

# Evacuation of a Highly Congested Urban City: the Case of Beirut

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## Abstract

For a given transportation network, evacuation route planning identifies routes and route schedules to minimize the time to evacuate the vulnerable population due to an imminent disaster. In this paper, we present a capacity-constrained routing optimization approach to maximize the total evacuees for short notice evacuation planning in case of both natural and/or man-made disasters. The methodology is scaled to a highly congested urban city with a transportation network capacity well below daily peak demands. As the evacuation route planning is computationally challenging, an evacuation scheduling algorithm was adopted to expedite the solution process. The algorithm uses Dijkstras algorithm to find the shortest path(s) and a modified greedy algorithm to assign maximum flows to selected paths given a specific schedule per time interval. A case study using real population and transportation network data was tested using the proposed methodology. The results show that the city is in grave danger due to the high population density and disproportionate network capacity.

**Keywords:** evacuation; route planning; disasters; capacity-constrained

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# 1 Introduction

Being sudden and dreadful, a disaster seriously disrupts the functioning of a community causing human, material, and economic losses that exceed the community's ability to cope with them. According to the Bureau for Crisis Prevention and Recovery of the United Nations Development Program (UNDP), over the past two decades, disasters have killed more than 1.3 million people, affected more than 4.4 billion and cost the global economy at least USD 2 trillion. It is estimated that each year, natural disasters in the form of earthquakes, hurricanes and cyclones cost more than USD 180 billion (United Nations Development Programme-Bureau for Crisis Prevention and Recovery, 2014). As such, emergency evacuation planning and management for natural or even man-made disasters, such as acts of war, is critical. Evacuation is the process of relocating people in danger from threatened places to safer locations in the most efficient and timely manner. As a result, preparation, modeling, testing and training of a proper evacuation plan are required as part of disaster preparedness. However, evacuation planning is a very complex problem involving many behavioral and management facets, including evacuee behavior, traffic control strategies, safe shelter locations/selection, and optimal route finding for displacement.

Besides efficiently and effectively conveying the warning system to the affected population, successful evacuation management plans should consider the capacity constraints inherent to most transportation networks (The Volpe National Transportation Systems Center, 2002). One complicating factor is that transportation infrastructure is neither planned nor designed to fully accommodate evacuation-level demand. In fact, it is simply not feasible, from an economic, environmental, or social point, to build enough transportation capacity to move an entire city population in a matter of hours. Therefore, efficient tools are needed to produce evacuation plans that identify routes and schedules to evacuate affected populations to safety in the event of natural disasters or terrorist attacks.

Evacuation planning methods can be categorized into two main approaches: the route-schedule planning approach and the traffic assignment-simulation approach. The former focuses on routing algorithms and network demands to produce origin-destination (OD) routes and schedules of evacuees on each route. Hamacher and Tjandra (2002) gave an extensive literature review of the models and algorithms used in these linear programming methods. The traffic assignment simulation-based method utilizes traffic simulation models to conduct stochastic simulation of traffic movements based on origin-destination traffic demands and uses queuing methods to account for road capacity constraints (Sheffi et al., 1982).

In this paper, we focus on an evacuation plan for a highly congested urban city with a transportation network capacity far below the daily peak demands. Realistic assumptions are made and tailored optimization techniques are devised to estimate the largest possible number of evacuees, the percentage evacuation given certain pre-disaster warning times, and the optimal routes to be taken and the schedule of each path adopted. Before we proceed to describe our strategy, we present relevant literature in Section 2. Subsequently, in Section 3, we define the problem and introduce our mathematical program for the path selection problem in emergency logistics management. In Section 4, we demonstrate the capabilities of our mathematical program applied to a case study on the highly congested city of Beirut, Lebanon and present the results. We then conclude with a discussion and directions for future research in Section 5.

## 2 Relevant Literature

Efficient evacuation planning involves identifying the best routes to be used, the time needed for evacuation, staging and others. Research focused on the route-schedule planning approach led to several methodologies to select optimal evacuation routes and the highest number of evacuees with the shortest clearance times. These mathematical methodologies can be divided into three different categories: static, dynamic (time-dependent) and continuous-time dynamic models. Consequently, traffic microsimulation models can then be used to assess the resulting route-schedule solution by tracking various network statistics, such as vehicle throughput, queuing and total delay times, and link/network utilization. Using such results, system bottlenecks can be identified and plans to resolve them can be proposed to reach optimized evacuation.

