a day or two prior to departure, an evacuating household may perform the activities (e.g., shopping) that would be performed in a week under regular conditions. The pre-evacuation activity module consisted of three sub-modules: an activity generation sub-module, passenger household assignment sub-module, and an activity scheduling sub-module. The pre-evacuation activity module allowed activity chaining as suggested by Murray-Tuite and Mahamassani (2004, 2003). The activity generation sub-module captured households' decisions about whether to engage in any out-of-home preparation activities. If a household participated in such activities, the sub-module then simulated households' decisions of the number of tours and the activities pursued in these tours, such as fueling automobiles and picking up friends. The decision outcomes of the activity generation sub-module were then used in the passenger household assignment sub-module. Since some households rely upon their friends or relatives to reach their evacuation destinations, this sub-module matched these passenger households with households that have picking-up responsibilities

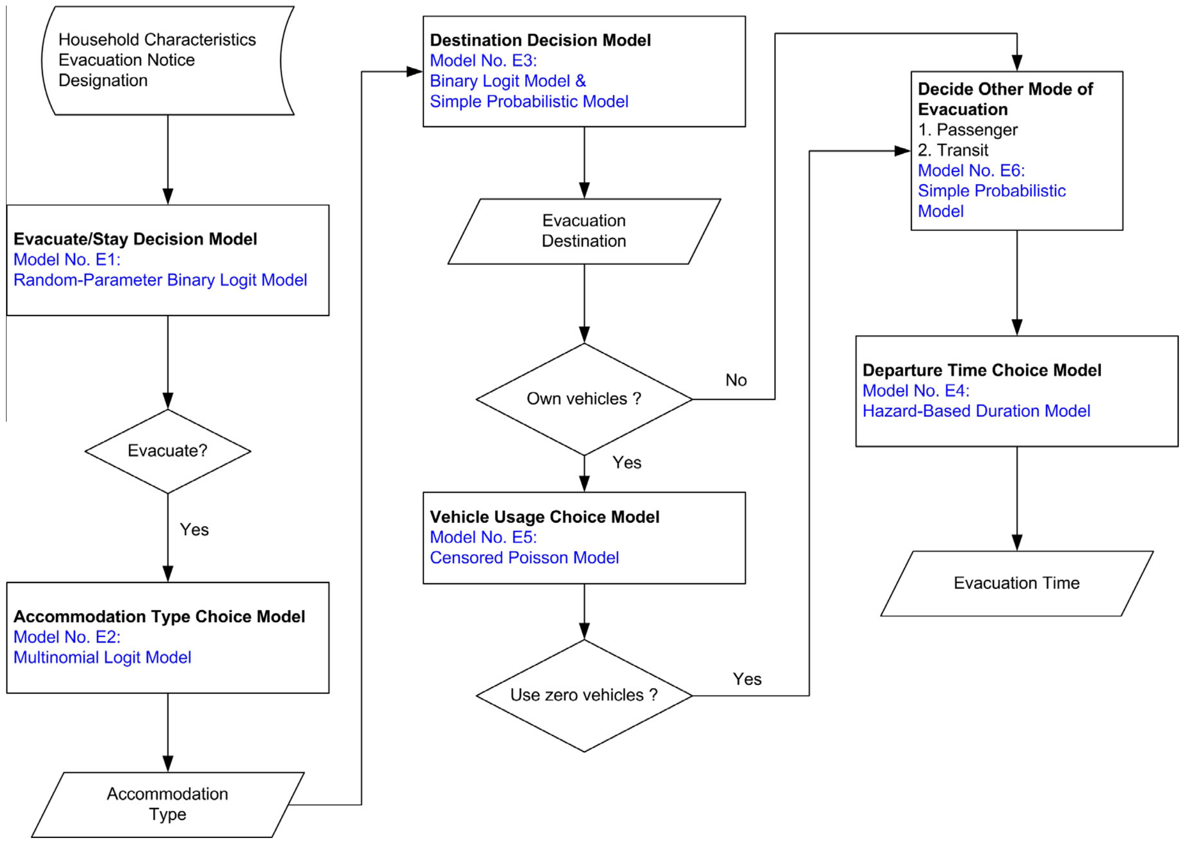

Fig. 1. Structure of the evacuation decision module.

generated by the activity generation sub-module. The third module, the activity scheduling sub-module, then assigned specific action days, times, and locations to these activities via simulation.

Since the objective of the model system was to derive evacuation demand, route choice modeling was beyond the scope of this study. The demand generated by the system presented here could be used with various routing and simulation methodologies that can handle activity plans or the plans can be aggregated into origin–destination matrices for more general traffic simulation tools. The routing rules could be selected from those available in the software.

2.2. Evacuation decision module

The evacuation decision module started with the decision of whether to evacuate for the approaching hurricane. This decision has been the subject of many behavioral and engineering studies (Hasan et al., 2011; Yin et al., 2012). To capture shadow evacuation, defined as people evacuating from outside the official evacuation zone (Zeigler et al., 1981), a random-parameter logit model was estimated using the post-Hurricane Ivan survey to determine agents' behavior for the evacuate/stay decision. The households' distances to the coast were calculated using their home coordinates and then normalized by the maximum distance to derive the relative distance to the coast, denoted by "[reldist]". Normally distributed random coefficients were associated with three variables, namely whether the household members had work duty ("[haswkdut]"), whether they received no evacuation notice ("[noevacnt]"), and whether they received a non-mandatory evacuation notice ("[nonmandn]"). The random coefficients of the latter two variables captured households' different perceived risk of the approaching hurricane, which contributed to their evacuate/stay decisions. In addition, a statistically significant heterogeneous mean was found for the random coefficient of "[noevacnt]," which associated the perceived risk with the distance to coast. The estimation results are shown in Table 1.

