A Transit-Based Evacuation Model for Metropolitan Areas

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Abstract

This paper develops a decision-support model for transit-based evacuation planning occurring in metropolitan areas. The model consists of two modules executed in a sequential manner: the first deals with determining pick-up locations from candidate locations based on the spatial distribution of the evacuees, and the second plans for the route and schedule for each transit vehicle based on vehicle availability and evacuee demand pattern. An overlapping clustering algorithm is first adopted in allocating the demands to several nearby clusters. Then, an optimization model is proposed to allocate available buses from the depots to transport the assembled evacuees between the pick-up locations and different safety destinations and public shelters. A numerical example based on the city of Baltimore demonstrates the applicability of the proposed model and the advantages compared to state-of-the-art models with overly strict and unrealistic assumptions.

Introduction

Under potential terrorist attack, harmful substances released from transportation and industrial accidents, fires, floods, and other emergencies require immediate evacuation from hazardous areas. In congested metropolitan areas, commuters are likely to depend on either transit or other modes for their daily commute and, thus, may not have access to their private vehicles. Once an incident occurs, responsible agencies, such as city transportation administration and emergency units, should quickly devise a plan to dispatch available public transit resources to evacuate carless populations.

Although aiding the carless during evacuations has been presented in recent research, planning details such as how to identify available buses and drivers, how to determine potential pick-up locations, how to allocate bus routes to collect evacuees, and how to provide a timetable for the drivers (USDOT and USDHS 2006) are not well studied. Litman (2006) and Renne (2008) highlighted the needs for transit-dependent people during evacuation planning based on their experience with hurricanes Katrina and Rita. Wolshon (2001) mentioned that about 15–30 percent of the evacuation population in New Orleans during the hurricanes was transit-dependent. Fittante (2012) demonstrated community transit's value in response to Hurricane Sandy. Transit agencies should be in a position

to render valuable assistance during emergencies. During the 9/11 terrorist attack, the transit system in New York City allowed free entry and led evacuees to safe locations. In Washington DC, buses contributed to the response effort, and additional buses were provided to the DC police to move officers to key locations. The Federal Transit Administration (FTA) and other agencies have issued many security guidelines for response before, during, and after a threat to ensure a quick recovery (FTA 2002; USDOT 2006). It is suggested that transit agencies to perform their own review on performance indicators for assessing emergency preparedness (Nakanishi 2003).

The transit evacuation model developed in this paper concerns the evacuation scenario occurring in metropolitan areas—for example, under a no-notice threat during a football game. The model consists of two modules executed in a sequential manner: the first deals with determining pick-up locations from candidate locations based on the spatial distribution of the evacuees. Once the pick-up locations are set, the evacuees are allocated accordingly, and the arrival pattern of each pick-up location is obtained. Fuzzy c-means (FCM), developed by Dunn (1974) and improved by Bezdek (1984), is applied to allow people at one location to be assigned to multiple clusters. The second module develops an integer-linear optimization module and plans the route and schedule for each transit vehicle based on vehicle availability and evacuee demand patterns.

Literature Review

Various studies have focused on different aspects of evacuation planning, such as demand modeling (Mei 2002; Wilmot 2004; Fu 2007), departure scheduling (Malone 2001; Mitchell 2006; Sbyati 2006; Chien 2007; Chen 2008), route choice (Cova 2003; Afshar 2008; Chiu 2008; Yazici 2010; Zheng 2010; Xie 2011;), contra-flow operation (Theodoulou 2004; Wolshon 2005; Tuydes 2006; Xie 2010) and relief operation (Haghani 1996; Barbarosoglu 2004; Ozbay 2007; Xie 2009). Most of these are specific to the control and management of passenger car flows. Compared to these evacuation research efforts, there are only a limited number of studies on modeling transit-based evacuation. Elmitiny (2007) simulated different strategies and alternative plans for the deployment of transit during an emergency situation. Chen (2009) proposed a bi-level optimization model to determine waiting locations and corresponding shelters in a transit-based evacuation; the model was applied on the network within the University of Maryland. Song (2009) formulated transit evacuation operation during a natural disaster as a location-routing problem aiming to minimize total evacuation time; the problem identified the optimal serving area and transit vehicle routings to move evacuees to safety shelters. Abdelgawad (2010) developed an approach to optimally operate the available capacity of mass transit to evacuate transit-dependent people during no-notice evacuation of urban areas; an extended vehicle routing problem was proposed to determine the optimal scheduling and routing for the buses to minimize the total evacuation time. Sayyady (2010) proposed a mixed-integer linear program to model the problem of finding optimal transit routes during no-notice disasters; a Tabu-search algorithm was designed and an experiment was conducted using the transportation network of Fort Worth, Texas. Naghawi (2010) systematically modeled and simulated transit-based evacuation strategies applying the TRANSIMS agent-based transportation simulation system to the assisted evacuation plans of New Orleans. Kaisar

(2012) addressed the optimal allocation of bus stops for the purpose of evacuating special needs populations; to evaluate the solution quality, a microscopic traffic simulation model was developed to represent the downtown Washington DC area in an evacuation scenario.

In carefully examining the similar study efforts, it can be concluded that most of the above models assumed one or several of the following:

- The pick-up locations serving as convening points are given and known in advance.

- All evacuees are present at the pick-up locations shortly after the evacuation starts.

