A Two-Stage Optimization Framework for Optimizing Large-Scale Vehicular Evacuation Routing and Scheduling Operation with Uninterrupted Traffic Flow

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Abstract

In many emergency management operations, an efficient evacuation strategy is of great importance because if it is successful, it has the ability to significantly reduce the loss of property and human life. This paper develops a routing and scheduling optimization framework for large-scale vehicular evacuation. To guarantee high optimization efficiency, we consider the routing and scheduling optimization as a twostage problem instead of optimizing them as a whole (i.e. using time-space network). In the first phase, a multiple-objective mixed integer programming (MIP) model, with the objectives of minimizing the total in-network time and network clearance time is proposed to find an optimal routing plan. In the second phase, a simulation-based scheduling Heuristic is proposed to dynamically generate the time-dependent departure rates. A real-world evacuation scenario in Eastern Shore of Maryland is studied by using the proposed optimization model. The calculation results indicate a good optimization capability and flexibility of the proposed model.

Keywords: Vehicular Evacuation, Routing, Scheduling, Optimization, Heuristic

1. Introduction

Potential hazards exist in people's daily lives every day. From the perspective of cause, hazards can be classified into two categories: manmade hazards and natural hazards. Manmade hazards are events like terrorist attacks, chemical leaks or explosions and nuclear leakage. Natural hazards are events like hurricanes, earthquakes, tsunamis and other naturally occurring disasters. To prepare for these events, society should be alert and have a set of integrated operation plans to respond to these hazards. Due to high population density, urban areas are extremely vulnerable to the above-mentioned hazards. In urban areas, designing efficient evacuation plans is the responsibility of emergency management agencies or authorities. Emergency evacuation is generally defined as the immediate movement of human and properties from the potential threat or actual occurrence of a hazard. Appropriate routing and scheduling of the whole evacuation process are the most critical questions need to be addressed. Specifically, evacuation routing optimization aims to figure out a set of transportation routes, by which the evacuees can be evacuated out as soon as possible. On the other hand, the scheduling optimization is to find out a set of time stamps, when the evacuation should start (at different locations) in order to optimally utilize the transportation facilities. In evacuation scenarios with extremely high demand, another necessary output of the scheduling optimization is the time-dependent evacuee discharge rate. In other words, the evacuee should be evacuated in a proper order so as to maintain the maximal throughput of the evacuation process.

However, the problem is not that easy to solve. The high density of evacuee population and the complexity of the urban transportation network can pose challenges. The most critical problem for a large-scale urban evacuation is the intersection control and bottleneck identification. Actually, the intersection cannot be viewed as simply a network transshipment node. One reason is that the movements happening inside an intersection have multiple constraints. Another important reason is that a turn movement inside an intersection always has a relatively low travelling speed in comparison with the travelling speed in a general roadway link. As a consequence, the bottleneck is more likely to occur at an intersection due the low speed of turn movements. The proposed optimization framework consists of two parts. They are, evacuation routing optimization, which aims to figure out a set of transportation routes delivering the evacuee, and evacuation scheduling optimization, which calculates the time-dependent discharging rate of the vehicles at each origin. Moreover, traffic movement within intersection is explicitly considered in the routing optimization model to guarantee evacuation being conducted in a smooth way (*i.e.*, without traffic flow conflicts).

The paper is organized as follows. In Section 2, a brief literature review is provided in terms of the related evacuation planning techniques in three levels. They are, macroscopic level, mesoscopic level and microscopic level. Section 3 describes the development of the evacuation routing optimization model from a macroscopic level. In Section 4, to come up with an optimal demand discharging strategy, a simulation-based evacuation heuristic is developed and discussed. Section 5 conducts a real-world case study to test the proposed optimization framework, and the experiment results are summarized and discussed. Finally, Section 6 concludes the overall work.

2. Literature Review

Evacuation research can be further divided into two main tracks. One is pedestrianspecific evacuation, and the other one is vehicle-based evacuation. Detailed literatures on pedestrian-based evacuations can be found in [1][1]. Only vehicle-based evacuation techniques are reviewed here.

Macroscopic approaches are mainly used to approximately estimate the lower bounds for the evacuation time, like network clearance time and total evacuation time [3]. Models belonging to this type of approach do not consider any individual behaviors during the evacuation process. Yamada proposed a network flow approach to a city emergency evacuation planning[4]. Prescriptive evacuation routes and lower bounds of evacuation time were outputs of his model. However, due to the absence of a real-world simulation study, the lower bound is not validated. Cova et al., formulated the evacuation process as a lane-based mixed-integer programming problem with the objective of minimizing total evacuation distance [5]. With the consideration of traffic conflict within intersections, this model firstly distinguished the vehicle-based evacuation problem with other flow-based evacuation problems in history. Kim et al., presented the first macroscopic approach for finding a contraflow network reconfiguration to minimize the evacuation time[6]. Using the same concepts as [6], Xie et al. came up with a bi-level optimization model in which lane reversal and conflict elimination were optimized to assist the dynamic traffic assignment optimization[7], and Kalafatas et al., developed a CTM-based optimization model[8]. In addition, the geographical information system (GIS) has gradually become an important part in evacuation optimization and management because of its excellent capacity of processing big data and a more intuitional visualization. For instance, a multi-objective evolutionary algorithms under GIS system with the goal of optimally routing the evacuees into the safe areas was proposed in [9].

In the microscopic level, optimization models are mostly simulation-based since it is difficult to capture all network operational constraints and driver responses fully with mathematical formulations. Zou *et al.*, developed a simulation-based framework for the Ocean City area (Maryland) and investigated the efficiency of six given evacuation plans[10]. With consideration of traffic dynamics, an agent-based microscopic simulation model was used to analyze the efficiency of simultaneous and staging evacuation strategies, respectively[11]. A key conclusion is that staging evacuation strategy has a better performance in an urban evacuation scenario given the high evacuee demand. In addition, Lämmel *et al.*, developed a simulation model based on the MATSim framework to generate an optimal evacuation traffic assignment (*i.e.*, Nash equilibrium)[12]. By studying the human behavior in an emergency, Lindell developed an empirically based large-scale evacuation time estimate model (EMBLEM2)[13]. Different from the macroscopic models, human preparation time during an evacuation is always considered as part of the overall evacuation time. A comprehensive review on travel behavior modeling in dynamic traffic simulation models for evacuation can be found in [14].

