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Hurricane Evacuation Modeling Using Behavior Models and Scenario-Driven Agent-based Simulations

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Abstract

Transportation modeling and simulation play an important role in the planning and management of emergency evacuation. It is often indispensable for the preparedness and timely response to extreme events occurring in highly populated areas. Reliable and robust agent-based evacuation models are of great importance to support evacuation decision making. Nevertheless, these models rely on numerous hypothetical causal relationships between the evacuation behavior and a variety of factors including socio-economic characteristics and storm intensity. Understanding the impacts of these factors on evacuation behaviors (e.g., destination and route choices) is crucial in preparing optimal evacuation plans. This paper aims to contribute to the literature by integrating well-calibrated behavior models with an agent-based evacuation simulation model in the context of hurricane evacuation. Specifically, discrete choice models were developed to estimate the evacuation behaviors based on large-scale survey data in Northern New Jersey. Monte-Carlo Markov Chain (MCMC) sampling method was used to estimate evacuation propensity and destination choices for the whole population. Finally, evacuation of over a million residents in the study area was simulated using agent-based simulation built in MATSim. The agent-based modeling framework proposed in this paper provides an integrated methodology for evacuation simulation with specific consideration of agents' behaviors. The simulation results need to be further validated and verified using real-world evacuation data.

Peer-review under responsibility of the Conference Program Chairs.

Keywords: Hurricane evacuation; demand modeling; agent-based simulation; MATSim

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1. Introduction

Hurricanes are one of the worst natural disasters that cause critical evacuation challenges in highly populated coastal areas. Since mass evacuation is highly anticipated prior to the severe weather conditions, one important task is to understand the evacuation demand to facilitate decision makers to prepare an informed emergency management plan. However, investigating the evacuation demand is a very challenging task because of the complexity and uncertainty associated with large-scale transportation systems. Consequently, many researchers sought to use macroscopic simulation models for evacuation modeling.

Despite their popularity, the performance of the macroscopic simulation models for evacuation modeling is often determined by two main factors: (a) how to estimate the evacuation demand; (b) and how to couple the demand with capacity of highway network, according to Yazici and Ozbay[1]. Both factors are influenced by socio-economic characteristics and intensity of extreme events, yet with uncertainties. Previous studies have shown the potential of using regional transportation planning models for evacuation modeling. However, the effectiveness of these models is heavily determined by simplified assumptions made to specific evacuation conditions[2, 3]. According to Zhu, Ozbay[4], typical assumptions may include: time of day, evacuation rate, and auto ownership. Evacuation assignment can also be affected by probabilistic road capacity constraints[5, 6]. In general, the evacuation process will be significantly delayed if traffic demand exceeds capacity for one or more critical links of the highway network, and therefore jeopardize the timeliness of evacuation. Thus, many researchers simulating evacuation behavior have great concern about these factors.

Due to the limited data collected in actual hurricane conditions, some research efforts in recent years attempted to obtain empirical information regarding evacuation behaviors. Particularly, in the post-Irene and Sandy context, there have been surveys aimed at capturing the socio-economic information and evacuation preferences of residents living in surge zones in New Jersey (NJ)[7].The main objective of this paper is to leverage these valuable survey data to model evacuation behaviors and to integrate evacuation demand generated from behaviors models with agent-based simulation. Baseline and experimental scenarios are developed based on the severity of hurricanes.

2. Data and Tools

This study uses a random digit dial telephone survey conducted in 2008 in 7 counties in the metropolitan area of north New Jersey[8]. The data contains answers to a set of questions regarding evacuation preparedness, choices and destinations, and characteristics of interviewees such as income, auto ownership, education, etc. The survey data were cleaned by removing those without full responses. In total, 1,221 households provided valid responses to the interviewed questions. Readers can refer to our previous study[9] for more detailed description on this dataset. To estimate evacuation demand in northeastern New Jersey using behavioral model, socio-economic demographic (SED) data is needed. The SED data was obtained from the United States Census Bureau. Data of year 2012 were obtained in terms of census tracts.