Starting with the static route-scheduling models, those are mainly focused on user equilibrium assuming that travelers have knowledge of the network utilization and that they select their corresponding routes to minimize the total system travel time rather than being selfish (Sheffi, 1985). Sherali et al. (1991) introduced a model that properly allocates shelters in order to reduce evacuation risks and costs. The model was formulated as a nonlinear mixed integer programming problem. Kongsomsaksakul and Yang (2005) tackled a similar problem using genetic algorithm (GA) based methodology (Saadatseresht et al., 2009). Cova and Johnson (2003) developed routing plans that minimize traffic delays at intersections, without considering the evacuation start and end times. Feng and Wen (2005) devised a multi-objective model to generate traffic control strategies, which is similar to the static two people Stackelberg model. Within the static route-scheduling problem, the level of service (LOS) of the highway network is assumed constant. However, during an evacuation, the network traffic conditions are highly dynamic - if not chaotic - which renders static assumptions inexact being unable to capture traffic queuing and congestion build-up over time. Thus, the forecasted network performance would most probably be different from the calculated optimal scenario (Xiongfei et al., 2010). As such, dynamic route-scheduling models gained more attention.

Though static route-scheduling models are easier to solve and capable of considering larger networks, dynamic route-scheduling models are more suited for evacuation applications. Dynamic models are time-expansion of a static network. Hence, these models are more complex and almost always require origin-destination (OD) data over predefined analysis time periods. Ford and Fulkerson (1958) discussed the classic dynamic traffic problem, without considering priority, impact time and variable link travel times. Miniéka (1973), Hajek and Ogier (1984) presented the universal maximum flow model which focused on maximizing the number of evacuees per safe area. Burkard et al. (1993) tackled the quickest flow problem minimizing the total time for evacuation using multiple exit paths. Barrett et al. (2000) proposed a dynamic modeling framework for both long-term and short-term hurricane evacuation planning, which was also applicable during real-time operations. (Ziliaskopoulos, 2000) applied the cell transmission model (CTM) by Daganzo (1994) to dynamic traffic assignment for evacuation modeling. The CTM-based dynamic model is able to capture traffic propagation and phenomena on highway networks, including congestion, incidents and shock-wave propagation. For a no-notice mass evacuation problem, Chiu et al. (2007) formulated the joint evacuation destination-route-flow-departure into a single-destination CTM-based system optimal dynamic traffic assignment program (Xiongfei et al., 2010).

Most recently, Osman and Ram (2011) presented the capacity constrained evacuation route scheduling (CCERS) model, which considers the network capacities at any discrete instant of time. By optimizing over a discrete period of time, the model identifies evacuation routes and scheduled departure from the start nodes of individuals. However, the model assumes that the optimal evacuation paths are readily available input, which is difficult for large networks. Similarly, the capacitated network flow problem (CNFP) addressed

82 by Lim et al. (2012) accounts for several challenges of evacuation modeling such as prioritizing the zones  
 83 based on the time of the impact and utilizing staging by allowing flow to be held at arcs not at nodes. Yet,  
 84 the CFNP requires the number of paths per centroid (a centroid is a node of positive supply) as input and  
 85 needs excessive computational time. Considering the time factor and the capability of arc reversal, Kim  
 86 and Shekhar (2005) and Rebennack et al. (2010) show that certain dynamic network flow problems are NP-  
 87 complete. To handle this issue, Lu and Shekhar (2005) propose a heuristic approach to solve the problem  
 88 of the minimization of evacuation egress time with time-dependent node and arc capacity. The heuristic  
 89 algorithm produces evacuation plans with specific routes and schedules using the static network. Kim et al.  
 90 (2007) improve the heuristic proposed in (Lu and Shekhar, 2005) in terms of reducing the runtime using the  
 91 min-cut max-flow theorem.

### 92 3 Problem Definition and Formulation

93 Lebanon is a country at permanent risk of small or large seismic threats since it lies along the 1000-km  
 94 long left-lateral Levant fault system. The latter fault system caused a tsunami-generating earthquake that  
 95 destroyed its capital, Beirut, in 551 AD. The UNDP (2004) Reducing Disaster Report highlights Lebanon as  
 96 one of the earthquake prone countries coupled with high urban growth rates and high physical exposure; thus,  
 97 is associated with higher risk levels. In particular, Beirut is highly vulnerable to earthquake and tsunami  
 98 risks being the largest most populated city in the country with about 1.5 million inhabitants (greater Beirut  
 99 area) of whom 50 percent are living on the coastline. Unfortunately, despite the commitment of the municipal  
 100 council to develop risk sensitive strategies for the city, the Municipality of Beirut has not received support  
 101 in this area.