The model was statistically significant as shown by the likelihood chi-square test whose null hypothesis that all coefficients are zero was rejected at the 0.001 significance level. The fixed coefficients generally showed signs similar to existing studies (e.g., Yin et al., 2012). For instance, households with higher income and education attainment were more likely to evacuate. Households that did not receive mandatory evacuation notices were less likely to evacuate. The household-level heterogeneity of the random coefficient for the variable "[noevacnt]" was manifested via the inclusion of the relative distance to the coast variable. This allowed households who did not receive any evacuation notice to assume different distri-

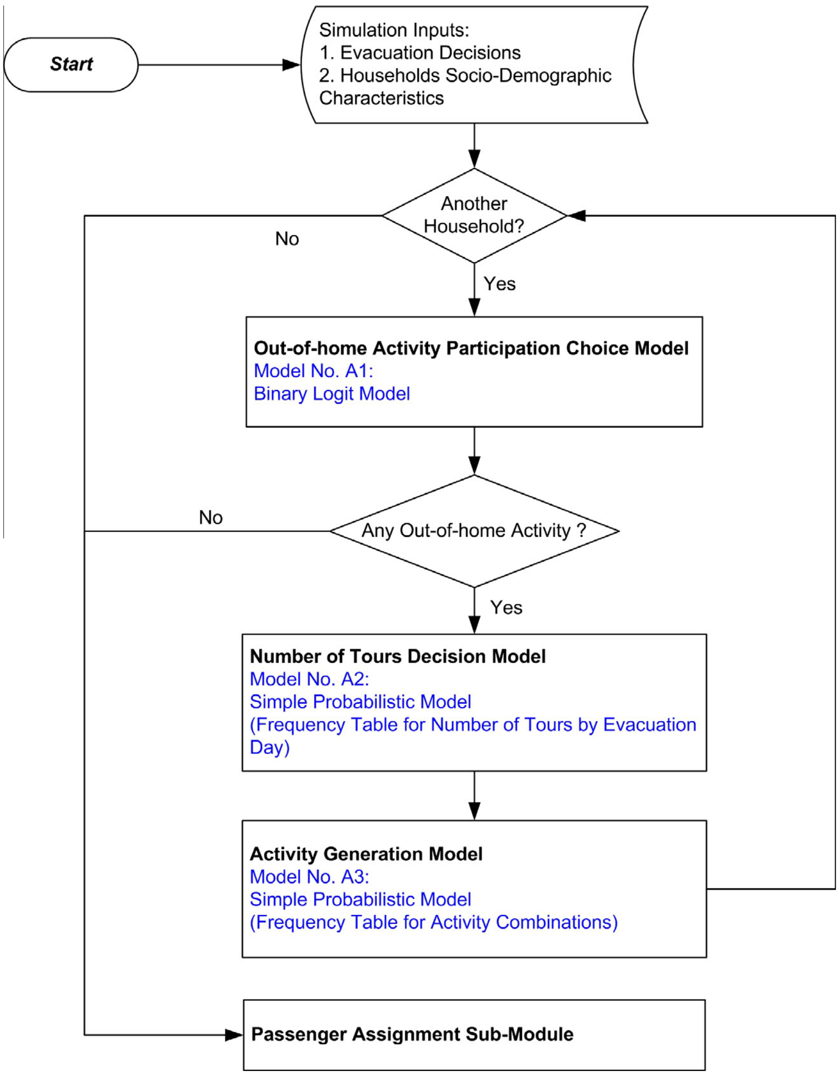

Fig. 2. Structure of the activity generation sub-module.

butions for the random parameter depending on their distance to the coast. Specifically, the sign of the relative distance to coast was −0.976 for the mean of the random parameter of variable "[noevacnt]", suggesting that the likelihood of evacuation for households that did not receive any evacuation notice decreased as their distance to coast increased, on average. A later application to the Miami-Dade area demonstrated this effect.

Evacuating households need accommodations, such as a public shelter, a friend's or family members' home, or a hotel, among other choices. Accommodation type choice, studied by previous researchers like Mesa-Arango et al. (2013), was modeled by a multinomial logit model with three alternatives: a friend's/relative's home, shelter, and hotel. Since the later application was for the Miami-Dade area, the model was estimated using the corresponding behavioral intention survey. The estimation results are shown in Table 2.

The model was statistically significant at the 0.001 significance level. The coefficients indicated that households with income less than 10,000 USD were less likely to go to a hotel compared to a friend/relative's home. Households living in rented properties were more likely to go to a public shelter than to a friend/relative's home.

After selecting the accommodation type, the modeling system proceeded to the evacuation destination choice. This choice was captured by a two-step model using the Miami survey data. The first step determined whether a household evacuated to a local destination or one outside the Miami-Dade area. This choice was captured by a binary logit model. If the household decided to go to a local destination, then a specific city was assigned as their evacuation destination region based on a city-by-city frequency count from the Miami survey. If they chose a non-local destination, they were assigned to one of the super destinations representing the out-of-Miami destinations. The estimation results of the local/out-of-Miami destination choice model are shown in Table 2. The model was statistically significant at the 0.001 significance level. The coefficients suggested

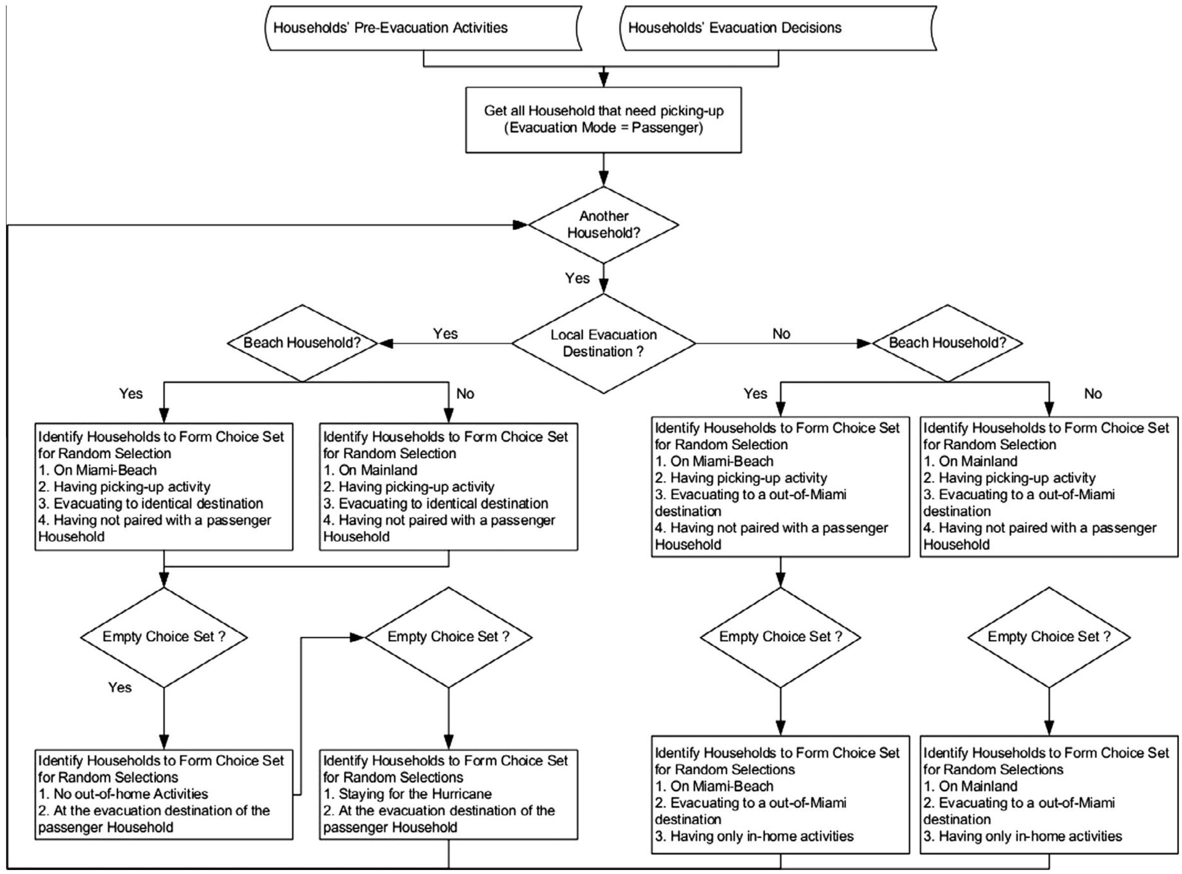

Fig. 3. Structure of the passenger household assignment sub-module.

