Simulation of Hurricane Irma Evacuation Process

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ABSTRACT: Hurricane evacuation management is very challenging, due to the lack of experience/data for extreme events, the complexity of human decision making and travel behavior, and the large uncertainty in storm prediction. Recent Hurricane Irma (2017) created the largest scale of evacuation in Florida's history, involving about 7 million people on mandatory evacuation order and 10 million evacuation vehicles. Here we reorganize the traditional hurricane-prediction and governmental-order-based traffic demand generation model into an agent-based mean-field model that considers also human decision making, to perform fast evacuation modeling, using Irma as a study case. With a fast simulation algorithm, the model can be evaluated and calibrated with (often very limited) traffic observation, partially overcoming the problem of data deficiency. The calibrated model is found to well capture the global features of the evacuation process in Irma. The analysis also reveals that people may have put more weight on the predicted hurricane category than the governmental order when making evacuation decisions during Irma, indicating possibly a higher panic level than that in previous storms. The developed model can also be used to help improve evacuation management.

1. INTRODUCTION

Communities on the Atlantic and Gulf coasts are vulnerable to hurricanes and may need to evacuate a large number of people when a major storm threatens. When Hurricane Irma flited Florida,people evacuated at nearly the same time, exceeding the capacity of road networks. Fortunately, the evacuation process finished before Irma made landfall. However, Irma reveals the challenge of the local government in balancing between the competing goals of waiting long enough to avoid the cost of an unnecessary evacuation and evacuating early enough to avoid a loss of life. This is a problem faced not only under Irma's situation. During many other hurricanes, people also face the same dilemma(Czajkowski and Kennedy (2010)). For example, during Hurricane Sandy (2012), New York City issued evacuation orders about only 8 hours before the Subway System was shut down and the NYU Medical Center was evacuated after the power failed. Conversely, if the decision is made prematurely, many people will leave needlessly and may encounter more risk in the evacuation than had they remained in their homes. This occurred in Hurricane Floyd (1999), in which more than 2.5 million people from Florida to Virginia evacuated, many unnecessarily and at great expense (Dow and Cutter (2002)). To solve that problem, the hurricane evacuation mechanism should be studied further.

The evacuation process can be understood as a feedback system with two types of participants: householders and local government take action under exogenous information: probabilistic or ensemble hurricane prediction. Government release order to evacuate and people act based on both

governmental organization, personal condition and hurricane prediction.Evacuation model is hard to design because of two hard obstacles (Robinson et al. (2017)): 1) complex human behavior under changing hurricane prediction and governmental evacuation order and 2) data deficiency of time-varying traffic condition and household level decision. The first obstacle makes the traffic condition difficult to model and requires large computational resource due to the need of agent-based modelling accounting for individual behaviors (Yin et al. (2014)) or large-scale optimization for dynamic traffic analysis (DTA) based on game theory (Brown et al. (2009)). And higher demand on computational resources restrict the size of searchable model parameter space which make the evacuation model under fit. The second obstacle makes the traffic model hard to validate (Mesa-Arango et al. (2012)). These two points together lead to the scarcity of researches that comparing the results with the real-traffic data (Yin et al. (2014)). In this paper, by coupling the en-route model for individual evacuation route choice (Dia (2002)) and a Time-Dependent Sequential Logit Model(TDSLM) for individual evacuation demand simulation (Gudishala & Wilmot 2012) and re-organizing them into a link flow based mean-field model, we succeeded in a rapid simulation of the entire evacuation process In this framework, the behavior model is as flexible as traditional agent-based en-road models and the dynamic traffic simulation based on mean field theory defused the problem borrowed by the giant agent numbers in agent-based model. With efficient differential equation solver to solve the mean-field model, we are able to search large parameter space for the tunable parameters in our model and succeeded in reproducing the dynamic evacuation behavior of the traffic system during Irma based on the real data.

