

# Hurricane Evacuation Decision Model in a Stochastic Dynamic Network

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## Abstract

In the case of a hurricane event, uncertainties and corresponding impacts during a storm event can quickly cascade. Failure to incorporate these uncertainties can significantly affect the efficiency and effectiveness of the emergency responses. Note that, storm hazards, such as strong winds, torrential rain, and storm surges, can inflict significant damage on the road network, affect population's ability to move during the storm event. A methodology is proposed to generate a sequence of actions that simultaneously solve the evacuation flow scheduling and suggested routes which minimize the total flow time, or the makespan, for the evacuation process from origins to destinations in the resulting stochastic time-dependent network. The methodology is implemented for the 2017 Hurricane Irma case study to recommend an evacuation policy for Manatee county, FL. The results are compared with evacuation plans for assumed scenarios and suggest that evacuation recommendations based on single scenario reduces the effectiveness of the evacuation procedure. Overall contribution of the research presented here is the new methodology to determine the quickest evacuation schedule and routes under the uncertainties within the resulting stochastic transportation networks.

## Keywords

Network Flow, Hurricane Evacuation, Stochastic Dynamic Networks, Uncertainty

## 1. Introduction

Disasters triggered by natural hazards can occur suddenly (e.g., earthquakes) or with some warning (e.g., hurricanes, wildfire, and volcanic eruptions). In a short-notice disaster that may require evacuation, some advance predictions are available with varying degrees of uncertainties (Çelik et al., 2012), allowing people to depart at different times, giving them enough time to prepare for evacuation (Mirchandani, Chiu, Hickman, Noh, & Zheng, 2009).

Evacuation management plays a significant role in ensuring (potentially) affected population arrive to safety in a timely manner. It guides the activities, operations and directions for avoiding disaster impacts and minimizing casualties, particularly in the case where a large area is affected, and many people need to travel over more route-miles (Wolshon, Urbina Hamilton, Levitan, & Wilmot, 2005). The case of the 2017 Hurricane Irma reminds how *uncertainty* is pervasive, which makes hurricane evacuation decisions complex and complicated. About three days prior the landfall, Irma is predicted would go along the east coast of Florida, which resulted in mandatory evacuation order for residents in the Miami-Dade and Monroe County (including Florida Keys). Within a day later, as the storm hit Cuba, the forecast predictions shifted towards the west of Florida, which resulted in another mandatory evacuation order but for residents in Collier County. The massive flow of evacuees from both east and west of Florida resulted in severe congestion on I-95 and I-75 as these highways are the only two main Interstates going

north. According to the Florida Department of Transportation (FDOT), during these times, the hourly traffic volume on the I-75 northbound, in the Ocala area, increased by 1236% over the same days the previous year (FDOT, 2018). The takeaway message in here is that the essence of uncertainty in disaster should not be overlooked when deriving response operations, emphasizing the need to think probabilistically about the catastrophic event. Generally, evacuation planning is done based on past experience as the impacts from a short-notice disaster are uncertain, over wide range of area, and cascade in time and space. When impact predictions can be made with no uncertainty, “what-if” scenario predictions (often through simulations) can be made 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 evacuation decisions are made as the impacts and its cascading effects become clearer over time and our predictions improve.

In this paper, we propose a new methodology to solve an evacuation problem in 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 working forward through the tree to generate recommend actions to be taken at each decision point. Its performance is then compared with the evacuation plans that assume a single scenario with its attendant uncertainties. It should be noted that the developed evacuation 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. 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.

The organization of this paper is as follows. The next section provides a brief literature review; followed by a section documenting the model framework and brief explanation on the corresponding algorithms. Applications of the proposed methodology to determine the evacuation strategy for Manatee county during the 2017 Hurricane Irma is presented next. Concluding remarks and future research directions are offered in the last section of this paper.

## 2. Literature Review

Evacuation involves moving residents from danger zone to safety as quickly as possible and with utmost reliability (Hamacher & Tjandra, 2002). When the estimation of the potential risk and evacuation time can be done a priori, evacuation acts as a precautionary action. However, when insufficient warning has prevented the possibility to act a priori, evacuation becomes a life-saving operation rescuing injured evacuees in and around the damaged area. Evacuation should ideally be ordered only for areas where foreseeable hazards represent a significant risk to human life. However, it is not possible to determine the hazardous conditions precisely because uncertainty prevails in disaster. One possible solution is to evacuate all locations having any potential risk. Yet, doing so will simultaneously overstress the transportation system and possibly reducing access of those who are most at risk and in need of evacuation. A *stage evacuation* is an orderly withdrawal of people and is commonly used to minimize the possibility of overstressing the system while simultaneously ensure evacuees reach safety in a timely manner (Mirchandani et al., 2009).