- The loading and unloading times at pick-up locations are negligible or are assumed to be a constant value.

- Each vehicle is assigned a fixed route and runs in a cycle.

- The destinations have infinite holding capacities for evacuees.

Most of these assumptions are over-restrictive and, thus, prevent the application of the model outcome to real-world evacuation scenarios. To overcome these restrictions, our model tries to relax these assumptions and has the following unique characteristics that distinguish it from the previous studies:

- Both pick-up location allocation and transit bus scheduling are considered. During evacuations, the massive number of evacuees first needs to be coordinated and guided to nearby convene points, and then the transit vehicles are scheduled depending on the time-dependent arrival patterns of the evacuees at these pick-up points.

- The demand pattern is treated as time-dependent. Most prior research assumes that all evacuees are queued at pick-up locations at the beginning of the evacuation. This is almost never true because the evacuees may begin to evacuate at different times and it takes time for them to walk to the designated pick-up locations, and also because the pick-up locations, such as bus stops, have limited holding capacities, thus accumulating crowds and causing a huge bottleneck at that location.

- The loading/unloading times depend on the actual boarding/deboarding times. Negligence of this will overestimate the transport efficiency in generating the bus route and scheduling the timetables.

- Although pick-up locations are determined beforehand, the bus route is more flexible than the daily fixed route, servicing different pick-up locations at different runs based on actual need. Sometimes it is inefficient for a bus route to service fixed pick-up locations back and forth during evacuations. Instead, once a bus drops off evacuees at a safety area, it will be dispatched to the most-needed pick-up location.

- Capacity constraint is incorporated into destinations that are commonly public shelters, such as stadiums, schools, parks etc. Without such constraint, the model is subject to generate solutions in which all evacuees are sent to one or two nearest shelters and may cause overcrowding problems.

Modeling Pick-Up Location Selection

The set of pick-up locations should cover all carless evacuees and limit their total walking distance, as per FTA requirements. This study grouped all evacuee generation points into several clusters of demand zones, and then allocated a pick-up location within each zone. For each demand point, the evacuees were distributed based on the proximity of the nearby pick-up location within walking range. An overlapping clustering algorithm to tie a particular demand point to several nearby clusters was adopted. Developed by Dunn (1974) and improved by Bezdek (1984), Fuzzy c-means (FCM) allows one piece of data to be assigned to multiple clusters, which is based on the following objective function:

$$J = \sum_{i=1}^{N} \sum_{j=1}^{C} u_{ij} \| x_i - c_j \|^2 \tag{1}$$

where,

x_i = the ith measured data

c_j = the center of the cluster

u_{ij} = the degree of membership of x_i in the cluster j

$\| * \|$ = the second-norm expressing the similarity between measured data and the center

In the context of determining bus pick-up locations, x_i is the ith evacuee's position, c_j is the jth pick-up location, $\| * \|$ is the distance between the evacuee and the pick-up location, and u_{ij} measures the likelihood the evacuee i will move to the pick-up location j.

The entire algorithm for determining the pick-up locations and the evacuee's allocation plan is composed of the following steps:

(1) Initialize c_j and $u_{ij} = \dfrac{1}{\sum_{k=1}^{C} \left(\dfrac{\| x_i - c_j \|}{\| x_i - c_k \|} \right)}$.

(2) Calculate $c_j = \dfrac{\sum_{i=1}^{N} u_{ij} x_i}{\sum_{i=1}^{N} u_{ij}}$.

(3) Calculate $u_{ij} = \dfrac{1}{\sum_{k=1}^{C} \left(\dfrac{\| x_i - c_j \|}{\| x_i - c_k \|} \right)}$.

(4) If $\Delta U = \max(\Delta u_{ij}) \leq \varepsilon$, go to step 5; otherwise, go to step 2.

(5) If $\| x_i - c_j \| > \xi$, set.

Note if any of the final pick-up locations is geographically feasible (e.g. river, rail-road, and building), then it needs to be adjusted to the closest geographically location, which can serve the pick-up purpose.

Transit Vehicle Routing and Scheduling

Define Pick-Up Request and Vehicle Route

Each pick-up request is associated with the following parameters: pick-up location, number of evacuees (usually equal to load capacity), and time-window with an upper and lower bound. The bound for the time window can ensure people being picked up on time and prevent intolerably long waiting times. For each pick-up location i, we divide the time horizon into time segments with lengths $t_{ij}, j=1,2,3...$., and let d_{ij} be the demand reaching pick-up location i during time interval t_{ij}, then $t_{ij} = \arg\min(d_{ij} = C, t_{ij} = W)$, where C is the bus capacity and W is the maximum waiting time. For each time segment $t_{ij}, j=1,2,3...$,

a pick-up request node is created with a time window $$\left(a_{ij} = \sum_{0<k<j} t_{ik}, b_{ij} = a_{ij} + W\right).$$ For example, given the capacity and the maximum waiting time to be 20 passengers and 2 minutes, Figure 1 and Table 1 show the pick-up requests I to VI created from the cumulative arrival curves at a particular pick-up location i.

FIGURE 1.