2. METHODOLOGY

Under a hurricane, people choose evacuation routes first, then they book a hotel or find a friend's place to stay against the hurricane. So their logic can be separated into three parts: 1) decide whether leave or not and decide when to leave their original place 2) find a destination where there still remain enough capacity for evacuators and 3) take a route to that place (Evacuation Guide 2017). Following this logic, the traffic dynamic simulation is composed of Traffic Demand Model, Dynamic OD model and Route choice model.In the following sections,we first introduce each of these sub-models then these sections are integrated together an integrated mean-field differential equation model that solves the global dynamic traffic condition time step by time step and traces the origin for traffic on each road. In section 2.5, we invite real data including hurricane prediction and governmental order (for agent decision making) and local population and road network (for traffic amount evaluation) into the modeling process and validate the model by a genetic algorithm to minimize the difference between simulated traffic condition and observation globally.

2.1. Traffic Demand Model

Evacuation decision making is a sequential choice process. If time is discretized into time intervals, in time interval (t) a household has the binary choice to evacuate or not to evacuate, provided that the decision to not evacuate was made in all earlier choices. If the choice in time interval (t) is not to evacuate, the household will have the same binary choice in time interval (t+1), and so on, until either a decision to evacuate is made or the end of the analysis period is reached and no decision to evacuate has been made. For each time interval, the evacuate decision can be made for each householder using random utility theory (Fu and Wilmot (2004)). The probability that a household will evacuate at time t [P(t)], given that it did not evacuate earlier, can be expressed in the form of a regular binary logit model for each time period t:

$$P(t)_{e/s} = \frac{e^{V_t^e}}{e^{V_t^e} + e^{V_t^s}}, t = 1, 2, ..., T \qquad (1)$$

where V_t^e / V_t^s represents the utility of a household choosing to evacuate/stay in time interval t and it is based on the time point of the day, the evacuation order, the hurricane position and the surge risk, and T is the total number of time intervals.

In later analysis, the parameter of the utility function is tuned to meet the real traffic condition

during Irma. In this study, 5 factors for evacuation decisions are considered following , they are evacuation order (boolen factor for voluntary or mandatory evacuation), Hurricane category (forecast category); Time of the day (reflected by 3 Boolean dummy variables: TOD1(12:00a.m.∼6:00a.m.); TOD2(6:00a.m.∼12:00p.m.);TOD3(12:00p.m.∼18:00p.m.)); Time-dependent distance(log-normed distance with location and scale parameters of 6.5 and 0.35) and storm surge(forecasted 10 ft surge above mean sea level or not).

2.2. *Dynamic OD model*

The classical gravity model is used to generate a destination for each origin, depending on the distance between the OD pair and the traffic attraction of each destination (Simini et al. (2012)). An adjusted gravity model is chosen to assign a destination for each evacuation-willing household dynamically, and the probability $G_{t,i}(j)$ for a household at node i decided to evacuate at time t to choose node j as the destination is:

$$G_{t,i}(j) = \frac{m_{t,j}^{\alpha} \bar{P}_j^{\beta}(t)}{f(TT_{t,ij})} \tag{2}$$

where α and β are adjustable exponents, $m_{t,j}$ is the volumn of unoccupied shelter/hotels volume at time t and the deterrence function $f(TT_{t,ij})$ is increasing with the real-time traffic time from node i to node j at time t and chosen to fit the real traffic data during Irma. The probability that a household will stay at the original place can reflect people's weariness of hurricane risk time t as $[\bar{P}(t) = 1 - P(t)e/s]$(Eq.1).

2.3. *Route choice model*

A limitation with traditional game-theory based model(DTA) is that they rely on pre-specified rules of behavior that are difficult to validate for evacuations. Lindell and Prater (2007) and Pel et al. (2012) criticize the use of user equilibrium for evacuations due to the inability of evacuees to learn traffic conditions by experience since the evacuations are rare events. The routing behavior assumptions should be further explored through interactions of social science and engineering based studies that focus on the individual with behavior-rule-based simulation model.