Evacuation operates on a transportation network which may be characterized by supply and demand attributes. *Transport supply* is defined by the capacity of the transport infrastructure, which can be affected by various factors ranging from physical characteristics (e.g., road conditions, number of lanes) to the management of the network (e.g., control measures). The need to travel defines the *transport demand*, or sometimes referred to as *travel demand*. Interaction between the supply and demand results in variations of *travel times*. During normal conditions, travel demand tends to be variable in time and space, whereas transport supply is commonly fixed (Rodrigue & Notteboom, 2013). During disaster event; however, both demand and supply vary in time and space. Depending on the severity of the weather impacts, transport infrastructure can often be temporarily inaccessible due to damages or destruction of roads, leading to reduction in transport supply. The corresponding locations and severity of the road impacts; however, are only revealed over time as the disaster unfolds.

Significant amount of evacuation research that is network related has appeared in the past few decades, most of which simply assume static networks, whereas cascading impacts on the networks makes them dynamic. Nevertheless, reviewing some of the recent static network research; (a) Cova and Johnson (2003) and Bretschneider and Kimms (2011), propose evacuation models with aim to prohibit conflicts within intersections; (b) Campos et al. (2012) and Coutinho et al. (2012) develop model to identify two disjoint evacuation paths from origin to destination; (c) Lim et al. (2012) propose decision making tool for assigning evacuation routes and schedules to evacuees in different evacuation areas; (d) Üster et al. (2018) propose and analyze a strategic planning tool to facilitate preparedness for large scale evacuations. Arguably, one of the most salient characteristics which ought to be considered when developing effective evacuation model is the uncertainties in the disaster event with respect to its time of occurrence, magnitude, and impacts on the transport infrastructure. Surveys conducted by Galindo and Batta (2013b), Hoyos et al. (2015), Kovács and Spens (2007), and Liberatore et al. (2012), agree on the importance of incorporating uncertainty into the evacuation models. Yet, majority of the literature in evacuation rely on deterministic models that adopt a single hazard scenario, for examples the most probable scenario and the worst case scenario (Bayram, 2016). In a recent survey conducted by Kunz et al. (2017) the actual impact of research on the practice of national emergency management claimed to fall short because the scenarios considered are not grounded with empirical evidence. Hoss and Fischbeck (2016) claims the lack of inclusion of probabilistic nature of the event in the currently available models makes them less useful.

Among the subset of the literature that does consider uncertainty, the overwhelming majority focus on inclusion of uncertainty in the travel demand resulting from evacuees' behavior. Other focus, to a lesser extent, is on uncertainty in infrastructure availability or road capacity. Ben-Tal et al. (2011) and Yao et al. (2009) address the uncertainty travel demand. Their models assume evacuation demand in each origin is a random variable and its uncertainty belong to a prescribed uncertainty set. In the same spirit, travel demand distribution is assumed to follow S-curves in Ozbay & Yazici (2006), follow Rayleigh distribution in Noh et al. (2009), or a Markovian process in Stepanov & Smith (2009). Analogously, as probabilistic route choice behavior is considered as a major contributor in travel demand uncertainty, some literatures assume logit model to represent the evacuees' behavior. For example, Wolshon et al. (2015) propose an agent-based traffic simulation to analyze evacuation traffic in megaregion road networks, where the behavior of individuals is explicitly described through a time-dependent sequential logit model. In contrast, Chiu and Mirchandani (2008) claim that route choice behavior of evacuees cannot precisely be modeled or predicted. Hence, they propose an online behavior-robust feedback information routing model that captures the uncertain nature of evacuees' behavior through information feedback that update advised optimal routes for evacuees. In a similar spirit, Liu et al. (2007) propose a model reference adaptive control for real-time traffic management for emergency evacuation. Chiu and Mirchandani (2008) and Liu et al. (2007) are among the very few papers in the literature that propose a real-time dynamic evacuation model to capture uncertainty and regularly update the strategy over time. However, uncertainty in the road capacity was not considered in their models.

