A Shared-mobility-based Evacuation Planning and Operations Framework under Demand Uncertainty

Huiwen Jia
Department of Industrial and Operations Engineering, University of Michigan, Ann Arbor, hwjia@umich.edu
Kati Moug
Department of Industrial and Operations Engineering, University of Michigan, Ann Arbor, klmoug@umich.edu
Siqian Shen
Department of Industrial and Operations Engineering, University of Michigan, Ann Arbor, siqian@umich.edu

1. Motivation

In recent years, natural disasters such as flooding, wildfire, hurricane, and tornadoes occur frequently and cause tremendous damage to both the economy and human life (Chowdhury et al. 2017). A disaster center (DC) is responsible for evacuation planning and operations. However, the information that DC receives is often imprecise and uncertain, especially the demand information (see, e.g., Lim et al. 2012). During Hurricane Rita, the actual number of evacuees ($1,800,000$) was nearly three times the predicted value ($686,000$), which led to dramatic traffic congestion and delay (Lindell and Prater 2007).

In addition to uncertain demand, non-shareable personal vehicles also cause evacuation delay and inefficiency. The one-evacuee-one-vehicle evacuation form, which is wasteful and inefficient, is mainly due to limited ways to communicate. Today's smart-phone technologies enable ubiquitous connectivity, allow instant peer-to-peer communications, and give rise to a transformation from individual travel forms to shared-use mobility forms, which can pool resources and reduce traffic.

Evacuation buses have been identified as a method to effectively help large carless populations (see, e.g., Goerigk, Deghdak, and T'Kindt 2015), however, the elderly and disabled population with particular needs can not be served well by an evacuation bus and thus often left out in traditional evacuation systems (Renne, Sanchez, and Litman 2011). In this paper, we propose a shared-mobility-based evacuation planning and operations framework to address the uncertain demand and inefficient individual travel forms. Shared-mobility can help under-served carless, elderly, and disabled populations to evacuate and receive personalized assistance.

2. Problem Statement

Planning phase At the beginning of the year, DC builds a demand prediction model according to historical evacuation event data and census data. Then DC recruits a fleet of personal vehicles, who will share their spare space and perform pick-up services guided by DC during the evacuation.

Operational phase During certain disaster, DC performs evacuation operations over multiple periods. DC receives new requests at the beginning of each period and then dispatches personal and emergency vehicles to help evacuees.

3. Approaches

We model the evacuation process as a maximum flow problem, where vehicles are guided to pick up evacuees in different demand nodes and then travel on roads towards safe zones. We employ a spatial-temporal network where node i^t denotes location i in time period t. For optimizing the personal vehicle employment plans in the planning phase, we formulate a two-stage stochastic program, where the second-stage decisions are emergency vehicle employment decisions and routing decisions for all employed vehicles. In the operational phase, we formulate a multi-stage robust optimization model to decide which personal and emergency vehicles would go out and assign routing solutions to them in each period.

3.1. Planning Phase

We make personal vehicle employment decisions by minimizing the employment cost and the expected objective values in the future. Denote the cost for employing vehicle s as α_s and discount rate as γ. We create a demand scenario set Ω by Monte Carlo Sampling according to the demand prediction model, where $\tilde{a}_j^t(\omega)$ is the number of arrivals to pickup location j at period t in scenario ω. Based on the Sample Average Approximation (SAA), the problem is formulated as

$$\min_{x} \quad \gamma \sum_{s\in\mathcal{S}} \alpha_s x_s + \frac{1}{|\Omega|}\sum_{\omega\in\Omega}[\mathbb{Q}(x,\tilde{a}(\omega))] \tag{1}$$

$$x_s \in \{0,1\}, \quad s\in\mathcal{S} \tag{2}$$

where $x_s = 1$ denotes that we employ personal vehicle $s\in\mathcal{S}$ and $\mathbb{Q}(x,\tilde{a}(\omega))$ is given by

$$\min_{y,z,q} \quad -\lambda \sum_{v\in\mathcal{V}}\sum_{j^t\in\mathcal{N}_P} q_{vj^t\omega} + \sum_{v\in V}\sum_{(i^t,j^{t'})\in A} y_{vi^tj^{t'}\omega} d_{ij} \tag{3}$$

$$\text{s.t.} \quad \sum_{j^t:(o_s,j^t)\in\mathcal{A}} y_{so_sj^t\omega} = x_s,\ s\in\mathcal{S} \qquad \sum_{j^t:(o_r,j^t)\in\mathcal{A}} y_{ro_rj^t\omega} = z_{r\omega},\ r\in\mathcal{R} \tag{4}$$

$$\sum_{i^t:(i^t,j^{t'})\in\mathcal{A}} y_{vi^tj^{t'}\omega} - \sum_{i^t:(j^{t'},i^t)\in\mathcal{A}} y_{vj^{t'}i^t\omega} = 0,\ j^{t'}\in\mathcal{N}, v\in\mathcal{V} \tag{5}$$