Pick-up requests generated from cumulative arrival curve
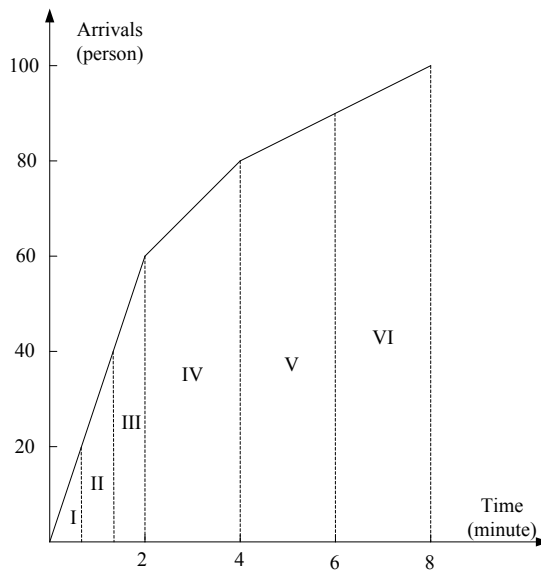
TABLE 1.

Details of Pick-Up Requests

Pick-up Request	Time Window	Pick-up Number
I	0–120s	20
II	40–160s	20
III	80–200s	20
IV	120s–240s	20
V	240–360s	10
VI	360–480s	10

Define N^P be the set of pick-up request nodes, N^O be the set of origin nodes for buses, N^D be the set of destination nodes for drop off, and N^E be the set of the end depot nodes where the bus mission is completed upon arrival. Each pick-up request node i is associated with a time window $[a_i, b_i]$. Herein we consider the hard time window so that i must be visited by a bus before b_i. Let V be a set of homogenous buses to be used in evacuation. The route for each bus is designed in the following manner: pull out of N^O; visit several (no more than two in this study) pickup-request nodes, satisfying their time windows, and go to a destination node to drop off; come back to visit another pick-up request node within the time window; go to another destination node to drop off, and so on, until no pickup-request can be satisfied within allowed time window; finally, go to the end-depot. Each bus is dispatched in such a manner until all pickup-requests are visited exactly once.

Figure 2a shows the typical route for one bus, which consists of multiple runs. Each run includes one or two pick-up request nodes and one drop off node. Figure 2b illustrates two example bus routes. We tried to assign buses starting from N^O and visiting nodes in N^P and N^D alternately and continuously.

FIGURE 2.

Illustration of bus routes

(a) Typical route for one bus
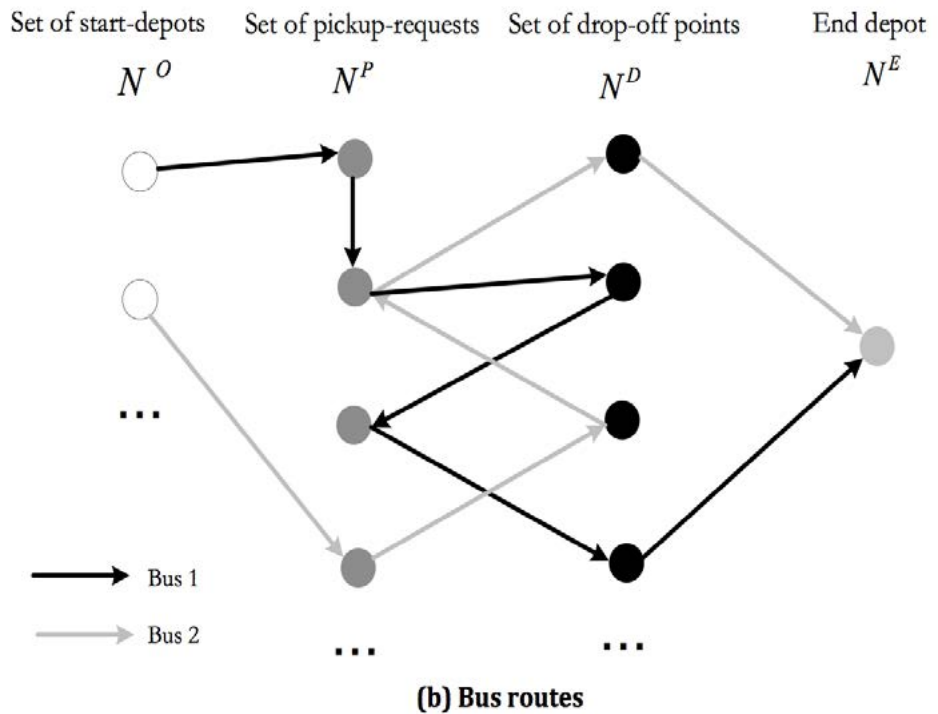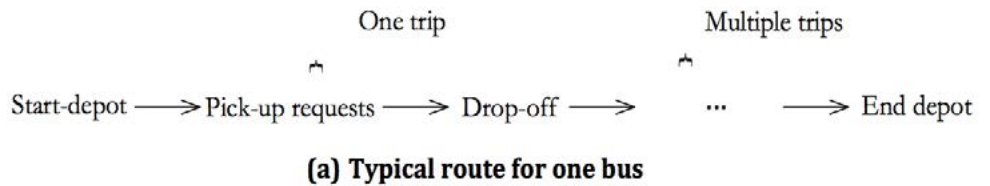
(b) Bus routes

Variable Definition

The decision variables employed in this model are defined below. The indicator variables represent the sequence of the bus routes, and the other integer variables represent the arrival times, departure times, and the bus loads.

