Data-driven Agent-based Models for Optimal Evacuation of Large Metropolitan Areas for Improved Disaster Planning

Extended Abstract

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ABSTRACT

Evacuation plans are designed to move people to safety in case of a disaster. It mainly consists of two components: routing and scheduling. Joint optimization of these two components with the goal of minimizing total evacuation time is a computationally hard problem, specifically when the problem instance is large. Moreover, often in disaster situations, there is uncertainty regarding the passability of roads throughout the evacuation time period. In this paper, we present a way to model the time-varying risk associated with roads in disaster situations. We also design a heuristic method based on the well known Large Neighborhood Search framework to perform the joint optimization task. We use real-world road network and population data from Harris County in Houston, Texas and apply our heuristic to find evacuation routes and schedules for the area. We show that the proposed method is able to find good solutions within a reasonable amount of time. We also perform agent-based simulations of the evacuation using these solutions to evaluate their quality and efficacy.

KEYWORDS

Evacuation; Routing; Scheduling, MIP; Heuristic; Simulation; Large Neighborhood Search; Individual and Social Utility

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1 OVERVIEW

Evacuation plans are essential to ensure the safety of people living in areas that are prone to potential disasters such as floods, hurricanes, tsunamis, and wildfires. Large scale evacuations have been carried out during the past hurricane seasons. For instance, before the landfall of Hurricane Rita (2005), about 2.5 million individuals were evacuated from the coastal areas of Texas [3]. At such a scale, it is essential to have an evacuation plan to ensure that people can evacuate in a safe and orderly manner. A plan consists of two components: (*i*) Evacuation Routes, which are paths that the evacuees will follow to reach safety, and an (*ii*) Evacuation Schedule which dictates when people should leave from different regions. The goal is to minimize the average evacuation time. Jointly optimizing over the routes and schedule is a computationally intractable problem and thus finding optimal evacuation routes for a large fraction of the population in a city becomes especially challenging. Furthermore, the availability of all road segments throughout the entire evacuation time period is not guaranteed. For instance, before a hurricane makes a landfall, roads in low lying areas can become flooded due to heavy rainfall.

Our contributions in this paper are as follows: **First**, we present a heuristic method, designed based on the Large Neighborhood Search framework [8, 9], to perform joint optimization over evacuation routes and schedule. We model the evacuation planning problem as a Mixed Integer Program (MIP) and use the heuristic method to solve this MIP. **Second**, we choose Harris county in Houston, Texas, with a population of ~ 1.5 million and a history of major hurricanes, as our study area and propose an evacuation plan for it. We use real-world road network data from HERE [6] and population data generated by Adiga *et al.* [1] to construct a realistic problem instance. We show that our method can find good solutions in a reasonable time. We also validate the efficacy of the solution by simulating evacuations in the study area using our agent-based discrete event queuing simulation system (QueST) [7]. **Third**, we propose a way to model the time varying risk associated with each road during evacuation. **Finally**, we define individual utility for each evacuee that represents how good an evacuation plan is for the evacuee, and a social utility to quantify the quality of an evacuation plan. We then perform experiments to observe how these values are affected by failure of edges during evacuation.

2 PROBLEM FORMULATION

For the joint optimization problem, we have the following as input: (*i*) A directed graph $\mathcal{G} = (\mathcal{N}, \mathcal{A})$ representing a road network. Here, $\mathcal{N}$ denotes the set of vertices, $\mathcal{A}$ denotes the set of edges. Each edge has a constant travel time and a flow capacity. (*ii*) A set of source nodes $\mathcal{E} \subset \mathcal{N}$ and the number of evacuees at each of these nodes. (*iii*) A set of safe nodes $\mathcal{S} \subset \mathcal{N}$.

The goal is to find: (*i*) A set of convergent routes, one route from each source node to one of the safe nodes. A route is a sequence of edges where no edge is repeated. 'Convergent' means evacuees coming to the same intersection follow the same path afterwards. (*ii*) A schedule for evacuation, i.e., when should evacuees leave from their source nodes. Evacuees are not allowed to stay/wait in *transit* nodes (nodes that are not source or safe nodes).

The objective is to minimize the total evacuation time, which is equivalent to minimizing the average evacuation time.