that households with income between 10,000 and 20,000 USD were more likely to go to a local destination. Households choosing friend/relative's homes as accommodations were more likely to go to a local destination. On the other hand, households living in single family houses and those with post-graduate degrees were less likely to choose a local destination and the likelihood of staying locally decreased if a household had more children under 12 years old.

Following the evacuation destination choice, the evacuation mode choice was addressed. Many studies found that personal vehicles remain the dominant evacuation mode (e.g., Wu et al., 2012). For households owning vehicles, a vehicle usage choice model estimated the number of vehicles used. The model explicitly considered the factors contributing to households' choice of the number of vehicles used and the constraint imposed by the number of vehicles owned by the household. The right-censored Poisson model developed by Yin et al. (2013a) using the Hurricane Ivan survey data was used here and the estimation results are reproduced in Table 3. The variable of the length of stay before the household left ("[dur]") in the vehicle usage choice model was derived from a simulation using the observed sample departure curve. Later, the departure time choice model assigned the ultimate departure time.

Households not using personal vehicles (i.e., the household did not own a vehicle or chose not to use it) either relied on public transit or their friends' evacuation vehicles. The modal assignment was based on a frequency table derived from the Miami survey.

The final decision was the departure time, which was captured by a semi-parametric hazard-based duration model, or the well-known Cox model (Greene, 2012). Since the baseline hazard of the Cox model was a non-parametric specification, this offered great flexibility for capturing the shape of the departure curve, which generally is a multiple S-curve due to concentrated departures in the morning and afternoon. The profile of the departure curve will become clear in the application section. The model, shown in Table 2, was estimated using the Miami survey data.

The model was statistically significant at the 0.05 significance level. The estimated coefficients suggested that households evacuating to a shelter or a friend's or relative's home were more likely to evacuate late compared to those evacuating to a hotel. Households using their own vehicles were more likely to evacuate earlier compared to those relying upon transit or a friend/relative. More household members over 64 years old contributed to increased likelihood of early departure.

The specific sequence of decisions presented above was based on the available survey data. The simulation framework is not constrained by the model specification and can take other behaviorally justifiable decision orders.

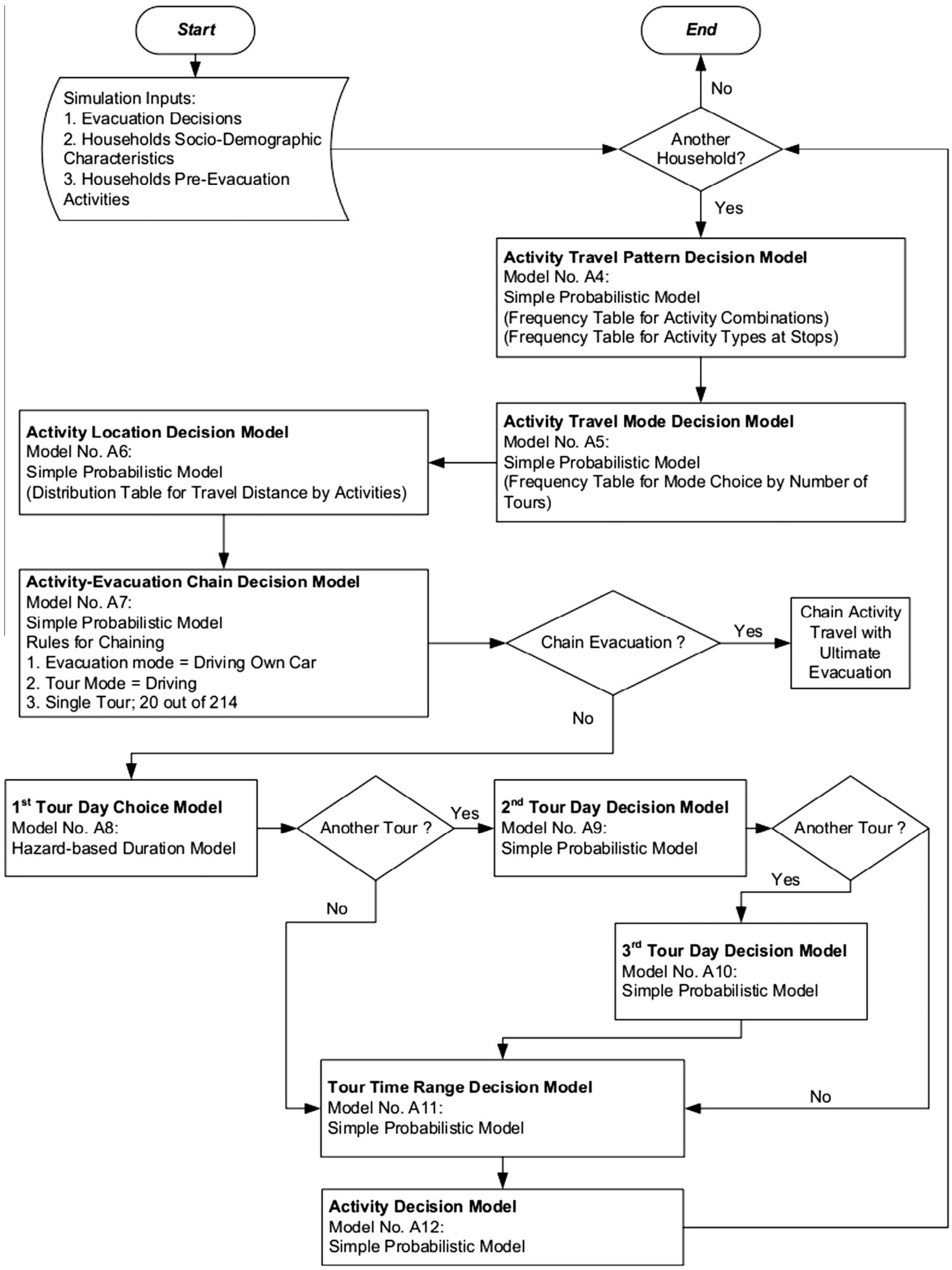

Fig. 4. Structure of the activity scheduling sub-module.