$b_{i,j,k}$ = indicator whether bus k moves from node i to j

$b_{i,j,m,k}$ = indicator whether bus k moves from node i to destination j and then to node m

$w_{i,k,i}$ = indicator whether node i is routed by the kth vehicle at lth run

$t_{i,k}^{A}$ = the time bus k arrives at request node i

$t_{i,k}^{D}$ = the time bus k departs from request node i

$t_{i,j,m,k}^{A}$ = the time bus k arrives at destination node j following node i and preceding node m

$t_{i,j,m,k}^{D}$ = the time bus k departs from destination node j following node i and preceding node m

$l_{k,l}$ = the load for bus k at run l

$l_{i,k,l}$ = the load to destination i for bus k at run l

The known variables are defined as follows:

N^{O} = the set of origin nodes for buses, e.g. bus depots

N^{D} = the set of destination nodes for evacuees, e.g. shelters

N^{P} = the set of pick-up request nodes for evacuees, e.g. shelters

N^{E} = the set of virtual end depots

$TT_{i,j}$ = the travel time from node i to node j

n_{i} = the number of pedestrians for request i

$L_{\max}$ = the maximum load of each bus

C_{i} = the capacity of destination i

a_{i} = the lower bound of the time window of node i

b_{i} = the upper bound of the time window of node i

Mathematical Formulation

Objective Function

The objective of the model in equation (2) is to minimize the time for the last evacuees to arrive at safe destinations. The definition of the time window for the pick-up request guaranteed that the evacuees would not wait more than the maximum waiting time to board the bus.

$$\text{Minimize} \quad \max(t_{m,k}^{A}), \forall m \in N^{E}, \forall k \in K \qquad (2)$$

The model formulation also includes travel time constraints, time window constraints, pick-up requests constraints, bus load constraints, and destination capacity constraints, which are detailed in the following sections.

Travel Time Constraints

$$t_{j,k}^A - t_{i,k}^D \leq TT_{i,j} + M(1 - b_{i,j,k}), \forall i \in N^P \cup N^O, j \in N^P, \forall k \in K \tag{3}$$

$$t_{j,k}^A - t_{i,k}^D \geq TT_{i,j} - M(1 - b_{i,j,k}), \forall i \in N^P \cup N^O, \forall j \in N^P, \forall k \in K \tag{4}$$

$$t_{i,j,m,k}^A - t_{i,k}^D \leq TT_{i,j} + M(1 - b_{i,j,m,k}), \forall i \in N^P, \forall j \in N^D, \forall k \in K \tag{5}$$

$$t_{i,j,m,k}^A - t_{i,k}^D \geq TT_{i,j} - M(1 - b_{i,j,m,k}), \forall i \in N^P, \forall j \in N^D, \forall k \in K \tag{6}$$

$$t_{m,k}^A - t_{i,j,m,k}^D \leq TT_{j,m} + M(1 - b_{i,j,m,k}), \forall i \in N^P, \forall j \in N^D, \forall m \in N^P \cup N^E, \forall k \in K \tag{7}$$

$$t_{m,k}^A - t_{i,j,m,k}^D \geq TT_{j,m} - M(1 - b_{i,j,m,k}), \forall i \in N^P, \forall j \in N^D, \forall m \in N^P \cup N^E, \forall k \in K \tag{8}$$

Constraints (3) and (4) set the travel time needed from the pick-up node i to j, constraints (5) and (6) set the travel time from the pick-up node i to destination node j, and constraints (7) and (8) set the travel time from destination node j to pick-up node m.

Time Window Constraint

$$t_{i,k}^D - t_{i,k}^A \geq n_i \Delta t, \forall i \in N^p, \forall k \in K \tag{9}$$

$$t_{i,j,m,k}^D - t_{i,j,m,k}^A \geq l_{k,l}\Delta t - Mw_{j,k,l}, \forall i, j, m \in N, \forall k \in K, \forall l \in L \tag{10}$$

$$t_{i,k}^A \leq b_i, \forall i \in N^p \tag{11}$$

$$t_{i,k}^D \geq a_i, \forall i \in N^p \tag{12}$$

Constraint (9) considers the loading time at the pick-up request node i. Constraint (10) calculates the unloading time needed at the destination node j based on the bus load. Constraints (11) and (12) force the arrival time to be earlier than the upper bound of the time window and the departure time to be later than the lower bound of the time window at the pick-up request i.

Each pickup request can be served by only one bus:

$$\sum_i \sum_k b_{i,j,k} = 1, \forall j \in N^p \tag{13}$$

$$\sum_j \sum_k b_{i,j,k} = 1, \forall i \in N^p \tag{14}$$

$$\sum_j b_{i,j,k} = 1, \forall i \in N^O, \forall k \in K \tag{15}$$

$$\sum_{m \in N^P} b_{i,j,m,k} = 1, \forall i \in N^P, \forall j \in N^D, \forall k \in K \tag{16}$$

$$\sum_{i \in N^P} b_{i,j,m,k} = 1, \forall m \in N^P, \forall j \in N^D, \forall k \in K \tag{17}$$