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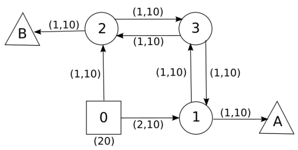

Figure 1: Sample Network. Edges are labeled with their travel time and flow capacity respectively. The number under square nodes denote number of evacuees.

A sample road network is shown in Figure 1. Here, we have three types of vertices: sources (squares), safe nodes (triangles), and transit nodes (circles). Their respective sets are denoted by $\mathcal{E}$, $\mathcal{S}$, and $\mathcal{T}$ ($\mathcal{N} = \mathcal{E} \cup \mathcal{T} \cup \mathcal{S}$).

$$\min \sum_{e \in \delta^-(v_t)} \phi_e * t_s(e) \tag{1}$$

$$s.t. \sum_{e \in \delta^+(k)} x_e = 1 \qquad \forall k \in \mathcal{E} \tag{2}$$

$$\sum_{e \in \delta^+(i)} x_e \leq 1 \qquad i \in \mathcal{T} \tag{3}$$

$$\phi_{e(v_s,u_0)} = w(u) \qquad \forall u \in \mathcal{E} \tag{4}$$

$$\sum_{e \in \delta^-(i)} \phi_e = \sum_{e \in \delta^+(i)} \phi_e \qquad \forall i \in \mathcal{N}^x \setminus \{v_s, v_t\} \tag{5}$$

$$\phi_{e'} \leq x_e * c_e \qquad \forall e \in \mathcal{A}, e' \in e^x \tag{6}$$

$$\phi_e \geq 0 \qquad \forall e \in \mathcal{A}^x \tag{7}$$

$$x_e \in \{0,1\} \qquad \forall e \in \mathcal{A} \tag{8}$$

Following Hasan and Hentenryck [5], we use a time expanded graph (Appendix A), denoted by $\mathcal{G}^x = (\mathcal{N}^x = \mathcal{E}^x \cup \mathcal{T}^x \cup \mathcal{S}^x, \mathcal{A}^x)$, to capture the flow of evacuees over time and formulate the evacuation planning problem as an MIP given by (1–8). Here, we have two types of variables: (i) binary variable x_e, which is equal to one if and only if the edge $e \in \mathcal{A}$ is used for evacuation; otherwise it will be zero. (ii) continuous variable ϕ_e, which denotes the flow of evacuees on edge $e \in \mathcal{A}^x$. The objective (1) is to minimize the total (i.e. sum) evacuation time; here v_t denotes a super sink node that connects all safe nodes, and $t_s(e)$ denotes the arrival time at this node. Constraint (2) ensures that there is exactly one outgoing edge from each source node, and constraint (3) ensures that the routes are convergent. Constraint (4) sets the initial flow from each source node to the number of evacuees ($w(u)$) at those nodes. Constraint (5) and (6) corresponds to the flow conservation and the flow capacity constraint respectively.

3 HEURISTIC OPTIMIZATION

Solving the model (1-8) is computationally expensive. In fact, the problem of minimizing the evacuation completion time, with the constraints (2-8), is hard to approximate too [4]. For this reason, we present a heuristic optimization method, to find good solutions in a reasonable amount of time.

First, we calculate an initial feasible solution by taking the shortest path from each source node to the nearest safe node (by road) and determine the minimum time required to evacuate everyone using these paths. The latter is used to set the time horizon. We then apply Algorithm 1 to optimize the model (1-8). It runs for n iterations, in each iteration we randomly select some source locations (line 2) and keep the routes from these sources fixed. We then optimize the model over the rest of the routes and the schedule. If we find a better solution, with an evacuation completion time smaller than the current time horizon, then we also apply pruning strategies (lines 7-9) to reduce the size of the model.

Algorithm 1: Heuristic Method for Optimizing model (1-8)

Input: Initial solution: *sol*, Time Horizon: T, Percentage of routes to update: p, Number of Iterations: n
Output: Solution of the model (1-8)
1 **for** *1 to n* **do**
2   Select (100-p)% of the source locations uniformly at random. Let their set be S
3   Fix the routes from the source locations in S, by setting $x_e = 1$ if e is on any of the routes from S in *sol*
4   *sol* ← Solution of optimized model (1-8)
5   T' ← evacuation completion time for solution *sol*
6   **if** $T - T' > +threshold$ **then**
7   Update the model (1-8) by setting the time horizon to T'. Prune the Time Expanded Graph by removing
8   (i) nodes that are unreachable from the evacuation nodes within time horizon T', and
9   (ii) nodes from which none of the safe nodes can be reached within time horizon T'
10   Increase p
11 **return** *sol*

Using our method, we calculate an evacuation plan for our study area. The road network for this area consists of 1338 nodes and 1751 edges. We have 374 sources and 8 safe nodes. The execution of our algorithm takes ∼ 3.5 hours and returns a solution that evacuates ∼ 1.5 million evacuees in ∼ 8 hours. We validate our results by simulating the evacuation using QueST [7] (Appendix B).

