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A-RESCUE: An Agent based Regional Evacuation Simulator Coupled with User Enriched Behavior

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Abstract Household behavior and dynamic traffic flows are the two most important aspects of hurricane evacuations. However, current evacuation models largely overlook the complexity of household behavior leading to oversimplified traffic assignments and, as a result, inaccurate evacuation clearance times in the network. In this paper, we present a high fidelity multi-agent simulation model called A-RESCUE (Agent-based Regional Evacuation Simulator Coupled with User Enriched behavior) that integrates the rich activity behavior of the evacuating households with the network level assignment to predict and evaluate evacuation clearance times. The simulator can generate evacuation demand on the fly, truly capturing the dynamic nature of a hurricane evacuation. The simulator consists of two major components: household decision-making module and traffic flow module. In the simulation, each household is an agent making various evacuation related decisions based on advanced behavioral models. From household decisions, a number of vehicles are generated and entered in the evacuation transportation network at different time intervals. An adaptive routing strategy that can achieve efficient network-wide traffic measurements is proposed. Computational results are presented based on simulations over the Miami-Dade network with detailed representation of the road network geometry. The simulation results demonstrate the evolution of traffic congestion as a function of the household decision-making, the variance of the congestion

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across different areas relative to the storm path and the most congested O-D pairs in the network. The simulation tool can be used as a planning tool to make decisions related to how traffic information should be communicated and in the design of traffic management policies such as contra-flow strategies during evacuations.

Keywords Agent based modeling · Hurricane evacuation · Dynamic routing · Discrete choice model · Traffic simulation

1 Introduction and Motivation

Integrated models of household-level behavior and dynamic traffic flows are important in determining appropriate strategies in hurricane evacuations. However, current hurricane evacuation models largely overlook the complexity of household-level decision making behavior and as a result, lead to oversimplified traffic assignments and evacuation clearance times in the network. To fully capture the complexity of hurricane evacuation, one has to integrate the process of household decision-making and the resulting traffic interactions that follow after a decision to evacuate has been made. In this paper, we present a high fidelity multi-agent simulation model called A-RESCUE that integrates rich activity level behavior including *pre-evacuation* and *shadow evacuation* with the network level assignment to predict and evaluate clearance times. This captures *the complexity of household-level decision-making* and *the adaptive dynamic routing behavior of the evacuees* during an evacuation process.

In spite of the considerable advances in dynamic network modeling, most network models for hurricane evacuations (Yao et al. 2009; He and Peeta 2014; Tarhini and Bish 2015; Zhang et al. 2015) still suffer from an overly simplified representation of behavior, which limit their usefulness. At a conceptual level, in tandem with a traditional transportation planning process, the evacuation clearance time determination can be divided into four phases – trip generation, modal split, trip distribution and traffic assignment.

In the trip generation phase, households engage in a variety of preparatory activities prior to evacuation, which Lindell et al. (2007, p. 54) classified as "*psychological preparation* (seeking and processing additional information until they are certain evacuation is necessary) and *logistical preparation* (uniting household members, protecting property, and collecting clothes and other materials needed while away from home)". Previous studies do not fully understand the activities in which households participate pre-evacuation and it is unclear which, if any, of these activities can be simultaneous and which must be sequential. In this paper, A-RESCUE incorporates the logistical preparation of households using a rich behavioral model (Yin et al. 2014).

The *modal split* phase addresses the relative proportions of evacuees using private vehicles and public transportation, which accounts for a relatively small portion of the population outside urban areas. This has largely been an understudied problem by evacuation modelers until recently—see Bish (2011); Sadri et al. (2014a) and Naghawi and Wolshon (2012). A-RESCUE can incorporate a modal split framework but the data does not include a modal split. Additional details on the modal split by the authors can be found in Sadri et al. (2014a).

The *trip distribution* phase determines where most people evacuate - to the homes of friends and relatives or stay in commercial facilities rather than public shelters (Lindell et al. 2011; Mileti et al. 1992; Wu et al. 2012). These assessments of aggregate facility utilization have recently been extended by Mesa-Arango et al. (2013), where a nested logit model was used to predict evacuees' choice of accommodations in Hurricane Ivan. Results from this model are incorporated in A-RESCUE to determine the selection of the safe locations for evacuation.

The above three phases represent the demand side of the problem. On the supply side, the *traffic assignment* phase includes the route choice, which has a major impact on evacuation times (Tarhini and Bish 2015; Yu-Ting and Peeta 2015), but the basis for evacuees' route choices is not well understood. As Lindell and Prater (2007) noted, evacuation modelers have often assumed a computationally convenient reason for route choices such as a "myopic view" in which evacuees choose the least congested path in the network. However, this assumption conflicts with the limited behavioral data that indicate route choice is based primarily on familiarity. Though "familiarity" provides some explanatory power, it is useless for modeling unless we can identify generalizable rules for identifying which routes are most "familiar" to evacuees for specific origins and destinations. In addition, these route choices vary across households as shown in Sadri et al. (2014b). A-RESCUE has the capability to include both adaptive and familiarity based routing using empirical data obtained in this research.

The selected path can be compared with options indicated by the transportation network to derive behavioral based routing rules and learning mechanisms rather than relying on the traditional Wardropian principles, which have been criticized for lack of applicability to evacuation conditions (Lindell and Prater 2007). The data will show locations where travelers switch routes due to delays. Switching routes will indicate some comfort, and possibly familiarity, with the network. Familiarity with the network for the evacuation trip will also be indicated to some degree by the pre-evacuation tours.

The objective of this study is to develop a high fidelity integrated agent-based simulation model based on a high resolution demand model capturing the complexity of evacuation choices and the dynamics of routing behaviors during an evacuation process.

There is a considerable amount of research efforts in modeling traffic during evacuations. A few of the evacuation models developed earlier include NETVAC (Sheffi et al. 1980), MASSVAC (Hobeika and Jamei 1985; Hobeika and Kim 1998), TEDSS (Sherali et al. 1991), IMDAS (Franzese and Han 2001), OREMS (Rathi and Solanki 1993), and CEMPS (Pidd et al. 1993). Typically these models are developed for specific types of emergency situations. For example, MASSVAC is developed for traffic simulation in hurricane evacuation; it requires evacuation routes as model input from all origins to all destinations, where the origins and destinations depend on the projected path of the hurricane. Very recently, the advancement in the development of dynamic traffic simulation models encourages researchers to apply them in evacuation scenarios. For instance, microscopic traffic simulation models, such as PARAMICS (Cova and Johnson 2003), CORSIM (Williams et al. 2007), VISSIM (Han and Yuan 2005), MITSIMLab (Jha et al. 2004) and INTEGRATION (Mitchell and Radwan 2006), and meso-scopic or macroscopic models, such as DYNASMART (Murray-Tuite 2007), DynaMIT (Balakrishna et al. 2008), DynusT (Noh et al. 2009), TransCAD (Wang et al. 2010), and INDY (Klunder et al. 2009) have been applied to study evacuation problems.

Agent-based simulation is a computational methodology to model systems comprised of interacting autonomous agents situated in an artificial environment (Macal and North 2005; Flötteröd et al. 2012). These autonomous agents are self-directed objects with the capabilities of making decisions and reacting to the environment. They also have the ability to learn and adapt based on their goals and interactions with each other. Such a framework is particularly suitable for simulating individual behaviors and exploring emergent collective phenomena in evacuation. To capture some of the phenomena and complexities during hurricane evacuations, we develop an agent-based model to simulate household-level evacuation decisions and the resulting interactions among the evacuee drivers.

The overall framework of the agent-based simulation model consists of two major components: Household Decision Making Module and Traffic Flow Module. The household decision making module sets the rules for household agents' evacuation behaviors obtained from advanced behavioral models. The behavioral model captures the complexity of different dimensions related to hurricane evacuations such as decision to evacuate (yes or no), evacuation timing, evacuation destination choice, mode choice, route choice and pre-evacuation and en-route evacuation activities as well as the number of household vehicles used to evacuate. These behavioral models are developed, estimated and validated using the data from Hurricane Ivan including the households from Alabama, Louisiana, Florida and Mississippi (evacuate/stay decision, number of household vehicles used), and data from a behavioral-intention survey for Miami (accommodate type, evacuation destination, mode assignment for non-personal vehicles, departure time for the ultimate evacuation trip, activity participation and scheduling). Behavioral models also address the issue of household level heterogeneity by incorporating random parameters in the models.