2.3. Pre-evacuation activity module

The pre-evacuation activity module was developed using the Miami survey in which households were asked for details regarding the activities they would engage in before they embarked on the ultimate evacuation trip, including the activity's purpose, location, and action time (i.e., day and time range); travel mode; and whether the activity was chained with the ultimate trip. The open ended questions requested the most important, travel-involving activities, but respondents also reported in-home activities. Respondents did not include their normal daily activities, such as work and school obligations. As the survey data suggested, the activities performed in a tour generally had similar characteristics. Most households reported that they would shop for essential items, such as food, gas, and medicine, and withdraw cash in a home-based tour. In this

Table 1
Estimation results of the evacuate/stay choice model.

Variable	Description	Evacuate/stay model
Nonrandom parameters		*Coefficient (standard error)*
[winprote][a]	The household has window protection	-0.309^{***} (0.077)
[bizown][a]	The household owns a business	-0.198^{*} (0.104)
[childu17]	Number of children under 17	0.105^{***} (0.034)
[mobile][a]	The household lives a mobile home	1.078^{***} (0.171)
[inco80 k][a]	The household's income is over 80,000 USD	0.202^{**} (0.088)
[lthighsc][a]	The household's education level is less than high school	-0.396^{**} (0.183)
[pgrad][a]	The household's education level is post-graduate	0.355^{***} (0.106)
[pet][a]	The household owns a pet(s)	-0.201^{**} (0.081)
[reldist]	The household's relative distance to coast	-0.530^{**} (0.231)
[statefl][a]	The household lives in Florida	-0.805^{***} (0.100)
[Constant]		1.470^{***} (0.164)
Means for random parameters		
[haswkdut][a]	The household's members had work duty before evacuation	-0.197^{**} (0.083)
[noevacnt][a]	The household did not receive evacuation notice	-1.428^{***} (0.163)
[nonmandn][a]	The household received non-mandatory evacuation notice	-0.667^{***} (0.113)
Variances for random parameters		
[haswkdut]		1.231^{***} (0.112)
[noevacnt]		0.628^{***} (0.080)
[nonmandn]		0.618^{***} (0.102)
Heterogeneity in the mean of [noevacnt]		
[stateFL]		1.020^{***} (0.210)
[reldist]		-0.976^{**} (0.425)

Number of observations: 2679, Log likelihood = −1183.348, Outcome = 1 represents a household chose to evacuate. $\chi^2 = 29.56$ and P-value for chi-square test = 0.003.
Standard errors in parentheses, $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.
[a] This variable is an indicator variable which takes value "1" if the statement is true.

way, the original responses were organized into a tour-based representation of the pre-evacuation activity travel throughout the entire planning horizon. In addition, it was assumed that the children in a household were picked up as usual and this was not considered in the picking-up activity generated for the pre-evacuation activity travel. These data have been analyzed and the findings were reported in Yin et al. (2013b). Here the general logic, as depicted in Figs. 2 and 4, for activity generation and scheduling is described.

The planning horizon of a household was defined as the time duration from the start of the planning horizon until their evacuation departure. The pre-evacuation activity module adopted the generation-scheduling paradigm used in some regular planning applications, such as Bhat et al. (2004). The activity generation sub-module started with the model that captured households' decisions of whether to engage in any out-of-home activities. This model was necessary since many respondents reported only in-home activities despite the request for only activities involving travel. The binary logit model developed in Yin et al. (2013b), shown in Table 2, suggested that larger households and those with college graduates were more likely to engage in activities that required travel; households choosing to drive their own vehicles were more likely to participate in out-of-home activities; and the number of people older than 64 had a negative impact upon engaging in out-of-home activities.

If a household did not perform any out-of-home activities, the remaining activity generation steps were skipped and the modeling system moved to the passenger assignment sub-module. If a household performed out-of-home activities, the number of tours was then determined. Since the number of households making two or more tours was limited in the dataset, the number of tours was not modeled econometrically. In addition, to ensure that the simulated number of tours could be completed within the household's planning horizon, a simple probabilistic model based on the frequency distribution of the number of tours and evacuation day was used. This approach reflected the observation that households evacuating late were more likely to make multiple tours. After the number of tours was determined, the activity generation sub-module assigned the specific activities pursued in these tours based on the cross-classification of activity combinations by number of tours. Specifically, the number of tours was used as the input and the activity combination was selected based on the frequency distribution corresponding to that particular number of tours. For example, if a household would make two tours, the possible activity combinations were those with non-zero percentages. For example, two possible activity combinations for making two tours included (1) purchase of food, gasoline, and medicine and (2) purchase of gasoline and withdrawal of cash. One of these two activity combinations was then assigned to the household based on a probabilistic distribution derived from the observed frequencies.

After all households were assigned activity combinations, the passenger assignment sub-module (Fig. 3) paired the households whose evacuation mode was "passenger" with those assigned picking-up activities. The sub-module first

Table 2
Estimation results of the accommodation type choice model, local/out-of-Miami destination choice model, departure time choice model and out-of-home activity participation choice model.

Variable	Description	Accommodation type choice model		Local/out-of-Miami destination choice model	Departure time choice model	Out-of-home activity participation choice model
		Hotel[b]	Public shelter[b]			
[incu10 k][a]	Household's income is less than 10,000 USD	−1.144** (0.497)				
[inc1020 k][a]	Household's income is between 10,000 to 20,000 USD		1.219*** (0.441)	0.717* (0.400)		
[hispn][a]	Household has Hispanic members	−0.759*** (0.273)		0.614** (0.236)		
[rent][a]	Household rents the current home		1.341*** (0.400)			
[friend][a]	Household evacuates to a friend/relative's home			1.425*** (0.270)	−0.319*** (0.118)	
[shelter][a]	Household evacuates to a public shelter				−0.358* (0.208)	
[colgrad][a]	Household's education level is college graduate					0.325* (0.198)
[pgrad][a]	Household's education level is post-graduate			−0.726** (0.269)		
[hhsize]	Household size					0.136* (0.0732)
[chldu12]	Number of Children under 12			−0.501** (0.232)		
[over64]	Number of household members over 64 years old				0.143** (0.067)	−0.273** (0.126)
[sfh][a]	Household lives in a single family house			−0.812** (0.290)		
[owncar][a]	Household uses their own vehicles to evacuate				0.221* (0.120)	0.919*** (0.231)
[constant]		−0.647*** (0.139)	−2.990*** (0.330)	−1.413** (0.273)		−0.893*** (0.268)
Number of observations		414		414	414	462
Log-likelihood		−315.85		−229.2247	−2094.355	−301.429
χ^2 statistic		42.88		57.99	16.44	37.47
P-value for chi-square test		<0.001		<0.001	0.002	<0.001