102 A mass evacuation problem due to a tsunami is examined in this paper. The objective is to determine  
 103 the evacuation routes which minimize the evacuation time, while considering the evacuation start time and  
 104 the dynamically varying arc travel times due to congestion. To account for the time component, no exact  
 105 approach can provide a solution in polynomial time. For this purpose, we combined the minimum cost  
 106 dynamic network flow model with a modified version of an evacuation scheduling algorithm (ESA) to obtain  
 107 the evacuation plan. An ESA proposed by Lim et al. (2012) was modified accordingly to fit the Beirut  
 108 evacuation problem. In particular, we proposed different search approaches for assigning evacuation routes  
 109 and schedules to evacuees in different evacuation zones.

#### 110 3.1 Notation

111 Table 1 presents the needed nomenclature relative to a static network  $G = (N, A)$ . For consistency, we  
 112 adopted the same notation presented in Lim et al. (2012). In this formulation, the set of nodes is divided  
 113 into two subsets: impact nodes corresponding to evacuation zones and safe nodes that the evacuees are  
 114 trying to reach. Impact nodes are further classified as centroids and intersections. Centroids are the nodes  
 115 with positive supplies whereas intersections can not carry any supply. Additionally, the impact time of node  
 116  $i$  is defined as the amount of time that is available for evacuees at node  $i$  to evacuate before the impact of  
 117 the projected threat reaches that node.

### 3.2 Time-Expanded Reduced Network Construction

To maximize the flow from the source node to the sink node in a network within a given time period, we time-expanded the static network to a dynamic network over the planning horizon. In particular, all nodes and arcs of the static network are duplicated at each time period. The resulting arcs are called movement arcs  $A_M$ . For each node, there are also holdover arcs  $A_H$  which hold the flow of the corresponding node for one time period. It must be noted that the flow of movement arc  $(i, j)$  is bound by its own arc capacity  $\vartheta_{ij}$  at node  $i$  and time  $t$ . Meanwhile the flow of a holdover arc  $(i_t; i_{t+1})$  is bound by either its supply from  $t$  to  $t + 1$  (if it is a centroid) or by the capacity (for a safe node) at node  $i$  at time  $t$ ,  $u_i$ . In addition, only source and destination nodes have a capacity different than zero; i.e., an intersection node is not allowed to hold any supply from other impact nodes. Let  $G = (N^T, A^T)$  represent a time-expanded network of a static network  $G = (N, A)$  over a given evacuation planning horizon  $T$ . A dummy safe node ( $d$ ) is added to the static network with an infinite capacity, an infinite impact time, and a zero supply. All safe nodes are connected to ( $d$ ) through arcs with the capacity of the safe node and zero traveling time. These dummy nodes and arcs are used to find the shortest distance from centroids to the closest safe node. Given the shortest path, the greedy algorithm is applied on the time-expanded network to obtain the maximum possible number of evacuees that can flow through the path. If a path reaches capacity, it will not be used for evacuation and a second shortest path is generated, and so on. Finally, all the evacuation paths, flows, and leaving times for each centroid are reported as the output of the algorithm.

### 3.3 Sample Network Example

In this section, the mathematical and heuristic approaches are demonstrated using a sample network. The network is composed of a total of 5 nodes, where nodes (1) and (2) are source nodes, (3) is an intersection node, (4) and (5) are safe nodes. A dummy super-safe node (6) is added to have one overall sink. The arc capacities, travel times, supply and node capacity are presented in Figure 1. The notation  $(t_{ij}, cap_{ij})$  corresponds to the time needed to cross arc  $(i, j)$  and its respective capacity.

Table 1: Static network notation

Notation	Description
$N_d$	Set of all impact nodes
$N_s$	Set of all safe nodes
$N_c$	Set of centroids, $N_c \subset N_d$
$N = \{N_d \cup N_c\}$	Set of all nodes
$A$	Set of all arcs in the network
$t_i$	Impact time at node $i$
$s_i$	Initial number of evacuation vehicles located at node $i$
$u_i$	Maximum number of evacuation vehicles which can be located at node $i$ per time period
$\vec{t}_{ij}$	Travel time on the connecting road between node $i$ and node $j$ , ( $\vec{t}_{ij} = 1$ )
$\vartheta_{ij}$	Maximum number of evacuation vehicles which can enter into arc $(i, j)$ per time period
Node $i \in N$	Physical location including impact nodes and safe nodes
Arc $(i, j) \in A$	Connecting road between node $i$ and node $j$