Macroscopic models only have the capability of roughly estimating the evacuation time. As a result, the corresponding optimal routing and scheduling guidance are generated in ideal conditions and by relying on too many assumptions. Even though evaluating an evacuation plan in a microscopic way is able to incorporate more realistic details, it always take a huge amount of calculation time. Thus, some mesoscopic optimization approaches emerged by considering the performance gap between these two methodologies. Based on a vehicular traffic flow queueing model, Stepanov et al., proposed an integer programming model to minimize the average travel distance and network clearance time[15]. However, only routing guidance was provided using this model. Afshar et al., developed a scheduling heuristic framework for dynamic evacuation with the Spread-Squeeze concept[16]. Traffic dynamics were incorporated by a mesoscopic traffic simulator. But only evacuation scheduling information was generated. In order to reduce the "stop-and-go" delay, Bretschneider et al., developed a mixedinteger programming model with constraints of eliminating movement conflicts at an intersection to optimize the routing and scheduling problem by using a time-space network [17]. Although they named their model as a basic mathematical flow optimization framework, traffic dynamics with lane-based resolution were integrated. However, due to extremely high complexity of the time-space network, their model could not be solved directly. Specific Heuristic was proposed.

In the literature so far, seldom are there works directly dealing with large-scale evacuation routing and scheduling planning inside an urbanized area with many of evacuation sources. For large-scale evacuation planning with extremely high evacuee demand, the traditional time-space based optimization model becomes invalid. On the other hand, any simple macroscopic planning model might underestimate the evacuation time to large extend. Specifically, the existing evacuation planning models often ignores the impedance effect of uncontrolled intersection. Since the bottleneck is more likely to occur at an intersection due to the low speed of turn movements. Therefore, this research uses these considerations to propose a realistic and efficient evacuation operation framework specifically in an urbanized area.

3. Routing Optimization Model

3.1. Transportation Network Representation

The real world transportation network is abstractly represented by a directed graph G (N, A) with node set N and arc set A. In this model, every roadway intersection of the evacuation network is replaced by a set of intersection nodes (Figure 1). The decomposition of an intersection aims to further model the movement conflicts within an

intersection. Thus, node set N consists of four types of nodes: source nodes, transshipment nodes, sink nodes as well as a dummy node connecting every sink. The travel time and capacity on any arc connecting the real destination node and the dummy node are set to 0 and infinity, respectively. In a real world scenario, a source node might be any evacuation assembly point, like exit point of a specific district block, or entrance ramp of a freeway. Sink nodes can be shelters or exits of a particular hazard area. Transshipment nodes usually denote intersections or some specific roadway inner points. Sometimes a source node or a sink node can also function as a transshipment node. Arc set A consists of all the directed arcs connecting nodes in N.



Figure 1. An Abstract Evacuation Network Representation

To facilitate the representation of movement conflicts within an intersection, a twoindex based node notation is used here. The detailed demonstration of this type of network element notation was illustrated in [17]. For this type of notation, any node is labeled with a unique number pair (i,m). The first index *i* usually classifies a set of nodes with common properties or sharing a common intersection. For example, all nodes adjacent to intersection *i* can be labeled as (i,m), which indicates this is the mth node within intersection *i*. Thus, a directed arc can be labeled as [(i,m),(j,n)], which represents the arc from node (i,m) to node (j,n). In addition, to facilitate the conflicts modeling within an intersection *i*, we assume the nodes are incrementally labeled clockwise within an intersection (see Figure 2).



Figure 2. Node Labelling Illustration on a 4-leg (Left) and a 6-leg Intersection (Right)

3.2. Mathematical Model Parameters and Variables

Network elements:

 N_s N_t N_i N_d N_0 $N = N_s \cup N_t \cup N_d \cup N_0$ A_s A_n A_0 A =(i,1 [(i,

 μ^{-} μ^+ θ_i $L_{[(i)]}$

 $R_{[(i)]}$

$= A_s \cup A_n \cup A_0$	Set of network arcs
m)	Index of network node, where $i > 0$, when node (i,m) belongs to
	intersection <i>i</i> . <i>i</i> =0, otherwise.
[m), (j, n)]	Directed arc from node (i,m) to node (j,n)
[(<i>i</i> , <i>m</i>)]	Set of successor nodes of node (<i>i</i> , <i>m</i>).
[(<i>i</i> , <i>m</i>)]	Set of predecessor nodes of node (<i>i</i> , <i>m</i>).
	Degree of intersection <i>i</i>
i,m),(i,n)]	Set of intersection leg indices which are at the left-hand side of
	arc $[(i,m),(i,n)]$. In terms of the above node labelling rules,
	$L_{[(i,m),(i,n)]} = \{m \ mod\theta_i + 1, \cdots, \theta_i - ((\theta_i - n + 1)mod\theta_i)\}.$
(i.m). $(i.n)$]	Set of intersection leg indices which are at the right-hand side of
,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,	arc $[(i,m),(i,n)].R_{[(i,m),(i,n)]} = L_{[(i,n),(i,m)]}.$
Traffic parameters:	
[,m),(j,n)]	Capacity of arc $[(i,m),(j,n)]$, measured in veh/min.
(in)	Expected travel time from node $(i m)$ to node $(i n)$

Set of evacuation source nodes

Set of intersection nodes, which is a subset of N_t.