[a] This variable is an indicator variable which takes value "1" if the statement is true.
[b] Friend/relative's home is the reference category. Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

identified all the passenger households and treated each one according to its evacuation destination. Since the Miami survey data suggested that the households living on Miami Beach would only pick up others living on Miami Beach, the sub-module also included the home location as one decision criterion. For instance, if a passenger household lived on Miami Beach, the sub-module initially searched for those on the island who would evacuate to an identical evacuation destination and were assigned picking-up activities. If such households existed, one household was randomly selected as the picking-up household for this passenger household. If no household matched these criteria, the sub-module then searched for those on the island who would evacuate to an identical evacuation destination and had only in-home activities. If the choice set formed by these households was not empty, one was randomly selected. Otherwise, the passenger household was paired with a household not evacuating for the hurricane and residing at the passenger household's evacuation destination. Similar steps were taken for households living off Miami Beach and going to an out-of-Miami destination. After all the passenger households were matched with picking-up households, the activity combinations were updated for those households that were not assigned picking-up activities initially. The updated activity combination for each household was the input for the subsequent scheduling.

The activity scheduling sub-module (Fig. 4) first assigned the activity travel pattern, including the number of stops for each tour and the specific activities pursued at each stop. The input to this model was the number of tours and activity combinations selected in the previous sub-modules. The distinct activity patterns were identified based on the survey responses. For instance, if a household's activity combination was withdrawal of cash and purchase of food for a single tour, three distinct activity travel patterns existed in the survey. The tour-maker from the household could first make a stop to withdraw cash and then buy food, make the stops in the opposite sequence, or make only one stop for cash and food together. The counts for these distinct travel patterns were used as a simple probabilistic model for simulation purposes.

After the activity travel pattern was determined, the travel mode for each tour was selected. The tour mode choice was based on the frequency table using the number of tours and activity combinations as decision factors. If purchase of gas was

Table 3
Estimation results of the vehicle usage choice model and action day choice model for the first tour.

Variable	Description	Vehicle usage choice model	Action day choice model for the first tour
[numveh]	The number of vehicles owned by the household	Censoring variable	
[logdist]	The log of the travel distance to the evacuation destination	−0.0618*** (0.0182)	
[dur][b]	The stay duration in hours until evacuation	−0.00367** (0.00143)	−0.036*** (0.004)
[num18to80]	The number of people between 18 and 80 years old	0.148*** (0.0309)	
[hurrexp][a]	The household had hurricane experience before Ivan	0.159*** (0.0554)	
[pgrad][a]		−0.129** (0.0559)	
[pet] [a]	The household had pets	0.144*** (0.0477)	
[mobile][a]	The household lived in a mobile home	0.264*** (0.0961)	
[stateFL][a]	The household lived in Florida	−0.119** (0.0511)	
[day2]	Dummy Variable for Day 2 (Sun.)		0.269 (0.257)
[day3]	Dummy Variable for Day 3 (Mon.)		1.480*** (0.279)
[day4]	Dummy Variable for Day 4 (Tue.)		2.725*** (0.359)
[day5][c]	Dummy Variable for Day 5 (Wed.)		
[numtours]	Number of Tours to be performed		1.549*** (0.363)
[med][a]	One Stop in Tour 1 is purchase of medicine		0.482* (0.285)
[pickup][a]	One Stop in Tour 1 is picking-up people		−1.308** (0.514)
Constant		0.515*** (0.156)	0.0859 (0.498)
Number of observations		767	579
Log-likelihood		−708.685	−309.377

Standard errors in parentheses, $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.
[a] This variable is an indicator variable which takes value "1" if the statement is true.
[b] For the action day choice model, this variable represents the length of the planning horizon in hours, calculated as the time duration from Saturday midnight to the selected evacuation departure time.
[c] The dummy variable for Day 5 predicts the occurrence of tour 1 perfectly and hence is removed from the regression model (13 observations).

among the activities pursued in a tour, the mode was driving. The survey also suggested that the mode for a picking-up tour was driving.

Following mode choice, an activity location was assigned for each stop based on the activity type pursued at that stop number. About half of the respondents provided addresses and location information for their activities and these locations were geocoded using ArcGIS. The distances between stops and home by activity type was used to simulate the travel distance between stops. The stop locations were fairly close to respondents' homes, with less than 2-miles average distance. The distance between the first and second stops for multi-stop tours had a mean of 0.90 miles and a standard deviation of 1.81 miles. The locations that were within half a mile of the simulated travel distance composed the choice set from which a random selection was made. The location of a pick-up activity was the passenger household's home.

Some households chained their tours with the ultimate evacuation trips. This decision was captured by the activity-evacuation chain decision model. The rules were developed from the observations involving the activity-evacuation chaining behavior in the Miami survey. Approximately 10% of the households who reported making a single tour in their own vehicles would chain the activities with the ultimate evacuation trip.

If the activity travel was chained with the ultimate evacuation, the action time was the evacuation departure time and no additional scheduling was necessary. Otherwise, the action day of the first tour was determined by the first-tour-day choice model taking the form of a hazard-based discrete duration model. The action day for the first tour was statistically significantly related to the activity type and the households' selected evacuation times. One important observation was that households generally purchased medicine early. For a complete discussion of the model, see Yin et al. (2013b). If a household made more than one tour, 75% of the households (16 out of 21) performed the second tour on the same day of or the day after their first tour. The third tour was uniformly one day after the second tour. The tour time range was assigned according to the frequency distribution found in Yin et al. (2013b). After the tour time range was determined, a specific time was determined using a uniform distribution constructed based on the time range. For example, if a household made a tour in the morning, the action time was randomly selected from 8 am to 12 pm.

The last piece of the activity scheduling sub-module was the activity duration decision model, which took the form of a truncated normal distribution. The duration for shopping activities was assumed to follow the truncated normal distribution with a mean of 25 min and a standard deviation of 15 min [$N(25,15)$] and a minimum of 10 min and a maximum of 60 min. The distribution for the duration of picking-up activities was assumed to follow $N(57,76)$ with a minimum of 45 min and a maximum of 120 min, based on Noltenius (2008).

These three sub-modules formed the pre-evacuation activity module. The outputs of this module were the activity plans that described the activity travel prior to evacuation departure and the ultimate evacuation trips. A sample activity plan was: a household made a two-stop tour on Monday at 2:23 pm by driving. The first stop was purchase of food and the second stop was fuelling the vehicle. The household evacuated at 8:20 am Tuesday to an out-of-Miami location by driving.