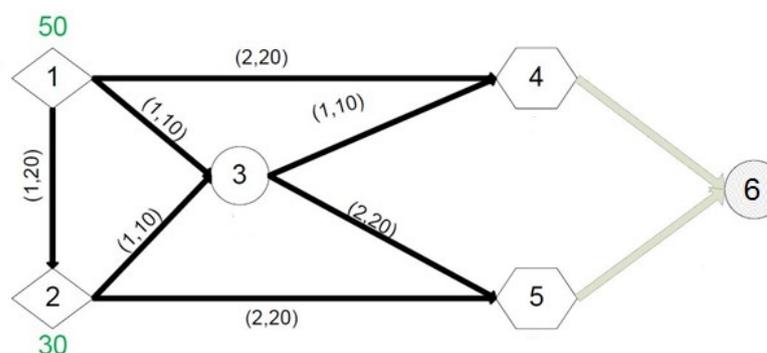


Figure 1: Sample network for demonstration

### 3.4 Network Optimization Techniques

The proposed algorithm utilizes the depth first search (DFS), the Dijkstra's shortest path algorithm (Dijkstra, 1959) and the greedy algorithm for maximum flow. The DFS technique is used to find all nodes connected to a centroid. As input, this technique needs the centroid in question and the time expanded network  $G$  of a static network over a given evacuation planning horizon  $T$ . The output is a smaller network  $G'$  that would facilitate and reduce the time needed to search for all paths starting with centroid  $v$ . Then, the shortest path algorithm is deployed to find the paths that require the least time. In fact, after applying the DFS for a centroid  $v$ , all nodes connected to  $v$  are stored and all paths emanating from  $v$  are enumerated. The paths are then ranked in order of increasing travel times. The greedy algorithm presented in Lim et al. (2012) uses a simplified version of the algorithm presented in Ford and Fulkerson (1958), by finding the maximum flow over a path  $P$  in the static network for each time interval. Since the maximum flow of a path,  $P$ , in the static network is limited by the lowest capacity of an arc associated with  $P$ , a more economical search is used. The search focuses on arc capacities between their relevant start and end time, where the start time is noted as the current time plus the time needed to cross the arc immediately preceding it.

### 3.5 Evacuation Algorithm

Our proposed algorithm is executed as follows:

A flowchart of the algorithm is shown in Figure 2.

## 4 Computational Tests

### 4.1 Case Data

Downtown Beirut is approximately 100 km<sup>2</sup>, which was divided into 15 population zones bound by major highways and intersections of the transportation system. Moreover, 135 nodes and more than 300 links were identified within the zones. The orientation, capacity per direction (number of lanes) and length of each roadway-link were obtained using Google Maps, measured using surveying equipment during site visits or based on the official plans provided by the Council for Development and Redevelopment (CDR). The road link lengths were used to calculate the corresponding free-flow travel times. Based on the 2004 reported data by the Lebanese Central Administration of Statistics (most recent available data), 390,503 persons lived

