EVACUATION EFFICIENCY UNDER DIFFERENT DEPARTURE TIME & DESTINATION CHOICE PREFERENCES

Jooyong Lee
Department of Civil, Architectural and Environmental Engineering
The University of Texas at Austin
jylee3302@utexas.edu

Kara M. Kockelman, Ph.D., P.E.
(Corresponding Author)
Dewitt Greer Centennial Professor of Transportation Engineering
Department of Civil, Architectural and Environmental Engineering
The University of Texas at Austin – 6.9 E. Cockrell Jr. Hall
Austin, TX 78712-1076
kkockelm@mail.utexas.edu

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ABSTRACT

This paper demonstrates two types of evacuee behaviors using cumulative prospect theory (CPT) for all evacuating agents and traffic simulation to evacuate flooding-vulnerable residents (12% of the region's population) along the coastline of Houston, Texas. The first model assumes panic behavior, with a desire to arrive as early as possible, subject to traffic congestion and travel times to different destination options. The second model relies on more "patient" preference behaviors (where evacuees seek to avoid heavy congestion), and results in a much more orderly evacuation. The two models' (panicked vs patient) departure time and destination choices are jointly optimized to evaluate each evacuee's most likely evacuation decision. The panicked assumption results in departures highly concentrated in the first 2 hours of a 6-hour departure window, with those residing closer to safe destinations departing earliest, on average. In contrast, the patient or orderly evacuation showed evacuees loading the 6-hour window, with many evacuees reluctant to depart in the final hour or two, to avoid rising late-arrival penalties. The patient case delivers a rather staggered evacuation, helping evacuate the most distant residents first (i.e., those with longest routes to cover, to reach safety). Results suggest that panic evacuees tend to evacuate to a closer destination, while patient evacuees tend to select more inland/distance destinations, thanks to less congested traffic conditions resulting from more orderly departures. Although each destination's safety level is assumed equal, more inland destinations are presumably advantageous, in terms of threat avoidance (from storms in the Gulf of Mexico).

KEYWORDS

Evacuation; Departure Time Choice; Destination Choice; Network Optimization; Cumulative Prospect Theory

INTRODUCTION

Hurricanes are becoming as one of the most common, but deadliest natural disasters in the United States. It can disrupt residents' ordinary activities, damage the urban infrastructure, and even result in considerable casualties or loss of lives. For instance, Hurricane Harvey caused $125 billion in damages, nearly a third of Houston, Texas was flooded, and 40,000 people had to evacuate to shelters (Blake & Zelinsky, 2018). Local authorities are the first line to prepare for the risk management plans, issue in-advance warning alerts, and assign evacuation shelters and routes. Accordingly, it is essential to facilitate the evacuation by managing the traffic infrastructures, prioritizing the vulnerable population, and responding to the emergency situations. If possible, the evacuees can decide when and where to evacuate, but their decisions are subject to individual preferences and the decisions will affect the overall evacuation performance.

The research on traveler's departure time choice have focused on reflecting the early and late arrival penalties on the traveler's decision-making process. Travel times are often considered as random variables, and the optimal "head-start" times for the travelers are chosen with safety margins (Noland & Small, 1995). For evacuation purpose, evacuees are facing more risky and uncertain conditions than daily travelers, and factors accounted for analyzing evacuees' departure time choices include evacuees' attitudes toward the risk (Dixit et al., 2012), probability of hazard occurrence (Golshani et al., 2019), length of the time span to depart (Tamminga et al., 2011), or the type and timing of the evacuation notice (Fu et al., 2007). As late departure may put the evacuee at risk, while early and simultaneous departure of evacuees may induce severe traffic congestion, findings from evacuees' departure time choices can be adopted on planning timely evacuation orders by distributing the departure times of evacuees to manage efficient evacuation.

The travel destination choice is another multifaceted decision process, in which demographics (Yang et al., 2010), trip purposes (Molloy & Moeckel, 2017), time-of-day (Zong et al., 2019), or mode choice (Janzen & Axhausen, 2017) can affect the decisions. When the research focused on evacuation destination choices, factors including the presence of nearby evacuation routes (e.g., interstate highways) (Cheng et al., 2013), regional geography (Parady & Hato, 2016), evacuees' risk attitudes (Parvin et al., 2019) are additionally considered to apply the model specifically for evacuation scenarios. The evacuation destination choice models provide the spatial range of evacuation traffics, which can be used to assign evacuation shelters and infrastructures at proper locations. Even spatiotemporal analyses of jointly modeling evacuees' departure time and destination choices have been conducted in an effort to account for the correlation of the two different decision making processes (Carver & Quincey, 2017; Wong et al., 2020).

In this paper, a joint model of evacuation departure time and destination choices is developed with a focus on the evacuees' preferences on arrival times by considering the traffic conditions. Depending on the evacuees' preferences, two models are developed, where the first model assumes panic behavior, with a desire to arrive as early as possible, subject to traffic congestion and travel times to different destination options. The second model relies on more "patient" preference behaviors (where evacuees seek to avoid heavy congestion), and results in a much more orderly evacuation. Cumulative prospect theory is used to describe human decision behaviors under risks and uncertainties by considering the valuation of a possible outcome of a decision, as well as the probability of that outcome being observed.

The remainder of this paper is organized as follows. Section 2 describes the network and data used in the analyses to estimate the travel times of evacuation routes as well as the probability of that travel time being observed. Section 3 introduces the methodology developed in this paper to model the departure time and destination choices of two different evacuee preferences, whereas the analyses results are discussed in Section 4. Section 5 summarizes the findings and recommendations obtained from the proposed methodology.

NETWORK AND DATA DESCRIPTION

This paper's evacuation scenario assumes a hurricane will make landfall on Houston's coastline within a few days. The region's network contains 36,124 links, across 5,217 traffic analysis zones (TAZs). There are 7.2 million persons residing across the region's 8 counties: Brazoria, Chambers, Fort Bend, Galveston, Harris, Liberty, Montgomery, and Waller (US Census Bureau, 2019). This paper assumes that only those living near the coastline will evacuate, while those inlands will remain but reduce background traffic volumes by 50 percent (versus a typical weekday). Thus, only TAZs in five counties (Brazoria, Chambers, Galveston, Harris, and Liberty) are included in the 'Hurricane Risk Zone' and subject to the evacuation plan (Texas Natural Resources Information Service (TNRIS), 2004).

The TNRIS defines 5 hurricane risk zones, where someone in zone 1 is threatened only by Category 1 hurricanes, while those in risk zone 5 are threatened by Category 1 through 5 hurricanes (with 5 being the strongest and heading furthest inland). Residents in Houston's risk zones 1 through 5 comprise 12.4% of the region's 7.2 million. Using the TAZ's population data, every resident's home location (origin) is randomly sampled from the set of links that are within that TAZ. The TAZs that are not included in the hurricane risk zone are assumed to have 50% of daily weekday traffic. The evacuation destination is assumed to be one of the 8 exit sites in the Houston network, and when the evacuee arrived at this exit point, no further evacuation trip is tracked in this paper. To improve the realism of the model, this paper assumed that the simulation has 30 minutes of warm start to fill in the empty network with daily traffic, and after warm start, the evacuation begins for 6 hours of departure time slots from 6 AM until noon. The colored regions in Figure 1 shows the hurricane risk zones and the locations of the 8 destinations with the recommended evacuation routes from the local metropolitan organization (Houston-Galveston Area Council).