Unlike some previous studies in the US, which were using small evacuation areas with simplified networks and limited evacuation routes, this study was conducted in large urban area with complex road networks, and it was necessary to address the significant background demand during evacuation process. Background demand were exported from period-based (AM Peak, Midday, PM Peak and Night Period) trip tables from the household travel survey by the New York Metropolitan Planning Council[10]. These trip tables provided well-calibrated background traffic demand trips for the metropolitan area of New York, including our study area. Traffic Analysis Zones (TAZs) were used as unit of analysis. Other than background traffic, these tables also provide possible destination choices for evacuees in each TAZ. Several GIS shapefiles are adopted in this study for demand estimation and result visualization, including surge zone maps of NJ during hurricane Sandy[11], shapefiles of TAZ[10], Census Tract[12], and the list of evacuation shelters in NJ[13].

This study uses an agent-based simulation tool, namely MATSim[14], for analysis. MATSim is a framework to implement large-scale agent-based simulations. Unlike most of previous studies using macroscopic simulations for large regions and microscopic simulation models, MATSim offers microscopic engine that is based on queuing model, which significantly reduces the complexity of computation and enables large-scenario analysis. In addition, it has full support of activity-based model and the simulation results can include details of each agent in terms of "events". Each simulated event specifies a transition of agent state, such as agent gets on the vehicle, vehicle enters traffic, vehicle enters or leaves a link, etc. Thus, the behavior of each evacuee is traceable. Written in Java, MATSim has better performance than similar tools in terms of computation time, and support large scenarios with millions of agents.[15].

MATSim uses Dynamic Traffic Assignment (DTA), with time-dependent evacuation demands and network capacities. In the beginning of simulation, each agent selects the best travel routes on an empty network. Then iterations start by loading the traffic into the network based on the departure time of agent, then network delays are computed, and after that the travel plan is adjusted based on network delays. Multiple iterations are made until agent-based user equilibrium (UE) is reached. MATSim also provides powerful APIs for multiple purposes. The demand generation, simulation and postprocessing approaches proposed in this study is empowered by its API and other Java-based tool such as GeoTools (Open source GIS library) and OTFVis (Open Source MATSim Result Visualizer). Other tools for result analysis and visualization include R and ArcGIS.

OpenStreetMap (OSM) is used to create simulation network of the studied area. The link and node attributes of the network include free flow speed, number of lanes, etc. To make agent-based simulation more accurate without sacrificing much computational performance, the detailed network was generated, which includes all the major and minor roads in the studied area. OSM network was converted into MATSim compatible XML format using the tool named Osmosis (Openstreetmap Library for map query and conversion).

3. Modeling of Agent-Based Evacuation Scenario

This approach aims to build a simulation scenario of pre-hurricane evacuation. The study area includes seven counties of north New Jersey, which is consistent with the area of abovementioned evacuation behavior survey. As part of New York metropolitan area, these counties have four million residents, and suffered from severe loss during Hurricane Sandy. Besides, a base-case scenario of typical-day trip table is built for calibration purpose.

The evacuation scenario is set up to replicate the evacuation situation during Hurricane Sandy, a Category 1 hurricane which hit NJ on midnight of October 29, 2012. The evacuation order was issued at noon on October 28. Therefore, the modeled evacuation period starts in 12:00 pm as well. Considering activity-based nature, there is no explicit end time, and the scenario is completed when all agents arrive at the destinations. In the scenario, mandatory evacuation zone is defined as census tracts affected by storm surges [7]. The percentage of background traffic is set such that total number of agents in evacuation scenario is close to that in base case scenario. The finding is consistent with that there was no significant change of traffic volumes for northern NJ during the evacuation period, according to Li, Ozbay[16].

Below sections of this paper introduce the procedure of demand-generation and agent-based simulation. Procedure of this approach is composed of several parts. In the first part, the logit model developed from the survey data. Then MCMC method is applied to the logit model to predict the probabilities of agents' behaviors. The third part is background and evacuation traffic buildup, which generates non-evacuation demand from daily traffic patterns, and evacuation demand from evacuation behaviors. Finally, generated demands are combined and loaded into road network for the simulation runs.

3.1. Modeling Evacuation Behavior

In this section, we estimate a realistic evacuation behavior model using survey data to generate demand for the accurately capturing of agent-based evacuation behavior for the entire population in the study area. This demand is then used as evacuation demand in the simulation model built in MATSim.