This paper employs an en-route model to capture the irrational household driving behavior other than traditional game-theory based model used in other evacuation simulation researches (Yi et al. (2017)). The assumption that travelers cannot deviate from their (pre-trip) chosen route is relaxed in case of en-route route choice. Here, travelers observe prevailing traffic conditions during their travel and make route choices accordingly. En-route choice models thus simulate travelers who travel from one intersection to the next, depending on the next downstream direction based on route guidance or the available information on the prevailing (instantaneous or predicted) traffic conditions . Few examples of evacuation studies are using en-route choice models: NETVAC allows myopic route improvisation (Lindell and Prater, 2007). The hybrid route choice models include, but are not limited to DYNASMART, DynusT, and EVAQ (used in (Pel et al. (2008))). The first two models are mesoscopic while the last is a macroscopic model.

When we simulate en-route route choice, link flow fractions (also called split proportions or turn fractions) are computed at all intersection nodes, and travelers are propagated from one intersection node to the next along the downstream links. The probability for a person at node i and aimed at node j to choose for a downstream link k ($f_{t,i,j,k}$) depends on the observed traffic on this link ($TT_{t,k,pre}$) and the belief of the shortest forth coming route (starting at the intersection node) travel time ($TT_{t,k,post}$) (Fig 1) based on random utility theory (Feng et al. 2018):

$$f_{t,i,j,k} = \frac{\exp(-\theta \sum_{pre}^{post} TT_{t,k})}{\sum_{s \in \xi_i} \exp(-\theta \sum_{pre}^{post} TT_{t,s})} \tag{3}$$

where θ is the diversion intensity parameter, which describes the capacity of drivers to predict the travel time of different routes in the model. If $\theta = +\infty$ the driver will select the route with the shortest time with probability 1 and if $\theta = 0$ the driver will select the route randomly(Patriksson (2015)). ξ_i is the set of downstream links for node i. $TT_{t,k,post}$ can be calculated with $TT_{t,k,pre}$ on each road at time t with a shortest road algorithm on sparse matrix (SPSM) (Johnson (1977)).

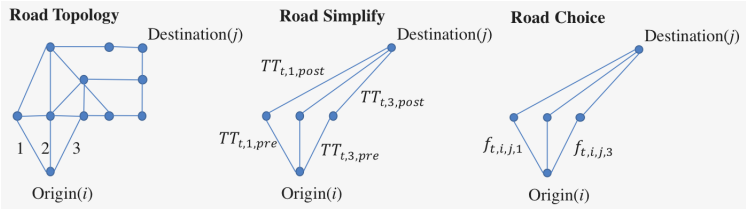

Figure 1: Road choice modular for a householder at Origin (i) to Destination (j)

Further, the link fraction at node i to the downstream link is:

$$f_{t,i,k} = \sum_{j \in \phi} f_{t,i,j,k} \cdot G_{t,i}(j) \tag{4}$$

where $G_{t,i}(j)$ is the gravity function mentioned before in Eq.2 and ϕ is the set of all the nodes (possible destinations) in the transportation system.

2.4. *Markov decision based mean-field dynamic evacuation model*

Composing the link fractions of all the nodes together, we obtain a Markovian transition matrix (M_t) for all the n nodes in ϕ and m links in ξ at time t:

$$M_t^{m \times n} = \begin{bmatrix} f_{t,1,1} & \cdots & f_{t,n,1} \\ \vdots & \ddots & \vdots \\ f_{t,1,m} & \cdots & f_{t,n,m} \end{bmatrix} \tag{5}$$

The evacuating population on all the nodes (listed in a column vector $N_{t,node}^{n \times 1}$) follows this matrix to flow into each road:

$$\delta \vec{x}_{t,in}^{m \times 1} = M_t^{m \times n} \cdot (P_t^{n \times 1} \otimes N_{t,node}^{n \times 1}) \tag{6}$$

where $\delta \vec{x}_{t,in}^{m \times 1}$ is the inflow into road network at time t, estimated by coupling the population remained at each node ($N_{t,node}^{n \times 1}$), the probability for them to go out for evacuation ($P_t^{n \times 1}$) and the probability for them to choose one specific road ($M_t^{m \times n}$). Operator "$\times$" is the matrix product and operator "$\otimes$" is the Hadamard product.