Among the literature that encompass uncertainty in transport supply, most assume without much justification that the uncertainty: (a) follows some given probability distributions (Sadri, Ukkusuri, Murray-Tuite, & Gladwin, 2014; Wolshon et al., 2015) ; (b) is modeled by time-dependent travel times (Sayyady & Eksioğlu, 2010; Zheng, Chiu, Mirchandani, & Hickman, 2010) ; (c) is defined as congestion factor (Ozbay, Yazici, & Chien, 2006) ; (d) has a constant variation (Huibregtse, Hegyi, & Hoogendoorn, 2011) , (e) has time-dependent parameters (Bayram & Yaman, 2015, 2017); or (f) is modeled scenario-dependent parameters (Garrido, Lamas, & Pino, 2015; Liu et al., 2007; Noh et al., 2009; Zheng et al., 2010). Few of recent papers explicitly incorporate hurricane weather conditions in their evacuation modeling (Blanton et al., 2018; Davidson et al., 2018; Nozick et al., 2019). A set of scenarios is utilized to describe a range of ways the hurricane might evolve. Storm surge, wind wave, and hydrological models are used to compute the coastal inundation levels. Evacuating zones are defined that meet predetermined thresholds, for example, the percentage of zone's area that is inundated. Multistage stochastic programming model is then used to determine when and where to issue the evacuation orders. The framework is later extended by including inland flooding (Nozick et al., 2019). To our knowledge, these papers incorporate disaster uncertainty but do not consider the cascading supplies/demands of transport network on which the evacuation occurs.

### **3. Evacuation Decision Tree Analysis (EDTA)**

The block diagram summarizing the proposed methodology to solve the evacuation problem on a stochastic dynamic network is shown in Figure 1. There are two loops utilized to solve this multistage decision problem. The first loop, referred to as the "inner loop", involves scheduling flows on routes that minimizes the makespan for a given action;

here, we have a set of evacuating nodes, and 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  $t_0$  and then assign flows to feasible routes with length 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 then solved them iteratively. The column generation algorithm is appropriate to solve a linear program with a large number of variables compared to the number of constraints (Ford, Fulkerson, & Kennington, 2004; Nemhauser, 2012). For a given time horizon  $[0, T]$  and makespan  $t_0$ , the goal of the RMP is to assign flows to each assumed possible route that minimizes the travel cost. Hence, 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 pricing problem SP in this case is solved using time-dependent shortest path (TDSP) algorithm introduced in Mahmassani et al. (1994). The iteration between RMP and SP stops when feasible schedule is obtained, or infeasibility is pronounced. The above was with candidate makespan which can be considered as an upper bound for the minimum makespan. Now, a binary search gives us the minimum makespan. This makespan search algorithm, from hereon will be referred to as BMS algorithm.

The “outer loop” involves forming a sequence of actions, defined at each decision time, over the horizon. *Decision tree analysis* is used to determine this sequence with objective to find optimal sequence of actions that minimizes the overall decision cost. As we are formulating decisions for 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* is basically the partition of the scenarios  $S$  into disjoint event sets at each decision epoch. The decision tree is created through iterating over the branches in 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.