Set of arcs connecting real sink nodes and the dummy sink node

Dummy node connecting every real sink node

Set of transshipment nodes

Set of evacuation sink nodes

Set of general roadway arcs Set of arcs inside intersections

Set of network node

$C_{[(i,m),(j,n)]}$	Capacity of arc $[(i,m),(j,n)]$, measured in veh/min.	
$t_{[(i,m),(j,n)]}$	Expected travel time from node (i,m) to node (j,n) .	
$D_{(0,k)}$	Evacuee demand in origin $(0,k)$, where $(0,k) \in N_s$.	
$SC_{(j,n)}$	Capacity of sink node (j,n) , measured in number of evacuees.	
М	A preset large number, which should be greater than total number of source nodes.	

Decision variables:	
$lpha_{[(i,m),(j,n)]}^{(0,k)}$	Equal to 1 if arc $[(i,m),(j,n)]$ is chosen by source $(0,k)$, and 0 otherwise.
$\gamma_{[(i,m),(i,n)]}$	Equal to 1 if arc $[(i,m),(i,n)]$ is chosen in the routing plan, and 0 otherwise.
$\lambda^{(0,k)}$	Bottleneck flow/capacity ratio of the route of source $(0,k)$.
$f_{[(i,m),(j,n)]}$	Traffic demand assigned to arc $[(i,m),(i,n)]$ during the evacuation.

Since we are going to explicitly consider the traffic flow conflicts within an intersection in the following routing optimization model, two key notations $L_{[(i,m),(i,n)]}$ and $R_{[(i,m),(i,n)]}$ are introduced here. Specifically, $L_{[(i,m),(i,n)]}$ represents the set of intersection nodes located at the left hand side of the intersection arc [(i, m), (i, n)] and $R_{[(i,m),(i,n)]}$ represents the set of intersection nodes located at the right hand side of the intersection arc [(i, m), (i, n)]. For example, in the 6-leg intersection shown in Figure 6, $L_{[(i,6),(i,3)]} = \{(i,1),(i,2)\} \text{ and } R_{[(i,6),(i,3)]} = \{(i,4),(i,5)\} \text{ . In general, } (i,n) \cup$ $(i,m) \cup L_{[(i,m),(i,n)]} \cup R_{[(i,m),(i,n)]} = \{(i,1), (i,2), \dots, (i,\theta_i)\}.$

3.3. Mathematical Model Formulations

In this evacuation routing model, two objectives are defined from a macroscopic perspective. They are, total in-network time T_{in-net} and network clearance time T_{clear} . To begin with, we define the in-network time of a specific evacuee as the total duration it spends to reach to its safety destination since the evacuation process starts. Then, the total in-network time is the summation of every evacuee's in-network time. We define the network clearance time as the time duration to evacuate the overall evacuees out of the emergency region. This measurement indicator is of great significance in evacuate the people to some safety areas as fast as we can. A graphical illustration of these two evacuation performance indicators is shown in Figure 3. As is demonstrated, the integral of the remaining evacuee demand curve is the total in-network time, and the end time point of the remaining demand curve is viewed as the network clearance time.



Figure 3. Representation of Total in-Network Time and Network Clearance time with Respect to a General Evacuation Curve

In our mathematical model, we assume the preparation time of each evacuee can be ignored in comparison with the average loading waiting delay and the evacuation traveling time. Therefore, the total in-network time can be analytically derived as two parts (as is shown in equation 1), one is the total evacuation traveling time and the other one is the average loading waiting delay. The total evacuation travelling time is calculated as the evacuees' total traveling time once they are loaded into the network. It is noted that in this routing planning model the average travel time of a route is a constant once it is specified. Due to the large evacuation demand and limited egress, the evacuation operation is quite different with the case in general traffic assignment problems. Specifically, the traffic managers or operation authorities always take a high level of traffic control during the evacuation process in order to avoid the "traffic explosion". In other words, to provide the maximal network throughput per time unit, the emergency authorities always expect the evacuation flow travels exactly at the capacity of the roadway segments in the planning stage. Hence, it is realistic to fix the link travel time as its capacity travel time when we are planning an evacuation, and this is always the case in the evacuation research literature. As is showed in the second part of equation (1), the average loading waiting delay of an evacuee is determined (or constrained) by the bottleneck capacity on its egress route. We further assume the serving time of an arc can be approximately equal to the ratio of its accumulative demand and its capacity. This is also referred as the reserve capacity of a network link, which is always used in uncertain

traffic demand assignment problem [18].Specifically, given a link *l* traversed by a particular amount of vehicles f_l at its capacity c_l , where $f_l \gg c_l$, the ideal minimal serving time of this link is equal to the ratio of the total demand and its capacity, i.e. $\lambda_l = \frac{f_l}{c_l}$. Based on the first-in-first-out rule, the minimal waiting delay for a vehicle is zero while the worst case (*i.e.*, last arrival vehicle) is λ_l . Therefore, given the linear flow process (*i.e.*, the traffic flow is constantly equal to the link's capacity in order to maximize the link throughput), the average waiting delay for a vehicle is equal to $\frac{\lambda_l}{2}$. In this model, the bottleneck's serving time of a particular route is specified in constraint (4).

Objective function 1:

Total in-network timeT_{in-net}

$$\sum_{(0,k)\in N_{s}} D_{(0,k)} \sum_{[(i,m),(j,n)]\in A} [\alpha^{(0,k)}_{[(i,m),(j,n)]} \cdot t_{[(i,m),(j,n)]}] + \sum_{(0,k)\in N_{s}} D_{(0,k)} \cdot \frac{1}{2} \cdot \lambda^{(0,k)} \right\}$$
(1)

To provide an approximation of network clearance time, we further define the network's bottleneck as the link which has the largest ratio of total serving demand and capacity given a set of equilibrium evacuation flow upon an evacuation network. Then, under condition of uninterrupted traffic flow, the network's clearance time is approximated as the demand-capacity ratio of the network bottleneck (equation 2). This numerical value was also named as the link overload degree, and was argued to be of high correlation with the value of the network clearance time[19]. When the traffic demand is constantly high, it is approximately equal to the network clearance time.