The traffic flow into each road at every time period and the out flow of each link can be captured by the governmental function of dynamic traffic simulation from the dynamic structure as illustrated in Fig 2.

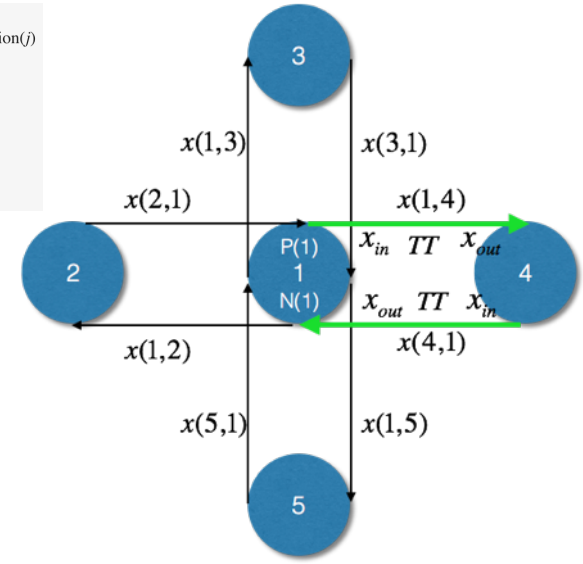

Figure 2: The Link Transformation Schematic Diagram

The governmental function can be described as:

$$\begin{cases} d\vec{x}_{t,in}^{m \times 1} = M_t^{m \times n} \cdot (\vec{P}_t^{n \times 1} \otimes \vec{N}_{t,node}^{n \times 1}) dt \\ d\vec{x}_{t,out}^{m \times 1} = (1 - \vec{TT}'(t)) \otimes \vec{x}_{t-\vec{TT},in}^{m \times 1} \\ \vec{TT}^{m \times 1} = BPR(\vec{x}_{t,in}^{m \times 1}) \\ d\vec{x}_t^{m \times 1} = d\vec{x}_{t,in}^{m \times 1} - d\vec{x}_{t,out}^{m \times 1} \\ d\vec{N}_{t,node}^{n \times 1}) = H_{out} \cdot d\vec{x}_{t,out}^{m \times 1} - H_{in} \cdot d\vec{x}_{t,in}^{m \times 1} \end{cases} \tag{7}$$

where t is the time point under discussion, $\vec{x}$ is the traffic flow vector composed of each road information; $\vec{x}_{in}/\vec{x}_{out}$is the traffic inflow/outflow vector of the road set; $\vec{TT}$is the traffic time cost vector calculated by BPR function,which reflects the monotonous relationship between traffic flow and time cost on a given link : $BPR(x) = tt_0(1 + \alpha \cdot \frac{x}{C_0 \cdot LN}^{\beta})$, where tt_0 is the free-flow (unimpeded) travel time of the road, C_0 is the traffic carrying capacity of one lane and LN is the number of lanes of that given road, $\alpha$and β are two parameter related to road type (Feng and Lin (2018)); H_{out} is a network topology matrix showing the end of each road (if node p is the end of road k,$H_{out}(p,k) = 1$;else $H_{out}(p,k) = 0$); H_{in} is the matrix shows the start of each road.

The Eq. 7-1 describes the outgoing population from one node into the traffic network as discussed in Eq.6. Eq. 7-2 shows the outgoing population from a road section into one node considering the

changing car density. Eq. 7-3 calculates the travel time of each road based on the traffic information. Since the travel time of one road is determined by the incoming traffic flow some time ago, so this equation has a time-lag. Eq. 7-4 is the continuity law of a road section: current number of cars on this road section is determined by the cars flow in/out at this time moment. Eq. 7-5 represents the relationship between nodes and roads: the cars flowing out of one road should be absorbed into one node and then be assigned into another road section or stay in that node. However, if the population of each node exceeds the capacity of it during the calculation process, the over-capacity population have no choice to stay at that node and will be directly assigned onto the following roads by the Markovian transition matrix. This is a Lipchitz full-rank ordinary differential equation set and can be solve with Euler method efficiently. Each time is recalculated using the SPSM method and is updated using a one dimension search. This process is highly matrixlized. Taking advantage of the high efficiency packages built for matrix calculation, the simulation for the full 5-day before hurricane landfall for Florida can be finished in 10 seconds on one core of a single PC. This brings the convenience to search a very wide parameter space for calibrating the model.