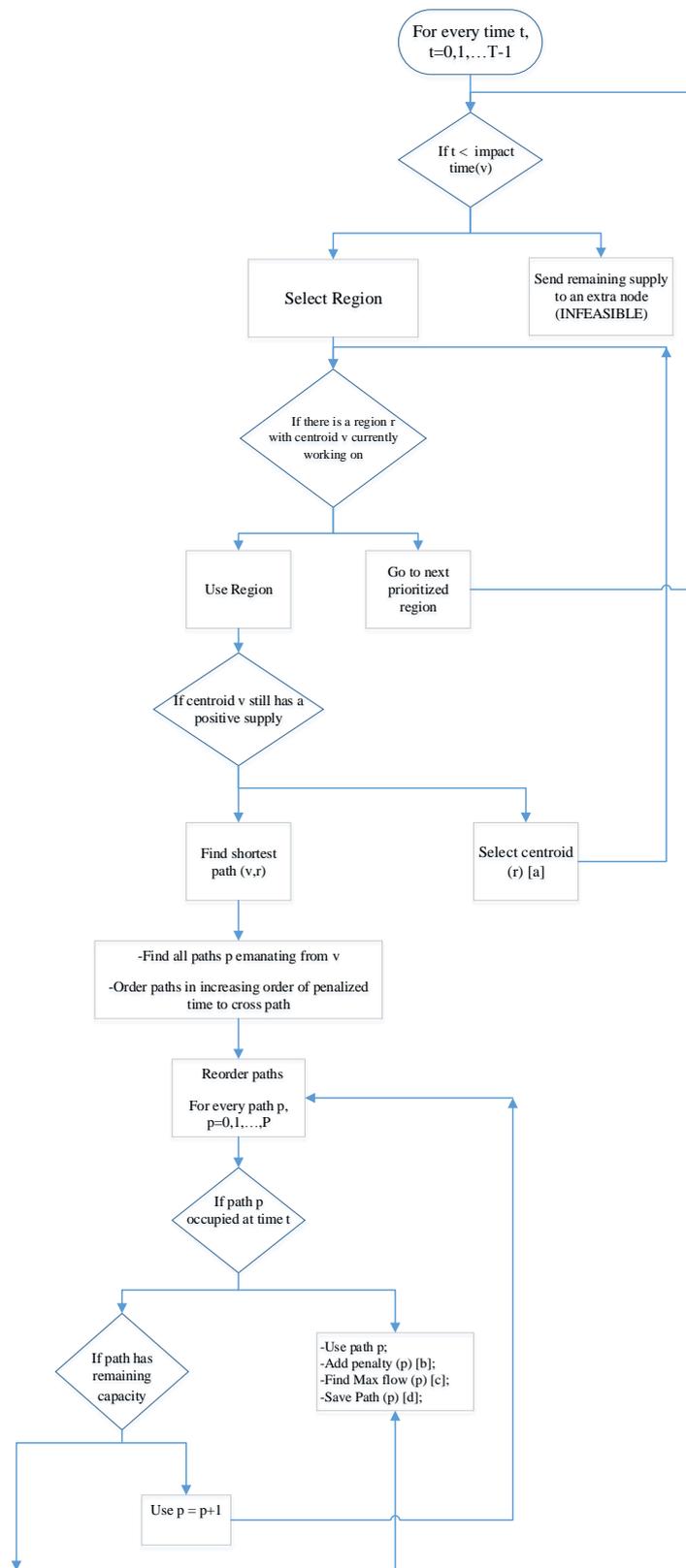


Figure 2: Proposed evacuation algorithm

**Algorithm 1** Proposed evacuation algorithm

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1: procedure INITIALIZE(network  $G = (N, A)$ )
2:   where,  $N$  is the set of all nodes;  $A$  is the set of all arcs
3:   for every node  $i \in N$  do
4:     determine the safe nodes,  $N_s \in N$ 
5:     determine the centroids,  $N_c \in N$ 
6:     determine the intersection nodes,  $N_i \in N$ 
7:     determine the impact time at every node  $i \in N$ 
8:   end for
9:    $N = \{N_s \cup N_c \cup N_i\}$ 
10:  for every arc  $(i, j) \subset A$  do
11:    define the time needed to cross arc  $(i, j)$ 
12:    define the capacity of each arc  $c_{ij}$ 
13:  end for
14:  for every centroid  $i \in N_c$  do
15:    define the supply  $s_i$ 
16:  end for
17: end procedure

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168 in Beirut. Given that the city is densely populated, we approximated each zone's population based on the  
169 ratio of its area to the total area of the city. The population of each zone was then divided by 4 to find the  
170 demand in vehicles rather than in persons (assuming each vehicle would carry 4 people during evacuation).  
171 The supply of each zone was further divided equally over the centroids within the zone. The impact time  
172 of the tsunami was calculated based on an assumed moving speed of 120 km/h. Accordingly, the nearest  
173 distance from the coast to each zone centroid was used to calculate the zone-specific impact times.

174 The zones were assigned priorities according to their respective impact times. Then, the 67 total zone  
175 centroids were grouped per zone. The nodes' data - type (centroid, intersection, or safe), impact and warning  
176 time - and the arcs' data - free-flow travel time and the link capacity - are input to the heuristic model. The  
177 proposed algorithm is coded using Java and complied with Netbeans7.0.1.

## 178 4.2 Analysis Scenarios

179 The link travel time from node  $i$  to  $j$  depends on the number of evacuated vehicles occupying link  $(i, j)$ .  
180 However, the dynamic nature of the link travel time was not accounted for in the input, which only considered  
181 the free-flow travel time. For that, the travel time is updated per time step according to the following  
182 relationship:

$$T_f = T_i \times \left(1 + \alpha \left(\frac{v}{c}\right)^\beta\right) \quad (1)$$

183 where,  $T_f$  is the link travel time given a certain evacuation flow,  $T_i$  is the free-flow travel time,  $v$  is the  
184 current evacuation volume over the link,  $c$  is the link capacity, and  $\alpha, \beta$  are constants based on the Bureau  
185 of Public Roads (BPR) function with values of 0.15 and 4, respectively (U.S. Department of Transportation,  
186 Federal Highway Administration, 2009).

187 In each scenario, a different volume-to-capacity ratio ( $v/c$ ) is used, ranging from 0.1 to 1. Regardless of  
188 the  $v/c$  ratio, the same fraction is multiplied by the paths capacity to render the scenarios more realistic.  
189 The scenarios were also tested given 6 different warning times. The end results are summarized in Table 2.

