Evacuation Decision Tree Analysis for Disaster Response in a Stochastic-Dynamic Network

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1 Introduction

In a short-notice natural disaster that may require evacuation, some advance predictions are available with varying degrees of uncertainties (Çelik et al. 2012), giving people enough time to prepare for evacuation (Mirchandani et al. 2009). When impact predictions can be made with no uncertainty, "what-if" scenario predictions (often through simulations) can be evaluated and good evacuation plans can be developed for each "what-if" scenario, which is the current state of practice. However, when the predictions are highly uncertain, then an *evacuation strategy* is needed where decisions are made as the impacts and its cascading effects become clearer over time and predictions improve.

In this paper, we propose a new methodology to solve an evacuation problem by using a stochastic-dynamic network. The methodology aims to optimally determine the quickest evacuation schedule and routes over the time horizon so the total evacuation makespan is minimal. The mathematical program formulation of this evacuation program is solved in two stages. In the first stage, column generation approach is used to solve the quickest flow for a given set of origins and destination in a stochastic dynamic network at each decision epoch. In the second stage, the evacuation strategy is derived by folding back the evacuation decision tree and then working forward through the tree to generate recommend actions to be taken at each potential decision point. Its performance is then compared with evacuation plans that assume a single scenario with its attendant uncertainties for hurricane Irma case study. The developed evacuation strategy suggests evacuation decisions as the impacts unfold over time and are dependent on real-time observations. Compared with evacuation plans, the results show that our evacuation strategies perform best or near best, with respect to several performance metrics. It should be noted that the concepts of (a) cascading stochastic dynamic networks, (b) evacuation strategies from origins to destinations on such networks and (c) dynamic decision making via decision tree analyses of scenario trees are all novel and they form the fundamental contributions of this research.

2 Methodology

The block diagram in Figure 1 summarizing the methodology to solve the evacuation problem on a stochastic dynamic network. There are two loops utilized to solve this multistage decision problem. The first loop involves scheduling flows on routes that minimizes the makespan for a given action; here we have a given set of evacuating nodes and the corresponding problem is formulated as a minimum cost network flow problem (*MCNFP*). To overcome the complexity of generating routes, assigning flows, and determining the minimum makespan concurrently, we first fix the makespan t_0 (which is updated iteratively in a binary search outer loop). We then assign flows to feasible routes whose temporal lengths are less than or equal to the makespan. Column generation approach is utilized to determine this flow assignment by partitioning the MCNFP into restricted master problem (RMP) and subproblem (SP) and which are solved iteratively. For a given time horizon $[0, T]$ and makespan t_0, the goal of the RMP is to assign flows to each potential route that minimizes the travel cost. At any point, the RMP contains routes considered up to the current iteration. The goal of the SP is to generate and add new routes with positive residual capacity having travel time less than the makespan t_0 to the set of routes for the next iteration of the RMP. The subproblem SP in this case is solved using time-dependent shortest path (TDSP) algorithm introduced by Mahmassani et al. (1994). The iteration between RMP and SP stops when feasible schedule is obtained, or infeasibility is pronounced. The t_0 is then a candidate feasible makespan, and can be considered as an upper bound in the minimum makespan binary search.

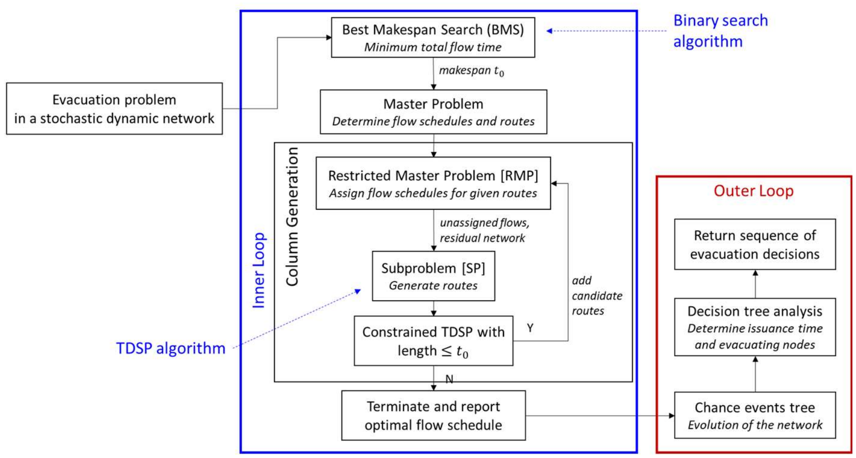

Figure 1. *Evacuation Decision Tree Analysis (EDTA) Framework*

The second loop involves determining a sequence of actions, defined at each decision epoch over the full decision horizon. *Decision tree analysis* is used to find optimal sequence of actions that minimize the overall disutility. To solve for decisions in a stochastic dynamic network, we first discretize the uncertainty through the use of chance events or scenarios tree. This tree represents how the network states evolve over the time horizon. The steps in the generation of this *scenarios tree* basically is the partition of the scenarios S into disjoint event sets at each decision epoch. The decision tree is created through iterating over the branches of the tree with the branching determined upon comparing the current and next decision epochs in the tree. Evacuation schedule and routes are computed for each decision branch. The iteration stops when all potential branches have been enumerated. The optimal sequence of actions is then identified by working forward through the tree.