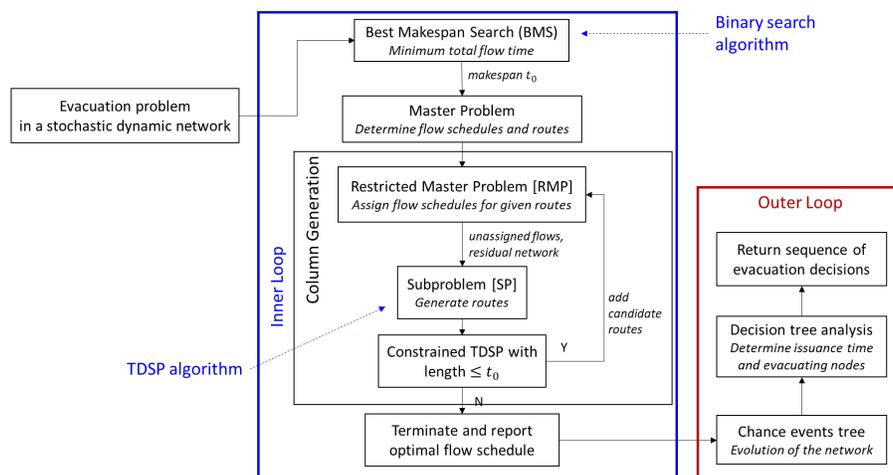


Figure 1. Evacuation Decision Tree Analysis Framework

### 3.1. Inner Loop – Minimum Makespan Search

The inner loop focuses on determining the feasible evacuation schedule. It employs column generation (CG) approach by partitioning the primal problem into restricted master problem (RMP) and subproblem (SP). For a given time horizon  $[0, T]$  and makespan  $t_0$ , the goal of the RMP is to assign evacuees to each assumed possible route that minimizes the total evacuation cost. Thus, the RMP contains routes considered up to the current iteration. The goal of the SP is to generate possible new routes with positive residual capacity having travel time less than the makespan  $t_0$  which are then added into the set of routes for the next iteration of the RMP. The pricing problem SP is essentially a time-dependent shortest path problem in a time-dependent network. It considers multiple evacuation routes for each origin-destination (OD) pair. The iteration between RMP and SP stops when feasible schedule is obtained, or it is pronounced the current makespan is infeasible.

Binary search algorithm is then employed in the loop to determine the best makespan  $t_0$  for the evacuation schedule. For a given set of OD pairs, the algorithm begins with initializing the left pointer  $L$  and right pointer  $R$  (used for binary search), optimal flow  $f_{opt}$ , and best makespan, denoted by  $ms$ . It also sets the initial makespan  $t_0$  as the midpoint time step of the time horizon. For the given makespan  $t_0$ , the algorithm calls the least-time paths (LTP) algorithm to generate the time-dependent shortest path matrix  $TD_{mat}$  for all OD pairs which are then taken as input of the subproblem SP to construct a list of possible routes with length less than the makespan  $t_0$ . If no route is present, the current makespan is infeasible and all other makespan values less than  $t_0$  will also be infeasible. Hence, we update the left pointer  $L$  to  $t_0$  and begin searching to the right side of  $t_0$  up to the time horizon  $T$ . If a set of routes is available, then the restricted master problem RMP assigns flows to these routes and determine the number of unassigned evacuees  $\Delta$ , if any. If all evacuees are assigned, then the current flow schedule is feasible and the current flow and makespan  $t_0$  are set as the *candidate optimal flow*  $f_{opt}$  and the *candidate best makespan*  $ms$ , respectively. In the next iteration with the right pointer set to  $t_0$ , the algorithm begins searching from  $L$  to the left side of  $t_0$ . If there are some unassigned evacuees (i.e.,  $\Delta > 0$ ), the algorithm initializes the status of the routes set as *false* and begins performing column generation until either all evacuees are assigned, or no further new routes can be added. Either way,  $t_0$  is set as the midpoint between the new left and right pointers and the binary search continues. The algorithm terminates when the  $t_0$  is less than or equal to the left pointer. Upon termination, it returns the optimal  $ms$ , flow schedule, and number of unassigned evacuees, if any.

#### Restricted Master Problem (RMP)

For a given network states over the time horizon, the RMP schedules flow of evacuees for each OD pair using the subset of feasible routes generated by SP. Each RMP's column represents a route-variable  $p = \langle k, d, t \rangle$ , an evacuation path for an OD pair  $\langle k, d \rangle \in \mathcal{K}$  where  $k$  is the origin node and  $d$  is the destination node for departure time  $t$ . Let  $T$  be the time horizon,  $\mathbb{P}$  be the set of routes with length no more than a given makespan  $t_0$ ,  $c_p$  be the cost of using route  $p$ ,  $\gamma_{e,p,t}$  be a binary variable which takes the value of 1 if arc  $e$  is in route  $p$  at time  $t$ ,  $\mathbb{P}_k$  be the subset of routes in  $\mathbb{P}$  corresponding to origin node  $k$ , and  $b_k$  be the total population to be evacuated from node  $k$ . Also let  $u_{e,t}$  and  $c_{e,t}$  be the capacity and cost to travel on arc  $e$  at time  $t$ , respectively. Hence, cost of using route  $p$  can be calculated by summing up all arc costs used in route  $p$ , that is  $c_p = \sum_{e \in \mathcal{A}} \sum_{t \in T} \gamma_{e,p,t} c_{e,t}$ . The decision variables for RMP are  $x_p$ , the number of evacuees assigned to use route  $p$  and  $\Delta_k$ , the number of unassigned evacuees from origin node  $k$ . Since all evacuees must evacuate, we introduce  $C_k$  as the penalty cost for any unassigned evacuees from origin node  $k$  to a safe destination.