$$b_{i,j,m,k} = 0, \forall j \in N^E \tag{18}$$

$$\sum_k \sum_l w_{i,k,l} = 1, \forall i \in N^P \tag{19}$$

$$b_{i,j,m,k} \le b_{i,j,k} + b_{j,m,k} - 0.95 \tag{20}$$

$$b_{i,j,m,k} \ge b_{i,j,k} + b_{j,m,k} - 1.01 \tag{21}$$

$$w_{i,k,l} - w_{j,k,l} \le M(1 - b_{i,j,k}) \tag{22}$$

$$w_{i,k,l} - w_{j,k,l} \ge M(b_{i,j,k} - 1) \tag{23}$$

Constraints (13) and (14) ensure each pick-up request is serviced exactly once. Constraint (15) ensures that the bus from the depot can head to only one pick-up location. Constraints (16) and (17) ensure only one preceding and following node for the destination node at each bus run. Constraint (18) dismisses the bus mission once it reaches the end depot. Constraint (19) ensures that each pick-up request be serviced exactly once. Constraints (20) and (21) ensure that the value of $b_{i,j,m,k}$ can be 1 only if $b_{i,j,k}$ and $b_{j,m,k}$ are both 1. Constraints (22) and (23) establish the relationship between the indicator variables b and w, which means that if pick-up request j is serviced by one bus followed by pick-up request i, then the indicator variable w value should be identical for pick-up requests i and j for the same bus run.

Bus Capacity Constraints

$$l_{k,l} = \sum_i n_i w_{i,k,l}, \forall k \in K, \forall l \in L \tag{24}$$

$$l_{k,l} \le L_{\max}, \forall k \in K, \forall l \in L \tag{25}$$

Constraint (24) calculates the total load for the bus k at the lth run, and constraint (25) limits the load to be less than the maximum load for each bus.

Destination Capacity Constraints

$$l_{i,k,l} \ge l_{k,l} - M(1 - w_{i,k,l}), \forall i \in N^D, \forall k \in K, \forall l \in L \tag{26}$$

$$l_{i,k,l} \le l_{k,l} + M(1 - w_{i,k,l}), \forall i \in N^D, \forall k \in K, \forall l \in L \tag{27}$$

$$l_{i,k,l} \le M w_{i,k,l}, \forall i \in N^D, \forall k \in K, \forall l \in L \tag{28}$$

$$l_{i,k,l} \ge -M w_{i,k,l}, \forall i \in N^D, \forall k \in K, \forall l \in L \tag{29}$$

$$\sum_k \sum_l l_{i,k,l} \le C_i, \forall i \in N^D \tag{30}$$

Constraints (26)–(29) calculate the number of evacuees unloaded at the destination i at the 1st run for bus k. Constraint (30) limits the total unloaded evacuees at each destination node to be less than its holding capacity.

Further Simplification

Note that, during evacuations, the evacuee volumes are high, especially at beginning. The number of evacuees at a single pick-up request is very likely to be close to or reach bus capacity. In addition, some pick-up requests may have restrictive time windows, such that the bus serving one of these types of request nodes will not have enough remaining capacity or time to service any other pick-up request at that run. Thus, we can divide the pick-up request nodes into two groups: N_1^p and $N_2^p = N^p \setminus N_1^p$. Any node i in the group N_1^p and any node j in N^p satisfies at least one of the following criteria:

(1) $n_i + n_j > L_{max}$

(2) $[a_i + n_i\Delta t + TT_{ij}, b_i + n_i\Delta t + TT_{ij}] \cap [a_j, b_j] = \varnothing$ and

$[a_j + n_j\Delta t + TT_{ji}, b_j + n_j\Delta t + TT_{ji}] \cap [a_i, b_i] = \varnothing$

The pick-up request in N_1^p either has a close-to-capacity number of pick-ups or an inflexible time window, which cannot accommodate other requests and thus should be serviced exclusively by one run. Constraint (31) excludes the possibility of servicing any two pick-up requests within N_1^p, which simplifies the formulation and, in turn, improves the computation speed.