3. Simulation implementation

The implementation of the agent-based travel demand model system included two components: the simulation algorithms for generating disaggregate predictions and the software architecture to coordinate the modules.

3.1. Simulation algorithm for generating disaggregate predictions

The modeling system's primary goal was to produce simulated activity-travel plans for each household in a given study area by stepping through each module outlined above to predict the corresponding choice outcome. There were two aspects to the prediction process: the generation of disaggregate predictions for each individual component model and the integration of the decision outcomes into one final activity-travel plan for each household.

One approach for predicting individual decision outcomes involved selecting the alternative with the highest probability for each of the model components with discrete outcomes and using expected value predicted by the model for a continuous choice variable. However, this methodology introduces systematic bias in the outcome of each modeling step (Bhat and Misra, 2001) and contradicts the probabilistic nature of the decision model (Train, 2002). Consequently, the cumulative prediction errors for a large model system such as the one proposed here can be quite significant.

An alternative approach involved a full decision tree in which the probabilities of all the alternatives are carried over to the root node (Bhat et al., 2004). The chosen set of alternatives can be subsequently determined by extracting the path with the highest probability in the decision tree (Bhat et al., 2004). But, this approach can be computationally intensive for many decision outcomes. More importantly, decision trees cannot handle models with continuous choice outcomes.

The general simulation mechanism adopted here resembled the one proposed by Bhat et al. (2004) which eliminated the bias of the first approach while avoiding the computational complexity of the latter approach. In the case of discrete choices, the chosen alternative was determined by identifying the distribution of the alternatives whose probabilities were predicted by the model component based on relevant covariate values derived from households' characteristics and previous decisions. Subsequently, a random draw was taken from the uniform distribution, and depending on the magnitude of this number, the corresponding alternative was selected as the chosen alternative. For the continuous choices, the outcome was determined by a random draw from the probabilistic distribution defined by the econometric model relating the outcome to various influential factors. Thus, the chosen continuous outcome was not identical for all agents with similar characteristics.

The econometric specifications for the model components included regular and random-parameter binary logit models, a multinomial logit model, continuous and discrete hazard-based duration models, a right-censored Poisson model, and simple probabilistic models. The algorithms for identifying the probability distribution of the choice outcomes for the regular binary logit models, multinomial logit model, and simple probabilistic models were established in Bhat et al. (2001) and were used here. The method for simulating probabilities of choice alternatives for the random-parameter binary logit model was outlined in Train (2002) and Greene (2012). The process for the right-censored Poisson model was described in Yin et al. (2013a). The algorithm for the continuous hazard-based duration model was presented in Bender et al. (2005) and Austin (2012) and a discretized version was developed by Rabe-Hesketh and Skrondal (2012).

3.2. Software architecture

The model system was developed using the object-oriented (OO) paradigm. Through the process of OO analysis, a number of major entities involved in the simulation of activity-travel plans were identified. The system architecture included the input/output database, the data entities, such as household, person, tour and stops, and modeling modules like the econometric models. A GIS engine, namely, Spatialite, was also embedded to provide the geospatial query capability required for the activity stop location decision model. The program was written in C++. On average, it took about 0.3 s to generate the activity plan for one household.

4. Application to the Miami-Dade area

To demonstrate the model system, it was applied to the Miami-Dade area for a hypothetical category-4 hurricane, which would make landfall on a Wednesday (Day 5). The evacuation warning was issued at 8:00 AM Saturday (Day 1). The evacuation zones were defined by the Miami Dade emergency management agency based on hurricane strength. In the Miami Dade area for a category-4 hurricane, the entire island of Miami Beach and part of the mainland coastal area were in the evacuation zone as shown in Fig. 5. The overall planning period was from midnight (12:00 AM) on Saturday to midnight on Thursday (Day 6). The reason for including the period before the evacuation notice and after landfall was that some survey respondents indicated that they would evacuate in these two periods. A synthetic population generator provided in the TRANSIMS package (Ley, 2009) was used to translate the aggregate demographics to a disaggregate population of households and individuals within the household for the Miami-Dade region. A total of 551,329 households were generated. Then the evacuation zones were identified based on the data provided by the Miami-Dade emergency management agency. Using these inputs, the program generated the activity plans for all the households in about 6 h on a desktop with 16 GB of RAM.

The comparison between the distributions of the evacuation decisions for the simulation and the survey response is documented in Table 4. The simulation results of all the evacuation decisions were compared to the observed survey results in a qualitative manner. Generally, the simulated results were consistent with observed percentages.

The simulated proportion of evacuating households was 88.98% in the evacuation zone, which was slightly higher than the reported 85.71% of the Miami survey. The current program assumed full penetration of the evacuation warning while some survey respondents suggested that they did not know whether they were in an evacuation zone. The shadow evacuation percentage was 22.85%, which was close to the average 26% reported by Sorensen and Vogt (2006). The geographical distribution of the evacuating population is depicted in Fig. 5, which suggests that the major proportion of the shadow evacuation population lies within 1.86–3.11 miles (about 3–5 km) of the mainland coastline.

The simulated distribution of the accommodation type choice outcomes was very similar to that reported in the Miami survey, evidenced by an absolute error less than 1%. The proportion of simulated households that chose their own vehicles as the evacuation mode was 90.61%, which was higher than that reported in the Miami survey. However, a similar percentage was reported in previous studies (Lindell et al., 2011; Wu et al., 2012). Approximately 15% of respondents from the Miami survey indicated they would use transit, which was higher than what existing studies (Lindell et al., 2011; Wu et al., 2012) reported. The Hurricane Ivan survey results indicated that all transit evacuees did not own vehicles. Unfortunately, the Miami survey did not ask whether a household owned any vehicles. Therefore, it was possible that the evacuees without vehicles were over-sampled which contributed to the higher percentage of transit evacuees. In addition, the Miami survey did not