#### Parameters and variables

|  |  |
|--|--|
| $\mathcal{G} = (\mathcal{V}, \mathcal{A})$ | network with a set of nodes $\mathcal{V}$ and a set of arcs $\mathcal{A}$  |
| $t_0$                                      | (given) makespan   |
| $\mathcal{K}$                              | a set of origin nodes  |
| $b_k$                                      | demand to evacuate from origin node $k$  |
| $u_{e,t}$                                  | capacity of arc $e$ at time $t$  |
| $c_{e,t}$                                  | cost to travel on arc $e$ at time $t$  |
| $\mathbb{P}$                               | a set of routes with length $\leq t_0$   |
| $\mathbb{P}_k$                             | a subset $\mathbb{P}$ departing from origin node $k$   |
| $p = \langle k, d, t \rangle$              | a route departing from origin node $k$ to node $d$ at time $t$   |
| $c_p$                                      | cost of using route $p$  |
| $\gamma_{e,p,t}$                           | $\begin{cases} 1, & \text{if arc } e \text{ is in route } p \text{ at time } t \\ 0, & \text{otherwise} \end{cases}$ |
| $x_p$                                      | number of evacuees assigned to use route $p$   |
| $\Delta_k$                                 | number of unassigned evacuees from origin node $k$   |
| $C_k$                                      | penalty cost for each unassigned evacuee from origin node $k$  |

$$\min \sum_{p \in \mathbb{P}} c_p x_p + \sum_{k \in \mathcal{K}} C_k \Delta_k \quad (4.1)$$

$$\text{subject to } \sum_{p \in \mathbb{P}_k} x_p + \Delta_k = b_k, \forall k \in \mathcal{K} \quad (4.2)$$

$$\sum_{p \in \mathbb{P}} \gamma_{e,p,t} x_p \leq u_{e,t}, \forall e \in \mathcal{A}, t \in T \quad (4.3)$$

$$x_p \geq 0, \forall p \in \mathbb{P} \quad (4.4)$$

$$\Delta_k \geq 0, \forall k \in \mathcal{K} \quad (4.5)$$

In the RMP formulation, we assume multiple origins with one destination, and it can be easily extended. The evacuation process starts at time  $t = 0$ . Equation (4.1) represents the model's objective to minimize the evacuation cost. Constraints (4.2) ensure that evacuees' demands at all origin nodes are fulfilled. As arc's maximum capacity varies over time, constraints (4.3) enforces the total flow on arc at each time step does not exceed its maximum capacity at any given time  $t$  and constraints (4.4) and (4.5) are nonnegative constraints on the decision variables.

#### Sub Problem (SP)

The subproblem SP aims to generate routes in time-dependent network with positive residual capacity having length not exceeding the makespan  $t_0$ . The SP begins with generating the time-dependent shortest routes for all OD pairs with arrival time no later than the makespan  $t_0$ . These routes are added into the subset only if they are unique. The updated subset becomes input to the RMP for flow scheduling.

Several algorithms have been developed to compute time-dependent shortest routes. In this research, the arc travel cost is assumed to be equivalent with the arc's travel time and adapt the one presented by Mahmassani (1994) to generate the routes. The least time path (LTP) algorithm begins with creating the scan eligible (SE) list and initialize all total travel time  $\Lambda$  and next node  $M$  matrices. The iteration begins by scanning the first node  $i$  in the SE list and stop when the SE list is empty. For each node  $i$ , iterate all nodes in  $\Gamma^{-1}\{i\}$ , a set of nodes that can directly reach node  $i$ , of all time steps, and update the travel time, total cost, and next node information only if the travel time of using node  $j$  to reach node  $i$  is less than the current travel time.

### 3.2. Outer Loop – Evacuation Decision Tree Analysis (EDTA)

Recall that the minimum makespan search or BMS algorithm determines the schedule (e.g., routes, departure time, and flow assignment) assuming the evacuation from origin(s) to destination begins at time  $t$  and over the time horizon  $[t, T]$ . This outer loop decides the sequence of evacuation order for a given set of predicted mobility network states over the time horizon, i.e. which origin(s) and when they should depart.