190 Three scenarios are specifically highlighted, which include:

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**Require:** to connect all safe nodes to a dummy node ( $d$ )

18: where, ( $d$ ) has infinite capacity, infinite impact time, and zero supply

**Require:** prioritize zones,  $R \leftarrow \{R_1, R_2, R_3, \dots, R_n\}$

19: where,  $R_1$  is the first in the priority list  $R$

20: **function** (Select Centroid ( $r$ )) ▷ select the next centroid in the zone

21:     **function** (Add Penalty ( $\Delta_{ij}$ ))

22:         **for** every path  $P$  **do**

23:             **for** every arc  $(i, j) \in P$  **do**

24:                 update arc travel times by adding a penalty term,  $\Delta_{ij} > 0$ , to the original  $t_{ij}$

25:                  $\Delta_{ij} = \mu \frac{\delta_v}{m_{P_v}}$

26:                 where,  $\mu > 0 \leftarrow$  penalty factor to the arc travel time in the generated path  $P_v$ ,

27:                  $m_{P_v}$  is the number of arcs of the path  $P_v$ ,

28:                  $\delta_v = \frac{s_v}{U_{P_v}} \leftarrow$  path utilization factor

29:                 where,  $s_v$  is the supply of node  $v$  and  $U_{P_v}$  is the capacity of the path  $P_v$

30:                 ▷ A large utilization factor of path  $P_v$  in the current iteration implies a substantially lower utilization in the next iteration, as arcs in this path have been highly utilized. This is translated by imposing a higher penalty on all arcs along this path.

31:                 ▷ Consider two paths having the same ratio  $\delta_v$ , then the path with a higher  $m_{P_v}$  will have a lower penalty so that some arcs within the path may be re-utilized in future iterations. The reason for this travel time update is to encourage new paths' usage.

32:             **end for**

33:         **end for**

34:

35:     **function** (Find Max Flow ( $P$ )) ▷ Find the maximum flow that path  $P$  can carry from time  $t$  to  $t - 1$

36:         ▷ For example, consider that path (1 - 3 - 5) is being used from  $t = 1$  to  $t = 3$ . At  $t = 2$ , we selected another path (1 - 2 - 3 - 5) to use. We know that arc (3 - 5) is being used at this time for the former path; thus, we only consider its remaining capacity not the initial one.

37:

38:     **function** (Save Path ( $P$ ))

39:         **for** every arc  $(i, j) \in P$  **do**

40:             record the path, start time  $t$  and finish time  $t + t_{ij}$

41:             update the supply of centroid  $v \leftarrow (s_v = s_v - flow(P))$

42:             **if** supply at  $v$ ,  $s_v = 0$  and zone  $r$  still has more centroids **then**

43:                 centroid ( $r$ ) is selected

44:             **else** another zone is selected

45:             **end if**

46:         **end for**

47:     **end function**

48:     **end function**

49:     **end function**

50: **end function**

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Table 2: Percent evacuated (PE) and evacuation time (ET) for each scenario

V/C	Warning Time (min)											
	10		30		60		120		180		240	
	PE (%)	ET (min)	PE (%)	ET (min)	PE (%)	ET (min)	PE (%)	ET (min)	PE (%)	ET (min)	PE (%)	ET (min)
<b>1</b>	5.0	17.6	11.3	37.6	19.4	67.6	33.8	127.6	45.8	187.0	54.1	243.4
<b>0.8</b>	6.2	17.7	13.3	37.7	22.5	67.7	37.4	126.8	48.5	186.4	52.2	246.9
<b>0.6</b>	5.2	17.7	11.8	37.7	19.9	67.7	34.4	127.4	45.0	187.4	51.3	245.9
<b>0.4</b>	4.1	17.7	8.6	37.7	15.2	67.7	26.0	127.3	35.1	187.3	43.1	247.3
<b>0.2</b>	2.1	17.7	4.7	37.7	8.2	67.7	15.1	127.7	20.8	187.7	25.9	247.3
<b>0.1</b>	1.1	17.7	2.6	37.7	4.7	67.7	8.2	127.7	11.9	187.7	15.5	247.7

191 1. Warning time 240 minutes and a  $v/c$  ratio of 1

192 2. Warning time 10 minutes and a  $v/c$  ratio of 0.1

193 3. Full evacuation

194 For the first scenario, assuming 240 minutes of warning time and a  $v/c$  ratio of 1, only 54% of Beirut's  
 195 inhabitants could be potentially evacuated taking a total of 243.4 minutes of evacuation time. As shown  
 196 in Figures 3 and 4, most zones got a share of evacuation except for Zone 8, which did not get any of its  
 197 inhabitants evacuated. This is due to two main reasons: Zone 8 is in the center of the city and it was assigned  
 198 a low priority, so evacuees from other zones went through it saturating its network capacity. In addition,  
 199 zones located near the coast, which were assigned highest priorities (specifically Zone 1 which comprises the  
 200 American University of Beirut and its Medical Center), were fully evacuated, similar to most zones near  
 201 the exits. Still, being a zone near the exit does not guarantee full evacuation (i.e. Zones 6 and 9), as  
 202 the evacuation flows from Zones 1, 2 and 3 supersede evacuation from those zones because of the priority  
 203 ranking. The remaining zones had evacuation percentages less than or equal to 45%.