Behavioral models are integrated with a microscopic traffic simulation module. This module uses the output from the household decision-making model to design its input (i.e. traffic demands). In the simulation, each household is an agent, which makes various evacuation related decisions. From household decisions, a number of vehicles are generated and entered in the evacuation transportation network at different time intervals. The traffic flow in the network is based on a car-following model (Yang 1997) that calculates a vehicle's acceleration rate based on its relationship with the leading vehicle.

To mimic the *dynamic routing behavior* of evacuees an en-route route choice model is integrated with traffic simulation module. In this dynamic routing behavior, at each step, agents can update information from the network and take the shortest route to the destination. Finally, an *adaptive routing strategy* that can achieve efficient network-wide traffic operations during evacuations is proposed. Computational results are presented based on simulations over a medium-scale traffic network. The simulation results demonstrate the improvement of traffic operations against drivers' route switching behavior based on the prevailing traffic conditions. The specific contributions of this study include:

1. Develop A-RESCUE, a high fidelity agent-based evacuation simulation model integrating household evacuation behaviors and traffic flow behaviors.
2. Integrate a rich household level evacuation demand model governing the various evacuation decisions.
3. Develop an adaptive routing strategy that can achieve efficient traffic operations during evacuations.

4. Provide computational results using the simulation of a medium size transportation network for the evaluation of the proposed adaptive strategy against the instantaneous route switching behavior.

The remainder of the paper is organized as follows. The next section presents the framework for the agent-based simulation model. The subsequent two sections describe the household decision making module and the traffic flow module. The next section presents the proposed adaptive routing strategy algorithm. The next section gives a brief description of the developed simulation tool. The last two sections present a case study with results and some concluding remarks, respectively.

2 Framework of the Agent-Based Simulation Model

In this section, a framework for the agent-based simulation model is presented. The framework is developed based on the integration of household-level behavioral models with the traffic flow models to fully capture the complexity of hurricane evacuations. Based on the input household characteristics, the behavioral models set different decisions related to the evacuation including the decisions to evacuate or not, timing of the evacuation and destination of the evacuation for a household. Having made these decisions, the household creates vehicle agents to enter the network. The vehicles make en-route activity decisions and route choice decisions. Traffic interactions among the vehicles in the network are created based on a car-following model. Figure 1 presents a flow chart of the framework. The framework is built upon two major contexts: *household decision making context* and *traffic simulation context*.

Data containing spatial population distribution and socio-demographic characteristics from the census are used in the *Household Agent creation* module to assign geospatial locations and individuals attributed to each household. Household agents then belong to the *Household Decision Making* context where different decisions regarding evacuations are made by the household agent.

Household Decision Making context is one of the central components of the proposed agent-based simulation model. In this context, the inputs include the socio-demographic characteristics of the households and the characteristics of the approaching hurricane; and the outputs are the decisions moving the household agent during the evacuation. The most representative decisions are whether to evacuate or not, evacuation departure time and destination of the evacuation. First, a random-parameter binary logit model for evacuation choice is used to make the decision whether to evacuate or not. If the household decides to evacuate, the accommodation type choice is then modeled with a multinomial logit model. Third, a binary logit model and simple frequency based model are used for the destination. Fourth, the travel mode is assigned based on whether the household owns vehicles. If not, they are assigned as a passenger to be picked up by a family member, friend etc., or to transit. If the household owns vehicles, the number of vehicles used is determined from a truncated Poisson model. After the travel modes are assigned, the departure time is determined from a hazard-based duration model. Based on these main evacuation decisions, activity participation is then determined. First, a binary logit model determines whether a household participates in out-of-home activities. If so, then the number of tours is

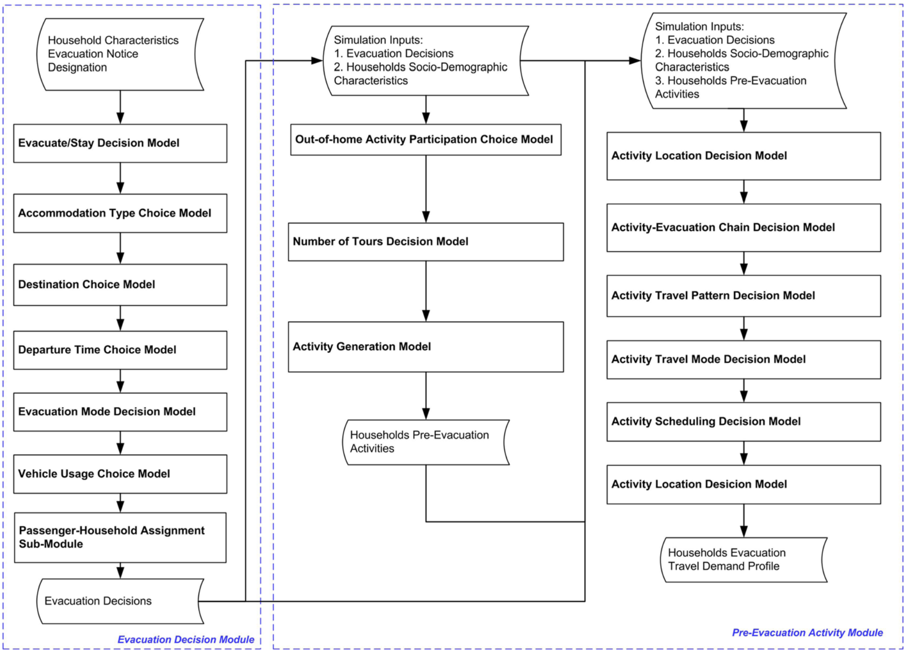

Fig. 1 Integration of the Household Decision Making Context with the Simulation Context

modeled with a frequency model and the specific activities are assigned based on frequency from the Miami behavioral intention survey data. Then based on the type of pre-evacuation activities and the households identified as passengers, pickups are assigned. The details of these models can be found in Yin et al. (2014). Finally, a multinomial routing strategy choice model is used to select a route from a set of routing strategies including using their familiar routes, following the suggested evacuation route, and switching routes based on the prevailing traffic conditions. For each household, this household decision making context determines the decisions using suitable models that were previously calibrated. The context then generates vehicle agents that interact with the transportation network in the *Traffic Simulation* context.

The *Traffic Simulation* context establishes the behavioral rules that guide the vehicles from their origins to their destinations. If a household agent decides to evacuate, a vehicle agent is generated and enters the transportation network at a specific evacuation time. A pre-evacuation activity choice model is implemented to determine the set of pre-evacuation activities of the household. An *En-Route Route Choice Model* is integrated in the *Traffic Simulation* context to mimic the routing behavior of the evacuees. This context uses a routing algorithm based on the *k*-shortest path adaptive routing algorithm to find optimal routes guiding vehicle agents to their destinations.

The *Traffic Simulation Module* requires a GIS map of the transportation network as an input to move the vehicles. Using a pre-processing step called data modeling, the GIS map is converted to a detailed lane-based network that is required for the simulation. Vehicles are moved in a lane based on a car-following model and can switch lanes based on lane-changing decision model. More details about the data modeling step and the traffic flow models are discussed in subsequent sections. Finally, an output module is designed to analyze vehicles' travel times and total clearance time.

The major distinction of the proposed decision-making context with the existing multi-agent simulation models is as follows. Traditional simulation approaches usually generate an evacuation demand for a region for a given population; and based on the demand, they generate the traffic demand for the transportation network. These two processes are done separately; specifically the vehicles moving in the network do not retain the characteristics of the households they belong to. As a result, different aspects of the decisions are not reflected in the subsequent decisions of the agents traversing the network. For instance, for these approaches, the routing decisions made in the transportation network cannot introduce the characteristics of the households used to generate the evacuation demand. On the other hand, the proposed integrated agent-based simulation approach can use the household-level characteristics to make the pre-evacuation and intermediate activity and routing decisions. This integrated approach can further be attributed to the feature of a truly dynamic simulation. The decisions made in the transportation network can easily be incorporated to the household decision making context. This will generate the evacuation demand *on the fly* based on the prevailing traffic condition whereas the traditional simulation-based approaches generate the *time-dependent* evacuation demand beforehand. This truly dynamic nature is of greater importance for an evacuation context where demand decisions change rapidly as a function of traffic conditions and other social conditions thereby impacting the supply side performance.

3 Household Decision Making Module

This section presents the household decision-making module that integrates household evacuation behavior into the simulation. Households located in an area under hurricane threat make multiple decisions for their evacuation. Researchers have developed models to understand how characteristics of the households and the evacuation-related factors such as hurricane trajectory and evacuation warning influence this decision.