Evacuation behavior of people in the study area is modeled in this subsection based on abovementioned survey data. The key variables used for modeling evacuation behaviors in this study are listed in Table 1. Please refer to [8] and our previous study [9, 17] for more detailed description of this dataset.

Table 1 . Key Variables Collected in the Evacuation Survey (N = 1007)

Variables	Responses
Response variables	
Evacuation decision	Likely = 1 (334), unlikely = 0 (673),
Destination choice	Public shelter = 1 (269), others = 0 (738)
Explanatory variables	
Gender	Female = 1 (536), male = 0 (471)
Employed	Yes = 1 (588), no = 0 (419)
Age over 65	Yes = 1 (199), no = 0 (808)
Education	College and above = 1 (704), others = 0 (303)
Income level	<$2500 = 1 (201), $25000 ~ $50,000 = 2 (216), $50,000 ~ $100,000 = 3 (298), ≥$100,000 = 4 (292)
Married	Yes = 1 (474), no = 0 (533)
Race	White = 0 (415); others = 1 (592)

Binary logit models were used to correlate agent-specific socio-demographic features with evacuation decision and destination choice. The binary logit model is specified as:

$$Y_i \sim B(n_i, \pi_i) \tag{1}$$

$$\text{logit}(\pi_i)=\ln\left[\frac{\pi_i}{1-\pi_i}\right]=\mathbf{x}_i^{'}\boldsymbol{\beta} \tag{2}$$

Y_i is the observation of response variable for agent i. Y_i follows a binomial distribution with denominator $n_i = 1$ and probability π_i. Parameter $\mathbf{x}_i$ is a vector of explanatory variables. $\boldsymbol{\beta}$ is a vector of regression coefficients to be estimated. Modeling results are reported in Table 2 and Table 3.

Table 2. A Binary Logit Model for Evacuation Decision

Parameter	Estimate	Std. Error	P-value
Intercept	-0.480	0.267	0.072
Gender	-0.294	0.143	0.039
Employed	-0.323	0.174	0.063
Age over 65	0.678	0.202	0.001
Education	0.221	0.185	0.233
Income level ($)			
< 25,000	0.000	-	-
25,000 ~ 50,000	0.067	0.247	0.787
50,000 ~ 100,000	0.438	0.244	0.072
>100,000	0.480	0.260	0.065
Race	-0.992	0.152	0.000

Table 3. A Binary Logit Model for Destination Choice

	Estimate	Std. Error	P-value
Intercept	-1.323	0.247	0.000
Employed	0.287	0.172	0.094
Age over 65	0.357	0.195	0.067
Income level ($)			
< 25,000	0.000	-	-
25,000 ~ 50,000	-0.019	0.212	0.930
50,000 ~ 100,000	-0.567	0.221	0.010
>100,000	-1.056	0.260	0.000
Married	0.432	0.162	0.008
Race	0.520	0.170	0.002

3.2. Simulating Agent-based Evacuation Behavior

SED data aggregated by census tract was used to generate agent-specific features. Based on agent-specific features generated, the developed binary logit models in Table 2 and Table 3 were used to predict evacuation behaviors like willingness to evacuate and destination selection. The detailed process is described in the pseudo code given below.

Algorithm 1. Pseudo Code for Simulating Agent-based Evacuation Behavior for the evacuation decision and destination selection

Step 1. Generate socio-demographic features for each agent

For $j = 1:J$ (j is the index for census tracts)

  For $k = 1:K$ (k is the index for socio-demographic features)

    Obtain the probability vector p_{jk} for k^{th} feature in j^{th} census tract (e.g., for a census tract with 40% males and 60% females, the probability vector for gender is (0.4, 0.6));

    For $i = 1:N_j$ (i is the index for agents, N_j is the population in j^{th} census tract)

      Use MCMC method to generate the feature F_{jik} from a categorical distribution with the probability parameter p_{jk};

Step 2. Generate evacuation behaviors for each agent

For $j = 1:J$

  For $i = 1:N_j$

    Predict the probability of evacuation $p_{eva,ij}$ using the logit model in Table 2 and F_{jik} as input;

    Use MCMC method to generate evacuation decision $D_{eva,ij}$ from a binomial distribution with the probability parameter $p_{eva,ij}$;

    If $D_{eva,ij} == 1$

      Predict the probability of evacuating to the public shelters $p_{shelter,ij}$ using the logit model in Table 3 and F_{jik} as input;

      Use MCMC method to generate destination choice $D_{dest,ij}$ from a binomial distribution with the probability parameter $p_{shelter,ij}$;

      If $D_{dest,ij} == 1$

        The agent will go to the nearest public shelter;

    Else

Use MCMC method to generate destination TAZ based on OD matrix obtained.