$$q_{vj^{t'}\omega} \le \mathcal{M} \sum_{i^t:(i^t,j^{t'})\in\mathcal{A}} y_{vi^tj^{t'}\omega},\ j^{t'}\in\mathcal{N}_P, v\in\mathcal{V} \qquad \sum_{j^{t'}\in\mathcal{N}_P} q_{vj^t\omega} \le Q_v,\ v\in\mathcal{V} \tag{6}$$

$$\sum_{v\in\mathcal{V}} q_{vj^t\omega} \le \sum_{t=0}^{t'} \tilde{a}_j^t(\omega) - \sum_{v\in\mathcal{V}}\sum_{t=0}^{t'-1} q_{vj^t\omega},\ j^{t'}\in\mathcal{N}_P \tag{7}$$

$$\sum_{s\in\mathcal{S}} \alpha_s x_s + \sum_{r\in\mathcal{R}} \beta_r z_{r\omega} \le C \tag{8}$$

$$z_{r\omega}\in\{0,1\},\ r\in\mathcal{R} \quad y_{vi^tj^{t'}\omega}\in\{0,1\},\ v\in\mathcal{V}\ (i^t,j^{t'})\in\mathcal{A} \quad q_{vi^t\omega}\ge 0,\ \text{Integer},\ i^t\in\mathcal{N}_P, v\in\mathcal{V}. \tag{9}$$

In the second stage, we make the following decisions: (i) $z_{r\omega}=1$ when we employ emergency vehicle $r\in\mathcal{R}$; (ii) $y_{vi^tj^{t'}\omega}=1$ when vehicle $v\in\mathcal{V}$ travels from node i^t to node $j^{t'}$; (iii) $q_{vj^t\omega}$ is evacuees that

vehicle v picks at node j^t. In (3), we maximize evacuees picked up and minimize driving distance. Constraints (4) and (6) ensure that available evacuees are picked up by employed vehicles with enough capacity. (5) are flow balance constraints. Constraints (7) compute evacuees in need at j^t. (8) is the budget constraint.

3.2. Operational phase

We build a time series to analyze the demand of nodes along time periods and formulate a demand uncertainty set $\mathcal{U}_{\text{VAR}}$ based on Vector Autoregressive Model (VAR):

$$\mathcal{U}_{\text{VAR}} = \left\{ a^t = a_{const} + \phi t + \sum_{c=1}^{c_{max}} \Phi^c a^{t-c} + \epsilon_t,\ t = 2, \dots, T \quad \|\epsilon_t\|_1 \le \Omega_t^1 \quad \|\epsilon_t\|_\infty \le \Omega_t^\infty \right\}, \tag{10}$$

where the prediction parameters $\{\phi, \Phi^{1:c_{max}}, a_{const}\}$ and error norms $\{\Omega_t^1, \Omega_t^\infty\}$ can be estimated through statistical toolboxes from historical evacuation demand data. The hyperparameter $\{\Omega_t^1, \Omega_t^\infty\}$ can also be adjusted according to the desired robustness level.

In period $\tau \in \{1, ..., T-1\}$, the objective function is similar to (3), defined as:

$$g(x^\tau, y^\tau, z^\tau, q^\tau) = -\sum_{v \in \mathcal{V}} \sum_{j^t \in \mathcal{N}_P} q^\tau_{vj^t\omega} + \lambda \sum_{v \in V} \sum_{(i^t, j^{t'}) \in A} y^\tau_{vi^t j^{t'}\omega} d_{ij}.$$

Define the decisions $(x^\tau, y^\tau, z^\tau, q^\tau)$ as X^τ, and let $X^{\tau:\tau'}$ denotes the decisions made in periods τ to τ', then the feasible region $\mathcal{X}^\tau(X^{1:(\tau-1)}, a^\tau)$ in period τ with previous decisions during periods 1 to $\tau - 1$ and predicted demand a^τ is defined as:

$$\sum_{j^t:(o_s, j^t) \in \mathcal{A}^\tau} y^\tau_{so_s j^t} = x^\tau_s,\ s \in \mathcal{S}^\tau \qquad \sum_{j^t:(o_r, j^t) \in \mathcal{A}^\tau} y^\tau_{ro_r j^t} = z^\tau_r,\ r \in \mathcal{R}^\tau \tag{11}$$

$$\sum_{i^t:(i^t, j^{t'}) \in \mathcal{A}^\tau} y^\tau_{vi^t j^{t'}} - \sum_{i^t:(j^{t'}, i^t) \in \mathcal{A}^\tau} y^\tau_{vj^{t'} i^t} = 0,\ j^{t'} \in \mathcal{N}^\tau,\ v \in \mathcal{V}^\tau \tag{12}$$