3 Results

The transportation network in Manatee County, FL (Figure 2), is used to test the algorithm. The network consists of 26 nodes and 40 arcs. As Hurricane Irma traversed from south to north of Florida, we assume people evacuate North and towards the inland area as the storm moves upwards. This assumption allows us to simplify the network into a directed network with at most one arc connecting two nodes. Node 30 is further inland and is assumed as the (safe) terminal node. Four scenarios are considered. The storm forecast in each scenario is generated using the data-driven probabilistic scenarios simulation model that takes storm forecast data available in the National Digital Forecast Database (NDFD) consistent with the NHC advisory as the input parameters (Mirchandani, Ayu, and Maciejewski 2019). 48-hours predicted changes of the network states in each scenario is determined accordingly for the corresponding the cascading network failure model. In this example, we used the storm forecast consistent with the NHC advisory number 40 which was issued on September 9, 2017, at 3:00 UTC. The time step ℓ is set to be at 5-minute increments and the decision time epochs are assumed to be at 6-hour intervals. The cost to traverse a route is assumed to follow a disutility function, $u(tt, a) = \ln(tt) + \ln(a)$ where tt and a correspond to travel time and arrival time at destination, respectively. The penalty cost for each unassigned evacuee is assumed to be a large constant. Evacuees are assumed to fully comply with evacuation orders.

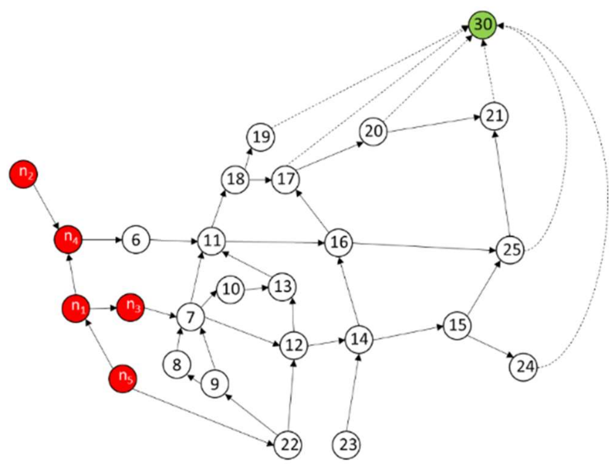

Figure 2. *Manatee County's Transport Network*

Figure 3. *Evacuation Costs for EDTA Strategy and Plan Assumed Scenario*

Three out of five evacuating nodes, i.e., n_3, n_4, n_5, are assumed need to be evacuated simultaneously. Hence $\{n_1\}, \{n_2\}$, and $\{n_3, n_4, n_5\}$ are defined as the sets of origin nodes. The proposed strategy proposed by the EDTA algorithm is to evacuate (n_3, n_4, n_5) at 6-h, n_1 at 24-h, and n_2 at 30-h if scenario s_1 is the foreseeable scenario at $t = 0$. Otherwise, evacuate n_2 at 0-h. At the next decision time $t = 6$, evacuate (n_3, n_4, n_5). At $t = 12$, if the foreseeable scenario is s_2, then evacuate n_1 at

18-h. For all remaining scenarios, evacuate n_1 at 24-h. Similarly, the "what-if" plan is obtained by running the scenarios independently and the resulting three distinct evacuation plans. That is, if the assumed scenario is s_1, then evacuate (n_3, n_4, n_5) at $t = 6$, n_1 at 24-h, and n_2 at 30-h. If s_2, then the plan suggests to evacuate n_1 at 0-h, $(n_3, n_4, n_5)n_3$ at 6-h, and n_2 at 18-h. Lastly, if s_3 or s_4, evacuate n_2 at 0-h, $(n_3, n_4, n_5)n_3$ at 6-h, and n_1 at 24-h. The evacuation cost comparison between the strategy proposed by the EDTA with the evacuation plans is illustrated in Figure 3. The proposed **EDTA strategies** lead to the least expected cost and is found to be among the best in each realized scenario – except in scenario $s_2$where the **evacuation plan** performs slightly better by 0.0002%, since the assumed scenario of the plan just happened to be the realized scenario.

4 Discussion

Short-notice sudden onset natural disasters, such as hurricanes, are laden with uncertainties. A methodology is developed to determine the quickest evacuation strategy and the corresponding evacuees' routes under the uncertainties modeled using an underlying stochastic dynamic transportation network representation. The methodology begins with discretizing the time steps and decision time epochs to model the uncertainties of the network states using probability trees. It then evaluates each possible decision at each decision time to generate an evacuation strategy. Its performance is compared for the real case of 2017 Hurricane Irma, with evacuation plans that assume a single scenario with its attendent uncertainties. It should be noted that the developed strategy suggests evacuation decisions as the impacts unfold over time and are dependent on real-time observations, whereas the evacuation plan provides a time-staged set of decisions for a single assumed scenario. The results show that the evacuation strategies perform best or near best, with respect to several metrics, in comparison to the evacuation plans. The concepts of (a) cascading stochastic dynamic networks, (b) evacuation strategies from origins to destinations on such networks and (c) dynamic decision making via decision tree analyses of scenario trees are all novel and they form the fundamental contributions of this research.

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