3.3. Generation of Background and Evacuation Demands

In this step, daily travel patterns in terms of OD Pairs, and evacuation demands based on simulation results of previous steps are processed and agentified. For each agent of background traffic, two activities, namely” home” (h) and “travel” (t) are defined. Each “home” activity contains coordinate of origin and “travel” activity has information of destination and departure time. The departure time of background traffic during evacuation period is assumed to be uniformly distributed. The procedure of background traffic generation is presented in Fig. 1.

The agent setting of evacuation demand is different with background demand. Each agent also has two activities, “home” (h) and “evacuation” (e). For different gender/age/income groups within a census tract, this approach calculates their probabilities of making evacuation choices based on the estimated model. For evacuation destinations, if the chosen destination is public shelter, location of the nearest public shelter was selected as destination; else, the demand generation program finds destination TAZ of the agent’s daily travel from the Trip Table but discards destinations in dangerous zones. The remaining destination zones are assumed to be friends and relative’s home, hotel or motel, or somewhere else, which is calculated based on the probability of destinations table obtained from background OD Matrix.

General methodology of the generation of evacuation trips is shown in Fig. 1.This approach first simulates evacuation decision of each household. If the person has “decided” to evacuate, then an agent of evacuee is produced. Next, the destination choices of agents are determined. If the agent chose to go to the shelter, we set nearest shelter as his/her destination; if not, we send the agent to a safe location to which the agent is most likely to go, according to the probability table of destinations. The departure times of evacuation follows logistic distribution, which is also called the S-Curve, according to evacuation response curve approach proposed by Li and Ozbay[18]. Finally, the evacuation and background demand are merged to build the final demand file.