The evacuation decision sub-module considers five decisions, as identified by Hasan et al. (2011); Mesa-Arango et al. (2013); Sadri et al. (2014a); Murray-Tuite and Wolshon (2013); Hasan et al. (2013) in a sequential manner. These decisions include (1) whether to evacuate, (2) accommodation type selection (e.g., friends/relatives homes, public shelters or hotels), (3) evacuation destination (the specific destination), (4) evacuation mode (auto-based evacuation or carpooling), and (5) departure time. If the household uses personal vehicles to evacuate this sub-module also determines the number of vehicles used. All these decisions are modeled via probabilistic (frequency) or econometric models relating relevant explanatory variables to the choice in question. The departure time decision dictates the time window available during which pre-evacuation activities such as purchasing gas, food/water, and medicine or withdrawing cash can take place. The pre-evacuation activity sub-module captures these pre-evacuation activities.

The pre-evacuation activity module adopts an activity-based approach, which views the pre-evacuation activity-travel from a tour-stop perspective. This sub-module has three components: (1) activity generation, which simulates the number of tours and activities performed by a household, (2) passenger household assignment, where households are assigned to pick up their friends and relatives with transportation needs, and (3) activity scheduling, that assigns days, times and locations to these activities via simulation.

For each household, the household decision making module determines a schedule of pre-evacuation trips plus a final evacuation trip. Each of these trips is described by an origin, destination, departure time, and activity duration. These trips are inputs into the simulator, which are then assigned into the traffic network as illustrated in Fig. 1.

4 Traffic Flow Module

In A-RESCUE, the traffic flow model is an important component since it represents the movement of vehicles in the traffic network and allows the modeler to capture various performance measures of interest. The vehicle is the basic unit of the traffic flow model. The traffic flow is implemented in three steps:

a) Vehicle loading
b) Computing acceleration or deceleration
c) Vehicle movement

4.1 Vehicle Loading

- At first, vehicles are loaded in pre-trip FIFO queue based on its evacuation time. To enter into the network, at their corresponding evacuation times, vehicles look for available leading spaces in the entrance link. If adequate leading spaces are not available on the entrance link, vehicles are stored in the FIFO queue and wait to enter the network during subsequent simulation steps.
- If necessary leading spaces are found, vehicles enter into the network through the entrance links. Its initial position and speed are determined by the simulation step size, the driver's desired speed, and the traffic conditions on the entrance link. If a vehicle enters into the network successfully, it is removed from the pre-trip queue of the link.
- When a vehicle arrives at an activity location, the new departure time of this agent will be computed based on its arrival time and the time duration it spends at the location. The agent then is loaded to the queue and sorted based on its new departure time computed. A vehicle is removed totally from the network only if it reaches the final destination.

4.2 Computing Acceleration or Deceleration

To set the acceleration or deceleration behavior rule for the vehicle agents, we implement a car-following model (Yang 1997) in the simulation. The car-following model computes a vehicle's acceleration rate based on its relationship with the leading vehicle. Depending on the magnitude of its headway with the front vehicle, a vehicle implements one of three rules: *free flowing, car following, and emergency decelerating* (Herman et al. 1959; Herman and Rothery 1963; Wicks 1977).

Free Flowing Rule If the time headway is larger than a pre-determined threshold h^{upper}, the vehicle does not interact with the leading vehicle. The vehicle acceleration rate is calculated based on the following relationships (Yang 1997)

$$a_n = \begin{cases} a_n^+ if\, v_n < v_n^{target} \\ 0 \quad if\, v_n = v_n^{target} \\ a_n^- if\, v_n > v_n^{target} \end{cases}$$

where:

a_n	acceleration rate;
a_n^+	maximum acceleration rate;
a_n^-	normal deceleration rate;
v_n	current speed;
v_n^{target}	target speed in current link

Emergency Decelerating Rule If a vehicle has a time-headway smaller than a pre-determined threshold h^{lower}, it is in the emergency stage. In this case, the vehicle uses an appropriate deceleration rate to avoid collision and extend its headway (Yang 1997).

$$a_n = \begin{cases} min\left\{ a_n^-, a_{n-1} - \dfrac{0.5(v_n - v_{n-1})^2}{g_n} \right\} if\, v_n > v_{n-1} \\ \min\ \left\{ a_n^-,\ a_{n-1} + 0.25 a_n^- \right\} if\, v_n \le v_{n-1} \end{cases}$$

Car-Following Rule Finally, if a vehicle has a time headway between h^{lower} and h^{upper}, it is in the car following stage. In this case the acceleration rate is calculated based on Herman's general car-following model (Herman et al. 1959)

$$a_n = \alpha^{\pm} \frac{v_n^{\beta^{\pm}}}{g_n^{\gamma^{\pm}}} (v_{n-1} - v_n)$$

Where $\alpha^{\pm}$, $\beta^{\pm}$ and $\gamma^{\pm}$ are model parameters; α^{+}, β^{+}, γ^{+} are used for accelerating ($v_n < v_{n-1}$), and α^{-}, β^{-}, γ^{-} for decelerating ($v_n > v_{n-1}$) cases, default values for these parameter are based on Subramanian (1996).

4.3 Vehicle Movement

Once the acceleration or deceleration rate of a vehicle is computed for a simulation step based on the car-following model described above, the vehicle's speed and position are updated. The movement function of the simulation tool is then used to move the vehicle using its current speed. In addition, while moving on the network, a vehicle needs to stay in a specific lane. Since road lanes of two consecutive links connect to each other using some rules, the vehicle must be on a proper lane in order to travel from an upstream link to a downstream link. The movement that allows a vehicle to shift from an improper to a proper lane is referred as lane changing. In a more advanced model, vehicles also change lanes to improve the driving condition such as desired speed, visibility, etc. The model is embedded in the simulation and is discussed in the next subsections.

4.4 Lane Changing Model

Lane changing is one of the fundamental components in the A-RESCUE traffic simulator. It significantly impacts the traffic flow and thus affects the congestion level of the transportation network. Lane changing, in most of microscopic simulators, is classified into two types; mandatory and discretionary, (Gipps (1986), Yang (1997) and Ahmed (1999)). Mandatory Lane Changing (MLC) happens when a driver must change lanes in order to get on the lane that connects to a downstream link. Discretionary Lane Changing (DLC) happens when a driver changes the lane to have a better perceived traffic condition. Since MLC has higher hierarchy, it overrides all other decisions in consideration. Figure 2 illustrates the two types of lane changes. Vehicle numbered 2 is going to make a left turn at the downstream junction, thus it needs to change to the left most lane, the mandatory lane change needs to be made. Meanwhile, the vehicle numbered 1 has no problem connecting to the downstream link in a through movement and therefore no lane changing is required. However, the driver of this vehicle might perceive a better traffic condition on the right lane and thus has an incentive to change to that lane under the discretionary lane changing state.

To execute lane changing, the driver first seeks the target lane, the lane which either connects to the downstream link in MLC or the lane with better perceived traffic condition in DLC. In the MLC, the driver might need to change the lane several times before getting to the target lane; however, the target lane in the DLC is most likely the lane adjacent to the current lane of the vehicle. After the target lane is determined, either in MLC or in DLC, the driver will seek acceptable gaps, the distances from his/her vehicle to the leading vehicle, referred as lead gap, and to the lagging vehicle, referred as lag gap, in the lane that the driver will change to. If these gaps are greater than critical gaps (minimum thresholds) then the driver will change lanes, otherwise the driver will stick to the current lane until the acceptable gap is available. Figure 3

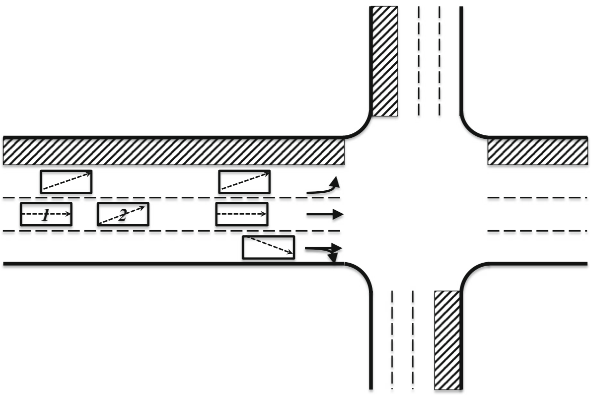

Fig. 2 Illustration of different types of lane changes

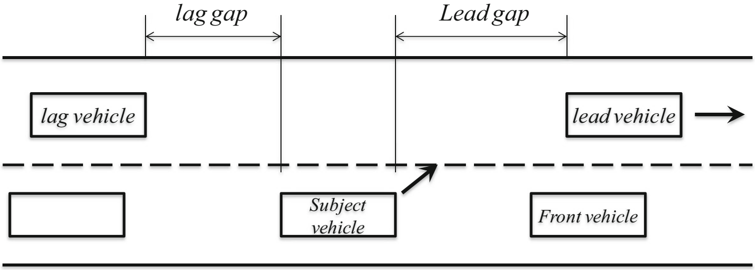

Fig. 3 Gap acceptance in lane change

illustrates different gaps in lane changing. The framework and parameters of the lane-changing model embedded in the simulation are based on the work from Ahmed (1999).