$$q^\tau_{vj^{t'}} \le \mathcal{M} \sum_{i^t:(i^t, j^{t'}) \in \mathcal{A}^\tau} y^\tau_{vi^t j^{t'}},\ j^{t'} \in \mathcal{N}_P, v \in \mathcal{V}^\tau \tag{13}$$

$$\sum_{j^{t'} \in \mathcal{N}_P} q^\tau_{vj^t} \le Q_v,\ v \in \mathcal{V}^\tau \qquad \sum_{v \in \mathcal{V}^\tau} q^\tau_{vj^t} \le \bar{a}^\tau_j + a^\tau_j - \sum_{v \in \mathcal{V}^\tau} \sum_{t=0}^{t'} q^\tau_{vj^t},\ j^{t'} \in \mathcal{N}^\tau_P \tag{14}$$

$$\sum_{r \in \mathcal{R}^\tau} \beta_r z^\tau_r \le C^\tau \tag{15}$$

$$z^\tau_r \in \{0,1\},\ r \in \mathcal{R}^\tau \quad y^\tau_{vi^t j^{t'}} \in \{0,1\},\ v \in \mathcal{V}^\tau\ (i^t, j^{t'}) \in \mathcal{A} \quad q^\tau_{vi^t} \ge 0,\ \text{Integer},\ i^t \in \mathcal{N}_P, v \in \mathcal{V}^\tau. \tag{16}$$

In the above formulation, $\mathcal{S}^\tau$ and $\mathcal{R}^\tau$ are current available personal and emergency vehicles; $\mathcal{N}^\tau_P, \mathcal{N}^\tau$, and $\mathcal{A}^\tau$ are nodes and arcs in the spatial-temporal network after period τ; $\bar{a}^\tau_j$ are the accumulated unmet demand in node location j before period τ.

Therefore, we reach the following multi-stage robust formulation, where we optimize the dispatching solution in the current period by minimizing the objective value in the current period and the worst objective values in the future periods:

$$\text{(RMS)} \min_{X^1 \in \mathcal{X}(a^1)} g(X^1) + \max_{a^{2:T}} \left[\min_{X^2 \in \mathcal{X}(X^1, a^2)} \left\{ g(X^2) + \cdots + \max_{a^T} \left[\min_{X^T \in \mathcal{X}(X^{1:T-1}, a^T)} g(X^T) \right] \cdots \right\} \right] \tag{17}$$

$$\text{s.t.} \quad a^{1:T} \in \mathcal{U}_{\text{VAR}}. \tag{18}$$

4. Numerical Studies

We test the performance of the proposed planning and operations framework under various demand patterns. In each demand pattern, we sample 20 groups of demand data as historical events data and compute the sample mean, variance, and support as additional demand information. In the planning phase, **S** denotes that DC employs personal vehicles and **NS** denotes no shared mobility. In the operational phase, **MS** denotes that DC dispatches vehicles via a multi-stage robust optimization model and **D** denotes that DC dispatches vehicles through a deterministic single-stage model according to the received requests in each period. We construct four models, **NS-D**, **NS-MS**, **S-D**, and **S-MS** (i.e., the proposed framework). We compare those models by computing the maximum, minimum, and average number of evacuees that they can help in 10 replicates. We also conduct sensitivity analysis to explore the effects of the number of available emergency vehicles and budgets on model performance.

5. Conclusion

We address two main problems of the existing evacuation process, uncertain demand and inefficient individual travel form, by proposing a planning and operations evacuation framework. We allow employing a fleet of personal vehicles to share their spare space with other evacuees, which can reduce traffic and help to facilitate evacuation. When a disaster strikes, we construct a time series demand prediction model and formulate a multi-stage robust optimization model to optimize the dispatching solution. We implement numerical studies and demonstrate that the proposed framework can help more evacuees, given limited emergency vehicles and budgets.

References

Chowdhury S, Emelogu A, Marufuzzaman M, Nurre SG, Bian L, 2017 *Drones for disaster response and relief operations: a continuous approximation model. International Journal of Production Economics* 188:167–184.

Goerigk M, Deghdak K, T'Kindt V, 2015 *A two-stage robustness approach to evacuation planning with buses. Transportation Research Part B: Methodological* 78:66–82.

Lim GJ, Zangeneh S, Baharnemati MR, Assavapokee T, 2012 *A capacitated network flow optimization approach for short notice evacuation planning. European Journal of Operational Research* 223(1):234–245.

Lindell MK, Prater CS, 2007 *Critical behavioral assumptions in evacuation time estimate analysis for private vehicles: Examples from hurricane research and planning. Journal of Urban Planning and Development* 133(1):18–29.

Renne JL, Sanchez TW, Litman T, 2011 *Carless and special needs evacuation planning: a literature review. Journal of Planning Literature* 26(4):420–431.