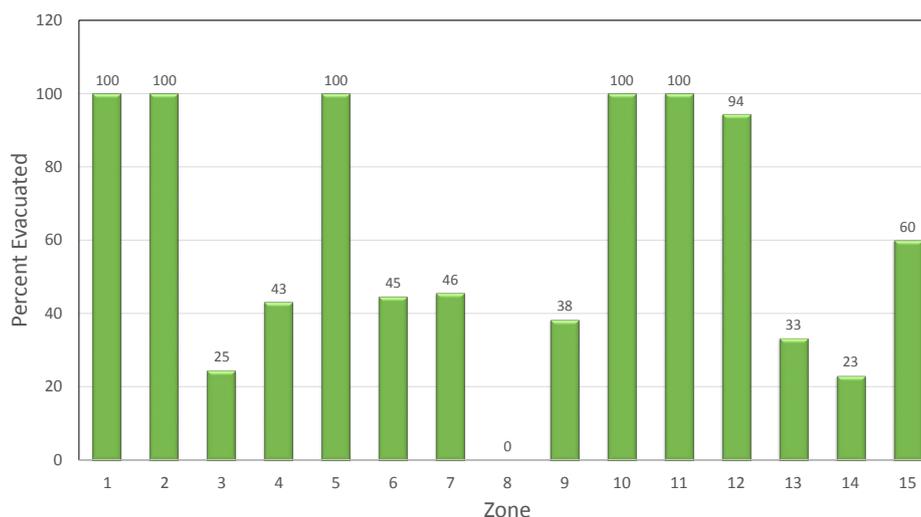


Figure 3: Percent evacuation per zone given warning time of 240 min and  $v/c$  ratio of 1.0

204 The second evacuation scenario assumes a very short warning time of 10 minutes and low link utilization

205 with  $v/c$  ratio of 0.1. In contrast to the first scenario, this scenario allowed the evacuation of only 5% of  
 206 Beirut's inhabitants. Figure 5 shows that zones located at the exists were mainly the ones capable of partial  
 207 evacuation, i.e. Zones 9, 10, 11, 12 and 15. Yet, the highest evacuation rate given this scenario is for Zone 1,  
 208 which comprises the largest university and medical center in the country, for which we intentionally assigned  
 209 extremely high priority. In future work, the authors plan to test various priority ranking schemes that would  
 210 optimize/maximize evacuation rates given certain warning times. Thus, a warning time of 10 minutes is  
 211 too small and evacuation management authorities should work on increasing the warning time by proper  
 212 coordination with the concerned parties. The variation of the evacuation percentage with respect to the  
 213 warning time and the  $v/c$  ratio is presented in Figure 6. It is clearly logical that the percent evacuated will  
 214 increase as the warning time increases. In addition, the percent evacuated also increases with the increase of  
 215 link utilization, represented by the  $v/c$  ratio. The more volume we allow on the links (higher  $v/c$ ), the more  
 216 people we can evacuate. However, the use of the BPR function leads to high travel times as the  $v/c$  ratio  
 217 approaches 1.0. As a result, we notice in Figure 6 that the curve with  $v/c = 0.8$  produces better evacuation  
 218 percentages than that of  $v/c = 1.0$ .



Figure 4: Percent evacuation per zone given warning time of 240 min and  $v/c$  ratio of 1.0

219 As for the third scenario, its purpose was to find the warning time needed to be able to evacuate everyone  
 220 from the city. Several warning times were tested; however, a minimum warning time of 1000 minutes (equal  
 221 to 16.67 hours) is needed to guarantee a complete evacuation effort. Such a warning time is relatively lengthy,  
 222 and it is normally not possible to predict such disasters 17 hours in advance. However, the results definitely  
 223 highlight the deficiency in the transportation network capacity, which is dependent on minor expressways  
 224 rather than major freeways. Usually, the highway network of major urbanized cities comprise main arterials  
 225 that convey traffic in and out of the city. Given the limited network, it would be virtually impossible to save  
 226 all Beirut's inhabitants from an imminent natural disaster.