5 Adaptive Routing Strategy for Hurricane Evacuation

In this section, an adaptive dynamic routing algorithm is presented that can achieve an efficient network-level traffic operation during evacuations. The algorithm will yield better travel times for the evacuees over switching routes based on the prevailing traffic conditions. The proposed algorithm is based on the notion of an adaptive and decentralized routing of agents (Mahmassani 2001; Farver 2005). An adaptive route choice model based on a simple logit-type splitting function is adopted. A good adaptive based dynamic routing can yield good system states. Such an adaptive model, correctly reacting to current traffic conditions, has a significant value especially when real-time information is lagged/delayed. This type of routing approach is particularly useful to model situations when traffic networks are congested due to emergency situations such as hurricane evacuations. Such evacuations will have rapid fluctuations of demand and capacity forcing travelers to take travel decisions based on the current traffic situation (i.e., instantaneous travel time).

In this approach, vehicles have information of link travel times at the intermediate nodes and, using this information, update their routes from the current node to the destination. Consider a vehicle i going from origin node r to a destination node s. A route p denotes the path from the decision node j to the destination node s. The problem is to assign vehicle i to an outgoing link $a \in B(j)$, where $B(j)$ is the set of links incident to node j; such decisions are made repeatedly upon reaching the next decision node, until vehicle i reaches destination node s.

Traffic assignment based on reactive dynamic user equilibrium requires each agent to follow the shortest route at every intermediate decision node. However, an iterative approach is necessary to anticipate the impact of following the shortest route at the intermediate node based on the instantaneous travel time. This will be computationally burdensome and may be difficult for real-time deployment. Thus different heuristic rules for route assignment can be developed based on the criteria for evaluating routes at intermediate nodes. Here we propose a heuristic where agents, instead of following the shortest route, adopt mixed routing strategies based on a logit-based splitting function.

Denote by $\psi_{i,p}^{js}(t)$ that the instantaneous travel time of route p, for vehicle i, from node j to node s at time t. The probability of any feasible route p is inversely proportional to the instantaneous travel time, $\psi_{i,p}^{js}(t)$ and is given by:

$$\beta_{i,p}^{js}(t) = \frac{\exp\left[-\theta\psi_{i,p}^{js}(t)\right]}{\sum_p \exp\left[-\theta\psi_{i,p}^{js}(t)\right]}$$

The above equation allocates a vehicle to a feasible route p based on $\psi_{i,p}^{js}(t)$. The θ parameter affects the probability of using each route by assigning higher probability to a route with less instantaneous travel time.

The pseudo code of the algorithm, as applied by a vehicle i, is described below. The algorithm describes the routing of a vehicle from its current node j to its destination s. We denote by $A(j)_p$ the node after j on route p. The vehicle's current route is denoted by p'.

Algorithm 1

$while\ j \neq s$
$P \leftarrow \emptyset$
$K \leftarrow the\ set\ of\ k - shortest\ paths\ from\ j\ to\ s$
$P \leftarrow P \cup K$
$\forall p \in P$
$\quad \psi_{i,p}^{js} \leftarrow travel\ time\ for\ vehicle\ i\ to\ reach\ s\ from\ j\ using\ route\ p$
$\forall p \in P$
$$\beta_{i,p}^{js} = \frac{\exp[-\theta\psi_{i,p}^{js}]}{\sum_p \exp[-\theta\psi_{i,p}^{js}]}$$
$p' \leftarrow generate\ a\ random\ number\ and\ split\ according\ to\ \beta_{i,p}^{js}$
$send\ vehicle\ i\ on\ the\ first\ link\ of\ p'$
$j \leftarrow A(j)_{p'}$

6 Data Modeling

An important module in A-RESCUE is the representation of various lanes in the traffic network that will allow realistic movement and routing of vehicles. The purpose of the data modeling module is to support the traffic simulation module in handling the complex network connectivity and improving the simulation visualization. Without this module, it's impossible to simulate the traffic movement on different lanes within Repast.

In addition, our data modeling is more advanced than the GIS modules from the traffic simulation software packages such as SYNCHRO or VISSIM because they automatically convert the large-scale link-based GIS data into the lane-based network with full connectivity.

The data modeling module is developed based on the work by some of the authors and is published in Su et al. (2015). The idea is summarized as follows. Before running the simulation in Repast, we prepare the supply side (road networks) in such a way that Repast can read and assign traffic demand directly. Specifically, the data modeling offers:

(1) Lane visualization

By using Repast directly without the data modeling module, the vehicles can only move on a center line and we cannot differentiate vehicles in opposite directions (Fig. 4).

With the data modeling module, we can separate vehicles by lanes. As the results show, we will never observe vehicles "crashing" when they are passing each other or moving on opposite directions (Fig. 5).

(2) The link and lane connectivity

Link-lane connectivity at intersections is extremely difficult to handle in Repast coding. On the other hand, the data modeling consists of a procedure to trim the lanes at intersections so that vehicles do not move in an unrealistic trajectory (Fig. 6).

In our data modeling module, we not only offset each link to obtain different lanes but also automatically trim the beginning and ending segment of the lanes. Without this step, vehicles will move along the entire lane before shifting to the next lane, which causes the impractical turns. By trimming the lane ends, vehicles can approach the next lanes allowing for appropriate movements. An example is shown in Fig. 6.

(3) Link-link connectivity and lane-link connectivity.

This feature keeps track of the connection among all segments in the network especially at the complex at-grade intersections and interchanges.

The data modeling module outputs a table for each link (Table 1) and another table for each lane (Table 2).

Those data allow us to determine all connectivity in the road networks which is very important for the traffic simulation. At a certain time when a vehicle is moving in a lane of a link, we know exactly which link and lane will be used next, given the routing for that vehicle has been defined.

A key difference from other simulation based tools such as SYNCHRO, VISSIM, etc., which require one to specify the link/lane connectivity manually, the proposed data modeling can automatically generate not only the connectivity but also the network visualization for very big networks.

Figure 7 shows the results of data modeling in the Miami-Dade county network. All roads have been offset and trimmed. The road and link connectivity is output in a data file and this can be used directly within Repast simulation. In Fig. 8, we magnify the view of one interchange. We can see how links and lanes connect together. In Repast simulation, vehicles will move along the purple lines which represent the center of the lanes.

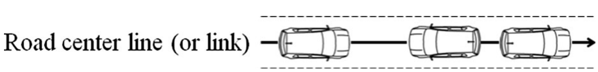

Fig. 4 Visualization of vehicles in a single lane without data modeling

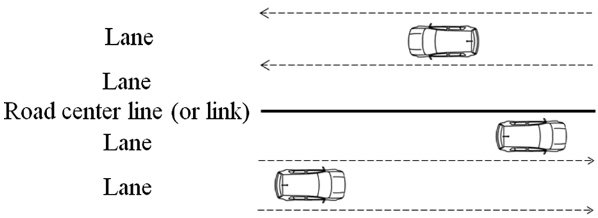

Fig. 5 Lanes are separated from link in data modeling

In addition to the three main features above, the data modeling module can also perform the following tasks:

1. Find the intersections with certain number of legs. This function enables us to enumerate the ID of intersections with different legs. For example, the five-leg intersections must be pre-processed before running the data modeling.
2. Prepare the signalized properties for intersections. This function is designed for the very detailed level of simulation with signal control. For each intersection (node), it enumerates all of the links that are going into it. The result will be displayed in the node layer.
3. Use the hybrid model with background traffic. It enables the data modeling to add additional columns to the road shape file that corresponds to hourly speeds (e.g. 24 h) in the link file extracted from TRANSCAD.
4. Find zigzags in the shape file and help avoid erroneous trajectories of vehicles in the Repast simulation.

The data modeling module is coded in Visual Basic as an add-on in ArcMap. It is called from ArcMap to run specific tasks such as building connectivity, trimming lanes, finding potential error (five-leg intersections), etc. The data modeling inputs a link-based map within a standard GIS shape file. The output of this procedure is the lane-based shape file and new link-based shape file, which can be input and used directly in Repast simulation module.