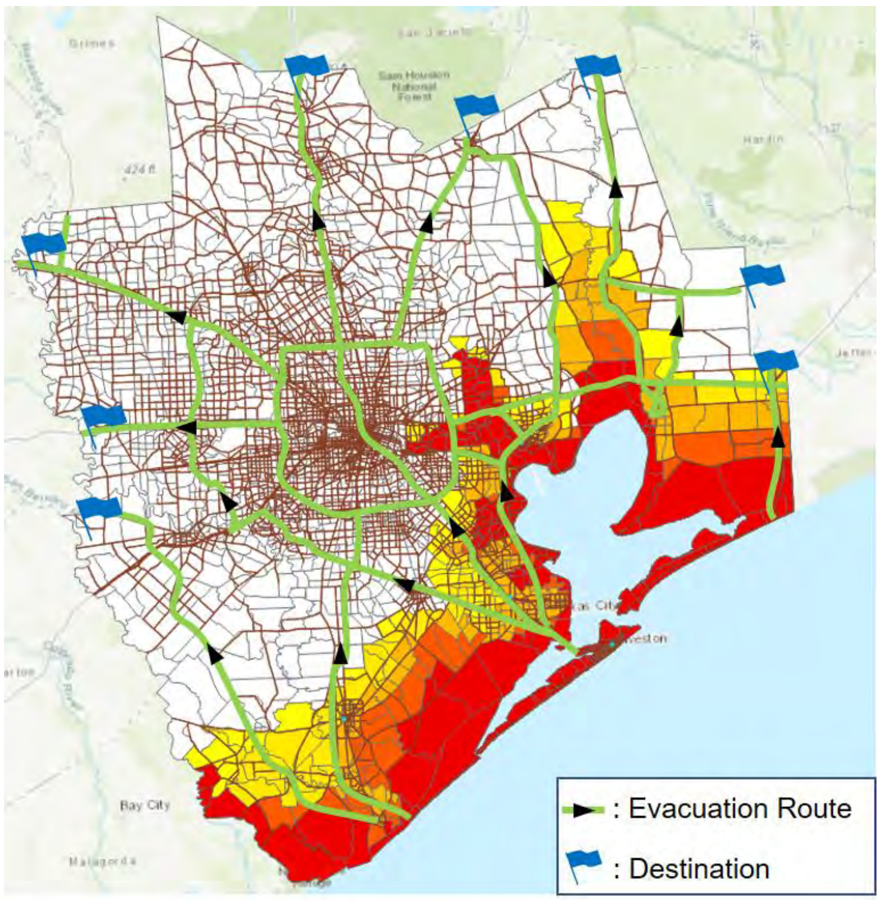


Figure 1. Evacuation Route and Destinations

Evacuation Travel Time Estimation

Travel times from evacuees' origins to destinations depend on departure times and evolving traffic conditions, which can become rather severe during mass evacuations. Evacuations are rare, so that simulation methods are needed to estimate the travel time during evacuation. Microsimulation is very helpful in understanding these traffic dynamics, over time and space. Staggered loading of evacuation demand may delay the onset of congestion and speed overall evacuation times (Sbayti & Mahmassani, 2006). However, evacuees may not follow a recommended, staggered departure schedule, so a variety of departure patterns are observed in real world. Figure 2 shows 4 example departure time schedules, based on a Beta distribution: early evacuation, late evacuation, uniform evacuation, and a bell-curved evacuation (with departure times resembling a normal distribution, so that the cumulative distribution resembles an S curve). Within a given departure time duration (e.g., everyone must depart within a 6-hour period), any cumulative distribution curve that can fill in the departure time (like those shown in Figure 2) is a feasible evacuation scenario.

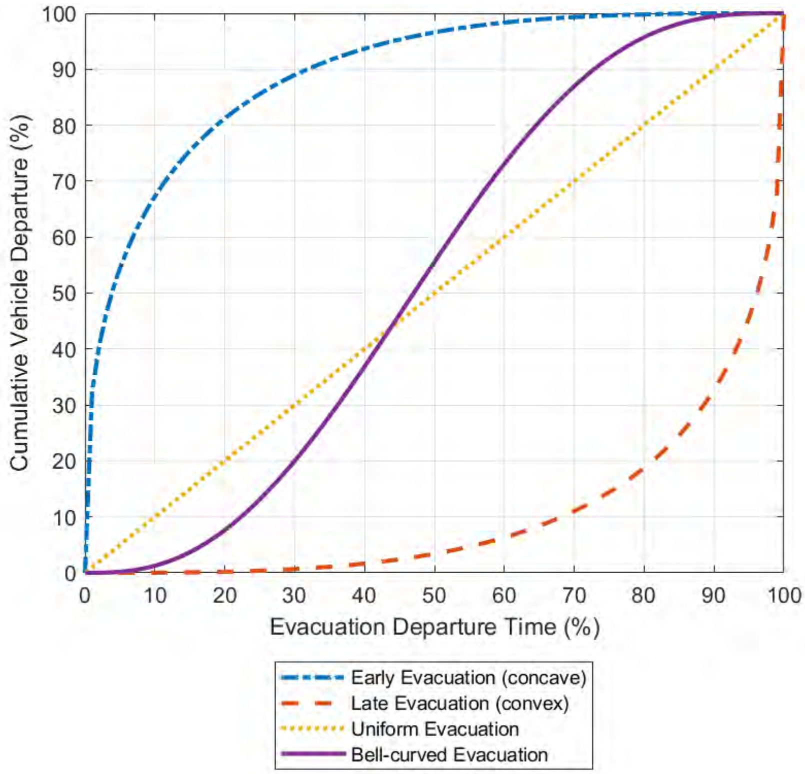


Figure 2. Example Departure Time Schedules

Here, Eq. (1)'s Beta distribution with two parameters, is used to describe the variety of feasible departure time schedules. The two shape parameters, a, b, are assumed to be a random number between 0 and 3.5 to describe a specific departure time schedule. This range is found via trial and error to get a good mix of the 4 different shapes as described in Figure 2. In fact, the early evacuation scenario in Figure 2 is derived from Beta(0.34, 2.88), lazy evacuation is from Beta(2.88, 0.34), uniform evacuation is from Beta(1.00, 1.00), and bell-curved evacuation is from Beta(2.85, 3.17). From the sampled departure time schedule, the evacuee's travel time from his/her origin to destination can be obtained via a traffic simulation. When numerous departure time schedules are sampled, and the corresponding travel time of origin, destination triplets are obtained from each of the schedules, the distribution of the travel time from an origin to a destination can be derived from various scenarios of evacuation departure schedules.

$$Departure\ Time \sim \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)}\, x^{a-1}(1-x)^{b-1}\ (= Beta(a, b)) \qquad (1)$$

where

$a, b \in (0, 3.5)$

$\Gamma(z) = \int_0^{\infty} y^{z-1} e^{-y} dy$ (Gamma function)

Using Eq. (1), 6,000 different departure time schedules and trip routings are simulated, for 6 hours of departure time duration. The departure times are aggregated into 15-minute intervals, or 24 intervals across the 6-hours departure period (as requested or required by authorities). Within each 15-minute interval, t, travel times between each origin link i to destination link j are aggregated across these 6,000 simulations to derive a travel time distribution for all *ijt* (origin – destination – departure time interval) triplet. An evacuee departing from origin i at departure interval t is likely to choose the destination j with the smallest travel time among the 8 exit sites with probability $Pr(j_{it})$, as specified in Eq. (2). This paper assumes that the travel time distribution of the *ijt* triplet will follow a normal distribution with mean μ_{ijt} and standard deviation σ_{ijt}. When fewer than 5 travel time samples are obtained for a given *ijt* triplet, μ_{ijt} is assumed to be the free-flow travel time (from i to j), and σ_{ijt} is assumed to be the largest observed value (5.05 hours) from the 6,000 simulations to reflect uncertainties in estimating the travel time of this specific *ijt* triplet. However, only 0.8% of the total evacuation demand are subject to this assumption.

From this $N(\mu_{ijt}, {\sigma_{ijt}}^2)$ distribution, the probability that the travel time will take no longer than TT_k in a given *ijt* triplet can be obtained using the cumulative density function of the normal distribution. As normal distribution is a continuous probability distribution, the probability that the travel time will be exactly TT_k cannot be estimated. Thus, the probability of the travel time being TT_k is approximated by discretizing the distribution. Define TT_{k-1} as the travel time value that is one step smaller from the sample results than TT_k, and the difference of the cumulative density function of TT_k and TT_{k-1}, in which a strict definition of this difference is the probability that travel time will be between TT_{k-1} and TT_k, is assumed to be the probability that the travel time will be TT_k.

$$Pr(j_{it}) = \frac{exp(-TT_{ijt})}{\sum_{d\in S} exp(-TT_{idt})} \tag{2}$$

where

$Pr(j_t)$: probability to choose destination j from origin i departing at t

TT_{ijt}: travel time from i to j departing at t $\left(TT_{ijt} \sim N(\mu_{ijt}, {\sigma_{ijt}}^2)\right)$

S: set of destinations

This paper assumed each household has only 1 privately-owned vehicle, and all household members will evacuate together in this vehicle. The traffic simulation is performed by an open-source traffic simulator named SUMO (Simulation of Urban MObility) with a Python API named TraCI (Krajzewicz et al., 2012). In the simulation, only 10% of the population are sampled due to the high computational cost. The roadway capacity is reduced proportional to the sampling rate to maintain the traffic characteristics. The outcome of this simulation, the travel time distribution from origin i to destination j departing at t, will be used to optimize the evacuee's departure time and destination choices.