Decision situations involve some chance events in addition to the sequence of decisions. Each chance event and the corresponding decisions taken can result in different outcomes and affect the future decisions. The chance events are determined mostly by the uncertainty on how the state of the network evolves over time. An algorithm to generate the chance events tree (CETree) that becomes input for the decision tree for the multiple scenarios is to be presented shortly. The fundamental procedure in creating the CETree is to cluster the scenarios such that each chance node provides a realization of the uncertain variable (e.g. arc travel times) up to that time and each path through the tree represents how the uncertainty is revealed over the time horizon. We adapt the event collection generation presented in Gao and Chabini (2002) to perform this task. The probabilities of the event sets are then computed iteratively by comparing each set in the *current* event sets (i.e. *sub-current*) with each set in the *previous* event sets (i.e. *sub-previous*). Let  $j \in J$  be the *sub-current* set from *sub-previous* set  $i$ ,  $p_{j|i}$  be the probability of *sub-current* set  $j$  occurs in the next chance node given *sub-previous* set  $i$  occurs at the present chance node, and  $p_{i|h}$  be the probability of *sub-previous* set  $i$  occurs given its *sub-previous* set  $h$  occurs at the past chance node. If the *sub-current* and *sub-previous* sets are identical, we set probability  $p_{j|i} = p_{i|h}$ , its predecessor probability. If the *sub-current* is the remaining set of the *sub-previous*, then we set  $p_{j|i} = (1 - \sum_{j \in J} p_{j|i})p_{i|h}$ , otherwise, the probability  $p_{j|i}$  remains as a decision variable multiplied  $p_{i|h}$ . The iteration stops when each set becomes a singleton, e.g.,  $\{s_1\}, \dots, \{s_n\}$ . As the scenario probability  $p_s$  is known, we set the last set of equations equal to  $p_s$  and solve the resulting nonlinear system of equations with  $|S| - 1$  decision variables.

Recapping, the size of the decision tree is governed by not only the number of available choices, that is the number of origin nodes, at each decision point, but also the number of possible events that could occur at each chance node. Put simply, as both the number of choices and scenarios being considered increase, the number of branches at each decision node also increases, resulting in a larger tree and significant increase in the runtime. We introduce some approaches to work around this issue. First, nodes in the nearby vicinity are expected to experience similar impacts due to the wide range of storm impacts. Assuming that all nodes are equally important, setting the "origin" nodes as a set of evacuating nodes can be seen as a mean to decrease the number of choices. This argument is also supported

with the fact that cities are commonly clustered into zones to ease the issuance of evacuation order during a hurricane event. Hence, it is justifiable to cluster origins into zone-sets for evacuation purposes. Alternatively, the number of branches emanating from each decision node can be reduced using choice subset elimination: (1) a branch with set of successor nodes can be removed if its successors have no feasible solution; (2) directly set a penalty at the consequence node if none of its outgoing evacuation branches has a feasible solution since it is unnecessary to wait because no better choices are foreseen to be available in the future; and (3) set the appropriate time horizon and decision time interval.

To generate the decision tree, we create branches emanating from the first decision node at time  $\mathcal{D}_t = \mathbf{0}$ . These branches represent all possible evacuation choices ranging from evacuating all origins at once to no origins at time  $t$ . The iteration begins with evaluating the first branch and stopping when all branches in the decision tree array have been evaluated. If the current branch being evaluated is a *chance event branch*, we create chance branches for the current decision time  $t$  and append them to the tree. Otherwise, if the current choice branch being evaluated has at least one evacuating node,  $\{k\} \neq \emptyset$ , then the algorithm calls the BMS to determine whether or not a best makespan for evacuating origin set  $\{k\}$  starting at time  $t$  exists. If infeasibility is pronounced, we delete the current branch and proceed to the next one in the tree. On the other hand, if the best makespan exists, we store the solution, update its information, (i.e., solution pointer and evacuation cost), and check the set of remaining nodes  $\mathcal{R}$ . When all origins have been already evacuated (i.e.,  $\mathcal{R} = \emptyset$ ), the future cost of this current choice branch is zero and we move to evaluate the next branch in the tree. Otherwise, we create new branches representing all possible evacuation choices for a given set of non-evacuated nodes  $\mathcal{R}$ , add them to the tree, and continue to evaluate the next branch in the tree. Once the tree is generated, we employed the *foldback* algorithm to compute the future cost of each branch and finding the *sequence of evacuation order*. The process is straightforward with some steps added to consider branching due to a chance event. The future cost is determined by folding back the tree from the last decision time in the sequence to the initial decision node at time  $t = \mathbf{0}$ . The future cost of a choice branch/node is the minimum total cost among all possible choices while of a chance branch is the sum of the total cost of all possible events. The sequence of evacuation decisions is then identified by a forward pass through the tree.