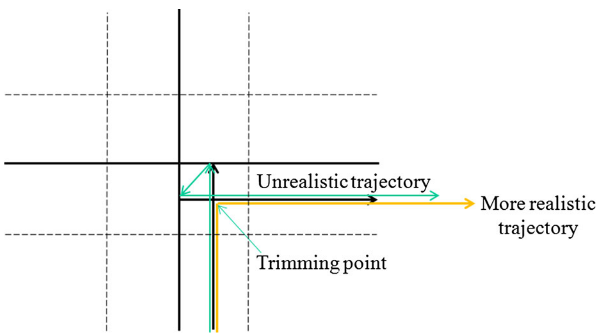

Fig. 6 Trimming lanes in data modeling to avoid unrealistic vehicle trajectory

Table 1 Link data from the data modeling

Link ID	To node
Length	Left number of lanes
Direction	Right number of lanes
Name	Lane #1
Class	Lane #2
Number of lanes	Lane #3
Speed limit	Lane #4
Left	Lane #5
Through	Lane #6
Right	Twin lane #1
Twin link ID	Twin lane #2
Twin link left	Twin lane #3
Twin link through	Twin lane #4
Twin link right	Twin lane #5
From node	Twin lane #6

7 Simulation Tool Development

The simulation model is developed using the Repast Simphony (Macal and North 2005; North et al. 2005) agent-based toolkit.

The model includes four high-level components that play an important role in the simulation.

a) Network Constructor: The purpose of this module is to build transportation networks from shape files generated by the data modeling. The shape files here include three types: Point, Poly Line (which generates roads and lanes), and Polygon (which generates traffic analysis zone (TAZ) centroids). The network includes roads and lanes on which evacuee agents travel, intersections, and TAZ centroids which are the origins, activity locations, and destinations of evacuee agents.

   Repast Simphony has an extensive library to incorporate shape files into the simulation. We have used data modeling (see Section 6) to modify the shape files of the networks to be used in the simulation. We then use the GIS library of Repast Simphony to read the network files.

Table 2 Lane data from data modeling

Lane ID
Link ID
Left lane
Through lane
Right lane
Length

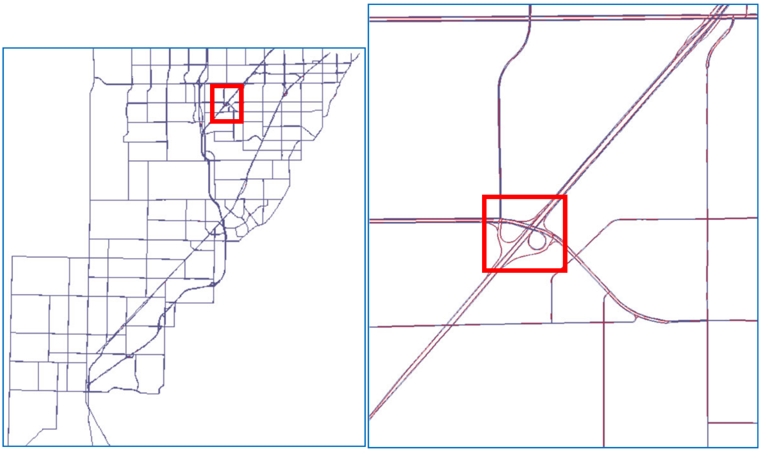

Fig. 7 Miami-Dade county road network after running the data modeling

b) Agent Constructor: This module generates agents on the basis of action rules that are pre defined. The evacuee agents first build the travel plan, i.e., the list and visiting sequence of the agents including duration the agents spend at intermediate locations. The agent's plan is based on the output of the behavioral models. The way evacuee agents are loaded to and travel on the network is discussed in Section 4.

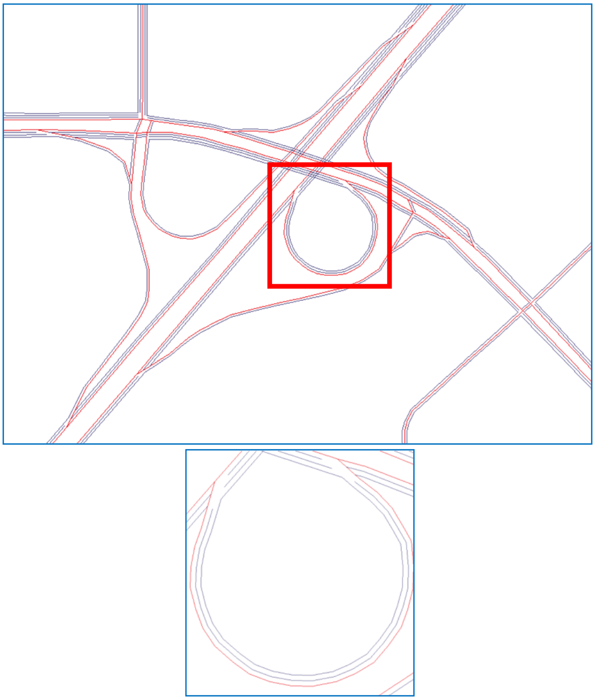

Fig. 8 Visualization in a specific interchange

The creation of agents in Repast starts by building a context for the agents. A context is a named set of agents. In simple words, a context is a bucket full of agents. A context is named and the agents are added to it. The current simulation implements various contexts to create agents including the network features. For example, we have the following contexts for different agents in our simulation: road, lane, junction, house and vehicle. The simulation structure in flexible enough to include any other agents. For instance, to include signals we just need to implement a signal context in the simulation.

A related concept is the geography. If a context is a virtual bucket to an agent, the geography is a physical bucket to the agent. If an agent is required to be visualized in the display, it must have geography. When creating contexts, we have to specify the schedule of the simulation events. A schedule is an instruction for the execution of the events. The simulation procedure followed here is time-dependent, hence the start time, end time and recurrence interval has to be mentioned in a schedule.

c) Displayer: This module mainly displays the animation of simulation dynamics and results. The display module shows vividly the interaction among evacuee agents and the level of congestion on the network. Through the display module, a specific vehicle can also be tracked and its trajectory can be visualized. It can also simultaneously show additional information (e.g., speed, origin, destination, next road and so on) about the vehicle in a separate window.
d) Simulation Context: This module is the global environment. In the environment, each autonomous agent proceeds to its destination subject to certain imposed constraints and interacts with the environment and other agents. It also provides real-time information about other household agents as well as the transportation network during the simulation.

The proposed simulation model is a decentralized multi-agent system. That is, there is no central control mechanism. The evacuee agent acts independently based on local information and the network conditions. Each agent has the ability to update the route information and change its route if necessary. From the simulation, statistical information of evacuation can be obtained. The information includes total evacuation time for each agent, network clearance time, maximum and minimum travel time, and more. Detail information of each evacuee agent, departure time, route, speed, and total evacuation time can also be obtained easily based on its trajectory.

The simulator can be run in both Windows and Unix operating systems. It is convenient to visualize the simulation in Windows as a desktop application. However, all the large-scale simulation runs are conducted in a Unix operating system in a cluster computing environment with 64 bit, dual 12-core AMD Opteron 6172 processors (24 cores per node) and 96 GB of memory for each node.

8 Data Collection

This section presents the data and scenarios designed for the numerical experiments. The data are extracted from the outputs of the behavioral models presented in Yin et al. (2014). The outputs from Yin et al. (2014) present overall data of evacuees' behavior and include all modes of transportation used in the evacuation. A-RESCUE uses the data from households that only use vehicles to evacuate. Thus, all households that do not use vehicles to evacuate are removed from the input data of the A-RESCUE model.

A-RESCUE was tested with a scenario which included pre-evacuation activities, en-route evacuation activities and direct evacuation. The network data and the demand data have the following characteristics:

- Network size: number of links: 8578, number of zones: 364
- Total number of evacuation vehicles: 89,379
- Total number of trips (including pre-evacuation trips): 162,002
- Vehicle classification according to trips:

– Vehicles make pre-evacuation activities (35168, 39.35 %)
– Make multiple trips and return to home (587, 0.66 %)
– Directly evacuate (53624, 60 %)

- Scenarios are based on different routing strategy, rather than demand level. Seventeen routing scenarios were tested:

– Single shortest path routing (1 case)
– K-shortest path routing (total 16 cases)

$k = 2$ and 3
$\theta = 0.25, 0.5, 0.75, 1, 1.25, 1.5, 1.75, 2$

9 Computational Results and Analysis

9.1 Demand Patterns

Figure 9 shows the departure time distribution across the 6 days of evacuation period. It is found that the peak demands occur in the middle of a day. This result is consistent with previous literature, which suggests that hurricane evacuees prefer to depart earlier in the day so that they can reach their destinations by nightfall (Lindell et al. 2005). A trip is made either to evacuate to a safe place directly or to participate in preparatory activities. About 40 % ($n = 35{,}168$) of these trips are made to participate in preparatory activities while about 60 % ($n = 53{,}624$) of these trips are directly related to evacuation to a final destination.