METHODOLOGY

This section includes the methodologies used to model and simulate departure time and destination choice during evacuation with cumulative prospect theory. Two different models are suggested, where the first model assumes that evacuees' departure time and destination choices are subject to the willingness of evacuees to arrive as early as possible, while the second model assumes evacuees will make optimal departure time and destination choices under the willingness to arrive exactly at the desired time.

Panic Evacuation Simulation using Cumulative Prospect Theory (CPT)

Theoretical Background

Cumulative prospect theory (CPT) is a descriptive model proposed by Tversky and Kahneman (Tversky & Kahneman, 1992) to describe human decision behaviors under risks and uncertainties. The utility of a certain decision is assessed by 1) the valuation of the outcome of the decision in terms of gains and losses and 2) a weighted function describing the probability to observe the outcome. The major difference of CPT compared to original prospect theory is that different attitudes towards probability for gains and losses can be adopted via using cumulative probability of the outcomes (Fennema & Wakker, 1997).

This paper defines Δx_k as the quantified difference between the decision's outcome (x_k) and a reference point (x^*), so that $\Delta x_k = x_k - x^*$. Assuming n different outcomes from making a decision, $\Delta x_1 \leq \cdots \leq \Delta x_l \leq 0 \leq \Delta x_{l+1} \leq \cdots \leq \Delta x_n$ are possible. to Δx_l to Δx_n that have larger value than the reference point are gains.

The value function is typically a non-linear two-stage function that has different equations for gains and losses. Eq. (3) shows one of the value functions used in this paper, which is obtained from (Liu & Li, 2019). χ and ω are the median exponent parameters to demonstrate diminishing sensitivity of the gains and losses, and λ is the loss aversion parameter to penalize losses over gains.

$$v(\Delta x_k) = \begin{cases} (\Delta x_k)^{\chi} & , \ \Delta x_k \geq 0 \\ -\lambda(-\Delta x_k)^{\omega}, & \Delta x_k < 0 \end{cases} \tag{3}$$

where
χ: 0.89
ω: 0.92
λ: 2.25

The probability that the outcome k and its corresponding value function, $v(\Delta x_k)$, can be observed is defined as p_k. Prospect theory including CPT defines that individuals do not weight outcomes directly by the objective probability p_k, but rather uses the decision weight, π_k^+ for gain and π_k^- for loss, which are the transformed probabilities to overweight low probabilities and underweight high probabilities (Barberis, 2013). This decision weight is used to model individuals' risk-taking behaviors under low-probability events by overweighting that probability or discounting the high-probability events since they are rather common. In this version of CPT model, the decision weights are defined by using the weight function, $w(\cdot)$, obtained from (Liu & Li, 2019) as written in Eq. (4). The summation part in Eq. (4) can be converted to an integral using a continuous function as written in Eq. (5).

$$\begin{aligned} \pi_k^+ &= w^+\left(\textstyle\sum_{m=k}^{n} p_m\right) - w^+\left(\textstyle\sum_{m=k+1}^{n} p_m\right), \quad l < k \leq n \\ \pi_k^- &= w^-\left(\textstyle\sum_{m=1}^{k} p_m\right) - w^-\left(\textstyle\sum_{k=1}^{k-1} p_m\right), \quad 1 \leq k \leq l \end{aligned} \tag{4}$$

where
n: number of decisions
l: number of losses

$$w^+(p) = \frac{p^{0.61}}{[p^{0.61}+(1-p)^{0.61}]^{1/0.61}}$$

$$w^-(p) = \frac{p^{0.69}}{[p^{0.69}+(1-p)^{0.69}]^{1/0.69}}$$

$$\begin{aligned} \pi_k^+ &= w^+\left(\int_l^n p(k)dk\right) - w^+\left(\int_{l+1}^n p(k)dk\right) \\ \pi_k^- &= w^-\left(\int_1^l p(k)dk\right) - w^-\left(\int_1^{l-1} p(k)dk\right) \end{aligned} \tag{5}$$

Using the value function, $v(\Delta x_k)$, and the decision weight, $\pi_k^{+/-}$, the expected utility of a decision that will have n different outcomes can be derived using Eq. (6). Since the utility equation uses both value function and decision weight, the individual will consider both the value of the outcome of the value function as well as the likelihood that the outcome will be observed. Assuming n different outcomes from a decision, (Δx_1, p_1;...;Δx_n, p_n) pairs can be expected from this decision.

$$V = \sum_{k=1}^{l} v(\Delta x_k)\, \pi_k^- + \sum_{k=l+1}^{n} v(\Delta x_k)\, \pi_k^+ \tag{6}$$

CPT for Evacuation Departure Time and Destination Choice

CPT has been applied to the field of transportation including emergency response problems (Liu et al., 2014), and to model traveler's route choice behavior (Xu et al., 2011). In the evacuation problem, the *k*th outcome of an evacuee departing from origin *i* to destination *j* at departure time interval *t* is the arrival time, AT_k^{ijt}, he/she will finish the evacuation. The decisions that this evacuee have to make are 1) the departure time choice to decide at which departure time interval *t* he/she should evacuate, and 2) the destination choice to decide which destination *j* he/she should evacuate at the departure time interval *t*. As the outcome of this *ijt* decision is the arrival time, arriving to the destination earlier than the desired arrival time, $AT^{*,ijt}$, can be posed as gain, while arriving later than $AT^{*,ijt}$ can be posed as loss. Therefore, the desired arrival time for *ijt* decision, $AT^{*,ijt}$, can be interpreted as the reference point, and Δx_k needed in CPT is defined as the difference between the evacuee's arrival time, AT_k^{ijt}, and the desired arrival time, $AT^{*,ijt}$.

The arrival time, AT_k^{ijt}, for an *ijt* decision is the sum of the actual departure time, *deptT*, which is the actual departure time randomly chosen within the 15 min departure time interval *t*, and the *k*th outcome of travel time, TT_k^{ijt}. The probability to arrive at AT_k^{ijt} is subject to the probability that the travel time will be TT_k^{ijt}, which is written as p_k^{ijt}. Therefore, the probability to observe the outcome AT_k^{ijt} from the *ijt* decision is subject to the travel time distribution of this *ijt* decision, which is defined as the normal distribution, $N(\mu_{ijt}, {\sigma_{ijt}}^2)$. Eq. (7) shows the application of CPT to the evacuation problem as described above.

$$v\left(AT^{*,ijt} - AT_k^{ijt}\right) = \begin{cases} \left(AT^{*,ijt} - AT_k^{ijt}\right)^{\chi} & , \ AT^{*,ijt} - AT_k^{ijt} \geq 0, early\ arrival \\ -\lambda\left(-\left(AT^{*,ijt} - AT_k^{ijt}\right)\right)^{\omega}, & AT^{*,ijt} - AT_k^{ijt} < 0, late\ arrival \end{cases} \quad (7)$$

$$\pi_k^{+} = w^{+}\left(\sum_{m=k}^{n} p_m^{ijt}\right) - w^{+}\left(\sum_{m=k+1}^{n} p_m^{ijt}\right), \ l < k \leq n$$
$$\pi_k^{-} = w^{-}\left(\sum_{m=1}^{k} p_m^{ijt}\right) - w^{-}\left(\sum_{m=1}^{k-1} p_m^{ijt}\right), \quad 1 \leq k \leq l$$

$$V_{ijt} = \sum_{k=1}^{l} v\left(AT^{*,ijt} - AT_k^{ijt}\right)\pi_k^{-} + \sum_{k=l+1}^{n} v\left(AT^{*,ijt} - AT_k^{ijt}\right)\pi_k^{+}$$

where
$AT_k^{ijt} = deptT + TT_k^{ijt}$
$deptT \in \{random\ actual\ time | actual\ time\ values\ in\ interval\ t\}$
V_{ijt}: utility of the decision *ijt*
$p_k^{ijt} \sim N(\mu_{ijt}, {\sigma_{ijt}}^2)$
$\chi, \lambda, \omega, w(\cdot)$: defined in Eq. (3) and Eq. (4)