#### 4. Numerical Example: Manatee County Network

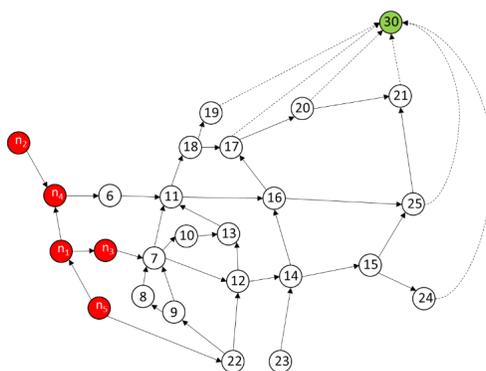


Figure 2. Manatee County's Transport Network

In this example, a real-life-size network, as shown in Figure 2, is utilized to test the EDTA algorithm. The transportation network in Manatee County, FL 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 in this example. 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. Further information on the data-driven simulation model can be found in Ayu et al. (2019). The 48-hours predicted changes on the network states in each scenario is determined accordingly. For this example, we are particularly interested with the storm forecast consistent with the

NHC advisory number 40 which was issued on Saturday September 9, 2017 at 3:00 UTC (Friday September 8, 2017 at 11:00 p.m. EST). The time step  $\ell$  is set to be at 5-minute increment and the decision time is assumed to be at 6-hour interval. The cost to traverse a route is assumed to follow a utility 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 the evacuation orders.

Two cases are considered in this example. The first case assumes three origin nodes with one destination node. That is, 613, 664 and 2686 vehicles are evacuating from  $n_1, n_2$ , and  $n_3$ , respectively, to node 30. The strategy proposed by the EDTA algorithm in this case is as follows. If at  $t = 0$ , scenario  $s_1$  is the foreseeable scenario, then the strategy recommends to evacuate  $n_3$  at 6-h,  $n_1$  at 24-h, and  $n_2$  at 30-h. Otherwise, evacuate  $n_3$  at  $t = 6$  and wait until the next decision time. At  $t = 12$ , evacuate  $n_2$  and if  $s_2$  is the foreseeable scenario, then evacuate  $n_1$  at 18-h. Otherwise, evacuate  $n_1$  at 24-h. The “what-if” plan is obtained by running the scenarios individually. A total of three distinct plans were obtained since the evacuation plan generated from running scenario  $s_3$  and  $s_4$  are identical. These plans are as follows. If the assumed scenario is  $s_1$ , then evacuate  $n_3$  at  $t = 6$ ,  $n_1$  at 24-h, and  $n_2$  at 30-h. If the assumed scenario is  $s_2$ , then evacuate  $n_1$  at 0-h,  $n_3$  at 6-h, and  $n_2$  at 12-h. Lastly, if assumed scenario is  $s_3$  or  $s_4$ , then the plan suggests to evacuate  $n_3$  at 6-h,  $n_2$  at 12-h, and  $n_1$  at 24-h. The issue is at the 0-h, we do not know which scenario will be realized until more information is gathered in the later time. Hence, executing any of these plans can be very expensive if the realized scenario happens to be not the one in which the plan is generated from. As can be seen in Figure 3, when the realized scenario is  $s_1$ , employing evacuation plan based on scenario  $s_2, s_3$ , or  $s_4$  leads to higher evacuation cost. Alike, implementing evacuation plan based on scenario  $s_1, s_3$ , or  $s_4$  leads to higher cost when the realized scenario is  $s_2$ . However, the strategy proposed by the EDTA is constantly giving the best or near the best solution that minimizes the evacuation cost.