Objective function 2: *Network clearance time*T_{clear}

 $\max\left\{\frac{\mathbf{f}_{[(i,m),(j,n)]}}{c_{[(i,m),(j,n)]}} | \forall [(i,m),(j,n)] \in A_s \cup A_n \right\}$

Subject to:

$$f_{[(i,m),(j,n)]} = \sum_{(0,k)\in N_s} D_{(0,k)} \cdot \alpha^{(0,k)}_{[(i,m),(j,n)]}, \forall [(i,m),(j,n)] \in A$$
(3)

$$\lambda^{(0,k)} = \max\left\{ \alpha^{(0,k)}_{[(i,m),(j,n)]} \cdot \frac{f_{[(i,m),(j,n)]}}{c_{[(i,m),(j,n)]}} | \forall [(i,m),(j,n)] \in A_s \cup A_n \right\}, \forall (0,k)$$

$$\in N_s$$
(4)

$$\sum_{(j,n)\in\mu^{-}[(0,k)]}\alpha^{(0,k)}_{[(0,k)(j,n)]} = 1, \forall (0,k) \in N_{s}$$
(5)

$$\sum_{\substack{(j,n)\in\mu^{+}[(i,m)]\\\in N_{t}}} \alpha_{[(j,n),(i,m)]}^{(0,k)} - \sum_{\substack{(j,n)\in\mu^{-}[(i,m)]\\\in N_{t}}} \alpha_{[(i,m),(j,n)]}^{(0,k)} = 0, \forall (0,k) \in N_{s}, \forall (i,m)$$
(6)

(2)

$$\sum_{(i,m)\in\mu^{+}[(j,n)]} \alpha_{[(i,m)(j,n)]}^{(0,k)} = 1, \forall (0,k) \in N_{s}, \text{and } (j,n) = N_{0}$$
(7)

$$\sum_{\forall (0,k)} \sum_{(i,m) \in \mu^{+}[(j,n)]} D_{(0,k)} \alpha_{[(i,m)(j,n)]}^{(0,k)} \le C_{(j,n)}, \forall (j,n) \in \mathbb{N}_{d}$$
(8)

$$\begin{aligned} \gamma_{[(i,m),(i,n)]} + \gamma_{[(i,h),(i,k)]} &\leq 1, \forall h \in L_{[(i,m),(i,n)]}, \forall k \in R_{[(i,m),(i,n)]}, \\ \forall (i,m) \in N_i, \text{and } \forall n \notin \{(m \mod \theta_i) + 1, (\theta_i + m - 2) \mod \theta_i + 1\} \end{aligned}$$
(9)

$$\begin{aligned} \gamma_{[(i,m),(i,n)]} + \gamma_{[(i,h),(i,k)]} &\leq 1, \forall h \in R_{[(i,m),(i,n)]}, \forall k \in L_{[(i,m),(i,n)]}, \\ \forall (i,m) \in N_i, \text{and } \forall n \notin \{(m \mod \theta_i) + 1, (\theta_i + m - 2) \mod \theta_i + 1\} \end{aligned}$$
(10)

$$\begin{aligned} \gamma_{[(i,m),(i,n)]} + \gamma_{[(i,h),(i,k)]} &\leq 1, \forall k \in L_{[(i,n),(i,m)]} \text{ and } h = n, \\ \forall (i,m) \in N_i, \text{ and } \forall n \neq (\theta_i + m - 2) \text{mod}\theta_i + 1 \end{aligned}$$
(11)

$$\begin{split} \gamma_{[(i,m),(i,n)]} + \gamma_{[(i,h),(i,k)]} &\leq 1, \forall h \in L_{[(i,n),(i,m)]} \text{ and } k = m, \\ \forall (i,m), \text{and } \forall n \neq (\theta_i + m - 2) \text{mod} \theta_i + 1 \end{split}$$
(12)

$$\sum_{(0,k)\in N_s} \alpha_{[(i,m),(i,n)]}^{(0,k)} \le M \cdot \gamma_{[(i,m),(i,n)]}, \forall [(i,m),(i,n)]$$
(13)

$$\alpha_{[(i,m),(j,n)]}^{(0,k)} \text{ and } \gamma_{[(i,m),(i,n)]} \in \{0,1\}$$
(14)

$$\lambda^{(0,k)} and f_{[(i,m),(j,n)]} \ge 0 \tag{15}$$

It is noted that the source node (0,k) mentioned in the above formulations can either be an original source node or a duplicated dummy source node. This is up to the abstracted network structure and the number of routes we expect. The traditional method to represent a source within a network is just abstract it as a single network node with a provided demand. Here we can choose to duplicate a specific source as multiple dummy nodes. For example, if we divide a single source node into four geographically identical dummy source nodes and use our routing optimization model to calculate based on this revised network, we can come up with at most four different evacuation routes for the original source. Therefore, by adding dummy nodes, the above formulations is able to calculate multiple evacuation routes for each physical source.