2.5. Summarize data set and Calibrate the model

Related data for Florida and the major highways in its surface transportation network is used in this simulation. Florida has an area of around 170000 km^2 and a population of $\sim$ 20 million in 2017; 6 million people are involved in this evacuation process with the mean travel distance 200 miles. The transportation network abstracted from the GIS data provided by Federal Highway Administration (FHWA) is modelled as consisting of 1520 nodes and 5767 links (Federal Lands Highway 2018). The speed Limit of each highway can be found in FHWA data set (Florida Traffic information 2018). Typically, a major Interstate Highway or Turnpike have design speeds of 70 miles/h. A state road has a design speed of 45 or 55 miles/h; and the parameters in BPR function come from the highway criterion and the over-normal-capacity part (x/c>2) is simulated as 10% of the limit speed (Bureau of Public Roads). Under hurricane evacuation, roadway shoulders were open for evacuation traffic on four corridors: I-75 Alligator Alley; I-75 from Wildwood to the Georgia state line; I-10 from Jacksonville to I-75; and I-4 from Tampa to Orlando. This requires fewer resources than previous plans that reversed lanes to make these highways one-way only. This is also considered in evacuation simulation. The hurricane prediction comes from NOAA (Irma Prediction and Record 2017), providing the hurricane observation at each time point and also the changing hurricane prediction; The surge prediction from NOAA is also included. The time series of spatial governmental evacuation order and traffic amount observation comes from Florida Traffic Administration (Florida Traffic information 2018).

To perform the evacuation simulation, the parameters in the human behavior models including: the traffic demand model,dynamic OD model and route choice model should be provided. However, these parameters are hard to observe or obtain due to the , so here we try to find the parameter set making the simulation result best fit the field measured data set. Here are 6 parameters in total for the discrete choice model in traffic demand model, 3 parameters in dynamic OD model and 1 parameter in route choice model as discussed in former sections.

The parameter still need to be estimated is the city capacity, which not only contains the shelters and hotels opening, but also the relative's house and other housing resources, so these parameters are difficult to be directly obtained though having physical significance. Here we estimate them with governmental reported shelters' number (TCpalm 2017) and hotel rooms number (STR 2017). The BPR function is also validated to fit the panic evacuation driving behavior and brings 6 unknown parameters for 3 kinds of highway section (Feng & Lin 2018).

Among these parameters require validation, the Traffic Demand Model affects simulation results most. Here a two-stage validation framework is implemented to ensure the validation quality:1. Traffic Demand Model pre-validation and 2. Global model validation. First we use a time series regres-

sion method to fit the pre-selected out-migration data (Fu et al. 2006). We employed the data reconstructed from Irma evacuation process for 15 Traffic Analysis Zones in Feng & Lin 2018. We directly obtain the results of traffic demand model by nonlinear regression. Then,MCMC is applied to capture other parameters (with confidence interval) in routing model and destination model.

3. Results

3.1. Global Quality

Compare to the bird view of real global traffic condition (Fig.3), our simulation gives a good match at two peak evacuation hours: 9/06/17 & 9/07/17 night. During the entire process of evacuation, our model also gives consistent high-quality projection. Our model is able to capture the time and spatial-varying traffic peak. In those areas we most interested in: Key West, Miami and Tampa (lower Florida), our model matches well with real data. In those remote downstream areas without much hurricane risk (Pensacola, Tallahassee), our model shows some distortion. This is partially because the cumulative error diffuses from the upstream evacuation simulation. Also,the daily traffic of these area may still be functional due to the low hurricane risk, which is not considered in our model. Our model shows larger traffic amount on east coast of Florida comparing to real data. And relatively, a lighter traffic on west coast. This problem may come from the estimated city capacity, which affects a robust estimation of evacuation OD.