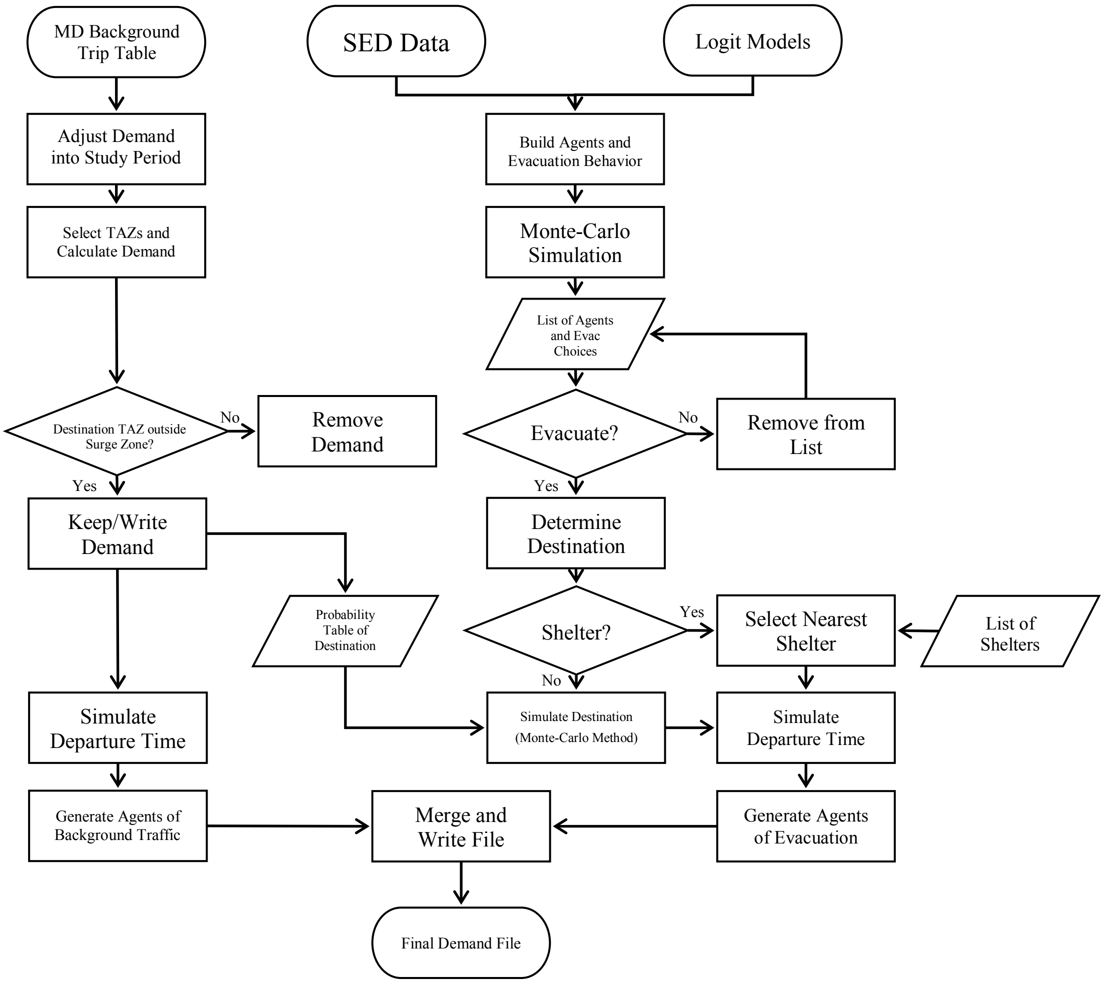


Fig. 1. Demand generation flowchart

In a typical MATSim simulation, at least three files are needed namely, the configuration file, which contains the most important parameters of simulation settings, including type of trips, number of threads for simulation, number of iterations, etc., network nodes and links file, which includes information of all roadway segments of the study area, such as capacity, direction and speed of the links, and the plan file (demand file), which contains activities of all background and evacuation agents. In this scenario, among over 4 million households in study area, more than 40% (1,460,554 agents) "chose" to evacuate. Together with background traffic, the total number of evacuees are 2,184,802. Simulation was deployed on a workstation computer using Intel Xeon 8-core processor, and MATSim was allocated 26 GB of memory. Multi-threaded computing was activated to maximize the computation efficiency.

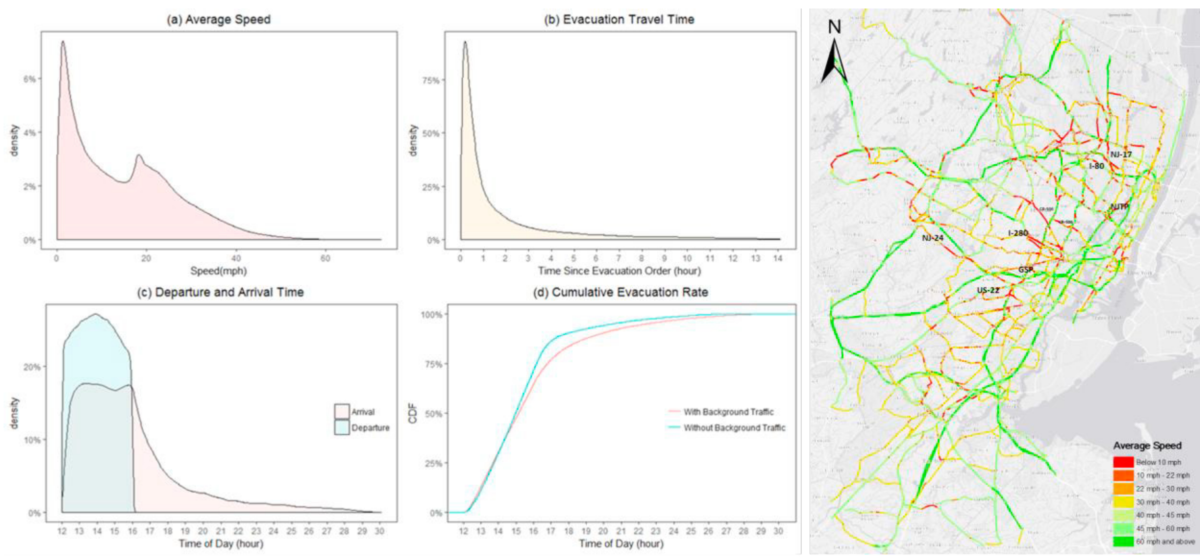
MATSim simulation was run for 40 iterations, which took 3 days and 5 hours. The size of event file generated was 2.9 GB, which contained 150 million "events" for all simulated agents. The result events were filtered by removing the outliers of which evacuation times are above 95th percentile and used for calculating travel times. Besides, for each roadway link, we can find the link travel times of evacuees by tracking link enter and exit events for link and agent, and average link speeds were calculated.