Constraint (3) assigns traffic demand to each arc based on the routing plan. Constraint (4) figures out the bottleneck demand/capacity ratio of each particular route based on the assigned traffic demand obtained in constraint (3). Constraint (5) guarantees that for each (dummy) source node, there is exactly one route outgoing from it. Constraint (6) indicates that, for each transshipment node, if a route goes into it, then the route must go out. Constraint (7) guarantees that for each source node there must be a sink node allocated to it. Constraints together (5-7) say that for each source node there is exactly one egress route linking it to a sink node. Constraint (8) limits the allocated evacuee demand at a specific exit point by considering the capacity of this destination node (*e.g.*, shelter capacity or exiting freeway capacity). Constraints (9-12) guarantee that there are no movement conflicts within any intersection or freeway interchange. This type of intersection conflicts elimination constraints were firstly proposed in[17], and explicitly

formulated the intersection-related constraint described [5].The model here takes advantage of the work in [17] and presents a more general form of the conflicts elimination constraints (as is shown in constraints 9-12). Constraints (9) and (10) guarantee that there are no movement conflicts depicted in Figure 4 (a), i.e. conflict between two arcs with no common nodes Constraints (11) and (12) eliminate the movement conflicts of the type depicted in Figure 4 (b), *i.e.*, conflict between two arcs with exactly one common node (*i.e.*, straight versus left turn or left turn versus left turn).In addition, to maintain the routing consistency within a controlled intersection, constraints (13) with the introduction of a big number M are added to the model (*i.e.*, if an intersection arc is prohibited then it cannot be used by any route). Finally, constraint (14) and (15) specify the feasible domain of the decision variables.



Figure 4. Two General Types of Intersection Movement Conflict

By observing the above formulations, the objective function related to constraint (4) is to be minimized, constraint (4) can be replaced by the following set of relaxed constraints (16). Thus, the routing model turns to be a quadratic programming model without any piecewise quadratic constraints.

$$\lambda^{(0,k)} \ge \alpha^{(0,k)}_{[(i,m),(j,n)]} \cdot \frac{f_{[(i,m),(j,n)]}}{c_{[(i,m),(j,n)]}}, \forall [(i,m),(j,n)] \in A_s \cup A_n, \forall (0,k) \in N_s$$
(16)

3.4. Solution Approach

In this section, a specific solution approach is proposed to transform the above quadratic model to a linear model, which can be generally solved. As is aforementioned, the routing optimization model is a multi-objective quadratic programming model with binary variables. Although there are some cutting-edge solvers which are capable to solve quadratic programming model, like Gurobi solver with barrier method, solving quadratic programming model with integer variables is still time-consuming. Here, we transform the above mixed integer quadratic programming (MIQP) model to an equivalent linear mixed integer programming (MIP) model by introducing the following auxiliary variables and constraints.

 $\omega_{[(i,m),(j,n)]}^{(0,k),(0,k')} \qquad \qquad \text{Auxiliary variable with respect to binary variable } \alpha_{[(i,m),(j,n)]}^{(0,k)} \text{ and } \alpha_{[(i,m),(j,n)]}^{(0,k)}, \text{ and } 0 \le \omega_{[(i,m),(j,n)]}^{(0,k),(0,k')} \le 1.$

By recalling the original formulations, we can find the only quadratic part is constraint (16), which can equivalently replace constraint (4). By plugging equation (3) in constraint (16), we can further express constraint (16) as,

$$\lambda^{(0,k)} \ge \alpha^{(0,k)}_{[(i,m),(j,n)]} \cdot \frac{\sum_{(0,k') \in N_s} D_{(0,k')} \cdot \alpha^{(0,k')}_{[(i,m),(j,n)]}}{c_{[(i,m),(j,n)]}},$$

$$\forall [(i,m), (j,n)] \in A_s \cup A_n, \forall (0,k) \in N_s$$
(16*)

Next, we introduce a new set of linear constraints that equivalently replace constraint (16*) by using the auxiliary variable $\omega_{[(i,m),(j,n)]}^{(0,k),(0,k')}$. The linear equivalent constraints (17-19) are given as below.

$$0 \le \omega_{[(i,m),(j,n)]}^{(0,k)} \le \alpha_{[(i,m),(j,n)]}^{(0,k)}, \forall [(i,m),(j,n)], \forall (0,k), and (0,k')$$
(17)

$$\lambda^{(0,k)} \ge \frac{\sum_{(0,k')\in N_s} D_{(0,k')} \cdot \omega^{(0,k),(0,k')}_{[(i,m),(j,n)]}}{c_{[(i,m),(j,n)]}},$$

$$\forall [(i,m), (j,n)] \in A_s \cup A_n, \forall (0,k) \in N_s$$
(18)

However, we also need to add another component to the original objective function 1, which desires a set of minimum values of $\lambda^{(0,k)}$. Let Q be a big positive number. Then the revised objective function is expressed as,

Minimize:
$$T_{in-net} - Q \cdot \sum_{\forall [(i,m),(j,n)]} \sum_{\forall (0,k)} \sum_{\forall (0,k')} \omega_{[(i,m),(j,n)]}^{(0,k),(0,k')}$$
 (19)

By replacing constraint (16) with (17-18) and replacing objective function (1) with (19), we equivalently transform the routing optimization model from MIQP to MIP.

Proof:

In constraint (16*), the nonlinear component is $\alpha_{[(i,m),(j,n)]}^{(0,k)} \cdot \alpha_{[(i,m),(j,n)]}^{(0,k')}$. This component is equal to 1 if and only if $\alpha_{[(i,m),(j,n)]}^{(0,k)} = 1$, and $\alpha_{[(i,m),(j,n)]}^{(0,k')} = 1$. If any of these two decision variables takes value 0, constraint (17) forces $\omega_{[(i,m),(j,n)]}^{(0,k),(0,k')} = 0$, and the same solution space will obtained by using constraint (18). If both of these two decision variables take value 1, constraint (17) as well as the additive big Q component in objective function will force $\omega_{[(i,m),(j,n)]}^{(0,k),(0,k')} = 1$ due to the minimization characteristic of the objective function, and the same solution space will obtained by using constraint (18). As is required.

Hence, the equivalent MIP model can be expressed as below.

Minimize:

$$T_{in-net} - Q \cdot \sum_{\forall [(i,m),(j,n)]} \sum_{\forall (0,k)} \sum_{\forall (0,k')} \omega_{[(i,m),(j,n)]}^{(0,k),(0,k')}$$
Minimize:

$$T_{clear} = \max\left\{\frac{f_{[(i,m),(j,n)]}}{c_{[(i,m),(j,n)]}} |\forall [(i,m),(j,n)] \in A_s \cup A_n\right\}$$
Subject to:
Constraint (3), (5-15), (17), and (18)

This two-objective MIP model can be solved iteratively by setting upper bounds for the second objective. Specifically, we can transform the two-objective MIP to a set of single-objective MIPs by incrementally setting an upper bound for the network clearance time.