## 227 5 Discussion

228 In this paper, we demonstrate that pre-disaster preventions are crucial for every urbanized area. For Beirut,  
 229 the evacuation plan focused on the number/percentage of evacuees and the schedule of optimal routes to be  
 230 adopted, with a time step of 0.01 minute. Several scenarios were tested, taking into account different  $v/c$

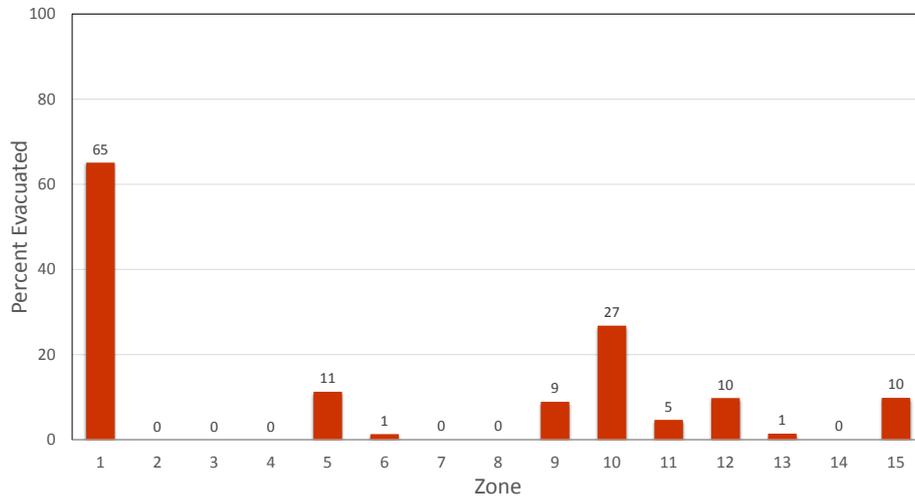


Figure 5: Percent evacuation per zone given warning time of 10 min and v/c ratio of 0.1

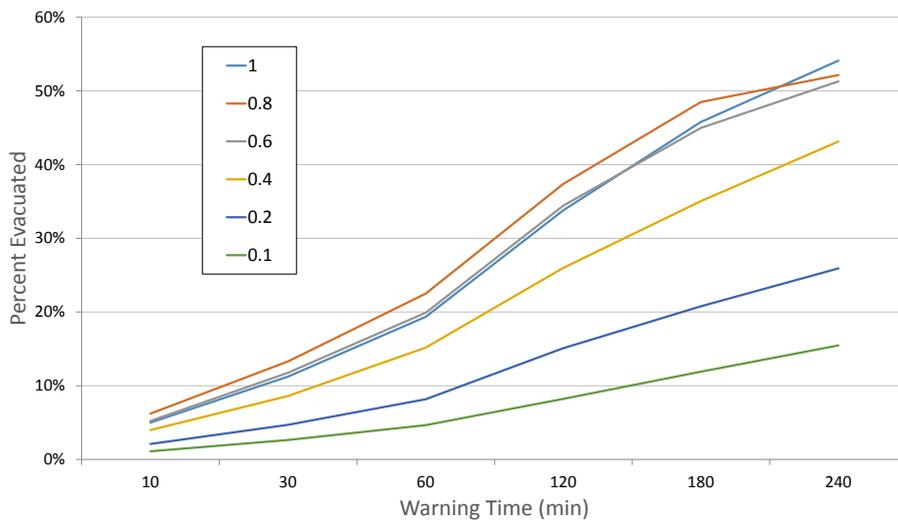


Figure 6: Variation of percent evacuation with warning time and v/c ratio

231 ratios and various pre-disaster warning times. We show that full evacuation of Beirut's inhabitants due to a  
232 massive tsunami - requiring a warning time of 17 hours - is not logically possible given the existing limitations  
233 in the transportation network. As such, a proper early warning mechanism is needed to maximize evacuation  
234 due to natural or man-made disasters. The findings in this paper emphasize the need for a concrete planning  
235 framework for disaster preparedness for Beirut. In addition, for any evacuation strategy to be effective, it  
236 should be complemented by other supporting procedures, such as installing early detection/warning systems  
237 for tsunamis. Enhancing the local watch centers and/or their collaboration with international agencies will  
238 further help the successful achievement of the evacuation plan. Most importantly, aiming for adequate level  
239 of public awareness of the steps needed during evacuation process is crucial. Finally, training policemen,  
240 civil defense, and Red Cross groups is a vital element of the process. On the other hand, a closed form  
241 analytical solution was not possible due to the size of the network modeled; a situation which reiterated  
242 the need for heuristic modeling when networks increase in size. Future work include the development of  
243 a traffic microsimulation model for Beirut which can then be used to assess the resulting route-schedule  
244 solution by tracking various network statistics, such as vehicle throughput, queueing and total delay times,  
245 and link/network utilization. Using such results, system bottlenecks can be identified and plans to resolve  
246 them can be proposed to reach optimized evacuation.

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