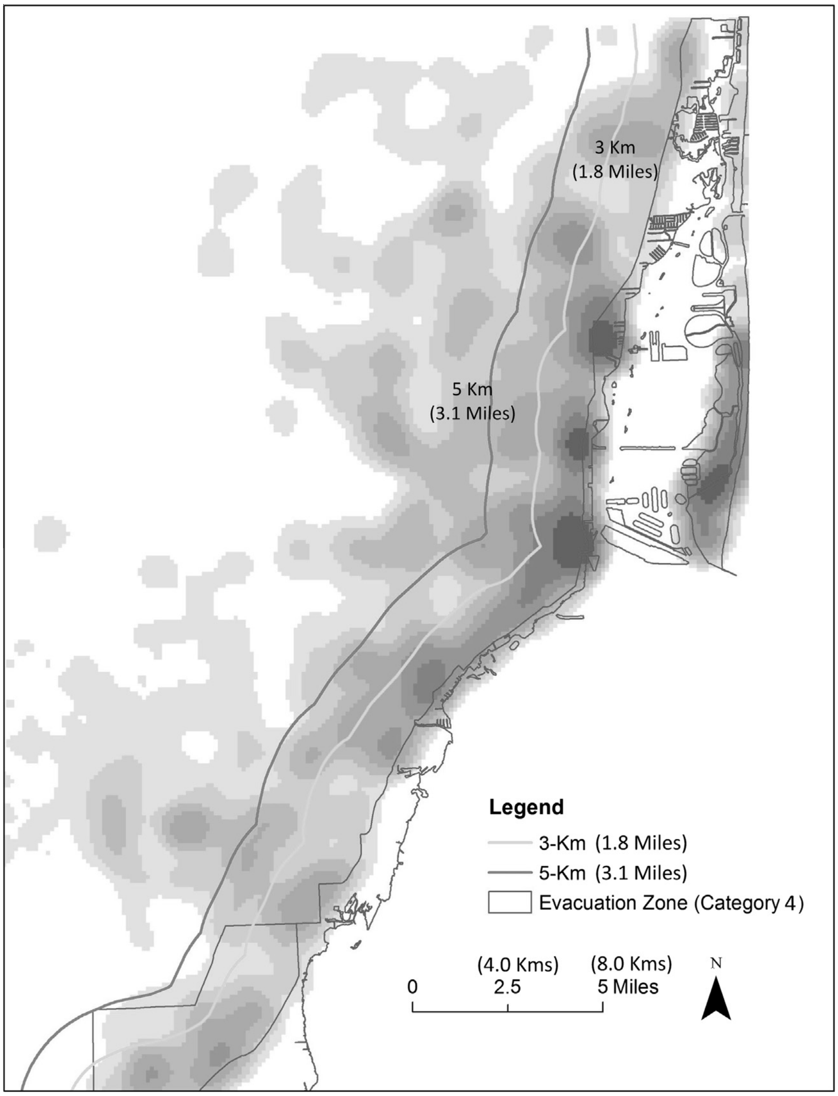

Fig. 5. Geographical distribution of the evacuation population (darker shade indicates more evacuees).

Table 4
Comparison of distributions of evacuation decisions.

Decision	Simulation	Survey
Evacuate/stay	Evacuate: 88.98% (in evacuation zone), evacuate: 22.85% (shadow evacuation)	Evacuate: 85.71%
Accommodation type	Friend: 65.82%, hotel: 24.59%, shelter: 9.59%	Friend: 67.15%, hotel: 24.40%, shelter: 8.45%
Evacuation mode	Car: 90.61%, passenger: 5.89%, transit: 3.49%	Car: 73.3%, passenger: 9.9%, transit: 16.8%
Local destination	Local: 36.45%	Local: 41.58%
Vehicle usage[a]	1 Vehicles: 71.78%, 2 vehicles: 21.51%, 3 vehicles: 3.82% 4 vehicles: 1.40%, 5 vehicles: 1.47%	1 Vehicles: 66.71%, 2 vehicles: 25.91%, 3 vehicles: 5.16%, 4 vehicles: 0.59%, 5 vehicles: 0.35%

[a] The vehicle usage was not reported in the Miami survey. Hence the simulation results are compared to the Hurricane Ivan survey.

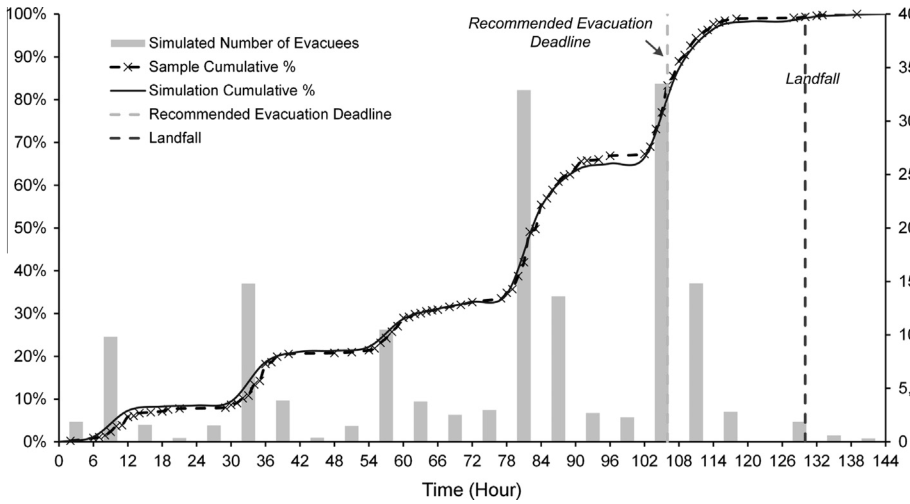

Fig. 6. Comparison between the simulated and reported departure time curves.

include respondents from the mainland, which may have contributed to this difference. This may also have been the reason for a slight difference in the distribution of destination choice outcomes and the vehicle usage choice.

The comparison between the simulated departure time curve and the reported one is shown in Fig. 6. The simulated departure curve closely aligned with the reported curve. More importantly, the multiple *S*-curve, due to concentrated departures in the mornings and afternoons, was well produced due to the non-parametric nature of the baseline hazard of the departure time choice model. A parametric duration model was not used due to its inability to capture the concentrated departures.

The activity plans were assigned to actual routes based on the all-or-nothing routing rule and posted speed limits using the Router utility in the TRANSIMS package (Ley, 2009). The 24-h cumulative vehicle count on the fourth day, on which the highest evacuation departures occurred, is shown in Fig. 7. The major roads, such as interstate 75 and 95, Palmetto Expressway, Florida Turnpike, S. Dixie Highway, and the bridges connecting Miami Beach and the mainland, carried considerable amounts of traffic. The authors and their colleagues are currently simulating the generated demand using an agent-based traffic simulation tool for the Miami-Dade region.