Final optimal solution are obtained by further evaluating the optimal solution of each sub problem.

4. Scheduling Optimization Model

The optimization model in the above section generates a set of evacuation route(s) for each source from a macroscopic perspective. Since the evacuation demand is high, the overall demand cannot realistically be loaded into the network simultaneously. Thus, a scheduling strategy based on which the demand is efficiently discharged is necessary. In this section, a simulation based scheduling model is proposed to further determine the departure rate of each source from a mesoscopic level. With the output of routing optimization model, the scheduling model takes advantage of a greedy loading concept [20]to dynamically determine the discharge rate for each source with traffic dynamics being considered. In addition, to guarantee a high calculation efficiency, a traffic simulator from a mesoscopic level [16] is used. Pseudo codes of the algorithm are listed in Table 1. Moreover, a flow chart describing the general logic of the proposed Heuristic is given in Figure 5.

Table 1. Pseudo Code of the Proposed Simulation based Scheduling Heuristic

Algo	rithm: Simulation-Based Capacity Constrained Scheduling Algorithm
Phas	e I (Initialization):
Inpu	t and Preprocessing:
1)	Directed Network G (N , A) with a set of nodes N and a set of arcs A ;
2)	Set of r evacuation routes $R = \{R(n) n \in \{1, 2,, r\}\}$, where $R(n) = \{a_{n_1}, a_{n_2}, \cdots, a_{n_k}\}$ and $a_{n_k} \in A$;
3)	Allocated demand $D(n)$ of each route;
4)	Evacuation priority $P(n)$ of each source (route);
5)	Capacity $c(a_k)$ (with unit vehicle/hour) of each arc $a_k \in A$;
6)	For each arc a_k , findits future serving source sets $S(a_k) = \{n \forall n \text{ and } a_k \in R(n)\}$;
7)	Loading attraction factor for each source α (usually greater than 1), and discharging reduction factor β (usually smaller than 1, but should be strictly smaller than α)
8)	Simulation time interval Δt , during which a batch of vehicles will be discharged
9)	Set the initial time point of the simulation with $t = 0$;
Nota	tions in the calculation iteration:
(1)	L(n, t): Time-dependent maximal discharging rate of route <i>n</i> at time interval <i>t</i>
(2)	$\boldsymbol{\theta}_{a_k}(t)$: Time-dependent flow attraction factor of arc \boldsymbol{a}_k
(3)	Discharge (n, t) : Number of vehicles discharged from route <i>n</i> during time interval $(t, t + \Delta t)$
(4)	$\boldsymbol{\Gamma}$: Total number of vehicles getting out of the network by time point \boldsymbol{t}
(5)	Aming $d(t = At t)$. Number of unbigles existing the network within time interval

(5) *Arrived*($t - \Delta t, t$): Number of vehicles exiting the network within time interval $(t - \Delta t, t)$

Phase II (DischargingIteration):

Do

Determine the flow attraction factors for each arc a_k by using the following logics:

For each arc $a_k \in A$:

If a_k is congested (i.e. traffic density is over than its critical density):

Set $\boldsymbol{\theta}_{a_k}(t) = \boldsymbol{\beta}$

Else

Set $\theta_{a_k}(t) = \alpha$

End

For each route R(n) with demand D(n) > 0:

Determine its maximal discharging rate according to the capacity and the flow attraction factor of each arc $a_k \in R(n)$ by the following logic function:

$$L(n,t) = \min\{\theta_{a_k}(t) \cdot c(a_k) \frac{P(n)}{\sum_{m \in S(a_k)} P(m) \cdot \mathbf{1}_{\{D(m) > 0\}}} | \forall a_k \in R(n)\}$$

where $\mathbf{1}_{\{x\}}$ is indicator function with respect to statement x.

Determine the amount of vehicles to be discharged on route *n* by using the following logic:

 $Discharge(n, t) = \min\{D(n), L(n, t) \cdot \Delta t\}$

Update the remaining demand of source n:

$$D(n) = D(n) - Discharge(n, t)$$

End

<u>Load the determined discharged vehicles into the simulation network and</u> <u>run Traffic Simulator for duration Δt ;</u>

<u>Update the simulation clock by</u>: $\mathbf{t} = \mathbf{t} + \Delta \mathbf{t}$;

Update and record the number of exiting vehicles by:

$$\Gamma = \Gamma + Arrived(t - \Delta t)$$

While: $\Gamma < \sum D(n)$

Phase III (Report Generation):

1) Output the time-dependent discharging rate with respect to each source;

- 2) Output the time-dependent traffic statistics for each link;
- 3) Output the network clearance time and total in-network time.



Figure 5. Flow Chart of the Proposed Simulation-based Heuristic

In this scheduling algorithm, two heuristic factors are introduced. They are, loading attraction factor α and discharging reduction factor β . This is because even though the traffic congestion of a specific route is due to the total arrived demand from multiple sources, these separate demands might not be arriving at this bottleneck simultaneously,

especially at the beginning of the evacuation process. If we determine the discharge rate for these sources strictly according to the capacity of their prescriptive routes, there might be capacity waste within some time period due to the different arrival time of the flow from these sources. Thus, during the evacuation process, we expect to fully make use of the roadway capacity by introducing this loading attraction factor α . However, this might also cause traffic congestion if these flows nearly arrive at the same network link simultaneously. Therefore, we additionally introduce the reduction factor β . It aims to reduce the traffic congestion. In other words, if a link (not necessary the current bottleneck) suffers a traffic congestion, the reduction factor will decrease the discharging rate of its sources below the normal condition in the next iteration. In addition, the evacuation priority of each source is also taken advantaged of to determine its discharging rate. The incorporation of the source specific priority in the loading heuristic is simple. That is, the roadways' capacities are divided and reserved for each of the sources based on their weighted evacuation priorities. As is indicated in the above algorithm, a source with a relatively high evacuation priority is usually assigned with a larger discharging rate by reserving more roadway capacity for it.