$$b_{i,j,k} = 0, \forall i, j \in N_1^P, \forall k \in K \tag{31}$$

Numerical Example

The model was tested on the city of Baltimore's downtown road network. A hypothetical evacuation after a sudden incident such as a terrorist attack was assumed. Figure 3 shows the spatial distribution of the demand points, bus depots, and safety destinations based on the aggregated 2010 MPO data from Baltimore County. There were around 40 pedestrian demand points, 2 transit depots, and 10 safety shelters in the vicinity area of the downtown area. The sizes of the demand points indicate the levels of the evacuee numbers at the locations and were estimated based on the traffic analysis data provided by Baltimore County. The two bus depots were the Bush Bus Division in the southwest and the Kirk Bus Division in the northeast and included high schools, community colleges, recreation centers, etc. For illustrative purposes, a constant evacuation rate every 10 minutes for the first 30 minutes was assumed at any given demand location. CPLEX 12.4 was adopted to solve the mixed-integer programming problem on a Windows7 computer with an Intel i-7 3770 CPU and 8GB of memory.
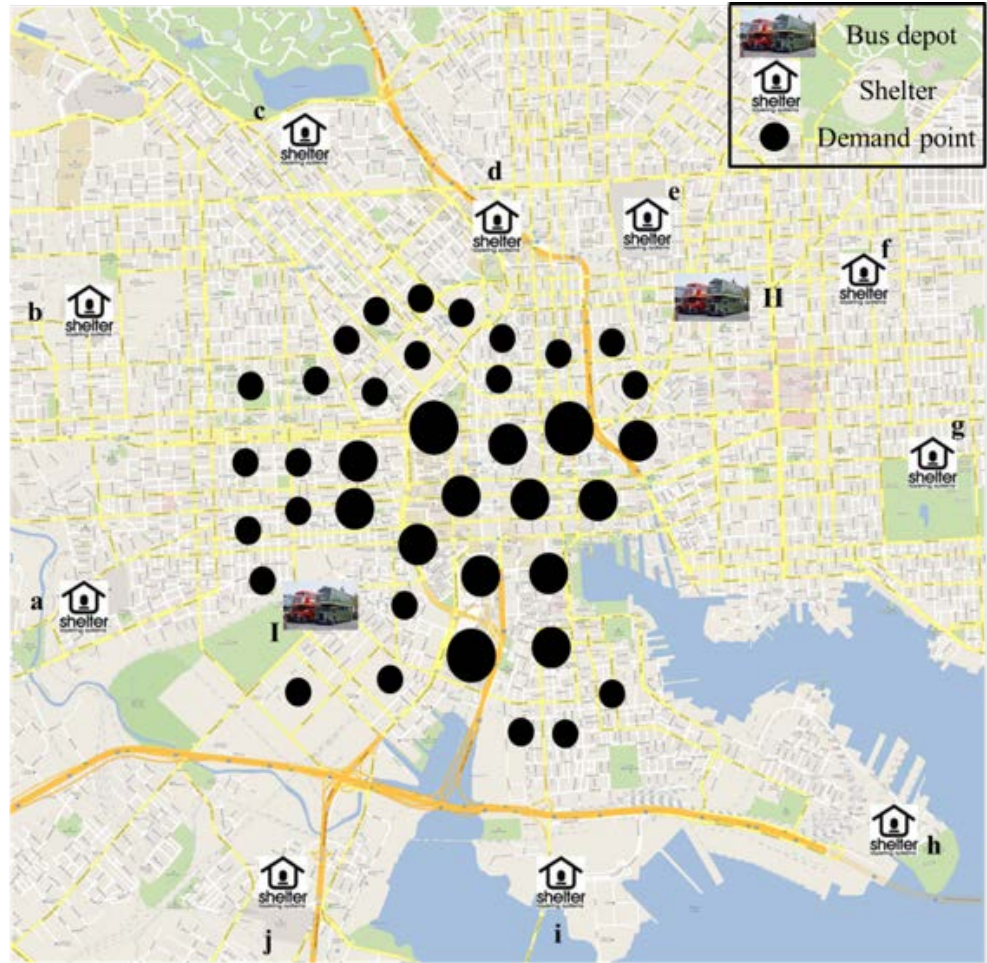
Table 2 lists the rate ranges in terms of pedestrian level, the capacities of the shelters, and the availability of buses in the depots. Figure 4 depicts the 11 candidate pick-up locations after the fuzzy clustering on the evacuee demand points. The average walking time for the evacuees to the pick-up locations was 3.1 minutes; the farthest was 9.8 minutes. Table 3 shows the cumulative arrival curve for the 11 pick-up locations based on the pedestrian levels and the degrees of membership of their nearby demand locations. Figure 5 shows two among the generated bus routes, and Table 4 lists the corresponding time and pick-up schedules.

TABLE 2.
Shelter Capacities,
Bus Availabilities,
and Demand Levels

Shelter ID	Capacity (person)	Depot ID	Bus Availability
a	1,500	I	50
b	1,000	II	50
c	1,500		
d	2,000		
e	1,000		
f	1,000		
g	1,000	Pedestrian level	Rate for first 10 min (person/min)
h	1,000	High	30
i	1,000	Medium	20
j	1,000	Low	10