In Eq. (7), all variables and parameters are defined except the desired arrival time of the *ijt* decision, $AT^{*,ijt}$. In the real world, the desired arrival time can vary by individuals and types of disasters that trigger the evacuation. In this paper, the $AT^{*,ijt}$, will be estimated using steepest hill climbing algorithm that results in the maximum utility, V_{ijt}^{*}. For a given evacuee with the origin *i*, initialize the $AT^{*,ijt}$ with a random number within 0-to-6.5-hour duration and its corresponding utility. In every iteration, explore a new $AT^{*,ijt}$ that is neighboring within 30 minutes, but does not exceed the 0-to-8-hour duration. Find the optimal departure time interval, $t*$, and the optimal destination choice at that interval, $j*$, that results in the maximum utility, V_{ijt}^{*} with the new $AT^{*,ijt}$. If the new V_{ijt}^{*} is larger than the V_{ijt}^{*} value from the previous iteration, accept the new $AT^{*,ijt}$, its departure time choice $t*$ and destination choice $j*$, and iterate until the algorithm converges. Algorithm 1 describes the pseudo-code of the method, and it is terminated if the percent change of the moving average of all evacuees' mean utility meets the convergence criteria or if the simulation reached its maximum iteration. With this method, the optimal desired arrival time, $AT^{*,ijt}$, and its corresponding optimal departure time choice, $t*$, and optimal destination choice, $j*$, can be found for any evacuee departing from any origin *i*.

Algorithm 1. Steepest Hill Climbing for Departure Time & Destination Choices

Step 1: Initialize

For all evacuees:

Initialize $AT^{*,ijt}$ and utility V_{ijt} with a random *ijt* decision.

$AT^{*,ijt} \in [0, 6.5\ hr.]$

Step 2: Explore

For all evacuees:

$AT_{new}^{*,ijt} = max\left(min\left(AT^{*,ijt} \pm 0.5rand, 8\right), 0\right)$ where the unit of $AT^{*,ijt}$ is in hours.

Find $t*$ that results in $V_{ijt^*}^*$, given the destination choice as j

Find $j*$ that results in $V_{ij^*t^*}^*$, given the departure time choice as $t*$

Step 3: Evaluate & Accept

For all evacuees:

If $V_{ij^*t^*}^* > V_{ijt}^*$:

$AT^{*,ijt} \leftarrow AT_{new}^{*,ijt}$

$t \leftarrow t*$

$j \leftarrow j*$

Step 4: Iterate until converge

Convergence criteria:

For iteration ξ, assume mean $\overline{V_{ijt}^*}$ of all evacuees as $\left(\overline{V_{ijt}^*}\right)_{(\xi)}$,

$$\left|1 - \frac{\left(\overline{V_{ijt}^*}\right)_{(\xi-9)} + \cdots + \left(\overline{V_{ijt}^*}\right)_{(\xi)}}{\left(\overline{V_{ijt}^*}\right)_{(\xi-10)} + \cdots + \left(\overline{V_{ijt}^*}\right)_{(\xi-1)}}\right| < 1e-4 \text{ or } \xi > 2{,}000$$

Go to Step 2 until converge.

Patient Evacuation Simulation using Cumulative Prospect Theory (CPT)

Patient Evacuation to Avoid Panic

The shape of the value function in the previous section implies the evacuees' behavior of 'arrive as early as possible'. The value function, $v\left(AT^{*,ijt} - AT_k^{ijt}\right)$, is maximized when AT_k^{ijt} is minimized representing that the evacuees pursue to arrive as early as possible; thus, the panic behavior during evacuation is modeled with this value function. However, as this value function may improve the realism of modeling human nature, it may not result in the optimal decision-making process that can improve the overall evacuation performance.

Staggered evacuations are known to perform better than simultaneous evacuation in terms of roadway capacity management (Liu et al., 2006) and overall evacuation time reduction (Chen & Zhan, 2014), so that the strategy of 'arrive as early as possible' should be avoided if possible. Nonetheless, the performance of optimal evacuation plan may vary with respect to the evacuees' compliance behavior (Fu et al., 2013). A well-planned staggered evacuation may not be implemented in the real world with expected evacuation performance if the evacuees do not follow the rule and fall into a panic. The order compliance problem during evacuation can be mitigated when the information technology is reliable enough so that the evacuees will trust the expected network conditions and avoid panic behavior by using networking devices including computers, smartphones, and automated vehicles (AVs). AVs can even be centrally controlled via communication devices to improve the compliance rate. With a more reliable travel time estimates, future evacuees may make a more patient and reasonable decision than before. In this context, the second model, namely patient CPT model, where the evacuees behave more patiently to avoid falling into panic suggests a transition from 'arrive as early as possible' to 'arrive exactly at your desired time'.

The core of the patient CPT model is that arriving at the desired arrival time, $AT^{*,ijt}$, will have the highest value from the value function thanks to evacuees behaving more patient and panicking less than before. By each evacuees arriving exactly at the desired arrival time, the evacuation becomes staggered with the conditions each evacuee will be facing (e.g., origin location, level of traffic congestion, destination choice, departure time choice, etc.). Two additional arrival times are introduced as well, namely early arrival time, $AT^{e,ijt}$, and late arrival time, $AT^{l,ijt}$ as proposed by (Li et al., 2018). Although the model from (Li et al., 2018) suggested that arriving earlier than $AT^{e,ijt}$ is defined as loss in the value function, it should be not defined as loss in the evacuation problem. Arriving too early should be still advantageous in the evacuation problem since the evacuee is more likely to survive by arriving early, although the amount of gain should converge to 0 with the amount of time arriving earlier. Likewise, in evacuation problem, arriving too late compared to $AT^{l,ijt}$ should be heavily penalized as loss since the evacuee may not survive if he/she arrives too late.

The evacuees' perception of early and late arrival time relative to the desired arrival time may be different by individuals. For instance, some evacuees will perceive arriving just for a few more seconds than the desired arrival time as late arrival since they are more cautious than others, while other evacuees will perceive arriving a few more hours than desired time as late arrival due to their optimistic personality. In this sense, each evacuee will have early arrival coefficient (τ_{early}) and late arrival coefficient (τ_{late}) to describe the evacuee's personality, which are random number between 0 and 1. Using the two coefficients, early and late arrival times for each evacuee can be defined as written in Eq. (8).

$$AT^{e,ijt} = AT^{*,ijt}\tau_{early} \tag{8}$$
$$AT^{l,ijt} = min\left(AT^{*,ijt}/\tau_{late}, 8\ hr.\right)$$
$$\tau_{early}, \tau_{late} \in (0,1)$$
Assuming 8 hr. is the maximum late arrival time

By comparing the arrival time (AT_k^{ijt}) to early arrival time ($AT^{e,ijt}$), desired arrival time ($AT^{*,ijt}$), and late arrival time ($AT^{l,ijt}$), four states of arrival times, namely 1) too early arrival, 2) acceptable early arrival, 3) acceptable late arrival, and 4) too late arrival can be defined. The patient CPT model's value function ($v(AT_k^{ijt})$), decision weight ($\pi_k^{+/-}$), and its utility equation of is as written in Eq. (9). The parameter η represents the inflection point, H represents the maximum of the value function, α, β represent the shape of the value function when the arrival time is later than the desired time, and γ represents the shape of the weight function, $w(\cdot)$. All the five parameters mentioned above should be calibrated to derive the optimal model performance. Thereafter, Algorithm 1 will be applied to the patient CPT model to find the optimal departure time and destination choices.