5. Conclusions and future directions

This paper presented an agent-based travel demand model system for hurricane evacuation simulation, which was capable of generating comprehensive household activity-travel plans. The system implemented econometric and simple probabilistic models that represented travel and decision-making behavior throughout the evacuation process. It generated the predicted activity-travel patterns for all households in the simulation sample. The intended use of the model system was not to forecast individual household's every decision accurately but to mimic aggregate results and provide a tool to generate alternate scenarios such as different shadow evacuation percentages. Traffic assignment methods can be applied to determine traffic patterns on the network. The system considered six typical evacuation decisions, namely evacuate/stay, accommodation type, evacuation destination, mode, vehicle usage, and departure time in addition to the pre-evacuation activity generation and scheduling. The model system was developed with the following major strengths:

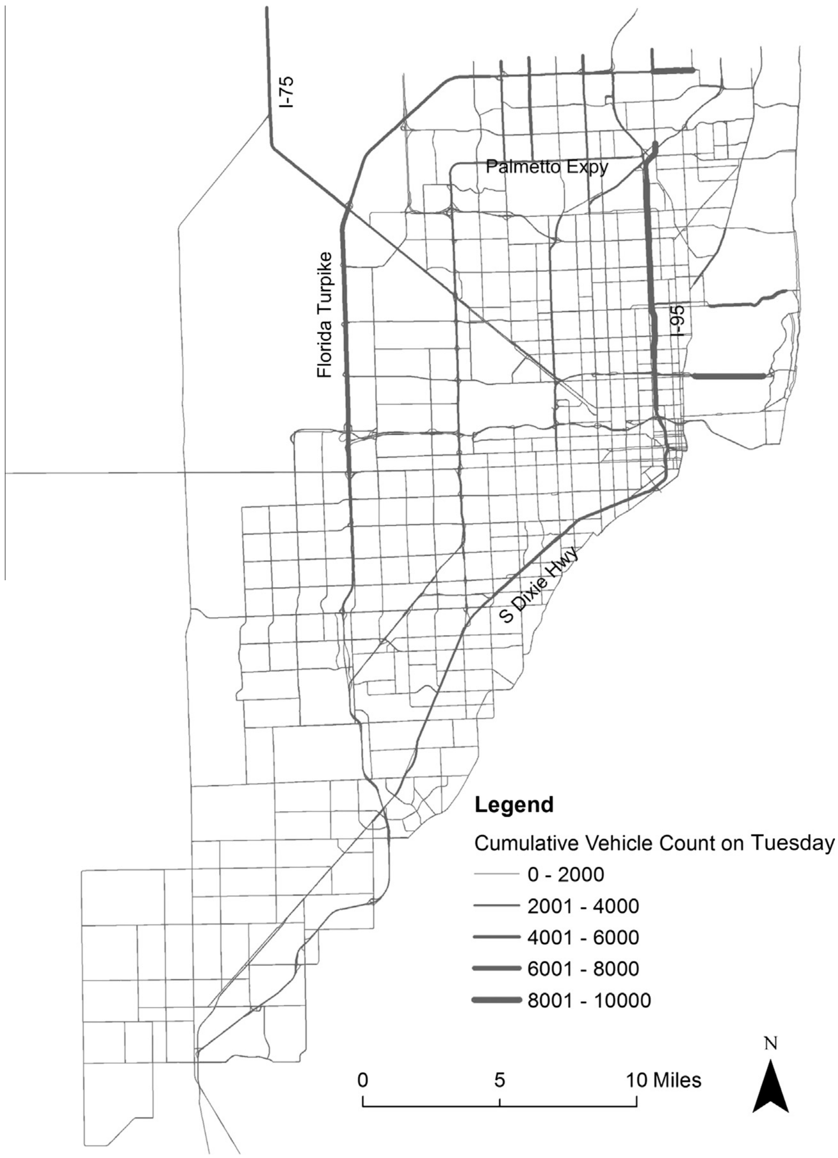

Fig. 7. 24-h Cumulative vehicle count for Tuesday under all-or-nothing assignment.

- Unlike most previous models, this system explicitly captured the shadow evacuation population and produced the percentage of shadow evacuation demand close to that reported in previous studies.
- The model system reproduced the desired temporal pattern for the evacuation departures and linked the departure time choice with household characteristics.
- The model system was among the first to explicitly capture the pre-evacuation preparation activities via the generation-scheduling paradigm.
- The simulation mechanism of the model system recognized taste variation and ensured that the chosen outcome was not identical for all agents with similar characteristics, which was a major distinction from the simulation models using a deterministic decision-maker matching algorithm, such as the demand module in TRANSIMS for regular planning (Ley, 2009).

A demonstration predicted activity-travel patterns using model parameters estimated for the Miami-Dade area. The simulation results indicated the model system produced the distribution of choice patterns that was consistent with sample observations and existing literature. The model system was also able to identify the proportion of the shadow evacuation population and their geographical extent. Specifically, approximately 23% of the population outside the designated evacuation zone would evacuate, which echoed previous studies. The shadow evacuation demand was mainly located within 5 km

(3.11 miles) of the coastline. A static traffic assignment (all-or-nothing) for the day with highest evacuation demand showed that the major roads would carry significant amounts of evacuating traffic, as expected. The output demand of the system also works with agent-based traffic simulation tools as evidenced by the ongoing effort of integrating the demand into an agent based traffic simulation model to determine travel demand patterns on the Miami-Dade network. The traffic simulation model is based on various routing considerations: (1) *k*-shortest path routing; (2) route updating at intersections based on instantaneous travel times; and (3) route type choice based on behavioral data from previous hurricanes (Sadri et al., 2014). This demand–supply integration provides an effective means of representing behavior in high fidelity traffic simulations to measure various performance metrics.

Since the important evacuation decisions and the general pre-evacuation activity travel were captured, the model system could be used for prediction of evacuation travel demand for a different region for a future hurricane, which would provide valuable insights for evacuation management. However, this generalization would need to be performed cautiously since the model components might need to be calibrated based on the characteristics of the population of the region, hurricane, and corresponding evacuation management policies (such as the timing of the evacuation notices), which all impact the travel demand.

This new agent-based demand modeling system allows numerous future studies of evacuation behavior and its impacts. The multi-day activity plans for hurricane evacuees have not been simulated as part of normal hurricane evacuation planning. Understanding the local traffic conditions and how they change between the issuance of an evacuation notice and hurricane landfall can lead to evacuation management strategies that specifically acknowledge the local patterns and facilitate rather than hinder activity participation. The model can also be slightly modified to examine the impact of resource shortages. For example, if some gas stations experience a shortage, evacuating households can be reassigned to other stations and the traffic impacts can be assessed. Similarly, grocery stores and pharmacies that run out of supplies or banks/ATMs that run short of cash can cause reassignment of tour stops and change local traffic patterns. These implications have not been able to be captured previously.

Another extension of the modeling system involves incorporating special populations, such as hospitalized patients and tourists. In addition, ideally, households' complete activity travel sequences over the entire evacuation planning horizon would be documented, including how normal activities, such as work and school travel coincide with evacuation preparation activities. However, it seems impractical to ask evacuees to keep a travel diary during an evacuation. Therefore, novel data collection methods are needed to obtain a complete travel record in order to fully model the pre-evacuation activities.

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