5. Case Study

In this section, an application of the proposed optimization framework is conducted on a real-world scenario, the Eastern Shore of Maryland, which is located east of Chesapeake Bay and consists of nine of the state's counties. This area has a population of around 420,000 (2004 census). However, the population of Ocean City in the summer peak season can reach 150,000 to 300,000 compared with 7,000 to 25,000 during the off-peak season. The large population as well as the unique geographic location make both the Ocean City and other recreation areas located in the shore vulnerable to the threat of hurricanes. The map of the studied area as well as the geographic structure of the entire evacuation network is shown in Figure 6.The routing optimization model is implemented with C++ and CPLEX_12.51 Concert, and the scheduling simulation model is implemented with C++ in Visual Studio 2012.

Source Node	Total Demand (Vehicles)	
2	45,850	
1	43,830	
3	20,700	
9	20,000	
20	17,400	
26	16,800	
16	11,400	
40	6,400	
36	6,200	
46	3,500	

Table 2. Evacuation Demand Distribution in Eastern Shore Maryland



Figure 6. Map (a) and Major Evacuation Network (b) of Eastern Shore of Maryland

The amount and location of the major demand generation points (evacuation sources) are obtained by aggregating the sparsely distributed demand generation points. For example, if there are minor roads linking several different demand generation points to the same freeway entrance ramp or arterial entrance point and these demand generation points are geographically close to each other, then these demand points can be further aggregated to be a major demand point with access to the network. By referring to the Maryland SHA technical report [21], the distributed evacuation demand is summarized in Table 2.

It is necessary to mention that there are four special network nodes, which neither belong to the type of intersection nor the interchange section between freeways. They are, node 16, 22, 23 and 29, which denote Salisbury, Federalsburg, Bridgeville and Denton, respectively (Figure 7). Actually, these four nodes are dummy nodes representing a central area of a small town (center of a major demand source). In addition, among all of the 50 network nodes demonstrated in Figure 6, totally 20 of them are arterial intersections with at most four legs. They are, node 11, 12, 2, 3, 6, 8, 10, 49, 19, 20, 21, 24, 25, 50, 28, 30, 33, 34, 36, 39 and 40.



Figure 7. Four Special Network Nodes (Dummy Node) in Case Study

Before we further seek for multiple routes optimization results, we introduce a lower bound (LB) calculation technique for the network clearance time. Suppose a directed network G(N,A), where N denotes the set of network nodes and A denotes the set of network arcs. Let S be the set of all source nodes within G and T be the set of all exit arcs (link connected to sink nodes) of G. Then the network clearance time must have a lower bound calculated by equation (20).

$$L_{NC} = \frac{\sum_{n \in S} d(n)}{\sum_{(i,j) \in T} c(i,j)}$$
(20)

where, d(n) denotes the demand at source n, and c(i,j) denotes the capacity of arc (i,j). This lower bound of network clearance time is very obvious, since all of the arcs in set T (*i.e.*, exit arcs) constitute the minimal cut between this evacuation network and the outside regions. In this network, if we cut all the demand in Ocean city (*i.e.*, node 1, 2, 3 and 9) from the egresses, we can obtained one lower bound of the network clearance time as 20.05 hours. On the other hand, if we cut the demand in the whole area (*i.e.*, all sources) from the five egresses, we can obtain one LB of clearance time as 14.5 hours. Obviously, we conclude 20.05 hours as a better LB in terms of the network clearance time.

By applying the routing optimization model, optimal routing solutions under three strategies are obtained. Figure 8 demonstrates the evacuation performance indicators of each optimal routing solution. For example, if we consider exactly one route for each of the sources, we find the optimal solution with minimal network clearance time 30 hours, total evacuation time 653611 hours and total in-network time 3.34082e+006 hours from the macroscopic level. As we can see, if we relax the maximal route numbers of each source to three, we can obtain relatively a good routing plan with decreased total in-network time, as well as a LB gap of network clearance time less than 3.24%. The routing details of this solution are listed in Table 3. However, one should note that lager number of evacuation routes is more likely to increase the management cost and complexity from the operation perspective.



Figure 8. Total Travel Time, Total In-Network Time and Network Clearance Time Gap of Three Optimal Routing Strategies

Source	Optimized evacuation route	Bottleneck (network link)	Average Network- Loading Waiting Time (hour)
1	1->4->45->7->15->17->19->23->24->28->35->39->43	17,3-19,4	10.2408
	1->4->45->16->17->19->23->24->28->35->39->43	17,3-19,4	10.2408
	1->4->45->7->15->16->17->19->23->24->28->35->39->43	17,3-19,4	10.2408
16	16->18->20->26->30->31->32	26,2-30,1	10.3415
	16->18->20->26->30->47->31->32	26,2-30,1	10.3415
2	2->1->4->45->7->15->16->18->20->26->30->31->32	26,2-30,1	10.3415
	2->5->7->15->17->19->23->24->28->35->39->43	17,3-19,4	10.2408
	2->5->8->10->49->21->50->27->48->44	2,2-5,4	10.1887
26	26->30->47->31->32	26,2-30,1	10.3415
	26->30->31->32	26,2-30,1	10.3415
	3->6->10->49->21->50->27->48->44	3,2-6,1	10.35
3	3->6->10->49->21->23->25->29->30->47->31->32	3,2-6,1	10.35
36	36->47->31->32	31,2-32,0	8.60911
40	40->42	40,3-42,0	2.133
15	46->11->13->16->17->19->23->25->29->30->47->31->32	17,3-19,4	10.2408
46	46->11->13->16->18->20->26->30->31->32	26,2-30,1	10.3415
9	9->10->49->21->50->27->48->44	31,2-32,0	9.999
20	20->26->30->31->32	26,2-30,1	10.3415
	20->26->30->47->31->32	26,2-30,1	10.3415