Figure 10 shows the spatial distributions of the evacuation trips aggregated over the entire period of evacuation of 136 h. Figure 10a shows the total number of trips (including evacuation and pre-evacuation trips) departing from the zones; Fig. 10b shows the total number of starting trips of the trips chains for each vehicle departing from the zones; and Fig. 10c shows the total number of final evacuation trips departing from the zones. In general, we find that

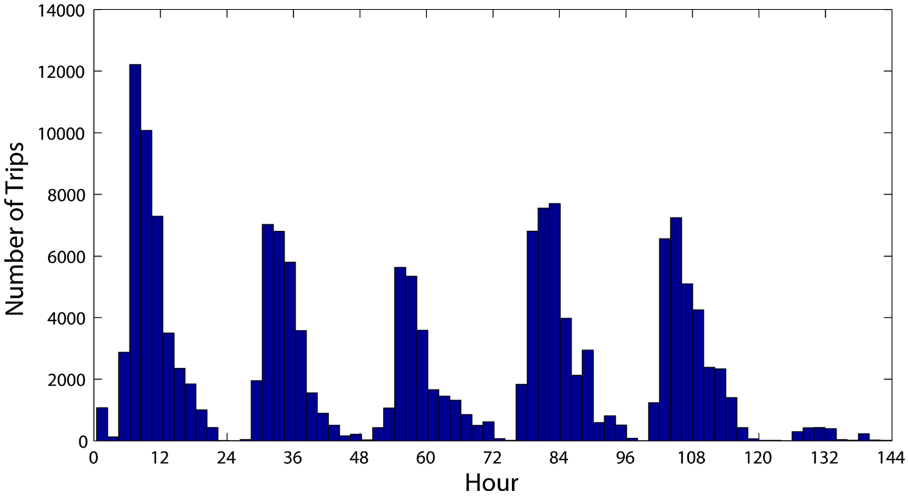

Fig. 9 Departure time distribution

southern zones generated most of the trips. This is due to the imminent threat of the hurricane to these zones.

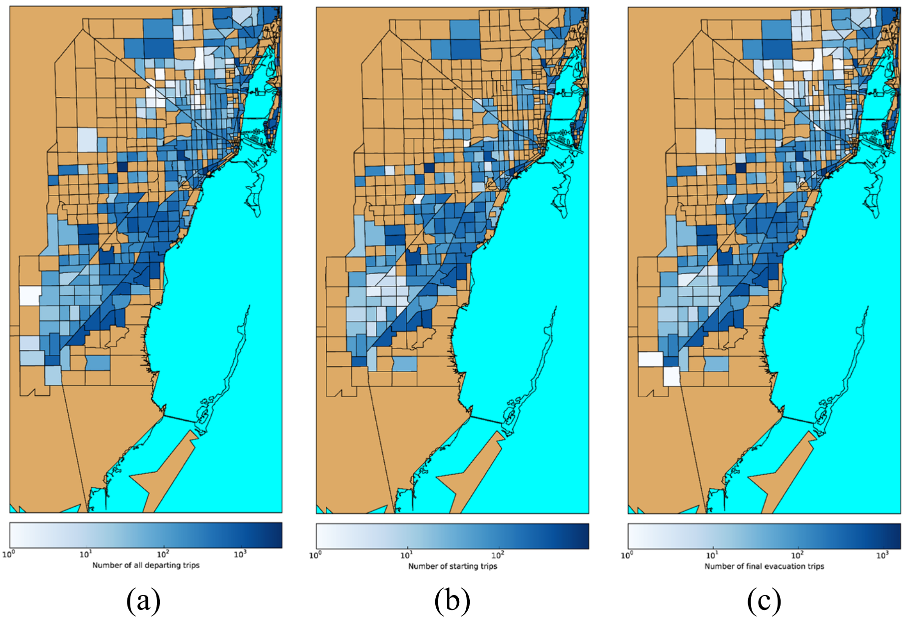

Fig. 10 Spatial distributions of evacuation trips

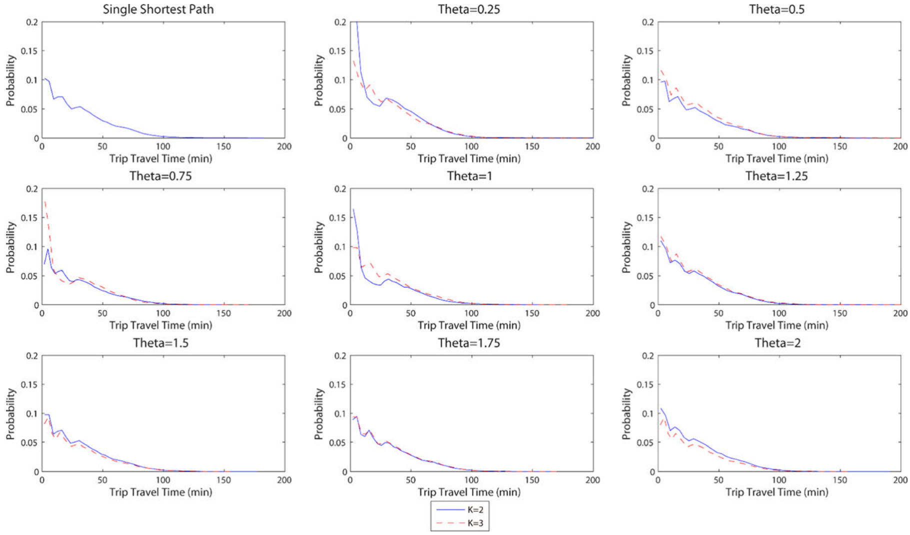

Fig. 11 Distribution of trip travel time under different routing parameters settings

9.2 Evacuation Travel Time Analysis

In a given demand scenario, we run the simulation for different routing parameters. Figure 11 shows the distribution of travel times. As a base case, we run the simulation for single shortest path routing. Then we run the simulation for k-shortest path routing for $k = 2$ and 3 and $\theta = 0.25, 0.5, 0.75, 1, 1.25, 1.5, 1.75, 2$. The higher the value of k the more options an evacuating vehicle will consider for choosing routes. The higher the value of θ the more sensitive the agent will be to the differences in travel times across different routes. We find that the improvement due to higher values of k is very modest. The improvements in reducing travel times become greater for higher value of θ when its value is below or equal to 1. It is observed that the different values of k and θ do not significantly impact the evacuation time.

9.3 Analysis of Pre-Evacuation Activities

We found that about 40 % ($n = 35{,}168$) of the total trips are made to participate in preparation related activities before evacuation. In this section, we investigate if the length of preparation time impacts the evacuation travel time. Figure 12 shows the scatter plots of evacuation travel times against pre-evacuation travel times over different routing parameters. High pre-evacuation trip travel times result in lower evacuation time, perhaps due to the selection of nearby final destinations reducing the overall travel time. It is found that routing parameter has an impact on local congestion reflected though the high pre-evacuation travel times. For instance, for $k = 2$ and $\theta = 0.25$ the maximum of pre-evacuation trip travel time is lower than that of for $k = 3$, and $\theta = 0.25$. This indicates that increasing the routing options has increased the pre-evacuation trip times for some of the travelers. However, for a higher value of θ, opposite results are found; consider the case $k = 2$ and $\theta = 0.75$ against the case $k = 3$ and $\theta = 0.75$.