$$v(AT_k^{ijt}) = \begin{cases} \frac{[1/H-1]}{1+\exp\left(-\eta\left(AT_k^{ijt}-AT^{e,ijt}\right)\right)}, & too\ early\ (AT_k^{ijt} \le AT^{e,ijt}) \\ \frac{[1/H-1]}{1+exp\left(-\eta\left(AT_k^{ijt}-AT^{e,ijt}\right)\right)}, & acceptable\ early\ (AT^{e,ijt} < AT_k^{ijt} \le AT^{*,ijt}) \\ \left[AT^{l,ijt} - AT_k^{ijt}\right]^{\alpha} \frac{\frac{[1/H-1]}{1+exp\left(-\eta\left(AT^{*,ijt}-AT^{e,ijt}\right)\right)}}{\left[AT^{l,ijt}-AT^{*,ijt}\right]^{\alpha}}, & acceptable\ late\ (AT^{*,ijt} < AT_k^{ijt} \le AT^{l,ijt}) \\ -\left[AT_k^{ijt} - AT_l\right]^{\frac{1}{\beta}}, & too\ late\ (AT^{l,ijt} < AT_k^{ijt}) \end{cases} \tag{9}$$

$$\pi_k^+ = \begin{cases} w^+\left(\sum_{m=k}^{s+c+s'+c'} p_m^{ijt}\right) - w^+\left(\sum_{m=k+1}^{s+c+s'+c'} p_m^{ijt}\right), & s+c+s'<k\le s+c+s'+c' \\ w^+\left(\sum_{m=s+c+1}^{k+1} p_m^{ijt}\right) - w^+\left(\sum_{m=s+c+1}^{k} p_m^{ijt}\right), & s+c<k\le s+c+s' \\ w^+\left(\sum_{m=k}^{s+c} p_m^{ijt}\right) - w^+\left(\sum_{m=k+1}^{s+c} p_m^{ijt}\right), & s<k\le s+c \end{cases}$$

$$\pi_k^- = w^-\left(\sum_{m=1}^{k} p_m^{ijt}\right) - w^-\left(\sum_{m=1}^{k-1} p_m^{ijt}\right), \qquad 1\le k\le s$$

$$w^{+/-}(p) = \frac{p^\gamma}{[p^\gamma+(1-p)^\gamma]^{1/\gamma}}$$

$$V_{ijt} = \sum_{k=1}^{s} v\left(AT_k^{ijt}\right)\pi_k^- + \sum_{k=s+1}^{s+c+s'+c'} v\left(AT_k^{ijt}\right)\pi_k^+$$

where
$\alpha, \beta, \gamma, \eta, H \in [0,1]$
c': number of too early outcomes
s': number of acceptable early outcomes
c: number of acceptable late outcomes
s: number of too late outcomes

Figure 3 graphically depicts the difference of the two CPT models. In Figure 3-(a), the maximum of the value function of the first CPT model, panic evacuation, can be expected when AT_k^{ijt} is minimized with a given $AT^{*,ijt}$. This model represents the strategy of 'arrive as early as possible'. The marginal impact of change in the value function diminishes when the distance from $AT^{*,ijt}$ increases. The diminishing sensitivity of loss especially represents that the evacuee becomes insensitive to the unit arrival time when he/she is expected to arrive too late compared to a reference time.

In Figure 3-(b), the second model's the maximum value function can be expected when AT_k^{ijt} equals $AT^{*,ijt}$, which represents the strategy of 'arrive exactly at your desired time'. This may become possible when evacuees are not under panic by understanding the traffic conditions better than before. Arriving earlier than the desired arrival time is always beneficial, since it still implies a successful evacuation. However, the amount of gain converges to 0 with respect to the amount of time arriving earlier, since arriving early is not the optimal arrival time.

The marginal impact of change in the proposed model's value function increases when the arrival time is expected to be too late. The increasing sensitivity of loss represents that the evacuee becomes more sensitive to the unit arrival time when he/she is expected to arrive too late. Thus, late arrival is more strictly avoided with the proposed model than the original model. In the real world, the evacuee would desperately attempt to avoid the worst case, since the ultimate loss from arriving late during evacuation would be the evacuee's life, which is indispensable. This may explain the evacuation behavior better than what was implied in the first CPT model, where the evacuee in the first model became insensitive to the loss when the arrival time is too late.

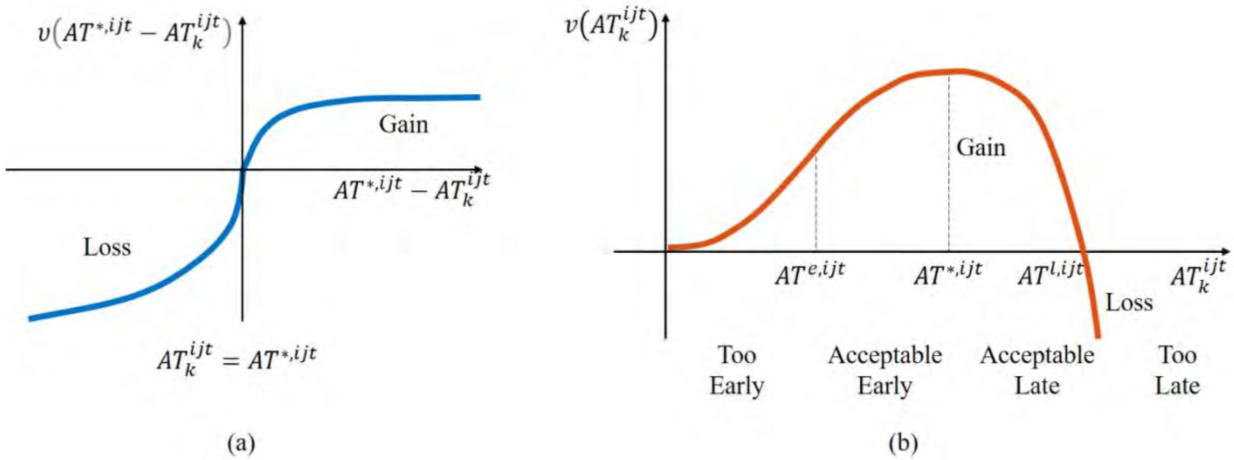


Figure 3. Value Functions of (a) the Panic CPT Model and (b) the Patient CPT Model

Parameter Calibration

The parameter vector, $[\alpha, \beta, \gamma, \eta, \mathrm{H}]$, of the patient CPT model should be calibrated before Algorithm 1 is implemented to find the optimal departure time and destination choices. All 5 parameters are between 0 and 1, and for simplicity, this paper assumed that these parameters are numbers with two decimal points (0.01, …,0.99). With a random $AT^{*,ijt}$ assigned to all evacuees, genetic algorithm is used to find the parameter vector $[\alpha, \beta, \gamma, \eta, \mathrm{H}]$ that results in the maximum mean utility, $\overline{V_{ijt}^*}$. The genetic algorithm used in this paper is based on single-point crossover method with population 48, selection rate 0.6 and mutation rate 0.1. Algorithm 2 describes the pseudo-code of the algorithm used to calibrate the parameters. For calculational simplicity, only 1% of the evacuation demand is sampled for the parameter calibration.

Algorithm 2. Parameter Calibration with Genetic Algorithm

Step 1: Parameter Initialized

48 different $[\alpha, \beta, \gamma, \eta, H] \in [0, 1]$ vectors randomly assigned (two decimal points).

Step 2: Initialize $AT^{*,ijt}$

For all parameter vector:

  For all evacuees:

    Initialize $AT^{*,ijt}$ and utility V_{ijt} with a random *ijt* decision.

    $AT^{*,ijt} \in [0, 6.5\ hr.]$

Step 3: Explore

For all parameter vector:

  For all evacuees:

    $AT_{new}^{*,ijt} = max\left(min\left(AT^{*,ijt} \pm 0.5rand, 8\right), 0\right)$ where the unit of $AT^{*,ijt}$ is in hours.

    Find $t*$ that results in $V_{ijt^*}^*$, given the destination choice as j

Find $j*$ that results in $V^*_{ij^*t^*}$, given the departure time choice as $t*$

Step 4: Evaluate, Crossover and Mutate

Objective function of the given parameter vector = $\overline{V^*_{ij^*t^*}}$ (Mean $V^*_{ij^*t^*}$ of all evacuees)

Rank order the 48 parameter vectors by its objective function.