3.2. Time series Quality

In local analysis (Fig.4), the observed traffic volume time series of several typical roads are also compared with simulated traffic condition. We can find that for Key West (No. 227 camera), our model gives a projection of highest quality. That's because we pre-condition our model parameter with the evacuation behavior model substracted from Key West. There is a overestimation for the traffic amount on I-95 near Miami (No. 217 camera), but an underestimation for the traffic peak at I-95 to Jacksonville (No.322 camera). This may be because the hotels and shelter ratio at Orlando, Ocala or Gainesville is over-estimated, so more people

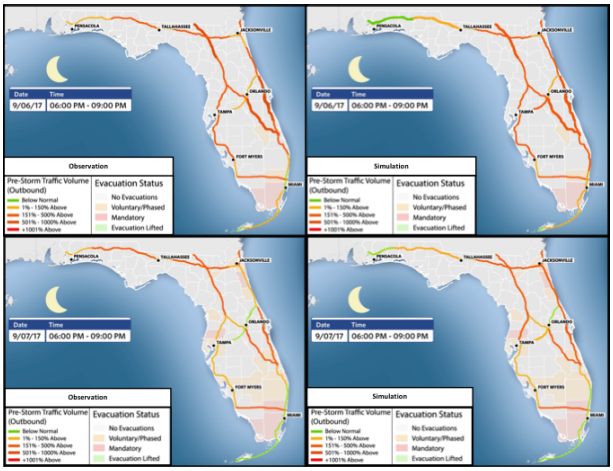

Figure 3: Global Validation Result of Florida Traffic Condition

are projected to choose Orlando as their destination. In reality, more people may go to Tampa. Another possible reason for this is because here are three main lines (I-95, No.1 Highway and Florida's Tumpike) together in same direction from Miami to upper Florida. The split-flow effect here is difficult to analyze. However, it is difficult to check whether this numerical bias comes from the road impedance estimation of these main roads, because the real-time car count data of No.1 Highway and Florida's Tumpike are not available. The over-estimation of traffic amount for I-95 downstream the Jacksonville (No.132 camera) is due to the under-estimation of Jacksonville capacity – all the vacancies of Jacksonville are occupied at evening 9/7/2017 in our model, which pushes all the people arrive at that time keep moving to Georgia. On the western coast, the calibration for Naples and Tampa works well. There is a problem at I-10 near Tallahassee. This bias is understandable as mentioned before, the daily traffic is not simulated in our model, however, the traffic flow in low-hurricane risk area may not prepare early before hurricane and also, the evacuation traffic flows are mixed into daily traffic flow and ignored while simulation which makes us under-estimate the traffic situation.

4. Conclusion

In this paper, we develop a physics-sociology based model to evaluate hurricane evacuation process.With the fast simulation algorithm, the model

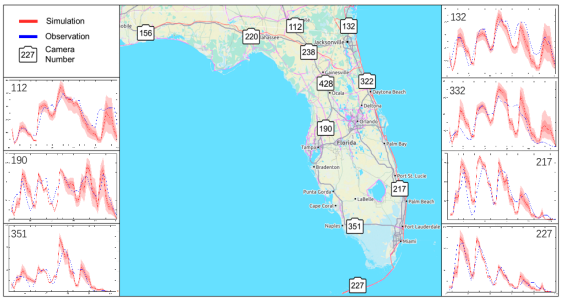

Figure 4: Local Validation Result of Florida Traffic Condition

can be evaluated and calibrated with (often very limited) traffic observation, partially overcoming the problem of data deficiency. By inputting hurricane prediction, road network and policy order, the model can be used specifically for Florida region. The calibrated model is found to well capture the global features of the evacuation process during Irma. The analysis also reveals that people may have put more weight on the predicted hurricane category than the governmental order when making evacuation decisions during Irma, indicating possibly a higher panic level than that in previous storms. The developed model can also be used to help improve evacuation management.

5. ACKNOWLEDGEMENT

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