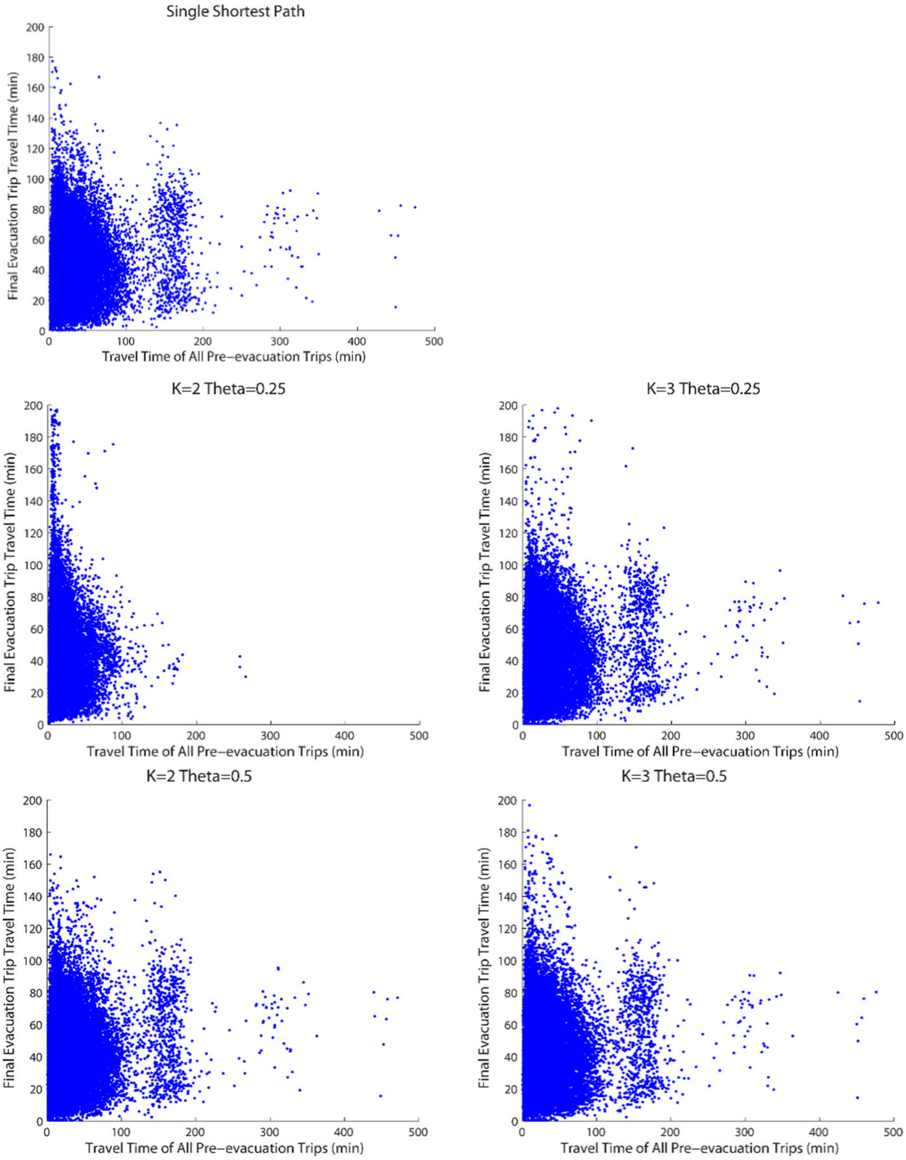

Fig. 12 Scatter plots of evacuation travel times vs. travel time of pre-evacuation trips

9.4 Spatial Level Analysis

In this section, we present the spatial distributions of various aspects of evacuation trips (Fig. 13). Note that these trips do not include the pre-evacuation trips.

Figure 13a, b, and h show the average evacuation trip travel time, average evacuation trip distance for each departing zone, and average evacuation trip departure time for each departing zone, respectively. We find that southern zones near the coast have higher evacuation travel times, and longer evacuation distance since they are directly in

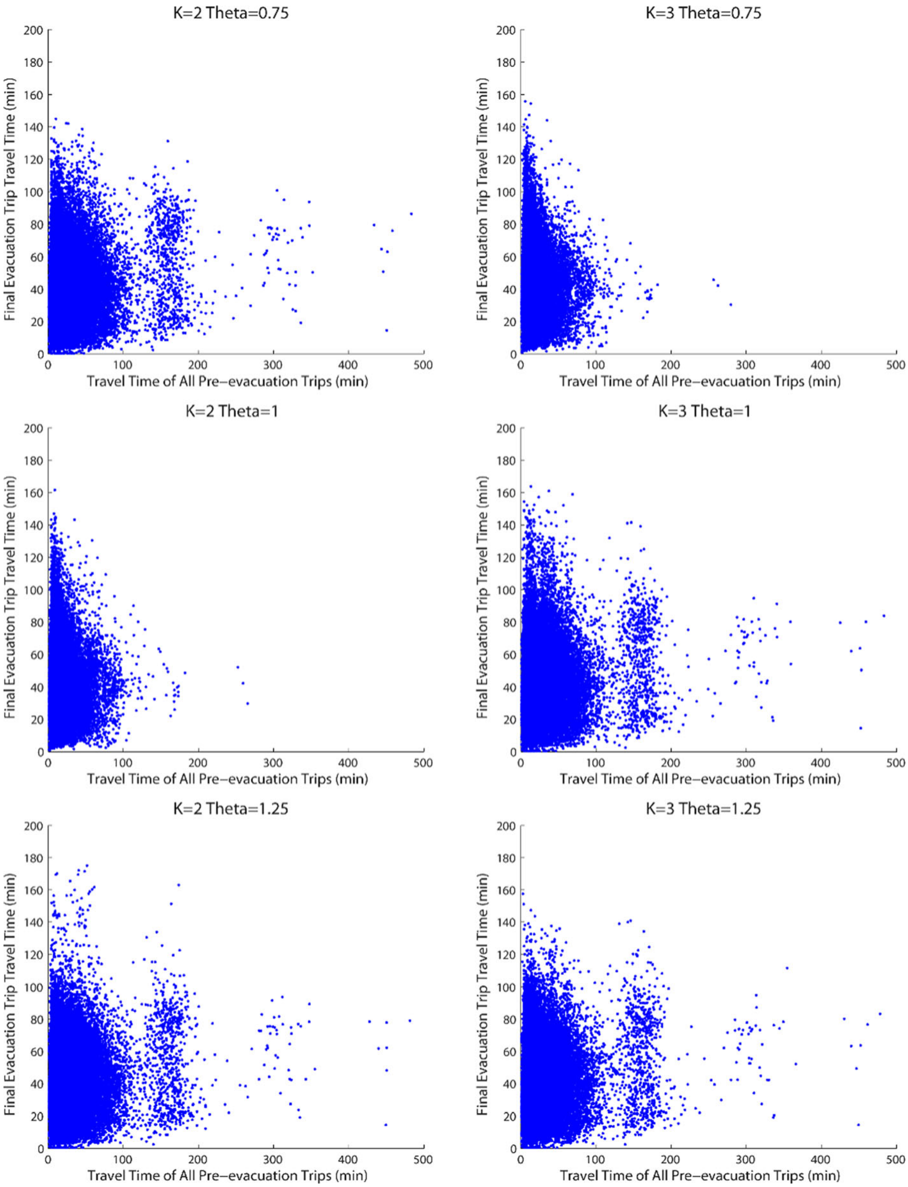

Fig. 12 (continued)

the path of the hurricane and choose destinations farther away. However, the departure times are evenly distributed across all the departing zones. This is due to impacts of various socio-economic characteristics of the households affecting the departure time choice.

Figure 13c shows the average final evacuation trip speed for each departing zone. Most of the zones have similar speeds.