Perform single-point crossover with selection rate 0.6, mutation rate 0.1 for all parameter vectors to maximize the objective function.

Step 5: Iterate until Converge

Convergence criteria:

For iteration ξ, assume the highest objective function among 48 parameter vectors as C^{ξ},

$\left|1-\frac{C^{\xi-9}+\cdots+C^{\xi}}{C^{\xi-10}+\cdots+C^{\xi-1}}\right| < 1e-4$ or $\xi > 100$

Go to Step 2 until converge.

Figure 4 shows the convergence results of the parameter calibration using genetic algorithm. Genetic algorithm is a heuristic approach with inherent stochasticity, so that a sudden jump in objective function can be observed when a random solution set is stochastically searched. Figure 4 shows that the objective function is improved greatly at iteration 4. After 24 iterations, the optimization satisfied the convergence criteria and stopped the iteration. The parameters found are $\alpha = 0.01$, $\beta = 0.83$, $\gamma = 0.96$, $\eta = 0.98$, and $H = 0.01$. These parameters will be used to simulate the patient evacuation throughout this paper.

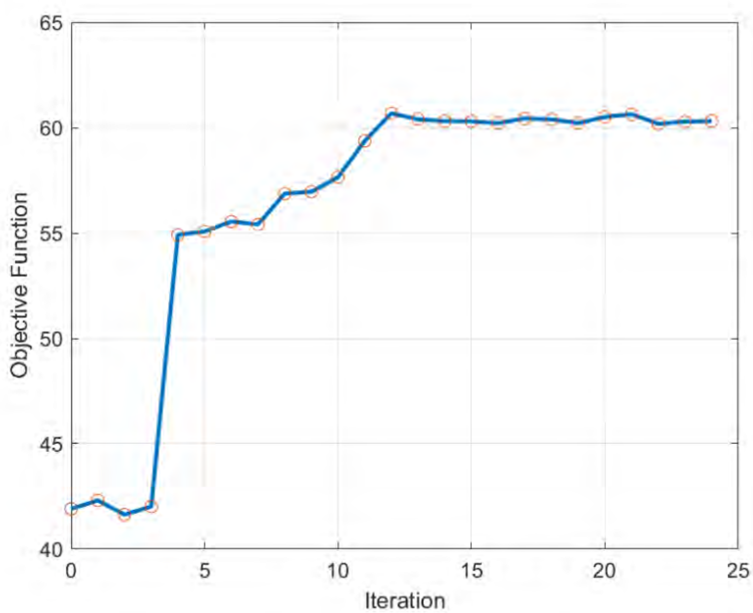
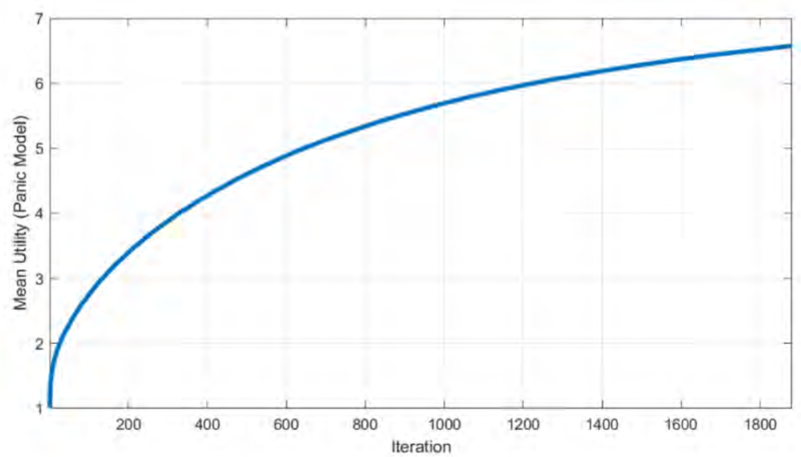


Figure 4. Genetic Algorithm Convergence Results

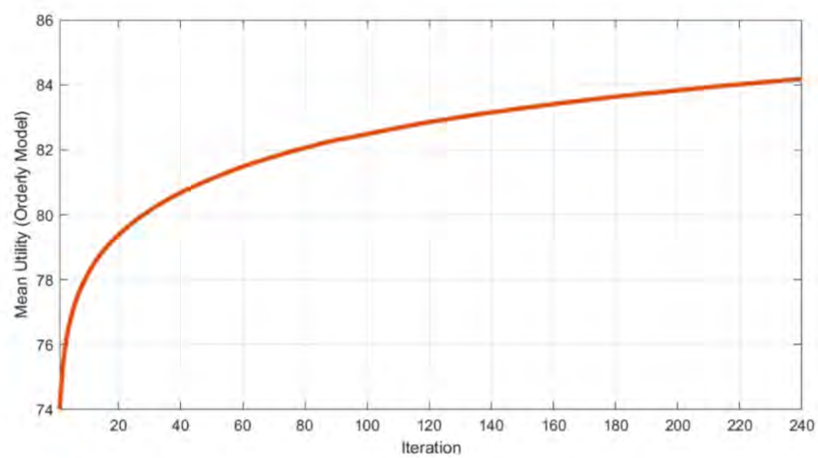
Model Convergence

In the simulation, only 10% of the population are sampled due to the high computational cost, and the non-evacuating regions are assumed to have 50% of daily weekday traffic. Each evacuee's departure time and destination choices are updated with Algorithm 1 to maximize his/her utility. Figure 5 shows the convergence results of the two models. For the patient evacuation model, the parameters obtained from Algorithm 2 are used. The panic and patient models are iterated for 1,876 and 240 iterations, respectively, and both models' iteration is terminated after the convergence criteria is satisfied. The mean utility of the panic and patient models after the iterations is 6.57 and 84.18, respectively.

The utility of the patient model is higher than that of the panic model, but it is the result of using different value function and does not represent that the patient model outperformed the panic original model by just having higher utility. The departure time and destination choices of all evacuees from each model's convergence results will be used hereafter to evaluate the evacuation performance of the two models.



(a)



(b)

Figure 5. Model Convergence Results for (a) Panic CPT Model and (b) Patient CPT Model

EVACUATION SIMULATION

The departure time and destination choices will be analyzed in macroscopic level to evaluate the two models' evacuation performance. The distribution of departure times suggest that two models will experience different levels of traffic congestions and travel distances.

Departure Time and Destination Choices

The two models' departure time histograms are shown in Figure 6-(a) and Figure 6-(b) in normalized results of each bin's count data with 12-minute bin width. Figure 6-(a) suggests that the evacuees are in panic and nearly everyone departs within the first 2 hour (6-8 AM). Figure 6-(b) suggests that the evacuees in the patient model have more time to prepare before they depart their origin by using the whole 6-hour duration (6 AM-noon) for the evacuation. Figure 6-(a) shows taller bars than Figure 6-(b), implying that more departures are concentrated in the panic model that may result in a more severe traffic congestion. The bars in Figure 6-(b) becomes shorter when the departure time becomes closer to 6-hour, which is the result of heavily penalizing late arrivals.