4. Results

Simulation results of evacuation performance are shown in Fig. 2(1). The average evacuation time of the entire study area is 1.83 hours, and the average speed is 14.63 mph. Average distance of each evacuation trip is 9.42 miles. In Fig. 2 (1)(a), most of speeds were distributed below 35 mph, and the two peaks of speeds are 3 mph and 20 mph, which implies severe congestion during evacuation and the existence of bottlenecks. Fig. 2 (1)(b) is the density plot of evacuation travel time. Most of evacuation trips are completed within 3 hours, while less than 10% of the agents failed to finish evacuation in 4 hours. Evacuation departure and arrival times are shown in Fig. 2 (1) (c), where departure times follow logistic distribution between 12pm and 16pm, and most of trips arrived at destination before midnight. Based on arrival times, cumulative evacuation curve was drawn, as shown in Fig. 2 (1) (d). It took three hours for half of the evacuees to reach the destination, and 90% of the people finished their evacuation before 10 pm, which takes one hour longer than situation not considering background traffic.

Compared with previous studies conducted in southern states such as Florida or Texas, the evacuation travel times and distances are shorter in our scenario. This is because lower intensity of the hurricane impact and higher density of evacuation centers (some are high-rise buildings within evacuation zone that allow vertical evacuation).

The average link speeds are presented in Fig. 2 (2). The visualization only selects the major expressways and highways in the network. As shown in the graph, there are multiple bottlenecks during evacuation, especially in Bergen, Union and Hudson counties, where average speeds are below 5 mph. Some of east-west bound arterials, such as I-80, NJ-24 and I-280 were blocked or partially blocked. Most of bottleneck places are located around the evacuation shelters.



(1) (2)

Fig. 2. (1) Results of agent-based simulation; (2) average link speeds

5. Conclusion

The study integrated a well-calibrated evacuation behavior model with an agent-based evacuation simulation model built in MATSim. Based on the empirical demographic data, statistically robust evacuation behavior models were developed for Northern NJ area. Then MCMC methods were adopted to determine evacuation decision and preference of destinations. An evacuation scenario was built to predict the evacuation times and other performance measures. The study took advantage of MATSim tool to make it possible to build an evacuation model for a large region with millions of agent-specific activities. Results also show that background traffic leads to significant decrease in evacuation speed, so it is inevitable that background traffic may affect the evacuation performance in actual situations.

Despite the innovations of demand modeling and agent-based evacuation simulation, additional effort is needed to verify the accuracy and realism of these results. Firstly, improved methods to estimate background traffic is expected. Current approach uses background traffic from OD tables obtained from regional travel surveys. However, assumptions are made regarding the percentage of background traffic. Although the total demand was calibrated using the base scenario, they are expected to change as a result of different factors. Besides, improvement may be needed to estimate destination choices for the evacuees. Current approach is based on preferred destination of typical days, but the preferences may change during an actual evacuation. Additional data is needed to find more probable destination choices rather than public shelters, which may also reduce the bias in current results that cause exorbitant evacuation times in certain zones with shelters. Another important improvement is the need to compare the link volumes from the simulation model with local traffic counts. However, link volumes during evacuations are not always available due to the loss of power and other environmental factors that cause malfunctioning of traffic sensors. Moreover, most of the highways do not have sensors in the first place. Thus, lack of data can be a major road block in achieving this goal.

Another possible improvement of this study is to extend the current activity-based model to multiple-day scenarios. Considering MATSim has a good support of travel plans of multiple activities, and storm events normally last for several days, the current model can be extended to simulate the recovery of the post-hurricane trips, especially home-based trips of evacuees. Next step also includes adding the hurricane intensity factor into the demand model, so that the evacuation behaviors can be associated with the categories of hurricanes.

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