Table 3. Optimized Evacuation Routes (at mo	ost Three Routes per Source)
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We accept the three-route routing plan as the optimal routing strategy due to its superiority over the other two and calculate the scheduling information based on it by using the proposed scheduling algorithm. By trial-and-error, Heuristic factors α and β are chosen as 1.6 and 0.9, respectively. At first, all sources are assigned with the same evacuation priority, and we call this as the homogeneous priority scenario. Figure 9 gives the time-dependent discharging rate of each source in this case. As is shown, finishing loading all of the demand into the network requires 1160 minutes (*i.e.*, 19.3 hours), and clearing all of the in-network demand requires 1320 minutes (*i.e.*, 22 hours). The dashed curve in Figure 10 is the corresponding evacuated demand curve. As is shown, the network throughput is relatively low at the very beginning of the evacuation process. This is because it usually takes evacuees sometime (*i.e.*, lead time) to reach the destination after they are loaded into the network. In this case, the lead time is around 2 hours.

In addition, we also investigate the impact of the evacuation priority on the evacuation process. As mentioned in Section 4, the heuristic discharging rate of a particular source will be affected by its prescriptive evacuation priority. Because we expect to allocate more network capacity to the source with a high priority. In this case study, sources located in Ocean City (*i.e.*, nodes 1, 2, 3 and 9) are assigned with a higher evacuation priority (*i.e.*, $P_i = 2$) to see what happens if the scheduling Heuristic is operating in such a hybrid priority scenario. As is shown in Figure 11, the network clearance time does not change too much for the scenario in which Ocean City has a larger priority. However, the time-dependent remaining demand in Ocean City area of the 'Hybrid' scheduling strategy is lower than that of the 'Homogeneous' strategy. In other words, if we assign a higher evacuation priority to the Ocean City area, the time-dependent throughput of its demand will increase. But the increased throughput will not be significant for this case (*i.e.*, increasing the priority of the whole Ocean City Area). The intrinsic reason for this is that Ocean City has a huge percentage of the total evacuation demand in the whole Eastern Shore Area (*i.e.*, 67.9%). In other words, the main competition of reserving the network capacity during the evacuation is coming from itself. Therefore, if we increase the evacuation priority of the Ocean City area simultaneously, the throughput of this area will be increased, but will not be that significant.



Figure 9. Time-dependent Discharging Rate of the Optimal Scheduling Strategy with Homogeneous Source Evacuation Priority







Figure 11. Time-dependent Remaining Demand Curves in Ocean City Area with Two Evacuation-Priority Scenarios

6. Conclusions

In this paper, a framework for large-scale vehicular evacuation routing and scheduling optimization was developed for the case of uninterrupted traffic flows. Instead of considering the routing and scheduling in a single problem (using a time-space network), we built the routing and scheduling models separately (*i.e.*, in two phases) so as to enhance the planning efficiency in an urgent real world evacuation scenario. In the first phase, a two-objective mixed integer programming model was formulated. Network clearance time and total in-network time were defined and adopted as the evacuation performance measurements in the routing model. In addition, to better guarantee the a smooth and more effective evacuation process, intersection movement conflicts were eliminated during the optimization process, since conducting the evacuation process based on uninterrupted traffic flow is proved to be more efficient and effective in recent studies. A general mathematical formulation of the intersection conflicts elimination constraints were provided as well. In the second phase, a simulation-based scheduling heuristic was developed with the concept from greedy algorithms. This heuristic is able to dynamically determine the discharging rate of each evacuation source with the assistance of an embedded mesoscopic traffic simulator. Meanwhile, the traffic condition of each time interval during the whole evacuation process can also be given from the embedded traffic simulator.

Moreover, the two-phase optimization of the routing and scheduling decision models also provides a high flexibility when using these models. In other words, either the routing optimization model or the scheduling heuristic can be separately adopted for a particular scenario, and they need not be used together. For example, if the evacuation routes have been pre-selected already by some other techniques, then one only needs to use the scheduling heuristic to further determine the demand discharging rate and view the simulation results.

A real-world evacuation scenario in Eastern Shore of Maryland was studied by using the proposed optimization model. Given extremely dense evacuation demand (around 190,000 vehicles), evacuation routes were firstly optimized by the routing model under three different route allocation strategies. They are, one route per source, at most two route per source and at most three route per source. As is indicated by the routing model, the last two routing strategies yield relatively better network clearance time and total innetwork time. The network clearance time is approximate 20 hours and the total innetwork time is around 660,000 hours. In other words, the average innetwork time of each vehicle is approximate 3.3 hours. With the optimized routing strategy as input, we applied the proposed scheduling Heuristic to iteratively figure out the time-dependent discharging rate for each route. As is shown in the last section, the discharging rate of each particular route is given as a time series, which can be referred for practical usage. The calculation results indicate a good optimization capability and flexibility of the proposed model.

The proposed evacuation optimization framework is still limited by two assumptions. They are, all evacuees will obey the routing and scheduling guidance, and there is no secondary incident happening during the evacuation process. However, this would not always be the case in a real-world evacuation scenario. For example, some of the evacuees might not strictly follow the disseminated evacuation guidance, or the prescribed plan might not be valid due to some secondary incidents. Therefore, the evacuation time calculated by the proposed optimization framework should be respected as a lower bound for the planning purpose. In other words, extra buffer time should be considered during the real-world application. Future research should be done in two aspects: (1) incorporating the impact of evacuee behavior in estimating the evacuation time; (2) extending the model to a dynamic optimization framework in order to deal with the occurrence of secondary incidents (*e.g.*, re-routing under traffic accident or secondary hazard).

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