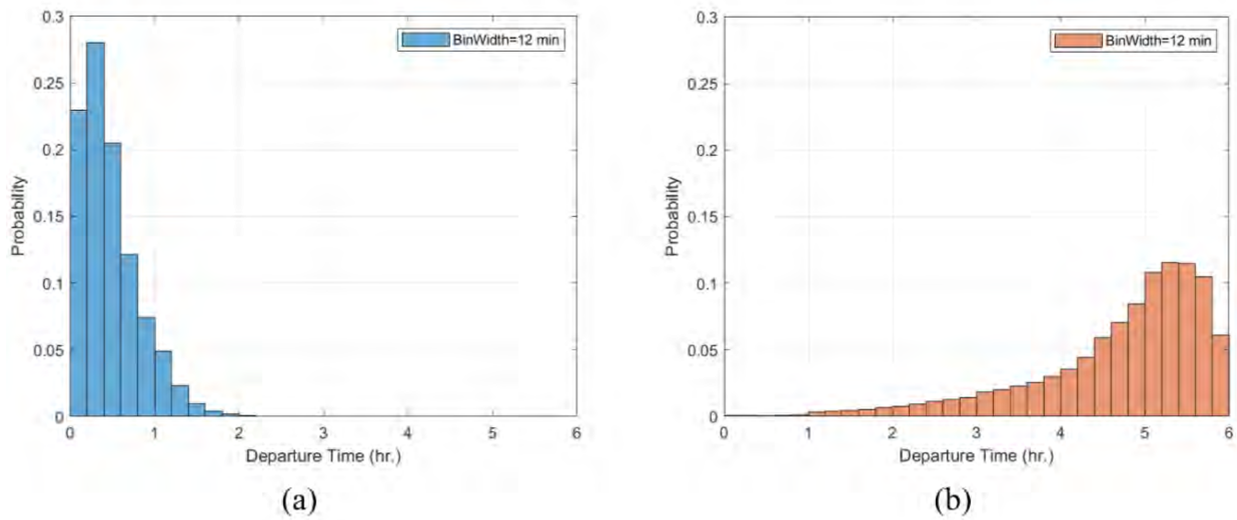
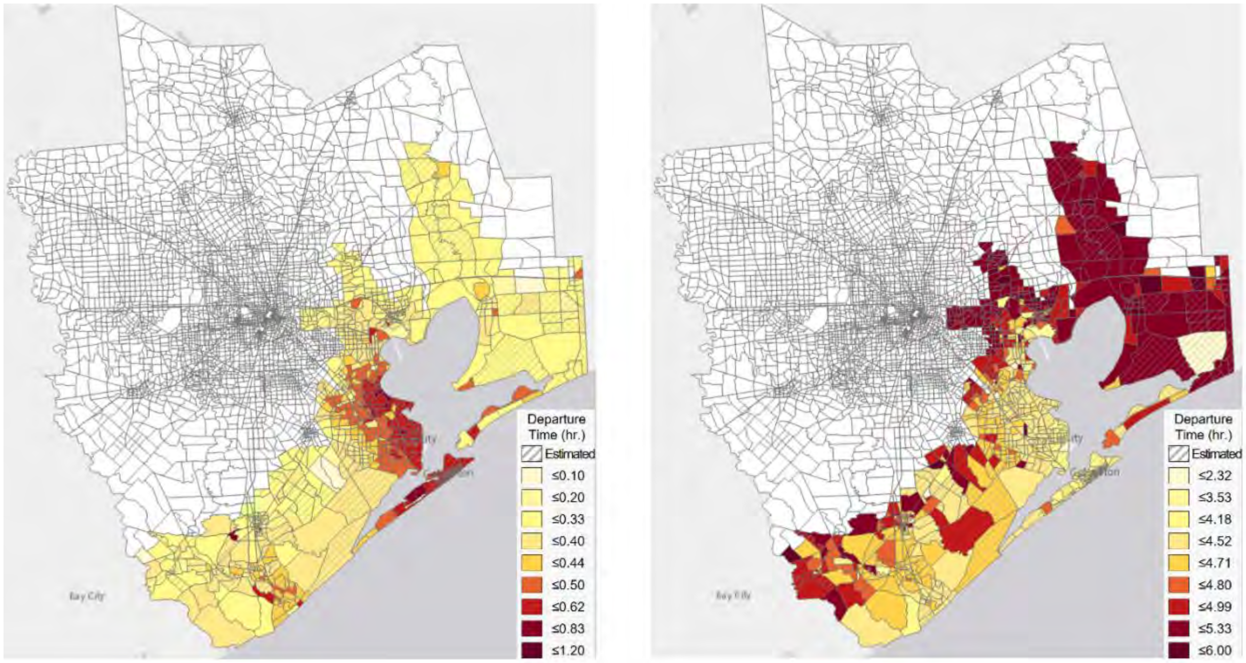


Figure 6. Departure Time Histogram for (a) Panic CPT Model and (b) Patient CPT Model

Figure 7 shows the spatial distribution of each TAZ's average departure time using ArcGIS Pro's geometric interval method. This method defines the class width based on a geometric series to give consistent frequency of observations per class. A number of TAZs are not sampled and no observations are made due to their low population. In this case, using K nearest neighbor method, the average value of its 30 nearest TAZs are assumed for the TAZs' value, and they are filled with patterns in Figure 7. In Figure 7-(a), the evacuees from the Galveston Island at the coastline depart too late, while the evacuees from the inland part depart early, which may threaten the evacuees who live in the most vulnerable zones. In Figure 7-(b), the evacuees from coastline zones evacuate earlier followed by the evacuees from inland zones, demonstrating a patient evacuee behavior resulting in staggered evacuation. In evacuation, the evacuees from coastline zones will have longer travel time than those from the inland; thus, they should depart earlier than others to facilitate the evacuation. In Houston network, Galveston Island is of special interest since a bridge connecting the Interstate 45 will be a major bottleneck for evacuating the residents. The spatial distribution of the two models' departure time choices implies that the evacuation from the panic CPT model not only experiences more severe traffic congestion from the concentrated departure time choices, but also the strategic prioritization of departure time by spatial characteristics cannot be expected.



(a) (b)

Figure 7. TAZ's Average Departure Time for (c) Panic CPT Model and (d) Patient CPT Model

Figure 8-(a) and Figure 8-(b) show the destination choice results by 1) the percentage of choosing each destination, and 2) lines to show each agent's destination choice in TAZ level. The width of the arrowed lines is normalized by the number of choices where thicker line represents that origin-destination triplet is chosen more often. Figure 8-(a) implies that the panic model's destination choices are focused on choosing the closer destinations from the origin, while Figure 8-(b) suggests that inland destinations are chosen more in the patient model. In the panic model, the concentrated departure time choices may induce severe traffic congestion in the network and the evacuees may consider the far-away destinations relatively unattractive than closer destinations. The relatively favorable traffic conditions in the patient model may have attracted the evacuees to choose the destinations located far away from their origin. Although this paper assumed that the risk levels of all destinations are equal, evacuating to the deeper inland area may be more favorable to avoid possible threats from the hurricanes.

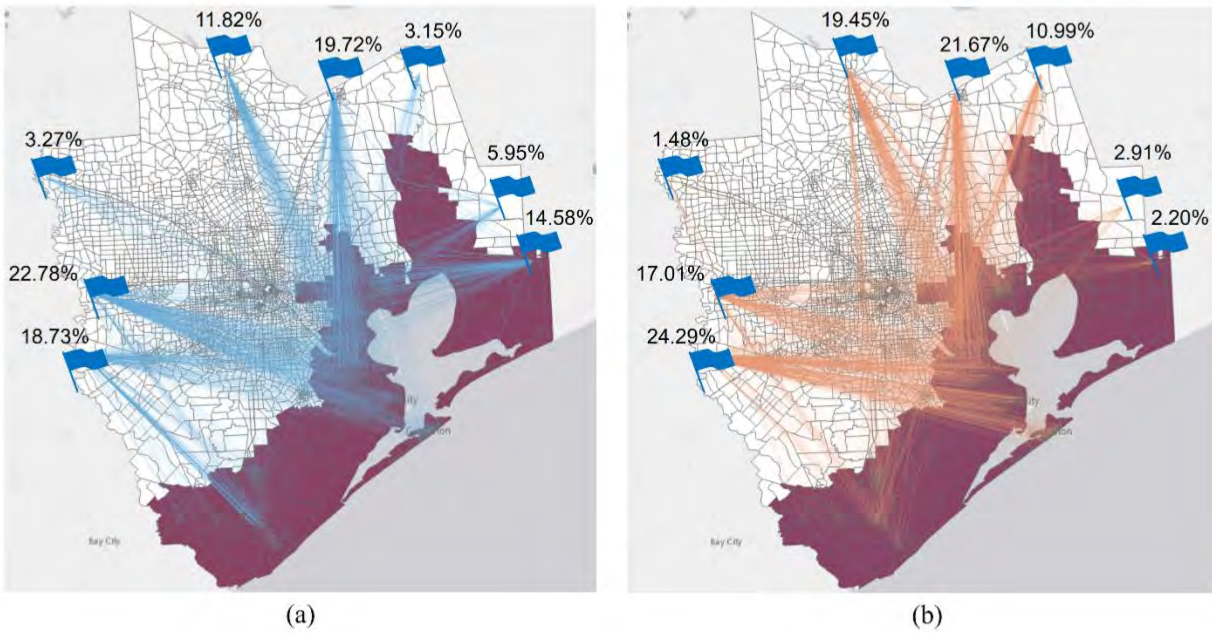


Figure 8. Destination Choice for (c) Panic CPT Model and (d) Patient CPT Model

CONCLUSIONS

This paper demonstrated two types of evacuee behaviors using cumulative prospect theory to evacuate residents from Houston, TX where a hurricane will make landfall within a few days. The two models both consider the valuation of a possible outcome that will be followed by an evacuee making a decision, as well as the probability of the outcome being observed, and derives the utility of the evacuee's decision under uncertainties. The first model, panic evacuation, demonstrated the willingness to arrive as early as possible, while the second model, patient evacuation, demonstrated the willingness to arrive exactly at the desired arrival time. The two models' departure time and destination choices are jointly optimized to evaluate each evacuee's most likely decisions for evacuation. While all evacuees in each model have homogeneous decision-making logic under the model assumptions, their location of the origin, neighborhood traffic conditions, and personality on perception of early or late arrival can result in distinct departure time and destination choices.