FIGURE 4.
Pick-up locations after
fuzzy clustering
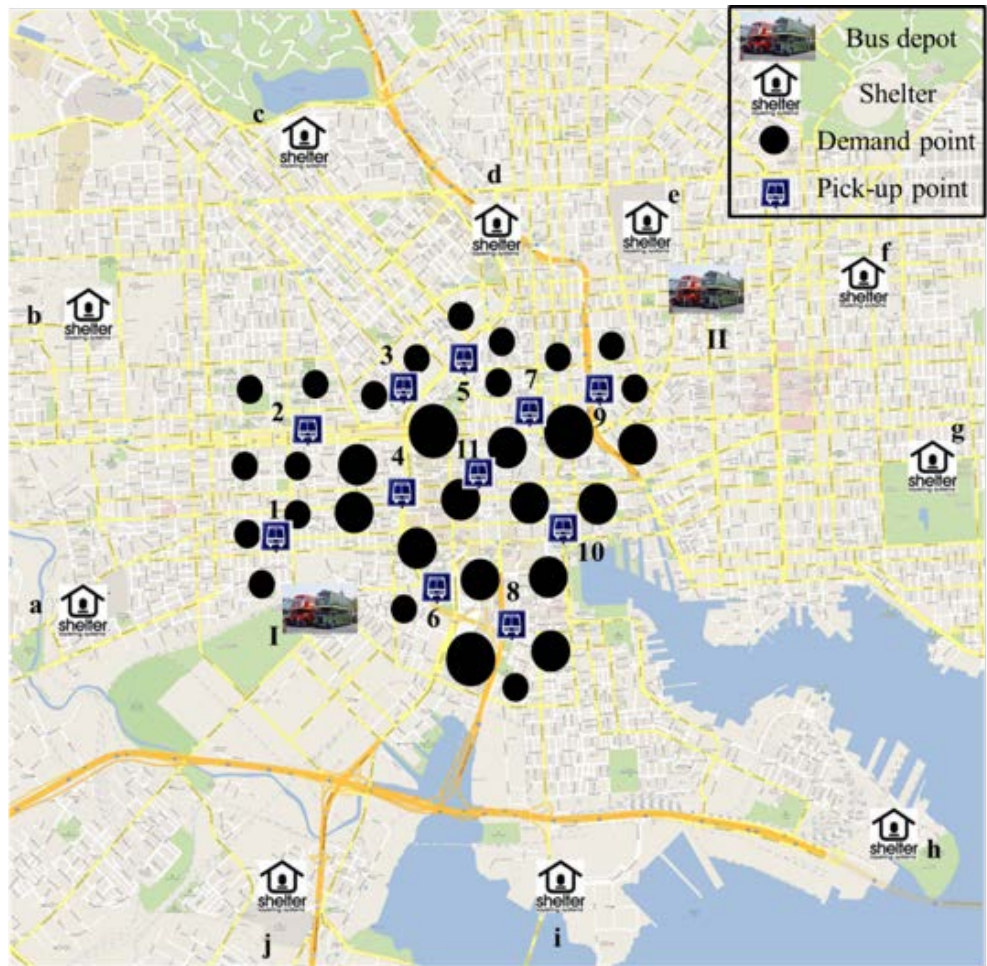
TABLE 3.

Time-Dependent Arrivals to
Pick-Up Locations

Pick-up Location	0–10 (min)	10–20 (min)	20–30 (min)	30–40 (min)
1	269	211	105	23
2	353	271	136	30
3	353	272	135	31
4	362	265	130	23
5	265	200	106	20
6	363	268	133	26
7	450	355	180	34
8	628	478	256	45
9	639	415	208	35
10	365	261	135	20
11	451	352	176	34

FIGURE 5.

Two examples of
generated bus routes.
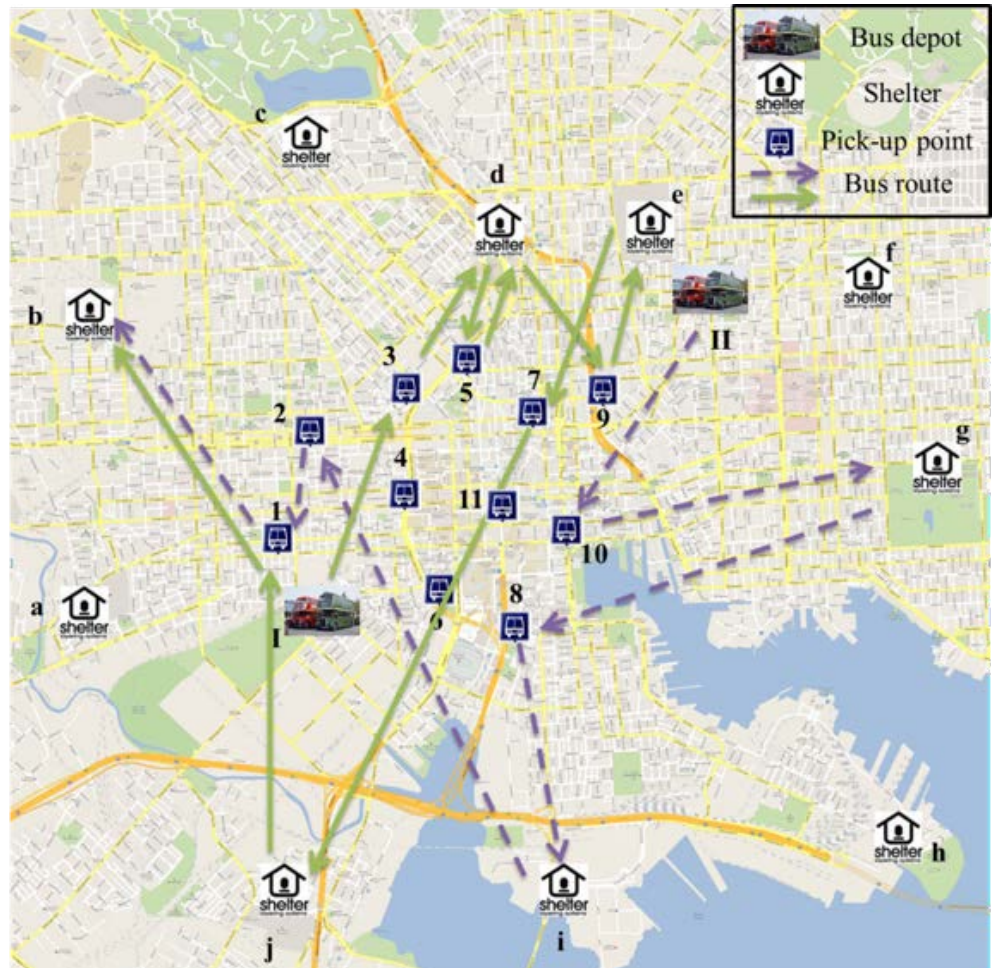
TABLE 4.