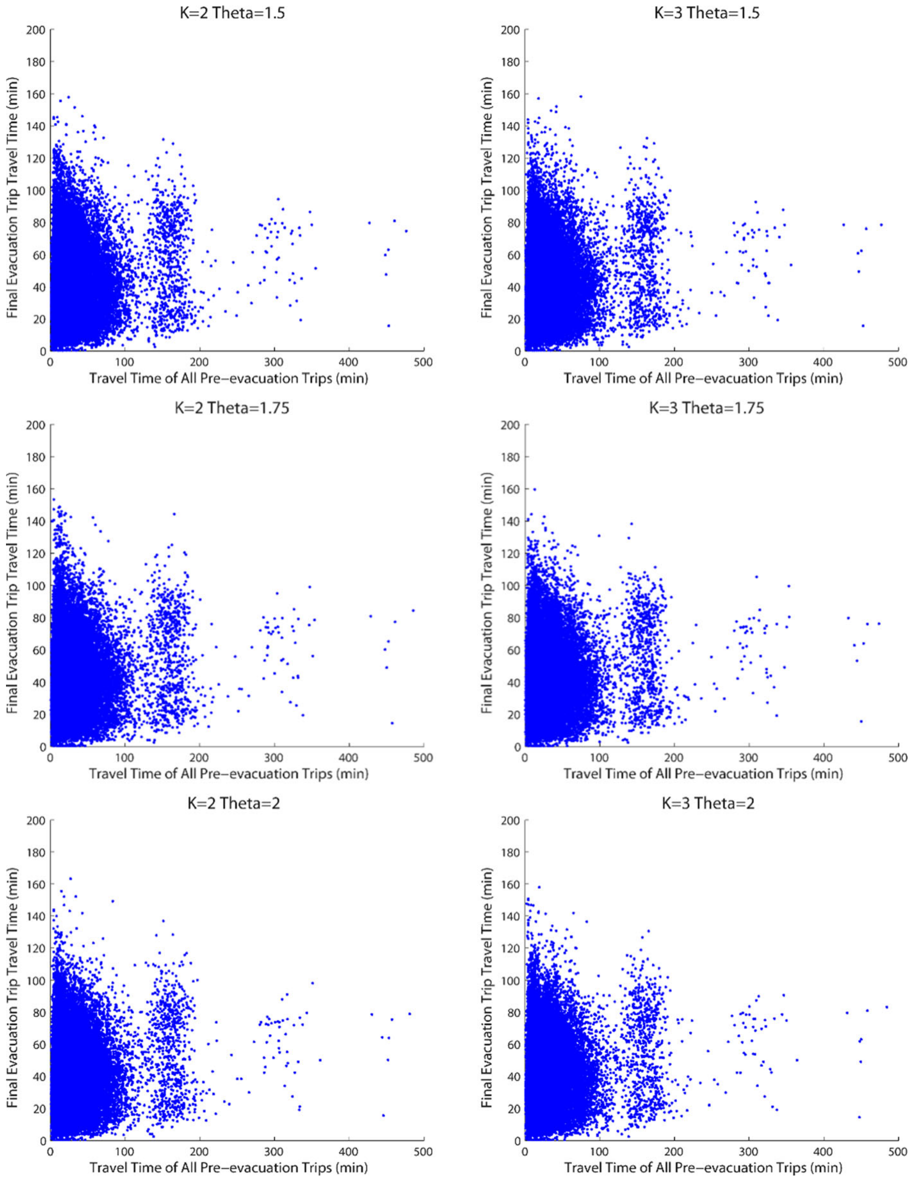

Fig. 12 (continued)

Figure 13d and e show the maximum evacuation trip travel time and maximum evacuation trip distance for each departing zone, respectively. A few of the southern zones experience very high maximum travel times because of the long distances traveled.

Figure 13g shows the clearance time for evacuation trips for each departing zone. Most of the southern zones have very high clearance times because of long distance and higher number of evacuation trips.

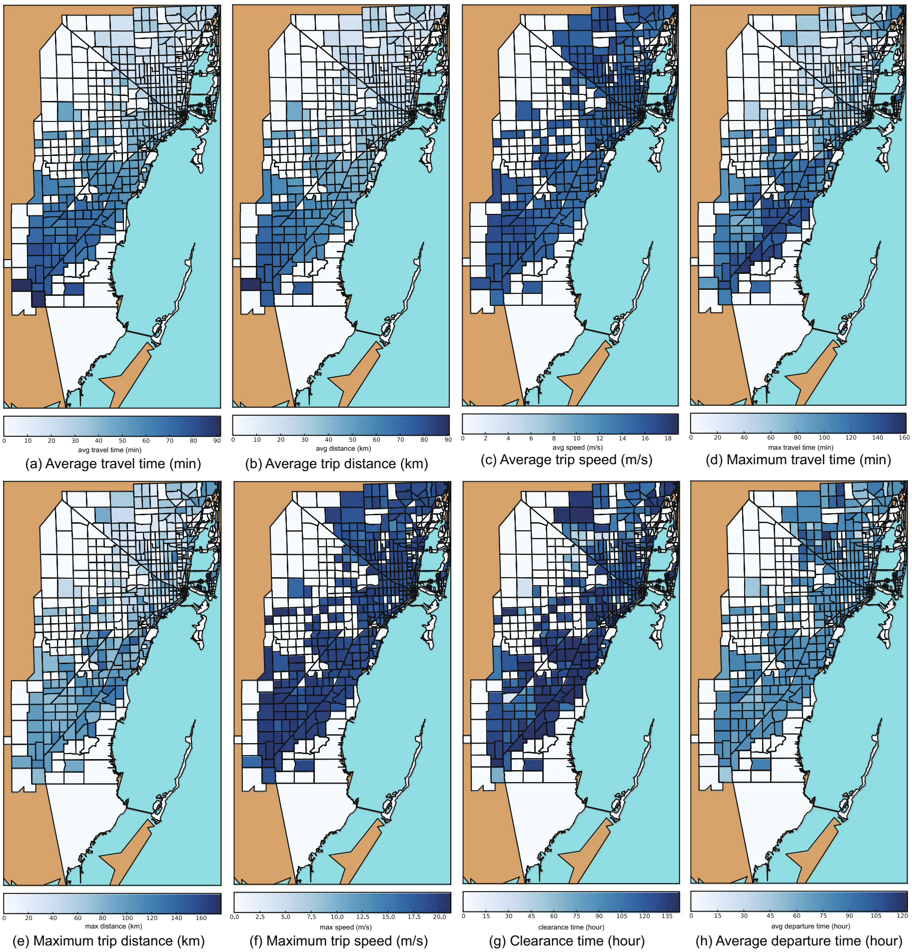

Fig. 13 Spatial distributions of evacuation trips (**a**) Average travel time (min) (**b**) Average trip distance (km) (**c**) Average trip speed (m/s) (**d**) Maximum travel time (min) (**e**) Maximum trip distance (km) (**f**) Maximum trip speed (m/s) (**g**) Clearance time (hour) (**h**) Average departure time (hour)

10 Summary and Conclusions

In this paper, we present A-RESCUE, a high fidelity multi-agent simulation model that integrates household-level activity behavior with a network-level traffic assignment to evaluate a broad range of evacuation strategies. The novelty of the proposed multi-agent simulation model lies as follows:

- The proposed integrated approach can use the household-level characteristics to make evacuation related decisions featuring a truly dynamic simulation. The situations observed in the transportation network can easily be incorporated to the household decisions generating evacuation demand *on the fly* based on the prevailing traffic condition. This feature is of greater importance for an evacuation context where demand changes rapidly as a function of traffic conditions, hazard information and other social phenomena. Thus, through an integrated modeling approach, A-RESCUE captures the complexity of household-level decision-making and the dynamic traffic flows during an evacuation process.

- The proposed simulation approach assigns a rich set of behavior for household agents including whether to evacuate, the pre-evacuation and intermediate activities, accommodation type selection, final evacuation destination, evacuation mode, and departure time. All these decisions are modeled via probabilistic (frequency) or econometric models relating relevant explanatory variables to the choice in question. One of the most important capabilities of the simulation is the pre-evacuation activity module, which adopts an activity-based approach and views the pre-evacuation activity-travel from a tour-stop perspective. Most evacuation models are likely to underestimate the demand because of ignoring these pre-evacuation activities.
- A-RESCUE implements an adaptive route choice model based on a simple logit-type splitting function. Such an adaptive model, correctly reacting to current traffic conditions, has a significant value especially when real-time information is lagged/delayed. Typically, evacuations have rapid fluctuations of demand and capacity forcing travelers to take travel decisions based on the current traffic situation where an adaptive routing approach is particularly useful.
- A-RESCUE represents the embedded traffic network in the most detailed way possible for a simulation allowing realistic movement and routing of vehicles. It uses data modeling approaches to support the traffic simulation module handling the complex network connectivity and improving the visualization. The data modeling module of A-RESCUE is more advanced than the GIS modules from the microscopic traffic simulation software packages as it converts a large-scale link-based GIS data into a lane-based network with full connectivity.

This paper presents the basic features of the multi-agent simulation model and the initial findings based on the simulation runs on a medium-scale regional traffic network. The various future directions that the opportunities of the simulation model can be utilized:

- The behavioral decisions modeled in A-RESCUE are made in a sequential manner. The model can be improved significantly if a dynamic joint decision-making context is simulated.
- Currently the simulation system does not model how the warning information is propagated and processed and how it influences the evacuation decisions. Considering an underlying social network among the agents and modeling a dynamic decision-making context, such phenomena can be simulated.
- We have not simulated the process of disseminating real-time information, the value of such information and the decisions resulting from it for managing evacuation traffic.
- On the traffic network side, there can be various traffic flow restrictions (e.g. contra-flow) and signal priorities for managing evacuation traffic efficiently. It will be particularly useful to test such traffic options in an integrated simulation system.

- We have not compared simulation run-times under various scenarios. A very important direction will be to test the scalability of our approach and to implement high-performance distributed computing algorithms for the simulation system without losing the fidelity of the social and engineering system characteristics.

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