The departure time distribution of the panic evacuation model shows that the evacuees' departures are concentrated at the first 2 hours assuming a 6-hour departure time duration, and the residents that live closer to the destinations departed earlier than others. The patient evacuation model's departure time distribution fully utilized the 6-hour duration, but the evacuees were reluctant to depart at the near-end of that duration to avoid arriving excessively late. For the spatial distribution of the departure time choices, the residents living at a faraway location (near the coastline of Gulf of Mexico) from the destinations evacuated first, demonstrating a staggered evacuation to evacuate the residents living at a distant location first.

The destination choice results suggest that panic evacuees tend to evacuate to a closer location with shorter travel distance, while patient evacuees tend to evacuate to a deeper inland part more than panic evacuees. As this paper jointly models both departure time and destination choices, the concentrated departure time distribution of the panic evacuation model induced severe traffic congestion, making the distant destinations unattractive. As evacuees' departure times become more widespread in the patient evacuation, the traffic condition became relatively favorable, and evacuees were attracted to evacuate to far-away destinations. Although each destination's safety level is assumed to be equal, evacuating to the deeper inland area would be advantageous to avoid possible threats from the hurricanes.

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REFERENCES

Barberis, N. C. (2013). Thirty years of prospect theory in economics: A review and assessment. *Journal of Economic Perspectives*, *27*(1), 173-196.

Blake, E. S., & Zelinsky, D. A. (2018). National Hurricane Center Tropical Cyclone Report - Hurricane Harvey (AL092017). Accessed on July 20, 2020 at: https://www.nhc.noaa.gov/data/tcr/AL092017_Harvey.pdf.

Carver, S., & Quincey, D. (2017). A conceptual design of spatio-temporal agent-based model for volcanic evacuation. *Systems*, *5*(4), 53.

Chen, X., & Zhan, F. B. (2014). Agent-based modeling and simulation of urban evacuation: relative effectiveness of simultaneous and staged evacuation strategies. In *Agent-Based Modeling and Simulation* (pp. 78-96). Springer.

Cheng, G., Wilmot, C., & Baker, E. J. (2013). Development of a time-dependent disaggregate hurricane evacuation destination choice model. *Natural Hazards Review*, *14*(3), 163-174.

Dixit, V. V., Wilmot, C., & Wolshon, B. (2012). Modeling risk attitudes in evacuation departure choices. *Transportation Research Record*, *2312*(1), 159-163.

Fennema, H., & Wakker, P. (1997). Original and cumulative prospect theory: A discussion of empirical differences. *Journal of Behavioral Decision Making*, *10*(1), 53-64.

Fu, H., Pel, A. J., & Hoogendoorn, S. P. (2013). Optimal traffic management to ensure emergency evacuation compliance. 2013 10th IEEE INTERNATIONAL CONFERENCE ON NETWORKING, SENSING AND CONTROL (ICNSC),

Fu, H., Wilmot, C. G., Zhang, H., & Baker, E. J. (2007). Modeling the hurricane evacuation response curve. *Transportation Research Record*, *2022*(1), 94-102.

Golshani, N., Shabanpour, R., Mohammadian, A., Auld, J., & Ley, H. (2019). Analysis of evacuation destination and departure time choices for no-notice emergency events. *Transportmetrica A: Transport Science*, *15*(2), 896-914.

Janzen, M., & Axhausen, K. W. (2017). Destination and mode choice in an agent-based simulation of long-distance travel demand. 17th Swiss Transport Research Conference (STRC 2017),

Krajzewicz, D., Erdmann, J., Behrisch, M., & Bieker, L. (2012). Recent development and applications of SUMO-Simulation of Urban MObility. *International Journal on Advances in Systems and Measurements*, *5*(3&4).

Li, X.-y., Li, X.-m., Yang, L., & Li, J. (2018). Dynamic route and departure time choice model based on self-adaptive reference point and reinforcement learning. *Physica A: Statistical Mechanics and its Applications*, *502*, 77-92.

Liu, W., & Li, L. (2019). Emergency decision-making combining cumulative prospect theory and group decision-making. *Granular Computing*, *4*(1), 39-52.

Liu, Y., Fan, Z.-P., & Zhang, Y. (2014). Risk decision analysis in emergency response: A method based on cumulative prospect theory. *Computers & Operations Research*, *42*, 75-82.

Liu, Y., Lai, X., & Chang, G.-L. (2006). Cell-based network optimization model for staged evacuation planning under emergencies. *Transportation Research Record*, *1964*(1), 127-135.

Molloy, J., & Moeckel, R. (2017). Improving destination choice modeling using location-based big data. *ISPRS International Journal of Geo-Information*, *6*(9), 291.

Noland, R. B., & Small, K. A. (1995). Travel-time uncertainty, departure time choice, and the cost of morning commutes. *Transportation Research Record*(1493), 150-158.

Parady, G. T., & Hato, E. (2016). Accounting for spatial correlation in tsunami evacuation destination choice:

a case study of the Great East Japan Earthquake. *Natural Hazards*, *84*(2), 797-807.
Parvin, G. A., Sakamoto, M., Shaw, R., Nakagawa, H., & Sadik, M. S. (2019). Evacuation scenarios of cyclone Aila in Bangladesh: Investigating the factors influencing evacuation decision and destination. *Progress in Disaster Science*, *2*, 100032.
Sbayti, H., & Mahmassani, H. S. (2006). Optimal scheduling of evacuation operations. *Transportation Research Record*, *1964*(1), 238-246.
Tamminga, G., Tu, H., Daamen, W., & Hoogendoorn, S. (2011). Influence of departure time spans and corresponding network performance on evacuation time. *Transportation Research Record*, *2234*(1), 89-96.
Texas Natural Resources Information Service (TNRIS). (2004). *Hurricane Risk Zones. Accessed on June 8, 2021 at: http://www.texascoastalatlas.com/download/CoastalAtlas/Hazards.html*
Tversky, A., & Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty*, *5*(4), 297-323.
US Census Bureau. (2019). *Quick Facts: Brazoria, Chambers, Fort Bent, Galveston, Harris, Liberty, Montgomery, and Waller County, TX-Population Estimates. Accessed on July 3, 2020 at: https://www.census.gov/quickfacts/fact/table/US/PST045219*
Wong, S. D., Broader, J. C., Walker, J. L., & Shaheen, S. A. (2020). Understanding California Wildfire Evacuee Behavior and Joint Choice-Making.
Xu, H., Zhou, J., & Xu, W. (2011). A decision-making rule for modeling travelers' route choice behavior based on cumulative prospect theory. *Transportation Research Part C: Emerging Technologies*, *19*(2), 218-228.
Yang, M., Wang, W., Chen, X., Xu, R., & Gu, T. (2010). Modeling destination choice behavior incorporating spatial factors, individual sociodemographics, and travel mode. *Journal of Transportation Engineering*, *136*(9), 800-810.
Zong, F., Tian, Y., He, Y., Tang, J., & Lv, J. (2019). Trip destination prediction based on multi-day GPS data. *Physica A: Statistical Mechanics and its Applications*, *515*, 258-269.