Time and Load Schedules for Bus Routes

Bus	Run	Depot	Pick-up Node	Destination	Bus load (persons)	Travel Time (min)
1	1	II	10	g	50	12
	2		8	i	50	14
	3		2, 1	b	40	18
2	1	I	3	d	50	10
	2		5	d	50	5
	3		9	e	50	7
	4		7	j	50	14
	5		1	b	30	12

As indicated previously, the improvements of this model compared to the previous studies are as follows:

- The time window of the pick-up request was used to restrict the maximum waiting time for evacuees.

- Pick-up nodes and targeted destinations do not have to be fixed in different runs.

- A time-dependent arrival curve at the pick-up locations is considered rather than assuming all evacuees are present at the location at the start.

To show the advantage of adopting the above improvements, we designed the following experiments:

- Use maximum waiting times of 2, 5, and 10 minutes.

- Fix the route in each bus run.

- Assume a full-demand start at pick-up locations.

Table 5 shows the minimum number of buses needed for the combination of the experiment settings. It can be seen that the longer the waiting time toleration, the fewer the number of buses are needed to service all evacuees. The strategy of fixing the route requires more vehicle resources than that of the flexible route. Assuming a full demand start, the number of buses needed is much higher, and most of the buses are scheduled simultaneously at the start of the evacuation, which may create a great burden on vehicle road traffic. The fixed and flexible route strategies under the full demand scenario do not make much difference, simply because most of the vehicles will be scheduled only for one run to meet the time window constraints.

TABLE 5.

Minimum Buses Required for Different Combination of Settings

Max Waiting	Arrival Curve		Full Demand
	Fixed Route	*Flex Route*	*Fixed Route*
2 min	87	73	87
5 min	73	53	73
10 min	46	31	46

Table 6 shows the distribution of evacuees to safety areas with and without destination capacity constraints. It can be seen clearly in the latter case that a few shelters closest to the pick-up locations become overcrowded and exceed their actual capacity. With the capacity constraints in the model, the evacuees are distributed more evenly among the destinations.

TABLE 6.

Minimum Buses Required for Different Combination of Settings

Destination ID	Capacity Constraints	
	With	*Without*
a	1,388	1,388
b	790	790
c	1,414	0
d	2,000	3,414
e	1,000	1,297
f	297	0
g	388	0
h	800	0
i	1,000	2,188
j	790	790

Conclusions

This paper proposed an optimization approach to determine pick-up locations for evacuees and allocate trips for buses for rescue purposes in transit-based evacuation planning. The proposed model was formulated as an integer linear program. In the model, evacuee demand points were clustered, and the center was defined as the pick-up location. Evacuees at each demand point were guided to nearby pick-up locations according to their proximity. The buses started from the bus depot to pick up evacuees and dropped them off at the safety area; after unloading, they headed towards other pick-up locations until all evacuees were picked up. An example using the Baltimore downtown area showed that the proposed model was more realistic and yielded better results compared to previous models under some given assumptions.

This research should be useful to planners, transit agencies, and emergency management officials, as effective and reliable transit evacuation planning is imperative and critical based on experiences from the past. For emergency management agencies, how to efficiently use available public transit resources without keeping citizens waiting too long is critical. The paper offers an analytical approach to provide answers to some of the issues for transit-based evacuation, such as the following: How many transit vehicles are needed and should be reserved in case of an emergency situation? How can a flexible rather than a fixed route for drivers be scheduled to increase evacuation efficiency? How can reasonable dispatch schedules for transit vehicles be generated to prevent unnecessary road congestion by sending all vehicles at once? How can pick-up points for emergency purposes be reasonably selected? In addition, since this model adopts a generalized approach and is based on a few location-specific assumptions, it can be applied to other cities as long as the input demand, road network, and transit data are present.

Although much has been done in this paper regarding transit evacuation modeling, the study is still exploratory and can be further improved. The limitations of this model include the following:

- The separation of the two modules (pick-up location selection and transit route optimization) may render non-optimality of the entire system. However, the current difficulty of combining these two lies in over-complexity of the model.

- Without distinguishing the categories and groups of evacuees, it is hard to preclude the possibility that people without special needs may occupy spaces reserved for special-needs groups, such as persons with disabilities and children.

- Although the computation speed is acceptable on a citywide transit network for evacuation within a reasonable time window, the NP-hardness of the integer-linear formulation may have an impact on the computation efficiency in the application of statewide networks and time windows in days and weeks.

- The model inputs currently rely on planning MPO data. However, there are numerous daily visitors in study areas that may not be captured by the data. Moreover, the actual number of evacuees at the time of evacuation is somewhat unpredictable. All these factors may impact the optimal solutions.

- Current travel estimation is not based on real-time traffic information during evacuation. Few previous studies have tried to combine passenger car and transit evacuation modeling under a unified framework. Thus, the capability of estimating travel time during evacuations will affect the solution quality of this model.

To address these modeling limitations, future studies could focus on directions such as integrating the two decision modules, paying attention to special group needs, designing an efficient algorithm to expedite the computation process, performing sensitivity analyses, and receiving real-time input data feeds and integrating them with the passenger car evacuation model.

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