4 TIME VARYING RISK MODEL AND INDIVIDUAL VS SOCIAL UTILITY

We extend the damage model proposed by Agarwal *et al.* [2] by considering the time varying aspect of risk during disasters. We calculate a failure probability for each road at each timestep (Appendix C) based on the following assumption: probability of a road becoming damaged increases as we temporally get closer to the time of disaster, and it is maximum at the time of the disaster.

Due to the failure of edges, different scenarios may arise during evacuation. To understand how it affects the evacuees and the efficacy of an evacuation plan, we define: (i) individual utility of an evacuee in a given scenario when following a given evacuation plan, and (ii) social utility of an evacuation plan in a given scenario. In our experiments, we generated five thousand scenarios in the study area using our risk model. Results show that our evacuation plan achieves good social utility, compared to the best utility achievable, in most of the scenarios (Appendix D).

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REFERENCES

[1] Abhijin Adiga, Aditya Agashe, Shaikh Arifuzzaman, Christopher L. Barrett, Richard J. Beckman, Keith R. Bisset, Jiangzhuo Chen, Youngyun Chungbaek, Stephen G. Eubank, Sandeep Gupta, Maleq Khan, Christopher J. Kuhlman, Eric Lofgren, Bryan L. Lewis, Achla Marathe, Madhav V. Marathe, Henning S. Mortveit, Eric Nordberg, Caitlin Rivers, Paula Stretz, Samarth Swarup, Amanda Wilson, and Dawen Xie. 2015. *Generating a Synthetic Population of the United States.* Technical Report NDSSL 15-009. Network Dynamics and Simulation Science Laboratory. https://nssac.bii.virginia.edu/~swarup/papers/US-pop-generation.pdf

[2] Pankaj K. Agarwal, Alon Efrat, Shashidhara K. Ganjugunte, David Hay, Swaminathan Sankararaman, and Gil Zussman. 2013. The Resilience of WDM Networks to Probabilistic Geographical Failures. *IEEE/ACM Transactions on Networking* 21, 5 (Oct. 2013), 1525–1538. https://doi.org/10.1109/tnet.2012.2232111

[3] S Kay Carpender, Paul H Campbell, Barbara J Quiram, Joshua Frances, and Jill J Artzberger. 2006. Urban evacuations and rural America: lessons learned from Hurricane Rita. *Public Health Reports* 121, 6 (2006), 775–779.

[4] Mordecai J. Golin, Hadi Khodabande, and Bo Qin. 2017. Non-approximability and Polylogarithmic Approximations of the Single-Sink Unsplittable and Confluent Dynamic Flow Problems. arXiv:1709.10307 [cs.DS]

[5] Mohd. Hafiz Hasan and Pascal Van Hentenryck. 2020. Large-Scale Zone-Based Evacuation Planning: Models, Algorithms, and Evaluation. arXiv:2003.11005 [math.OC]

[6] HERE. 2020. HERE Premium Streets Data set for the U.S. https://www.here.com/

[7] Kazi Ashik Islam, Madhav Marathe, Henning Mortveit, Samarth Swarup, and Anil Vullikanti. 2020. A Simulation-based Approach for Large-scale Evacuation Planning. In *2020 IEEE International Conference on Big Data (Big Data)*. IEEE. https://doi.org/10.1109/bigdata50022.2020.9377794

[8] David Pisinger and Stefan Ropke. 2018. Large Neighborhood Search. In *Handbook of Metaheuristics*. Springer International Publishing, 99–127. https://doi.org/10.1007/978-3-319-91086-4_4

[9] Paul Shaw. 1998. Using Constraint Programming and Local Search Methods to Solve Vehicle Routing Problems. In *Principles and Practice of Constraint Programming — CP98*. Springer Berlin Heidelberg, 417–431. https://doi.org/10.1007/3-540-49481-2_30