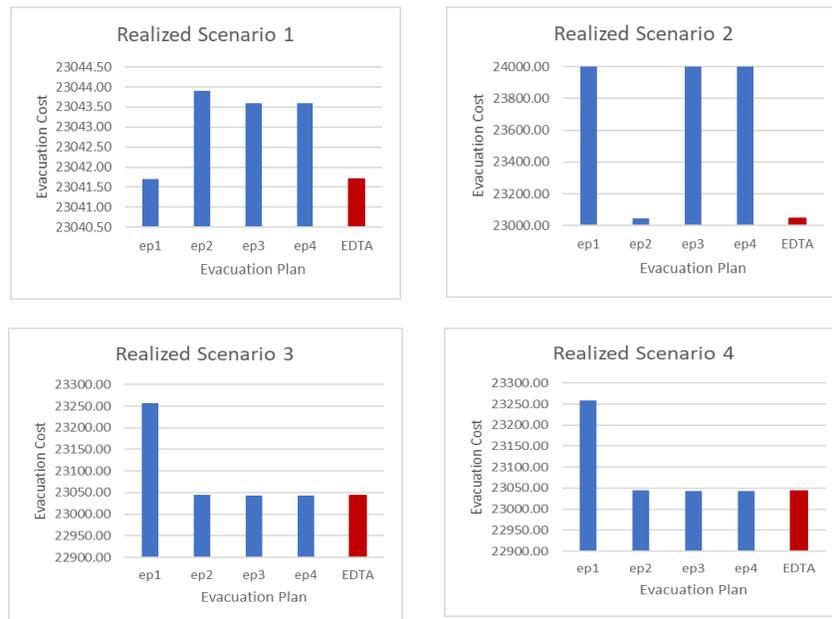


Figure 3. Performance of Evacuation Plan in Each Assumed Scenario (First Case)

The second case assumes five evacuating nodes but three of them (i.e.  $n_3, n_4, n_5$ ) have to be evacuated simultaneously. Hence the origin nodes are  $n_1, n_2$ , and  $\{n_3, n_4, n_5\}$ . The number of evacuating vehicles from node  $n_4$  and  $n_5$  are 2845, and 4928, respectively. 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 the assumed scenario is  $s_2$ , then 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 assumed scenario is  $s_3$  or  $s_4$ , then the plan suggests to 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 4. Similarly, the proposed EDTA strategies lead to the least expected cost in both cases and are found to be among the best in each assumed scenario except in scenario  $s_2$ . EP2 is better by 0.005% (Figure 3) in the first case and 0.0002% (Figure 4) in the second case.



Figure 4. Evacuation Costs for EDTA Strategy and Plan Assumed Scenario (Second Case)

## 5. Conclusion and Future Research Directions

Short-notice sudden onset natural disasters, such as hurricanes, are laden with uncertainties – in locations of occurrences, in extent of intensities, in nature of impacts, and in extent of disruptions. Commonly, such disasters can cause substantial levels of devastation and damages over space and time. Not accounting for the inherent uncertainties when forming response operations can substantially deteriorate their overall effectiveness.

A methodology is developed to determine the quickest evacuation schedule and the corresponding evacuees' routes under the uncertainties modeled via the 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 probabilistic trees. It then evaluates each possible decision at each decision time to generate an evacuation **strategy**. Its performance is then compared with the evacuation **plans** that assume a single scenario with its attendant 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. 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.

This research opens path to new alternatives to solve for evacuation decisions in a stochastic dynamic network, but the research is far from being mature. Yet, it provides encouragement for further research on evacuation response. In this research, we assumed full compliance in the evacuation response modeling which allows us to define evacuees' origins and destinations. However, due to uncertainty in human behavior, each evacuee's destination and choice of departures times can vary. Some evacuees may decide to stay while the others who decide to evacuate may have

their own preference on perceived safe destinations. The dissertation also assumed no shadow evacuation. Yet, shadow evacuation can create additional travel demand to be loaded onto the network which can result in longer travel times and hence longer makespan. This may suggest the need to issue an earlier evacuation order.

Another future research direction is to design time-efficient algorithms for determining optimal evacuation flow scheduling. In the current algorithm of the dissertation, the iteration in the inner loop, (that is, between subproblem and restricted master problem to determine the best makespan at each decision branch), is a major factor in the runtime. Shortening the time to obtain a feasible solution at each decision branch through approximations can possibly reduce the runtime and points to useful future research direction. Such an approximation can be done using a lookup table where the potential routes are stored and pre-checked for their feasibility; this reduces the need to generate the routes at each iteration in the inner loop. The caveat, however, is this approach may not be much beneficial if the potential routes are very diverse between decision times.

Lastly, as disasters commonly affect large areas, it is important to consider the impact of evacuation orders issued in neighboring locations as resulting traffic can affect the roadway capacities. A useful, but difficult, direction for future research would be develop evacuation strategies to jointly consider neighboring zones, where roadway connectivity, network topologies, and traffic management coupling mechanisms need to be considered to recommend routes and departure times for minimum makespan evacuation.

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